One Size Does Not Fit All: Foreign Direct Investment Promotion Policies across US States

Chen Wu
Plymouth State University

Cynthia L. Rogers
University of Oklahoma

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Abstract

US states employ a variety of policies to attract and enhance foreign direct investment (FDI). The uniqueness of state policy choices and economies suggest the effectiveness of given FDI policies is likely to be non-uniform across states. We address this issue by employing a simultaneous quantile regression (SQR) approach using state-level employment by foreign manufacturing firms for 50 states between 1997 and 2008. SQR methods are useful for identifying potential heterogeneous impacts when behavior is different in the tails of the distribution. The estimates provide evidence of heterogeneous responses to policies based on state-level characteristics: the estimated effects of the provision of foreign-trade zones, better infrastructure, and the number and location of promotion offices abroad vary significantly across the FDI-related employment distribution. Robustness tests are offered to address shortcomings of the SQR approach. The results provide nuanced guidance for state policy makers seeking to enhance FDI-related employment in manufacturing.

1 Introduction

Capturing twenty-one percent of the world investment in 2014, the United States remains the biggest recipient of global Foreign Direct Investment (FDI) (Organization for International Investment, 2016). In 2015, the stock of American inward FDI amounted to $3.13 trillion (on a historical-cost basis) after growing annually at an average pace of 8.5 percent since 1998. Meanwhile US FDI inflows reached $348.4 billion regaining a historic high over this period.[1] In 2013 foreign owned affiliates directly employed 6.1 million (or 5.2 percent) of private sector employment and indirectly supported 5.9 million jobs in the US (Telles Jr., 2016).[2] FDI-related jobs offered stability during economic downturns and paid earnings that were 33% higher compared with domestic jobs in both manufacturing and non-manufacturing sectors (Telles Jr., 2016).[3] FDI firms may also create a variety of positive spillovers such as technology transfer and increased competition, which may influence employment of domestic firms in the supply chain (See for instance Jordaan (2011)).

Seeking to attract and retain FDI, national and state level governments all over the world utilize a variety of policy tools, such as the corporation tax incentives offered in Bangladesh (Ahmed, 2015), the place-based policies like free trade zones in China (Wang, 2013), factor-usage subsidies or grants in the U.K. (Devereux et al., 2007; Girma and Gong, 2008), and overseas investment-promotion offices operated by the US states (Cassey, 2014). Despite the widespread proliferation of such policies across US states with most states using

[1] Data source: *SelectUSA STATS*. Retrieved from https://www.selectusa.gov/selectusa-stats.
[2] According to *SelectUSA STATS*, 6.4 million American workers were employed by the US affiliates of foreign firms in 2014. The data for the year of 2015 are not available as of April 2017.
[3] Breau and Brown (2011) discuss reasons for foreign-firm wage premiums. They find that a foreign firm wage premium occurs across industries and regions in Canada.

multiple programs, few studies attempt to incorporate multiple programs in a systematic analysis (Head et al., 1999; Rogers and Wu, 2012).

This paper adds to the small but growing literature investigating the implementation of FDI promotion programs in US states. It extends the literature by investigating the potential for heterogeneous impacts of state FDI-promotion policies on FDI-related employment for 50 US states between 1997 and 2008. It builds directly on Rogers and Wu (2012) who investigate average treatment effects using dynamic panel framework to account for endogeneity concerns. In contrast, we apply a Simultaneous Quantile Regression (SQR) to investigate heterogeneous responses.

An extensive literature focuses on the importance of heterogeneous responses of total employment and other economic outcomes to policy interventions (Görg and Strobl, 2002; Girma and Gong, 2008; Mata and Machado, 1996; Coad and Rao, 2011). Little, however, is known about the heterogeneous employment responses of foreign firms to state level investment promotion policies (Pfaffermayr and Bellak, 2002; Bellak, 2004). If the behavior in the tails of the employment distribution differ significantly from that of the average, as we document below, then policies based on estimates of central-tendencies would be misleading. States need to understand where they are in the distribution to know if average treatment impacts are applicable to them.

The analysis in this paper illuminates heterogeneity of state-specific policies designed to attract inbound foreign investment and enhance employment. Robustness tests are included to address the limitations of the quantile regression approach. Take as a whole the results provide nuanced guidance for state policy makers and reinforces concerns about using appropriate empirical specifications.

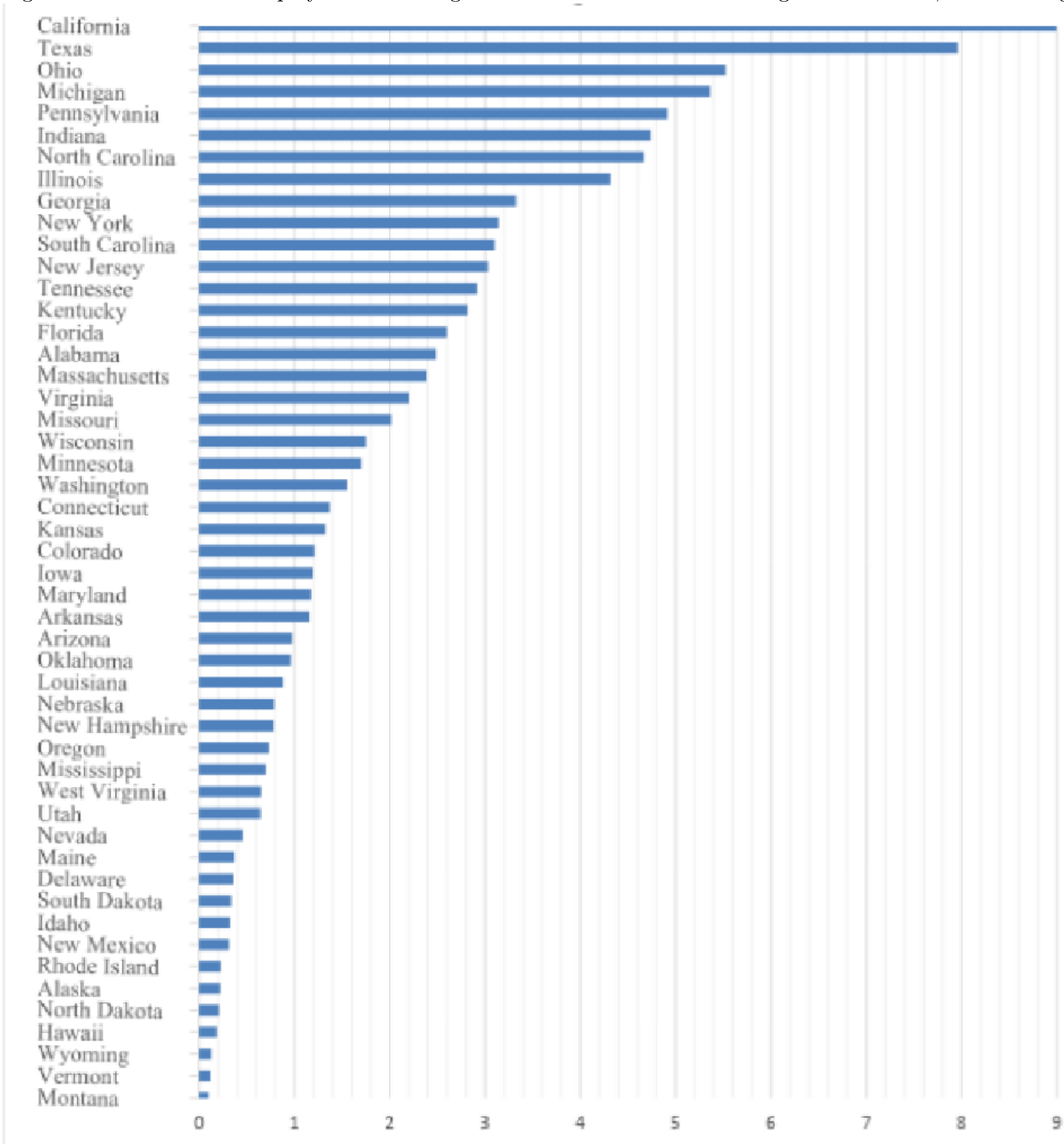
2 Modeling FDI Employment Impacts

The goal of FDI promotion activities is to leverage state investments to stimulate economic activity in the state. Recognizing competitive pressure from other states as well as other countries, states are cognizant of the policies in other states leading to policy mimicking behavior. However, the effectiveness of FDI promotion programs is likely to vary across states with inherently different economies. The literature discusses the strengths and weaknesses associated with different measures of foreign investment activity, such as the investment stock measure (Sun et al., 2002), the establishment count measure (List et al., 2004), the sales volume measure (Blonigen et al., 2005), and the employment measure (Rogers and Wu, 2012; Wu and Burge, 2017), but not potential differential impacts of a given measure. That is, states may have differential responses to particular policies for a given outcome measure. For example, such state-level heterogeneous responses have been documented for monetary policies (Schunk, 2005), and for environmental policies (Fredriksson and Millimet, 2002).

We investigate the potential of differential responses to the investment promotion policies by focusing on an employment measure, the employment in FDI-related industries. There are important reasons for focusing on employment measures rather than other possible outcome measures. State policy makers are particularly attentive to potential technology spillovers (Ford and Rork, 2010) and employment growth opportunities (Amuedo-Dorantes et al., 2015). Thus, the employment measure directly relates to the policy goal of FDI promotion policies. In addition, we focus on manufacturing employment in particular because the US manufacturing sector benefits more than other industries from inward FDI (Telles Jr., 2016). Growing at an annual rate of 9% over the past 10 years, FDI stock in the manufacturing sector totaled $1.2 trillion at the end of 2015 and represented 39% of all FDI stock in the US. FDI-related jobs in manufacturing have grown annually by 5% since the 2008-2009 Recession and reached $2.4 million (or 38% of the national total) in 2014 (SelectUSA, 2017) Notably, FDI-related employment, measured as employment by foreign firms in the manufacturing sector, varies considerably across US states. Figure 1 illustrates that the share of manufacturing FDI-related employment in 2014 ranged from less than 0.2% in Montana, Vermont, Wyoming and Hawaii, to more than 5% in Michigan, Ohio, Texas and California.

The empirical approach described below accounts for this heterogeneity and incorporates common investment-promotion policies as explanatory variables. Following the previous literature, a basic log-linear model can be specified as:

Figure 1: State Share of Employment of Foreign Firms in the US Manufacturing Sector in 2014, in Percentage



Data Source: *Foreign Direct Investment in the U.S., Majority-Owned Bank and Nonbank U.S. Affiliates, Employment – Manufacturing*, 2014, U.S. Bureau of Economic Analysis.

$$logMFGEMP_{i,t} = \beta_0 TAXRATE_{i,t} + \beta_1 SUBSIDY_{i,t} + \beta_2 FTZ_{i,t} + \beta_3 OFFICES_{i,t} + \beta_4 OFFLOCATION_{i,t} + \beta_5 X_{i,t} + e_{i,t} \quad (1)$$

where $MFGEMP_{i,t}$ is the employment (in 1,000s) by foreign-owned firms in state i for years 1997 to 2008.[4] The first five variables account for employment-promotion policies, and the vector X accounts for the lagged FDI-related employment, agglomeration, market, labor, and geographic factors as discussed below.[5] See Table 1 for summary statistics.

Tax rates and subsidies are important state-level FDI promotion policies. $TAXRATE_{i,t}$ is the top corporate income tax rate (in percentage) for each US state.[6] Studies of state economic growth use a variety of tax policy measures such as the ratio of government corporate income tax revenues over personal income, gross state product, or corporate income taxes per capita. Reed and Rogers (2006) suggest using top statutory corporate income tax rate because, unlike other common measures, it reflects actual tax policy changes and is not influenced by non-tax factors. Setting low tax corporate income tax rates is viewed as an advantage in the competition for mobile investment. Accordingly, $TAXRATE$ serves as a proxy for the tax policy environment in a state. $SUBSIDY_{i,t}$, is the per-capita total state expenditure on subsidies.[7] The average per capita subsidy spending was \$183 for the top 5 states (Rhode Island, California, Arizona, Oregon and Connecticut), \$140 for the middle five states (Mississippi, Alaska, Delaware, Pennsylvania and North Carolina) and \$109 for the bottom five states (Idaho, Oklahoma, Utah, North Dakota and West Virginia).[8]

States also establish general purpose and special purpose foreign trade zones, which provide cost savings to FDI-related activities. $FTZ_{i,t}$ is sum of the states total number of general purpose and special purpose foreign trade zones, both of which may involve manufacturing firms. FTZs allow foreign and domestic merchandise to be stored, exhibited, assembled, manufactured, and processed free of US Duty or excise taxes. Special purpose zones are authorized for operations that cannot be accommodated within an existing general-purpose zone. The extent of FTZ use varies considerably across states: FTZ counts ranged from zero to 104 and averaged 13 per state over the panel period.[9]

States also promote FDI by developing and maintaining networks of foreign trade offices. Overseas representatives provide potential foreign investors with assistance related to investment and trade opportunities in the state hosting the office. Following Coughlin and Segev (2000) and Kozlowski et al. (1994), $OFFICES_{i,t}$ is the number of all overseas promotion offices established by each state. Figure 2 highlights the regional dynamics of the distribution of US foreign offices established by states using three years of the data. In 1991, 46 of the 76 foreign offices were associated with 13 eastern and southern coastal states, and the remaining 30 offices were associated with 9 non western states. By 2002, the total number of foreign offices increased sharply: 42 states had 236 foreign offices. Although most offices were established by states in the Atlantic coast and Great Lakes area, 23 were held by 3 Pacific Coast states. In 2009, California, Maine and Utah closed their foreign offices while Delaware, Mississippi, Nebraska, Nevada, New Hampshire and Vermont opened foreign offices for a total of 240 offices held by all but 5 states (Maine, Rhode Island, Utah, Wyoming and California).

Notably, the concentration and growth in office locations has not been uniform across the globe: in 1991 there were three offices in both China and Canada and only one office in Mexico.[10] In 2009, the top five

[4] Both Gross and Ryan (2008) and Rogers and Wu (2012) estimated log-linear models.

[5] In addition to these, Rogers and Wu (2012) also include state and year fixed effects to mitigate concerns of omitted variable bias. As discussed below the SQR method accounts for these concerns in a different manner. Robustness tests are used to investigate these concerns.

[6] Rates are given in the Tax Foundations *State Corporate Tax Rates* for various years.

[7] Data are from *Gross Domestic Product by State*, Regional Economic Information System, Bureau of Economic Analysis (1997-2008). The measure includes both employment and capital subsidies. Unfortunately, information on employment subsidies is not available from the BEA.

[8] Two-tailed tests of differences of means results in P-values of less than .0001 for the top group and the bottom group compared with the middle group. Data source: *State and Local Government Finances by Level of Government and by State: 1997-2008*, State and Local Government Finance, U.S. Census Bureau. http://www.census.gov/govs/www/financegen.html/

[9] The latest data is that at the year end of 2015, there were FTZs in every US state totaling more than 400 general purpose and 250 special purpose zones. Source: *Annual Report of the FTZ Board to the Congress of the United States*, various years, US Department of Commerce.

[10] See Figure 4 of Rogers and Wu (2012) (page 669) for a more detailed presentation of the growth in office locations from

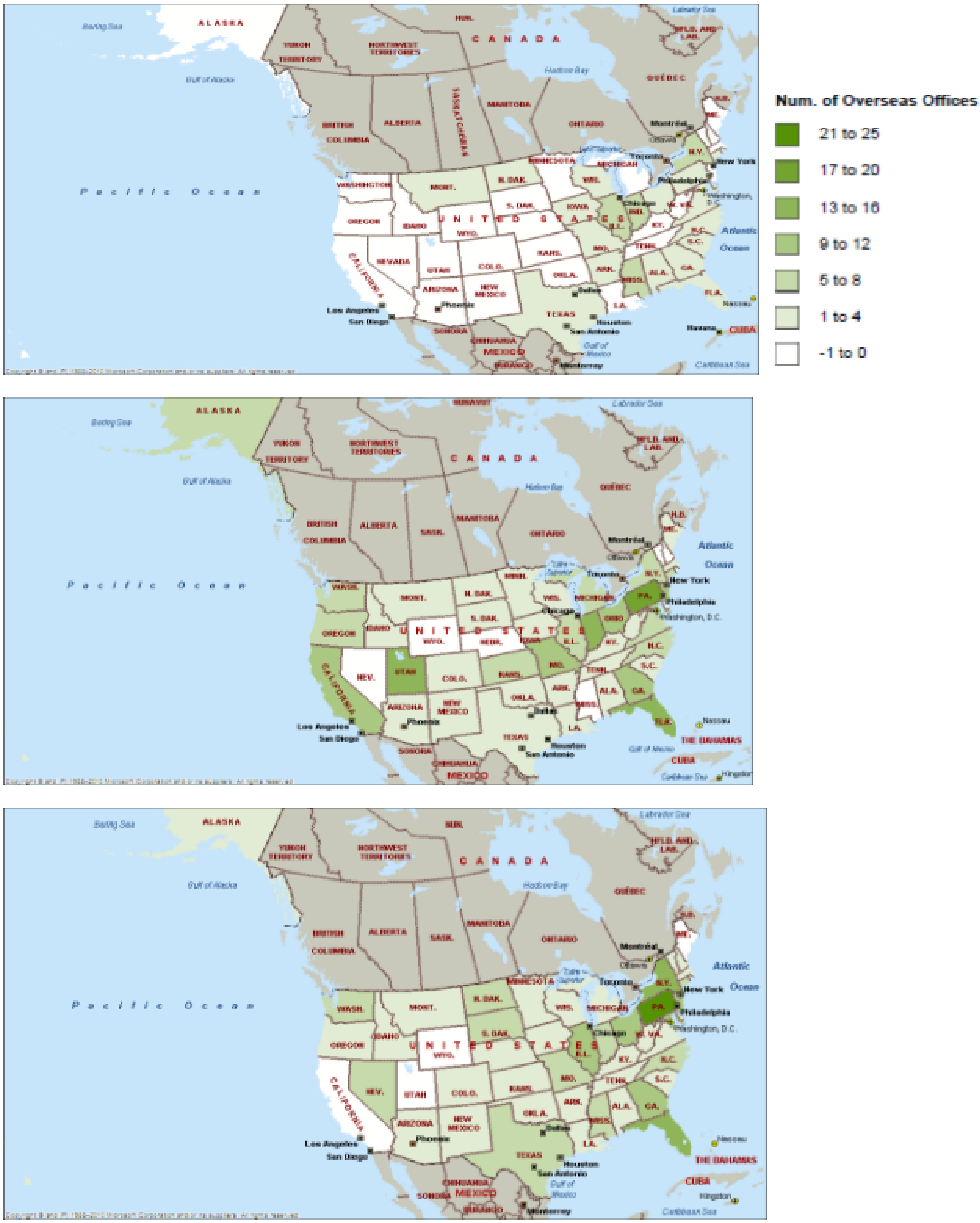
Table 1: Summary Statistics (1997 – 2008, by State)[a]

Variable	Description	Mean (S.D)	Min	Max
$\text{MFGEMP}_{i,t}$	Employment by foreign owned firms in manufacturing	38.78 (40.52)	0.5	208.2
$\text{TAXRATE}_{i,t}$	Top corporate income tax rate	6.76 (2.79)	0	12
$\text{SUBSIDY}_{i,t}$	Total expenditure on subsidies per capita	142.24 (77.78)	22.84	624.32
$\text{FTZ}_{i,t}$	Total number of foreign trade zones in state	13.37 (15)	0	104
$\text{OFFICES}_{i,t}$	Number of all overseas promotion offices established by state	3.75 (4.04)	0	23
$\sum \text{ALLEMP}_{i,j,t}$	Sum of FDI-related employment in all industries in adjacent states	111.56 (126.87)	3.7	749.4
$\text{INCOME}_{i,t}$	Personal income per capita	31,246.86 (6,255.13)	18,880	56,245
$\sum \text{INCOME}_{i,t}$	Sum of per capita personal income in all adjacent states	79,013.26 (10.40)	29,512.09	299,916.25
$\text{COMPENSATION}_{i,t}$	Average annual manufacturing compensation per employee	53,844.67 (11,508.01)	30,635.35	92,279.29
$\text{UNEMP}_{i,t}$	Unemployment rate (%)	4.68 (1.14)	2.3	8.3
$\text{HSEDU}_{i,t}$	Share of population over 25 years of age with at least a high school diploma (%)	84.77 (4.15)	72.9	92.8
$\text{HIGHWAY}_{i,t}$	Miles of highways per square mile of land area	1.64 (0.96)	0.02	4.50
Border Dummies: MEX_iCAN_i	Dummy variable indicating if state borders Mexico and Canada, respectively	4 states border Mexico; 12 border Canada	0	1

[a] BEA state-level data on US affiliates employment include both bank and nonbank affiliates after 2008 but not before. As a result, state FDI-related employment data are for the years 1997-2008 for consistency.

Note: The number of observations is 600 except for $\text{MFGEMP}_{i,t}$ and $\sum\text{ALLEMP}_{i,j,t}$

Figure 2: Distribution of Overseas Offices by US States in 1991, 2002 and 2009 (from top to bottom)[a]



[a] Based on the data collected and compiled by the authors, Figure 1 is made originally using Microsoft MapPoint 2011 and all rights are thus reserved.

office locations were China (34), Japan (30), Mexico (25), Canada (14), and Taiwan (14). Following Rogers and Wu (2012) differential impacts are investigated using $OFF\ LOCATION_{i,t}$, which represents a set of dummy variables for all foreign office country locations (refer to the note on Table 3 for the list of countries and related abbreviations).[11]

The other explanatory variables are also informed by the previous literature. $INCOME_{i,t}$ is per capita personal income in state i and year t (in current US dollars) and $\sum_{j \neq i} INCOME_{i,j,t}$ is the sum of per capital personal income in all states adjacent to state i. It accounts for potential spillovers from neighboring states and likely regional income affects. Regions with higher incomes are likely to have more investment opportunities, ceteris paribus. $COMPENSATION_{i,t}$ is the annual manufacturing compensation per manufacturing worker.[12] $UNEMP_{i,t}$ is state unemployment rate in year t (as a percent).[13] $HSEDU_{i,t}$ is the share of population over 25 years of age with at least a high school diploma (as a percent).[14] $HIGHWAY_{i,t}$ is miles of highways per square mile.[15] MEX_i and CAN_i are dummies set to 1 if the state borders Mexico and Canada, respectively.

Within a cross-sectional framework, the interpretation of time effects indicated in Equation (1) is worth noting. The estimation of Equation (1) could reasonably yield long-run parameters by utilizing state-level, cross-sectional data (Goel and Ram, 2004). Accordingly, the estimation results presented below refer to the long-run effects on state-level FDI-related employment. In addition, lagged FDI-related employment ($MFGEMP_{i,t-1}$) measures the intra-industry-within-state FDI agglomeration effect (Blonigen et al., 2005; Barrios et al., 2006). More importantly, a quantile regression approach with bootstrapped standard errors treats Equation (1) as an error-correction model (Rogers, 1992). Therefore, even when time dummies are excluded, the short-run dynamic components, i.e. the lagged FDI-related employment variable, capture the cyclical shock (Dufrenot et al., 2010).[16]

Inter-industry-cross-state agglomeration is captured by the sum of FDI-related employment in all industries in adjacent states ($\sum_{j \neq i} ALLEMP_{i,j,t}$), which reflects regional effects for locations that are particularly attractive to FDI activity.[17]

3 Econometric Issues

Analysis of the data reveals that state-level manufacturing FDI-related employment in the US does not have a normal distribution, even though it is measured in a logarithmic form (log *MFGEMP*). Figure 3 shows that both the real density and the Kernel density estimates of *MFGEMP* depart from the normal distribution. This is also confirmed by the 1st column of Table 2, which describes the summary statistics for the dependent variable: the reported P-values from both Shapiro and Francia (1972) test for normality and D'Agostino et al. (1990) skewness and kurtosis test for normality are statistically significant at 1 percent level, rejecting the null hypothesis that *MFGEMP* is normally distributed. Figure 4 compares the real density and the Kernel density estimates of log *MFGEMP* with that of a normal distribution. Although the departure from normality is subtle in the figure, the results from two normality tests strongly reject the null hypothesis of a normal distribution (see Column 2 of Table 2).

Because the distribution of the dependent variable violates the normality assumption, estimated average

2002 to 2009.

[11]Data are available from *Directory of Incentives for Business Investment and Development in the United States: A State-by-State Guide, 1991*, National Association of State Development Agencies (NASDA); *State Officials Guide to International Affairs*, by Chris Whatley, the Council of State Governments.

[12]Income and compensation data are available from *Personal current taxes and Compensation of Employees by NAICS Industry*, Regional Economic Information System, Bureau of Economic Analysis.

[13]*Local Area Unemployment Statistics*, US Bureau of Labor Statistics, various years.

[14]*Educational Attainment by State: 1990 to 2009*, FactFinder, U.S. Census Bureau; *50 State Comparison - Fiscal, Economics, and Population Table*, Postsecondary Education Commission of California.

[15]*Highway Statistics*, various years, U.S. Federal Highway Administration and *U.S. States Area and Ranking* available at EnchantedLearning.com.

[16]Including this variable accounts for some concerns that some states are more closely tied to global international trade patterns. As we show below, the lagged dependent variable is robust through a variety of alternative specifications.

[17]Jordaan (2008) finds regional agglomeration to be important for the location choice of FDI in Mexican Regions using FDI-related employment as a share of regional manufacturing employment.

Table 2: Summary Statistics for State-Level Manufacturing FDI-Related Employment in US (*MFGEMP*) and Log *MFGEMP*, 1997-2008

Statistics	Variable			
	MFGEMP (1000s)		*log MFGEMP*	
Mean	38.78		4.298	
Standard Deviation	40.516		0.578	
Skewness	1.449		-0.496	
Kurtosis	4.842		2.455	
5th quantile	1.6		3.23	
10th quantile	2.75		3.447	
25th quantile	8.7		3.942	
Median	21.5		4.336	
75th quantile	57.2		4.765	
90th quantile	97.3		4.985	
95th quantile	120.3		5.08	
Num. of Obs.	600		600	
Test 1 (P-value)	0.000	***	0.000	***
Test 2 (P-value)	0.000	***	0.000	***

Notes:
Test 1: Shapiro and Francia (1972) test for normality
Test 2: D'Agostino et al. (1990) skewness and kurtosis test for normality

Figure 3: Density Estimates of State-Level FDI-Related Manufacturing Employment in US (*MFGEMP*), 1997-2008)

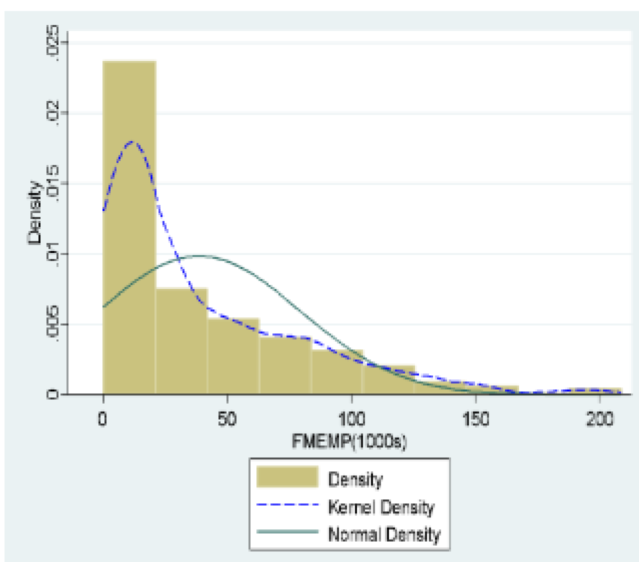
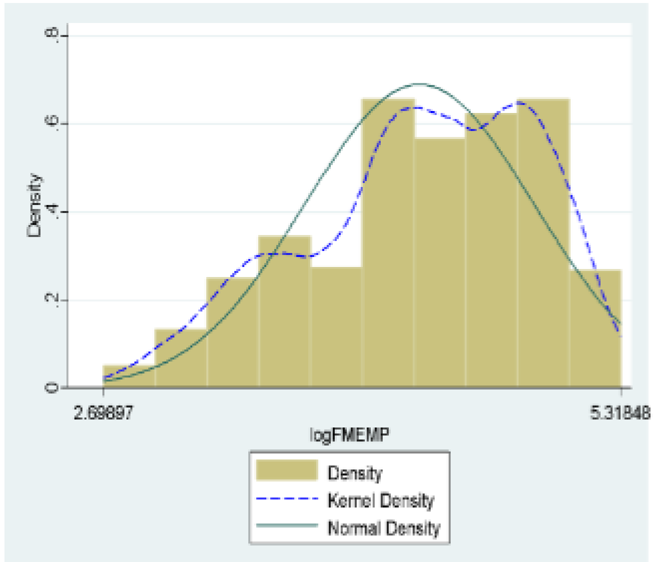


Figure 4: Density Estimates of log of State-Level FDI-Related Manufacturing Employment in US, Log *MFGEMP*, 1997-2008



effects generated using least squares regression techniques are problematic (Girma and Görg, 2005; Gomanee et al., 2005; Okada and Samreth, 2012). Quantile regression techniques center regressors around different quantiles to generate estimates of the effect of independent variables on the outcome of interest in the center as well as the lower and upper tails of the conditional distribution of the response variable (Koenker and Bassett Jr, 1978). This approach provides a more nuanced understanding of the dynamics of FDI-related employment responses across the entire distribution. Furthermore, the quantile regression approach is more robust to outliers and requires weaker stochastic assumptions to obtain consistency compared with least-squares regressions (Cameron and Trivedi, 2005; Okada and Samreth, 2012).

Our analysis applies a Simultaneous Quantile Regression (SQR) approach in a random effects model with a cross-sectional data. The SQR approach estimates the equation for multiple quantiles simultaneously using bootstrapping to obtain a robust variance-covariance matrix of estimators. This allows for hypothesis testing of coefficients both within and across equations. A primary benefit of using the SQR approach is that it accounts for unobserved heterogeneous effects. Specifically, the approach allows the τth quantile of state FDI-related employment to be conditional on (1) the explanatory variables X, and (2) the quantile of the state conditional on X. Accordingly, the response coefficients are obtained at multiple quantiles of both observed and unobserved factors (Sula, 2011). This makes the inclusion of individual fixed effects less beneficial and mitigates concern about potential bais due to unobserved state- and/or time-specific effects (Dufrenot et al., 2010). Moreover, the FDI-related employment in a given state falls within a particular range of quantiles. Thus, the SQR approach used in application accounts for the heterogeneous distribution of FDI-related employment among states.

Despite recent advances (e.g., Koenker (2004); Galvao Jr (2011); Lamarche (2010)), the application of quantile regression techniques to a fixed effects model is not straightforward (Sula, 2011; Gomanee et al., 2005). Differencing (or time-demeaning) the data, which is a typical way to estimate a fixed-effect model, is inappropriate for quantile regression: the sum of quantiles conditional on X is not equal to the quantiles of the sum of Y (Arias et al., 2001).[18] Specifying a model that includes a set of individual state– and/or time-specific dummy variables is also inappropriate and is not likely to produce credible estimates of time-varying effects.[19] Including too many individual fixed effects may inflate the variation of estimating other

[18] $\sum_{i=1,2,\ldots N} \mathrm{Q}_{Y\,i}\ (\tau \mid \mathrm{X}) \neq Q_{\sum_{i=1,2,\ldots N}}\ \mathrm{Y}_i\ (\tau \mid \mathrm{X})$

[19] Estimation of fixed effects in quantile regression models requires assumptions of a large number of time periods and that the number of time periods goes to infinity as the sample size goes to infinity. The T>n assumption is restrictive in our setting.

explanatory variables and as a result, it may not be credible to estimate an individual specific location-shift effect (Koenker, 2005). As discussed below, we investigate linear time trends to further investigate time-varying effects.

4 Results

Table 3 presents the SQR estimates where the basic model is estimated as simultaneous equations across quantiles of state manufacturing FDI-related employment. To allow for the presence of heteroskedasticity, standard errors are bootstrapped following the procedure introduced by Gould (1998). We report estimated coefficients for 10 percentiles of state employment by foreign manufacturing firms. To compare effects at various quantiles with the conditional mean effect, Table 3 also presents results from the OLS regression estimate with random effects as well as the results from Rogers and Wu (2012) that use the dynamic system GMM (DSGMM) estimator.

Figures 5a through 5n plots the estimated coefficients by quantile to illustrate the heterogeneity of FDI-related employment responses to each independent variable across its distribution. To further test whether these coefficients are statistically different across quantiles, Table 4 reports the results from F-tests of equality (Dufrenot et al., 2010; Gomanee et al., 2005). The discussion of results focuses primarily on coefficients for investment-promotion policy variables. Among the non-policy variables, only those whose estimated coefficients are statistically significant and/or statistically different across the distribution are discussed. Comparing the SQR estimate results with that of OLS and DSGMM approach highlights scenarios in which conditional mean effects may not be reliable.

Figure 5: Empirical Results _ SQR Estimate Results when All State Investment-Promotion Policies Are Included

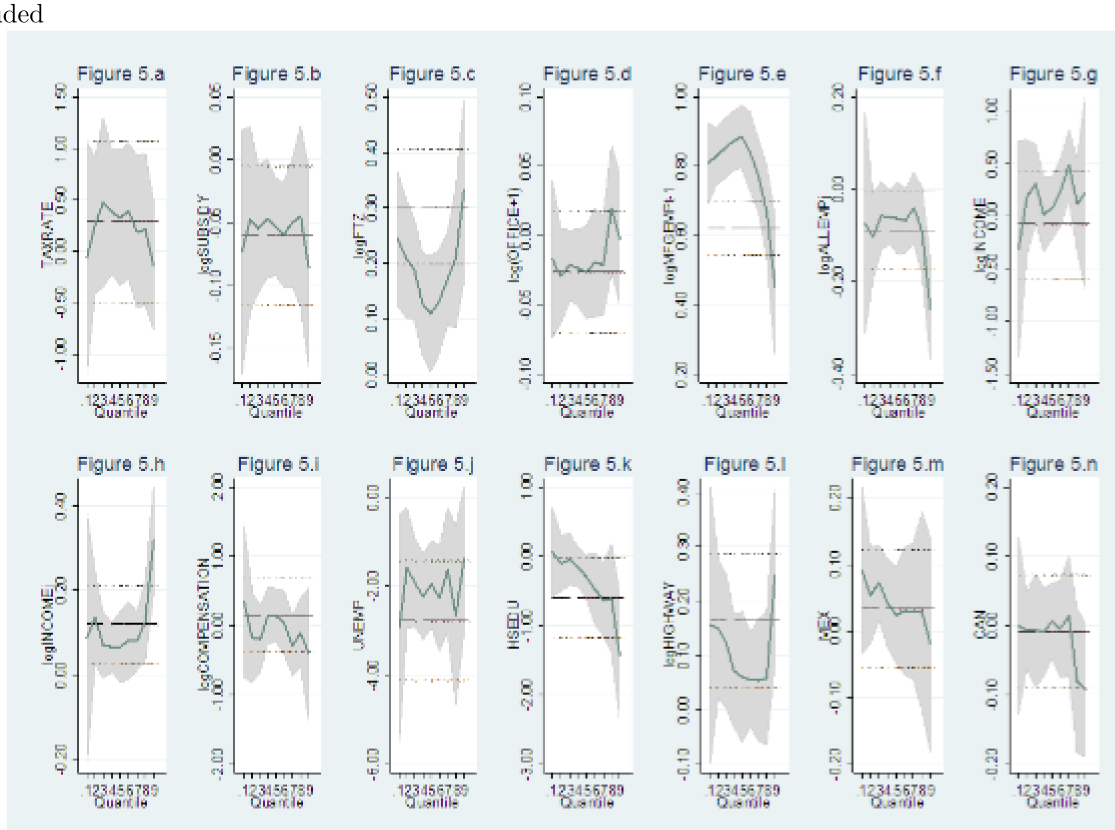


Table 3: Empirical Results, Dependent Variable: Logarithm of State Employment by Foreign Manufacturing Firms in US

Independent Variables[a]	**Quantile Regressions**									**OLS_RE**	**DSGMM_FE**
	10th	20th	30th	40th	50th Median	60th	70th	80th	90th	Mean	Mean
TAXRATEi,t	-0.063	0.253	0.476	0.382	0.327	0.391	0.189	0.211	-0.135	0.294	0.802
	[.627]	[.365]	[.381]	[.351]	[.340]	[.363]	[.410]	[.550]	[.575]	[.386]	[.455]*
logSUBSIDYi,t	-0.073	-0.047	-0.054	-0.046	-0.052	-0.059	-0.51	-0.045	-0.085	-0.06	0.048
	[.041]*	[.032]	[.031]*	[.026]*	[.026]**	[.028]**	[.030]*	[.039]	[.045]*	[.030]**	[.054]
logFTZi,t	0.244	0.208	0.189	0.126	0.108	0.129	0.171	0.209	0.331	0.302	0.323
	[.067]***	[.069]***	[.062]***	[.062]**	[.058]*	[.060]**	[.065]***	[.081]***	[.092]***	[.078]***	[.119]***
log(OFFICES+1)i,t	-0.017	-0.029	-0.021	-0.023	-0.026	-0.019	-0.021	0.019	-0.002	-0.026	-0.059
	[.025]	[.015]**	[.013]*	[.013]*	[.012]**	[.017]	[.022]	[.026]	[.025]	[.017]	[.048]
OFF_LOCATIONi,t[b]											
Positive and Significant	KO	IT JP KO ML MX RS SP	CN DB IT JP KO ML	CN DB IN JP KO	DB JP KO ML	CN JP KO	CN JP MX	CN IL	CN GM IL MX SP UK	CN EG IL JP KO ML MX SP UK	AR CN EG GN IR JP KO ML MX SG SP TK
Negative and Significant	TW	BZ EU NL TW	BZ CA EU FR KZ NL SL TW	AG BZ CA EU KZ TW	AG EU KZ	BZ EU CA	None	VN	HK LA NL SG TK VN	BZ CA EU LA NL SL TW VN	BZ CH EU GM KZ RS SA SL TW VN VZ
logMFGEMPi,t-1	0.809	0.829	0.851	0.873	0.885	0.843	0.771	0.669	0.452	0.621	0.514
	[.100]***	[.062]***	[.052]***	[.053]***	[.055]***	[.064]***	[.076]***	[.103]***	[.103]***	[.081]***	[.122]***
$log\sum_{j\neq i}ALLEMPi,j,t$	-0.073	-0.103	-0.057	-0.059	-0.062	-0.067	-0.04	-0.09	-0.258	-0.088	0.132
	[.094]	[.065]	[.058]	[.046]	[.047]	[.051]	[.060]	[.069]	[.081]***	[.044]**	[.075]*
logINCOMEi,t	-0.316	0.173	0.304	0.017	0.072	0.219	0.484	0.107	0.217	-0.078	0.058
	[.578]	[.350]	[.274]	[.225]	[.218]	[.238]	[.253]***	[.324]	[.415]	[.280]	[.600]
$log\sum_{j\neq i}INCOMEi,j,t$	0.086	0.135	0.07	0.065	0.066	0.081	0.08	0.128	0.317	0.119	-0.182
	[.114]	[.073]*	[.063]	[.054]	[.052]	[.059]	[.066]	[.080]	[.095]***	[.052]**	[.095]
logCOMPENSATIONi,t	0.341	-0.17	-0.197	0.148	0.139	0.04	-0.298	-0.102	-0.411	0.159	0.757
	[.616]	[.348]	[.290]	[.255]	[.237]	[.273]	[.290]	[.326]	[.385]	[.305]	[.772]
UNEMPi,t	-2.932	-1.584	-1.915	-2.233	-1.948	-2.266	-1.625	-2.65	-1.388	-2.775	-3.293
	[1.162]***	[.766]**	[.524]***	[.531]***	[.581]***	[.661]***	[.831]***	[1.035]***	[.973]	[.817]***	[1.192]***
HSEDUi,t	0.058	-0.102	-0.037	-0.154	-0.296	-0.47	-0.632	-0.603	-1.435	-0.597	-2.087
	[.424]	[.255]	[.243]	[.246]	[.252]	[.278]*	[.340]*	[.452]	[.543]***	[.282]***	[.635]***
logHIGHWAYi,t	0.155	0.148	0.124	0.071	0.06	0.055	0.054	0.057	0.246	0.164	0.247
	[.120]	[.066]**	[.052]**	[.060]	[.063]	[.068]	[.079]	[0.79]	[.110]**	[.066]***	[.075]***
MEXi	0.091	0.053	0.072	0.042	0.023	0.03	0.029	0.029	-0.019	0.033	-0.016
	[.077]	[.045]	[.043]*	[.045]	[.041]	[.051]	[.066]	[.084]	[.087]	[.048]	[.038]
CANi	-0.001	-0.006	-0.007	-0.009	0.006	-0.005	0.013	-0.08	-0.092	-0.007	0.168
	[.109]	[.039]	[.038]	[.038]	[.041]	[.045]	[.051]	[.067]	[.078]	[.042]	[.073]**
Constant	0.574	0.632	0.159	-0.064	-0.168	-0.084	0.542	1.779	4.222	1.512	
	[1.372]	[.809]	[.765]	[.754]	[.795]	[.918]	[1.046]	[1.214]	[1.196]**	[0.899]*	
Num. of Obs.	515	515	515	515	515	515	515	515	515	515	475
R^2	0.866	0.883	0.884	0.882	0.879	0.874	0.862	0.849	0.836	0.971	

[a] Bootstrapped standard errors for simultaneous quantile regressions and robust standard errors for the OLS method are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 level, respectively.

[b] Key Abbreviations: AG-Argentina; AT-Australia; AR-Austria; BZ-Brazil; CA-Canada; CH-Chile; CN-China; CZ-Czech Republic; DB-Dubai; EG-Egypt; EU-Europe Union; FR-France; GM-Germany; GN-Ghana; GR-Greece; HK-Hongkong; IL-Ireland; IN-India; IR-Israel; IT-Italy; JP-Japan; KO-Korea; KZ-Kazakhstan; LA-Latin American; ML-Malaysia; MT-Montenegro; MX-Mexico; NL-Netherlands; PL-Poland; QT-Qatar; RS-Russia; SA-South Africa; SB-Saudi Arabia; SD-Scandinavia; SG-Singapore; SL-Switzerland; SP-Spain; TK-Turkey; TW-Tai Wan; UK-United Kingdom; UR-Ukraine; VN-Vietnam; VZ-Venezuela

Table 4: Tests of Equality between Coefficients at Different Quantiles in Table 3

Independent Variables[a]	Quantiles													
	10-50	20-50	30-50	10-70	10-90	20-70	20-80	20-90	30-80	30-90	40-80	40-90	50-80	50-90
TAXRATEi,t	0.563	0.849	0.612	0.729	0.93	0.92	0.943	0.564	0.654	0.358	0.735	0.388	0.835	0.46
logSUBSIDYi,t	0.611	0.846	0.924	0.632	0.836	0.95	0.952	0.502	0.82	0.562	0.957	0.387	0.824	0.466
logFTZi,t	0.138	0.096*	0.062*	0.468	0.448	0.578	0.988	0.201	0.771	0.116	0.216	0.010***	0.096*	0.005***
log(OFFICES + 1)i,t	0.716	0.86	0.684	0.901	0.669	0.74	0.075*	0.38	0.094*	0.502	0.065*	0.386	0.029**	0.265
OFF_LOCATIONi,t b														
Positive and Significant	KO	JP KO ML	DB JP KO ML	None	None	JP MX	None	MX SP	CN	CN	CN	CN	None	None
Negative and Significant	None	EU	EU	None	None	None	None	NL	None	NL	None	None	None	None
logMFGEMPi,t-1	0.418	0.295	0.39	0.706	0.01***	0.409	0.065	0.001***	0.022**	0.000***	0.005***	0.000***	0.001***	0.000***
$log \sum_{j \neq i} ALLEMP_{i,j,t}$	0.928	0.52	0.909	0.798	0.157	0.415	0.853	0.05**	0.621	0.004***	0.618	0.005***	0.636	0.006***
logINCOMEi,t	0.493	0.703	0.251	0.174	0.363	0.358	0.856	0.909	0.556	0.823	0.771	0.558	0.905	0.697
$\sum_{j \neq i} INCOME_{i,j,t}$	0.879	0.297	0.924	0.968	.0146	0.503	0.925	0.050**	0.394	0.002***	0.327	0.001***	0.301	0.001***
logCOMPENSATIONi,t	0.725	0.322	0.11	0.276	0.233	0.736	0.874	0.618	0.794	0.59	0.468	0.145	0.434	0.135
UNEMPi,t	0.437	0.599	0.947	0.332	0.329	0.964	0.355	0.87	0.484	0.638	0.672	0.413	0.406	0.58
HSEDUi,t	0.428	0.463	0.253	0.17	0.028**	0.141	0.215	0.027**	0.136	0.019**	0.216	0.025**	0.328	0.028**
logHIGHWAYi,t	0.506	0.204	0.226	0.558	0.603	0.324	0.342	0.401	0.425	0.265	0.856	0.083*	0.965	0.060
MEXi	0.488	0.536	0.153	0.562	0.35	0.69	0.732	0.385	0.535	0.266	0.829	0.471	0.934	0.639
CANi	0.951	0.779	0.709	0.886	0.479	0.736	0.288	0.329	0.255	0.273	0.217	0.284	0.11	0.179

[a] P-values of F tests are reported. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 level, respectively.

[b] Same host country dummies whose coefficients are estimated to be statistically significant between regressions at different quantiles. Key abbreviations used here are the same with the ones reported in Table 3.

4.1 State Investment-Promotion Policies

The estimated impact of state top corporate income tax rate ($TAXRATE_{i,t}$) displays an inverted U-shape pattern with negative coefficients for the 10th and 90th quantile and positive coefficients for the 20th to the 80th quantiles (see Figure 5a). The reported F-tests of equality in Table 4, however, indicate a failure to reject the null hypothesis of equality for $TAXRATE_{i,t}$ across quantiles. This implies that the magnitude of the coefficients on $TAXRATE_{i,t}$ is about the same between quantiles. The coefficient estimates are statistically insignificant for all quantiles. With the presence of endogeneity, however, the SQR estimates will be inconsistent and affect the tests of significance.

Comparisons with previous estimates are not straightforward given differences in estimation techniques, empirical specifications and outcome variables. Other studies also fail to find significant tax rate impacts (Levinson, 1996; Blonigen and Davies, 2004). Studies that find a negative effect (Bartik, 1985; Head et al., 1999; Woodward, 1992; Coughlin and Segev, 2000) diverge in terms of which spending variables are included in the specifications. The closest comparison to the estimates in this paper is Rogers and Wu (2012) which finds a positive and statistically significant tax effect using GMM techniques with similar panel data. Given the presence of heterogeneity across the employment distribution, their estimates support the findings of positive coefficient for most of the quantiles outside of the tails. The notable departure when using the SQR technique is the negative estimated coefficients for the upper and lower tails of the distribution. Even though these are not found to be statistically significant or different from the middle quantiles, they still provide unbiased estimates of the impacts at these points in the distribution.

The estimated coefficients on government total subsidies/grants spending ($SUBSIDY_{i,t}$) are negative and statistically significant for most quantiles. The reported P-values of the F-tests suggest a failure to reject the null hypothesis of equality for coefficients on $SUBSIDY_{i,t}$ between quantiles. Accordingly, the average of coefficients at all quantiles seems to be consistent with the mean effect generated by the OLS estimate (Figure 5b). The reported negative relationship diverges from Head et al. (1999). Head et al. utilize the subsidies on jobs creation and capital usage which may be endogenous, whereas the SQR results in this analysis use government total spending on subsidies. Given that factor usage may be a small portion of total grants and subsidies, the results are not directly contradicting.[20] Herrera-Echeverri et al. (2014) reports a similar effect for emerging markets: government spending adversely affects the activities of venture capital investment conditional on a high quality of institutions in emerging markets. More notable is the divergence from the DSGMM estimates which suggest insignificant but economically large positive impacts of subsidies. The non-robustness across the estimation techniques points to the potential importance of accounting for non-normality. The SQR estimates in this paper suggest that size of total state subsidies tends to have a negative effect on FDI-related employment. This warrants further investigation into potential crowd out effects.

The provision of FTZs is estimated to have positive and statistically significant effects throughout the distribution of state manufacturing FDI-related employment. The positive coefficient estimates are consistent with the OLS and the DSGMM estimates. The magnitudes of the positive coefficients, however, vary significantly between quantiles: a 10 percent increase in the count of FTZs is predicted to correlate with various rates of employment growth ranging from 1.08 percent at the 50th up to 3.31 percent at the 90th. The reported F-tests of equality indicate rejecting the null hypothesis of equality for coefficients between the lower and the median, and between the median and the higher quantiles.

Plotting the estimated coefficients on $FTZ_{i,t}$ for different quantiles, Figure 5c reveals a U-shape pattern: the positive impact of FTZs on state FDI-related jobs first decreases with quantiles and then increases after reaching the minimum at the median. This is an interesting finding that warrants further investigation into the driving mechanism. It is possible, for instance that the characteristics of demand for labor by foreign firms is more elastic at the lower tail of the distribution than at the median. In this case, foreign firms would be more sensitive to a policy change at the lower tails. Firms located at the upper tail of the employment distribution, on the other hand, may face capacity constraints such that favorable policies encourage expansion of production scale and a corresponding increase in FDI-related employment.

The SQR estimated coefficients on $OFFICE_{i,t}$ suggest that the *total* count of state trade offices abroad

[20] Government subsidies and grants for factor usage may be a small portion of total governmental subsidies/grants. Thus, the results are not directly comparable.

has a predicted small and negative effect on the FDI-related employment for all quantiles except the 80th. The negative relationship is statistically significant at the lower and median quantiles. Furthermore, the reported F-tests of equality suggest that the null hypothesis of equal coefficients is rejected only between the 80th and other quantiles. This refines the DSGMM estimates by Rogers and Wu (2012) which predicts a negative and statistically insignificant average effect of having more overseas offices. The SQR estimates suggest that states located below the median of the employment distribution may fail to boost the FDI-related employment by establishing more overseas offices.

The SQR estimates reinforce the findings of Rogers and Wu (2012) who reveal a notable relationship between the selection of foreign office locations and US FDI-related employment. To be specific, holding foreign offices in East Asia (e.g. Korea, Japan, China, Malaysia, India) is predicted to have a significant and positive effect throughout the employment distribution; whereas having overseas offices in South America (e.g. Brazil, Argentina) and the European Union is estimated to have a negative effect. In addition, the SQR estimate adds to the conditional mean effects by revealing the heterogeneous effects of office locations across the employment distribution. For example, state overseas offices in China, Korea, Japan and Mexico all have estimated positive and significant effects according to the OLS and DSGMM estimates.[21] However, offices in China are not predicted to promote the US FDI-related employment at its lower tail; offices in Korea and Japan are predicted to fail at the upper tail and offices in Mexico may fail at quantiles around the median. The reported F-tests of equality further confirm that office locations rarely have uniform effects across quantiles. Notably, the conditional mean effects would miss some office-host countries, such as Dubai (positive) and Argentina (negative), which may have a significant relationship with the employment by US affiliates at some but not other quantiles. The estimates are informative for guiding states in the choice of office locations.

4.2 Other Explanatory Variables

Of note are the non-policy variables which have estimated coefficients that follow an inverted U-shape pattern across quantiles. For instance, the estimated coefficients on the intra-industry-within-state dimension of agglomeration ($MFGEMP_{i,t-1}$) are positive and significant at 1% level throughout the employment distribution. This is consistent with the OLS and DSGMM estimates as well as several previous papers (Devereux et al., 2007; Woodward, 1992; Coughlin and Segev, 2000; List, 2001; Head et al., 1999; Rogers and Wu, 2012) .[22] This suggests that US affiliates of foreign manufacturing firms tend to cluster within one state.[23] Figure 5e reveals an inverted U-shape pattern across quantiles: the positive intra-industry-within-state agglomeration effect first increases and peaks at the median (0.889). After that, its magnitude decreases with quantiles and drops by half at the 90th quantile. The reported F-tests of equality further confirm this pattern and suggest the null hypothesis of equal coefficients is rejected between the lower and the higher, as well as between the median and the higher quantiles. According to the SQR estimates, states that are located below the median of the employment distribution tend to incur an increasingly larger benefit from the within-state manufacturing FDI clustering compared with states in the high percentiles. Sawyer et al. (2015) offers a possible explanation: for the US based companies investing in Latin America and Caribbean, more recent foreign investment (usually smaller in scale and located in states in the low percentiles of FDI-related employment distribution) have higher expansion opportunities than the larger foreign companies.

The estimated coefficients for all-industry-cross-state FDI agglomeration effect ($\sum_{j\neq i} ALLEMP_{i,j,t}$) also display an inverted U-shape pattern. It is negative throughout the employment distribution but statistically significant only at the upper tail (-0.258). The negative coefficients are consistent with the OLS but not the DSGMM estimates of mean effects. The null hypothesis of equal coefficients is rejected between the 90th and all other quantiles. A similar crowding out effect has been reported by List et al. (2004) and Sun

[21] Our general finding reinforces Head et al. (1999), Woodward (1992) and Coughlin and Segev (2000), which report that holding investment-promotion offices in *Japan* is predicted to attract more Japanese firms.

[22] A few studies report that the agglomeration has negative effect on FDI location decisions. For reference, see List et al. (2004) and Sun et al. (2002).

[23] On a related note, evidence of similar agglomeration behavior is found for FDI activities outside of the United States. Sawyer et al. (2015), for example, utilize firm level data for the US based multinationals investing in Latin America and Caribbean, and find that US companies with prior investment experiences are more likely to commit equity expansion in this region.

et al. (2002). The SQR estimate reveals that the crowding out effect associated with FDI competition in neighboring states is not uniform across the employment distribution: states in the top percentiles suffer significantly more (Figure 5f).

For some the variables, the estimated coefficients display a U-shape pattern across quantiles. The market demand in adjacent states, $INCOME_j$, is estimated to have a positive and statistically significant effect (0.317) only at the top percentiles (Figure 5h). The reported F-test of equality confirms that FDI-related employment at the top quantiles responds todemand from the surrounding markets in a significantly different way than at other quantiles. Note that the coefficients are positive like the DSGMM estimates but opposite of the OLS estimates for average treatment effects.

The SQR estimate produces a positive but insignificant coefficient throughout the distribution for the host market size variable, $INCOME_{i,t}$. The positive coefficient diverges from the DSGMM estimate. The insignificance of the market potential effect at all quantiles except the upper tail of the distribution reveals a transition from the models of "vertical" FDI to that of "horizontal" FDI as the size of FDI activities expands.[24] This reveals nuanced effects which refines the understanding of FDI behavior in previous literature.

The estimated positive coefficients on the state transportation system variable, $HIGHWAY_{i,t}$, also follows a U-shape pattern where the two tails of the FDI-related employment distribution are impacted significantly more than the median (see Figure 5l). At the median, a 10 percent increase in the value of $HIGHWAY_{i,t}$ is expected to result in a 0.6 percent increase in the FDI-related manufacturing jobs; this effect is doubled at the 30th quantile and quadrupled at the 90th. The reported F-tests of equality indicate the null hypothesis is rejected between the median and the higher quantiles. This result combined with the estimated positive tax effect, suggests that different packages of public goods provision and corporate income tax rates should be considered by states according to their level of FDI-related employment.

The estimated coefficients for the state educational attainment variable ($HSEDU_{i,t}$) display a decreasing pattern across quantiles (see Figure 5k). Estimates are negative, increasing in magnitude with quantiles, and statistically significant for quantiles higher than the median. The reported F-tests suggest rejecting the null hypothesis of equal coefficients between the higher and other quantiles. This finding supports the DSGMM estimates (Rogers and Wu, 2012) and contrasts Coughlin and Segev (2000) and Woodward (1992) which find a positive effect of educational attainment on business location choices. The negative effect may be attributed to the unobserved wage effects (Bartik, 1985, p.21).

The estimated effect of the state unemployment rate, $UNEMP_{i,t}$, is centered around –2 across quantiles (see Figure 5j). The estimated negative coefficients are statistically significant at all quantiles except the 90th. The reported F-test of equality suggests that the null hypothesis of equal coefficients is rejected. This reinforces previous findings suggesting that a high jobless rate may deter foreign investment because it may indicate a weak economy or low quality of life (Woodward, 1992; Fredriksson et al., 2003).

4.3 Extensions

The benchmark estimation focuses on investigating the presence of heterogeneous effects of investment promotion policies. Whereas many refinements and robustness checks are possible, we focus on some key issues and extensions.

Following Rogers and Wu (2012) we examine the robustness of the results when investment-promotion policies in isolation rather than as a group. Accordingly each of the four alternative specifications includes only a single policy variable. Notably, investigating policy variables separately generates some controversial results.[25] For instance, when only $TAXRATE_{i,t}$ is considered, the SQR estimates suggest a significant and negative tax rate effect for the median and the upper quantiles. Studies that ignore the spending side of the government financial process also tend to find a negative tax effect (Head et al., 1999; Woodward, 1992; Blonigen and Davies, 2004). When only the location of overseas offices is examined, having offices in Korea is predicted to have a significant and negative effect rather than a positive effect. Furthermore, in all of these

[24] The "vertical" models predict that US affiliates of foreign firms produce in the US and then re-import the products back to the home country or export them to other countries (Helpman and Krugman, 1985). The "horizontal" models conclude that foreign investment would locate in economies with great market potential with a market-seeking purpose (Markusen, 1984).

[25] Detailed results for these robustness checks with appendix tables and graphic depictions are available upon request.

specifications, the estimated effect of state transport infrastructure variable becomes negative for most of quantiles and it is significant for quantiles lower than the median. Not only is this result controversial, it is also counterintuitive and inconsistent with the existing studies. The departures from the baseline estimates reinforce the potential fragility of estimates when investment-promotion policies are analyzed in isolation (Rogers and Wu, 2012).

Another concern is the potential of a common national trend in both FDI policies and FDI-related employment that is related to increased international trade over the period.[26] Some states may be more involved in the national trend of globalization than others, which could show up as heterogeneity. As discussed above, our baseline estimation uses the lagged value of FDI-related employment to capture short-run cyclical shocks which might influence the outcome measure of interest. Because the SQR methods estimates impacts in a piecewise fashion, estimating time trends is not as simple as adding a shifter variable in OLS or panel data models. Isolating heterogeneous responses to common shocks in quantile regression framework can require restrictive assumptions that do not fit our empirical environment.[27] We take a straightforward approach to investigating the potential influence of time varying effects by including a linear time trend variable in the benchmark specification.[28] Notably, the estimated trend coefficients are not significant for any of the quantiles and take on both positive and negative signs. The estimated impacts of our policy variables of interest are very similar in magnitude and significance. Thus, we conclude that time idiosyncratic variables do not appear to be driving our findings of heterogeneous impacts of investment promotion policies.[29]

Another concern is the possibility of reverse causality between state FDI-related employment and FDI policies. FDI promotion policies are implemented to attract foreign investment in a state, but these policies may also be influenced by the presence of increasing FDI (Rogers and Wu, 2012). This could lead to inconsistent estimates of causal effects of covariates on FDI-related employment. The benchmark estimation presented above accounts for potential reverse causality by including lagged values of the outcome variable. To further investigate the potential for reverse causality we introduce lagged values of all the co-variates in the SQR model. We find some fragility of our baseline estimates using the lagged values as instruments.[30] For instance, the estimated *LogSUBSIDY* coefficients change signs and significance across the 30th, 50th, 70th and 90th quantiles. The coefficients on the lag value of *LogFTZ* also change signs throughout and lose significance for the 30th, 50th and 90th quantiles. Similarly the estimated coefficients of the lag of *Log(OFFICE+1)* change signs and lose significance for several of the quantiles. We note that coefficients on *MFGEMP* (which were already lagged in the base estimates) become a little larger in magnitude and retain high levels of significance. Given results by Alexander et al. (2011) evidence of fragility when using lagged values of variables as instruments, is not unexpected. It does suggest the need for further investigation into potential reverse causality as SQR methods become more refined.

Another concern is that some of the explanatory variables could be endogenous.[31] Variables of particular concern are the state own income and unemployment variables. To address this concern, we estimate the benchmark model omitting these two potentially endogenous variables. The estimated coefficients on the investment-promotion policy variables and the lagged FDI-related employment variable are very similar to those in the benchmark estimation.[32] This suggests that our benchmark estimates are robust to excluding the state-own income and unemployment variables.

As a final test, we note that the combination of tax and spending policies can vary considerably across states. Notably studies that ignore the spending side of government finances tend to find a negative tax effect on growth outcomes. It is difficult to add all potential spending categories in a parsimonious model given

[26]We thank the referees for raising this concern and for suggesting robustness tests.

[27]Recent advances in quantile regression estimation attempt to estimate fixed effects largely rest on assumptions such as a large number of time periods and increasing time periods as the sample size increases. In our particular empirical setting, assumptions such as $T>n$ are restrictive, which undermines the credibility of estimates with time fixed effects in the SQR approach. See for instance Galvao and Poirier (2017) for a discussion.

[28]Detailed results are not provided due to brevity concerns. These are available upon request.

[29]See Galvao and Poirier (2017) for a discussion of different approaches to incorporating time varying and time invariant fixed effects in quantile regression settings.

[30]A table of detailed results is available upon request but are not included for brevity.

[31]We thank the referee for pointing out this issue.

[32]Detailed results are available upon request.

the likely correlation between spending categories.[33] The benchmark estimation includes a highway miles variable, which likely serves as a proxy for highway infrastructure spending. To further consider spending impacts, we add a key spending variable, i.e. the log of per capita state spending on welfare.[34] When LogWELFARE is included, the estimates of the investment promotion variables impacts are very similar to those of the benchmark estimates in Table 3.[35] This is not unexpected, given that the lag of *LogMFGEMP* variable is likely to pick up persistent impacts of state spending and tax policies.

5 Conclusions and Policy Implications

Using data for all 50 states from 1997 - 2008, this paper analyzes the potential for heterogeneous effects of state investment-promotion policies on employment by foreign-owned manufacturing firms in the US Implementing a simultaneous quantile regression approach to address non-normality of the employment distribution reveals the relative importance of each policy at various points of the employment distribution. The results indicate evidence of heterogeneous responses to investment-promotion policies based on different state-level employment characteristics of foreign-owned firms.

Table 5 ranks all 50 states according to their average FDI-related employment, and predicts the estimated increase associated with a 1 percent increase in each policy variable in isolation, holding other variables constant. The estimated positive effect of the provision of FTZs (both general-purpose zones and subzones) on state employment by foreign firms varies significantly along the distribution with a U-shaped pattern. The policy implication associated with this result is worth noting. For instance, if the count of FTZs in Colorado (at the median of the employment distribution) increased by 10 percent (or 28 * 10% = 2.8 more FTZs, on average) ceteris paribus, then the predicted increase in employment by foreign manufacturing firms is approximately 1.08 percent (or 20,137 * 1.08% = 218 jobs). A 10 percent increase of FTZs in New Mexico (at the 10th percentile of the employment distribution) and Indiana (the 90th percentile), ceteris paribus, is predicted to increase the FDI-related employment by 2.44 percent (or 2,855 * 2.44% = 70 jobs) and 3.31 percent (or 97,091 * 3.31% = 3214 jobs), respectively.

Having more trade offices abroad is not associated with a predicted increase state FDI-related employment throughout the employment distribution. There is a negative and statistically significant relationship for the lower and the median percentiles. Ceteris Paribus, a 100 percent (or 7 * 100% = 7 offices, on average) increase in the count of overseas offices by Colorado is associated with an approximate 2.6 percent drop (or 20,137 * 2.6% = 524 employees) in Colorados manufacturing FDI-related jobs. This result questions the efficacy of establishing overseas trade offices.

Finally, the predicted foreign firm employment-enhancing office locations include Japan, Korea, China, Malaysia, India, Mexico, Dubai, etc. In contrast, some office-location countries such as Brazil, Argentina, Taiwan, Canada and the European Union are negatively associated with the FDI-related manufacturing employment in the US. Furthermore, the SQR estimates reveal heterogeneity in the effects of office-location countries at different points of the employment distribution. For example, offices in Korea and Japan have an estimated positive effect for the lower and the median quantiles whereas office in the EU have a negative effect. Offices in China and Mexico, however, are predicted to promote the FDI-related employment at both tails of the distribution.

Our analysis suggests a nuanced understanding of the efficacy of FDI promotion policies. Clearly, one-size does not fit all regarding the efficacy of FDI promotion policies. To effectively create policies to enhance FDI-related employment, state policy makers need to understand where they are in the employment distribution as well as the estimated impacts across the distribution. As shown in Table 5, Colorado (at the median of the employment distribution) would get the biggest expected employment boost from a 1 percentage point increase in its tax rate (a change from 4.63% to 5.63%). In comparison, Indiana (at the 90th percentile)

[33] For instance, Wu and Burge (2017) investigates the effects of FDI promotion policies on employment across Chinese Provinces and includes the provincial spending on foreign affairs. Wang (2016) approaches this problem by estimating the impact of state spending on economic development incentives on individual public spending categories to uncover evidence of crowd out.

[34] Source for state welfare spending data: *Annual Survey of State and Local Government Finances*, and *Census of Governments*, multiple years, U.S. Census Bureau.

[35] Detailed results are available upon request.

Table 5: Summary of Predicted Change in Employment by Foreign Manufacturing Firms by State (in persons)

	State	97-08 Average Employment	TAXRATE	SUBSIDY	FTZ	OFFICES	HIGHWAY	Predicted Employment-Enhancing Locations of Foreign Offices
			Predicted Increase Associated with a 1 percent Increase each Policy Variable					
	Hawaii	1181.8	-0.7	-0.9	2.9	-0.2	1.8	KO
	Wyoming	1445.5	-0.9	-1.1	3.5	-0.2	2.2	KO
	Montana	1481.8	-0.9	-1.1	3.6	-0.3	2.3	KO
	Alaska	2118.2	-1.3	-1.5	5.2	-0.4	3.3	KO
10th	New Mexico	2854.5	-1.8	-2.1	7.0	-0.5	4.4	KO
	Vermont	2981.8	-1.9	-2.2	7.3	-0.5	4.6	KO
	North Dakota	3354.5	8.5	-1.6	7.0	-1.0	5.0	IT JP KO ML MX RS SP
	South Dakota	3781.8	9.6	-1.8	7.9	-1.1	5.6	IT JP KO ML MX RS SP
	Idaho	4363.6	11.0	-2.1	9.1	-1.3	6.5	IT JP KO ML MX RS SP
20th	Rhode Island	4890.9	12.4	-2.3	10.2	-1.4	7.2	IT JP KO ML MX RS SP
	Nevada	5436.4	13.8	-2.6	11.3	-1.6	8.0	CN DB IT JP KO ML
	Delware	8718.2	22.1	-4.1	18.1	-2.5	12.9	CN DB IT JP KO ML
	Nebraska	9309.1	44.3	-5.0	17.6	-2.0	11.5	CN DB IT JP KO ML
	Maine	9690.9	46.1	-5.2	18.3	-2.0	12.0	CN DB IT JP KO ML
30th	Utah	9890.9	47.1	-5.3	18.7	-2.1	12.3	CN DB IT JP KO ML
	Mississippi	12263.6	58.4	-6.6	23.2	-2.6	15.2	CN DB IT JP KO ML
	West Virginia	12881.8	61.3	-7.0	24.3	-2.7	16.0	CN DB IT JP KO ML
	Oklahoma	14536.4	55.5	-6.7	18.3	-3.3	10.3	CN DB IN JP KO
	Arizona	15190.9	58.0	-7.0	19.1	-3.5	10.8	CN DB IN JP KO
40th	Oregon	16134.4	61.6	-7.4	20.3	-3.7	11.5	CN DB IN JP KO
	New Hampshire	17800.0	68.0	-8.2	22.4	-4.1	12.6	CN DB IN JP KO
	Kansas	18745.5	71.6	-8.6	23.6	-4.3	13.3	CN DB IN JP KO
	Maryland	19945.5	65.2	-10.4	21.5	-5.2	12.2	DB JP KO ML
	Louisiana	20036.4	65.5	-10.4	21.6	-5.2	12.0	DB JP KO ML
50th	Colorado	20136.4	65.8	-10.5	21.7	-5.2	12.1	DB JP KO ML
	Iowa	21818.2	71.3	-11.3	23.6	-5.7	13.1	DB JP KO ML
	Arkansas	23754.6	77.7	-12.4	25.7	-6.2	14.3	DB JP KO ML
	Washington	25281.8	82.7	-13.1	27.3	-6.6	15.2	DB JP KO ML
	Connecticut	30836.4	120.6	-18.2	39.8	-5.9	17.0	CN JP KO
60th	Minnesota	31081.8	121.5	-18.3	40.1	-5.9	17.1	CN JP KO
	Virginia	41027.3	160.4	-24.2	52.9	-7.8	22.6	CN JP KO
	Massachusetts	43472.7	170.0	-25.6	56.1	-8.3	23.9	CN JP KO
	Alabama	43654.6	170.7	-25.8	56.3	-8.3	24.0	CN JP KO
	Missouri	44745.5	84.6	-22.8	76.	-9.4	24.2	CN JP MX
70th	Florida	45609.1	86.2	-23.3	78.0	-9.6	24.6	CN JP MX
	Wisconsin	46954.6	88.7	-23.9	80.3	-9.9	25.4	CN JP MX
	Kentucky	58190.9	110.0	-29.7	99.5	-12.2	31.4	CN JP MX
	South Carolina	61090.9	115.5	-31.2	104.5	-12.8	33.0	CN JP MX
	New Jersey	64500.0	136.1	-29.0	134.8	12.3	36.8	CN JP MX
80th	New York	69818.2	147.3	-31.4	145.9	13.3	39.8	CN IL
	Tennessee	71536.4	150.9	-32.2	149.5	13.6	40.8	CN IL
	Georgia	73772.7	155.7	-33.2	154.2	14.0	42.1	CN IL
	North Carolina	94209.1	198.8	-42.4	196.9	17.9	53.7	CN IL
	Illinois	94918.2	200.3	-42.7	198.4	18.0	54.1	CN IL
90th	Indiana	97090.9	-131.1	-82.5	321.4	-1.9	238.8	CN GM IL MX SP UK
	Pennsylvania	98654.6	-133.2	-83.9	326.5	-2.0	242.7	CN GM IL MX SP UK
	Michigan	100200.0	-35.3	-85.2	331.7	-2.0	246.5	CN GM IL MX SP UK
	Ohio	118200.0	-159.6	-100.5	391.2	-2.4	290.8	CN GM IL MX SP UK
	Texas	126527.3	-170.8	-107.5	418.8	-2.5	311.3	CN GM IL MX SP UK
	California	172881.8	-233.4	-146.9	572.2	-3.5	425.3	CN GM IL MX SP UK

***Data Source**: Employment and Manufacturing Employment of All Nonbank U.S. Affiliates, by State, 1997-2008, U.S. Bureau of Economic Analysis.

would get the biggest expected boost from increasing highway miles by 1%, while New Mexico (at the 10% percentile) would get the biggest boost from increasing FTZs.

The analysis warrants a few caveats. Causality is difficult to determine in complex models with potential spillovers and dynamic shocks. Our results are robust to numerous robustness tests, such as including a linear time trend, adding a key spending variable, and eliminating potentially endogenous variables. However, there remains concern about reverse causality given the fragile results when lagged variables were used as instruments. The research on how to incorporate SQR methods in panel data analysis with time-invariant and time-varying fixed effects is rapidly developing. These advances will offer opportunities to further delve into challenging estimation issues. We also note the possibility of future extensions using emerging databases that go beyond the top statutory corporate tax rate to better capture variation in state tax policy environments. Notably, Bartik (2017) provides an exciting new database which simulates state and local business taxes with and without state incentives offers. Accounting for such nuances in models that go beyond estimating average treatment effects will be valuable for assessing the efficacy of FDI promotion policies.

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