International Journal of Industrial Organization
19 (2001) 953–973
International Journal of Industrial Organization
www.elsevier.com/locate/econbase

US county-level determinants of inbound FDI: evidence from a two-step modified count data model

John A. List*[,1]

Department of Economics, University of Central Florida, Orlando, FL 32816-1400, USA

Received 1 July 1998; received in revised form 1 July 1999; accepted 1 September 1999

Abstract

We employ a two-step modified count data model to determine the county-level attributes that are conducive to attracting new foreign plants. Our estimation results indicate that previous counts of foreign direct investment, market size and accessibility, and land area are positively related to Foreign Direct Investment (FDI) occurrences; while higher input costs deter new foreign firm entry. Contrary to anecdotal evidence, our results suggest that stringent environmental regulations do not have a negative impact on FDI inflows. These findings have significant implications for policymakers, as flows of FDI are expected to increase dramatically given the economic integration of our global economy. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Foreign Direct Investment (FDI); County-level; Environmental regulations

JEL classification: Q28; R28

1. Introduction

Given that our economic system is rapidly evolving from many relatively small markets into an integrated global market, firms are more readily using foreign countries to source production, add product markets, and diversify. Consequently,

*Tel.: +1-407-823-3719; fax: +1-407-823-3269.
E-mail address: john.list@bus.ucf.edu (J.A. List).

[1] Visting scholar, CentER for Economic Research, Tilburg University, The Netherlands.

PII: S0167-7187(99)00051-X

to stimulate job growth and increase overall welfare levels, many countries have expended considerable effort to attract foreign multi-national corporations (FMNCs). Although many local attributes, such as factor prices, climate and available market, have proven to be key determinants in the site decision, there is limited evidence on the effects that environmental regulations have on FMNC location decisions. Since the United States alone has witnessed an eight-fold increase in total foreign direct investment (FDI) since 1975, it is essential for local and state policymakers to understand whether foreign firms are influenced by pollution regulations.[2]

As a first step in addressing this issue, we use a two-step empirical approach to examine the county-level determinants of FDI into the US. As such, our model has the flexibility to exclude inferior counties in the initial screening process. After this initial screening, remaining counties have an underlying Poisson process that describes their respective probabilities of attracting a new foreign entrant. Intuitively, this two-step approach appears to capture the location decision quite well, as many counties may not have the characteristics to attract new FMNCs and therefore are regularly excluded during the initial screening process. On the other hand, some counties may make the initial cut but fail in latter stages of the search.

Using California FDI county-level micro-data in 1983–1992, we find that agglomeration effects, measured as the number of previous FDI occurrences into the county, have very strong positive implications for attracting future FDI. This result suggests that there is a snowball effect associated with FDI, implying that, in the long-run, a county loses much more than one firm when it fails to attract a prospective new foreign plant. We also find that environmental regulations do not significantly alter new firm location patterns. This result implies that the (foreign) industrial makeup of certain regions has not been significantly driven by environmental regulations. Other results from the empirical models largely support previous findings as higher input costs deter new foreign firms while a larger market size and better accessibility are positive factors for prospective FMNCs.

The balance of this paper is organized as follows. Section 2 briefly reviews previous firm location studies, presents the empirical model, and provides a description of the data. Results are discussed in Section 3, and Section 4 provides concluding remarks.

2. Previous work, the location model, and the data

Our study of the FMNC location decision is closest in spirit to Friedman et al. (1992), Woodward (1992) and Greenstone (1998), while our empirical methodolo-

[2] The stakes are raised even further if one considers recent findings that suggest foreign firms not only provide jobs, but significantly increase area wages. For example, Figlio and Blonigen (1998) find that foreign entrants increase *overall* county wages by more than seven times that of domestic entrants.

gy relates most closely to recent domestic firm location studies by Papke (1991) and Henderson (1996).[3] Although the firm location literature has been surveyed by Gerking and List (1999) and Tannenwald (1997), a brief summary of the important empirical results is worthwhile.[4]

Friedman et al. (1992) use a conditional logit model to examine which state factors affect the location of new foreign plants entering the US in 1977–1988. They make use of the International Trade Administration (ITA) data on FMNC location decisions and find that access to foreign markets and a large US domestic market (proxied by a dummy variable for access to a container port and a gravity-adjusted measure of personal income) significantly affect the location decision of foreign firms. In addition, they find that the probability of choosing a state decreases with higher wage rates and state and local taxes, but increases with the available labor pool. Finally, using one measure of environmental stringency, they find that pollution regulations do not significantly alter location decisions of foreign firms. As Friedman et al. (1992) point out, this latter finding may be the result of industry aggregation.

Woodward (1992) investigates how state (and county) characteristics in 1980 affect the location decision of Japanese FDI into the US in 1980–1989. For the regressions using counties as the unit of observation, Woodward finds that the probability of attracting FDI increases with land area, population density, agglomeration economies, and the level of infrastructure. Woodward also finds that property taxes and wages are insignificant in Japanese new plant investment decisions, perhaps indicating that other area attributes are more important to the Japanese FMNC.

Although not strictly focusing on FMNC new plant location decisions, a few other studies are worth mentioning since their methodologies coincide with our approach. One such study is due to Greenstone (1998), which uses the 1967–1987 Censuses of Manufacturers to compile a database that includes 1.75 million plant observations at the county level. One result that stands out in Greenstone's (1998) work is that after controlling for a variety of factors including plant level characteristics, industry shocks, and county shocks, high environmental regulation counties, in comparison to low regulation counties, lost approximately 100 000 jobs, $50 billion in capital stock, and $30 billion of output (in pollution-intensive industries) in the first 15 years after the Clean Air Act Amendments became law (1972–1987). Although these losses are relatively modest in comparison to the size of the entire manufacturing sector, they imply that the industrial composition

[3] Another related study is by Coughlin et al. (1991). Since they aggregate all types of FDI in their empirical model the coefficient estimates are not directly comparable to ours.

[4] Another technique to measure the effects of environmental regulation on economic activity is surveys. Given the lack of incentive compatibility that plagues hypothetical surveys (see, for example, List and Shogren, 1998), we suppress discussion of the survey literature.

of some regions is partly determined by the stringency of local environmental regulations.

Other related studies include Henderson (1996) and Papke (1991). Henderson (1996) uses establishment-level county data to investigate factors that attract new manufacturing plants in pollution-intensive industries (SIC 282, 286, 291, 307, 331), while Papke (1991) uses state-level data from five manufacturing industries (SIC 233, 251, 273, 366, 367) to examine firm location patterns in 1982–1987. Both studies make use of the non-negative integer property of their dependent variables by using a Poisson count data model to analyze the location decision.[5] For the most part, they find relatively intuitive results: factor input prices deter new firm entry while market size and accessibility are positive attributes. Henderson (1996) also finds that county-level environmental regulations play an integral role in the evolution of industry.[6]

2.1. The location model

To estimate our location model, we make the probability of attracting a new foreign firm a function of county-specific attributes:

$$\mathrm{Prob}(y_i) = f(X_i) \tag{1}$$

where y_i represents the count of new plants in county i in1983–1992 and X_i are county attributes that affect the firm's spatial profit function. A common way to specify this type of discrete probability function is as a Poisson process.[7] A Poisson specification models the integer property of the endogenous parameter explicitly and is given by:

$$\mathrm{Prob}(Y = y_i) = \frac{e^{-\lambda i}\lambda_i^{y_i}}{y_i!}, \quad y = 0, 1, \ldots; \quad \ln \lambda_i = \beta' X_i \tag{2}$$

[5] Other studies that use the Poisson assumption include Kogut and Chang (1991), Blonigen and Feenstra (1997) and Blonigen (1996). Kogut and Chang (1991) use a counting approach to test whether Japanese FDI into the US are attracted to industry intensive in research and development. Blonigen and Feenstra (1997) use the same methodology to test whether US protectionist threats affect Japanese FDI into the US and/or whether FDI is used to defuse protection. Blonigen (1996) examines whether exchange rate movements affect FDI into the US.

[6] Given that tax rates are the focus of her study, Papke (1991) does not control for environmental regulations in any of her empirical specifications.

[7] To conserve space, we summarize our empirical models. Log-likelihood functions, gradient vectors etc. are available in Greene (1994).

where y_i and X_i are defined above, and β is the vector of unknown parameters.[8]

In the estimation of Eq. (2), it is important to recognize that there may be a two-step process associated with the location decision of new foreign plants. A zero plant occurrence in county *i* could arise through two separate processes. For example, consider a group of prospective FMNCs posed with the following question: Given that you have selected California, which county do you plan to choose? The answer to this question most naturally arises from a two-step process. First, due to specific (dis)advantages that are natural and policy-based, such as proximity to markets, natural resource amenities (climate, etc.), ease of labor force assembly, transportation investments, and agglomeration economies, many counties may not make the final choice set of any FMNCs, regardless of the circumstances involved.[9] Hence, these counties always attract zero new plants, independent of the data generation process. After this initial screening, in the second stage those counties that cleared the initial hurdle have an underlying Poisson process that describes their respective probabilities of attracting a new foreign entrant, but with a positive probability on zero (since some counties that were part of the final choice set may not attract any new firms during the sample period). This empirical approach has the advantage of delineating between factors that affect whether a county gets any FDI, and factors that affect the count of FDI occurrences for those counties that attract positive flows of FDI.

An empirical approach that accounts for this two-step process is discussed by Heilbron (1989), Lambert (1992), and Greene (1994), and has been termed a variety of names, including zero inflated Poisson (ZIP), zero altered Poisson (ZAP), hurdle model, or with zero's (WZ) model. The model (we will denote as ZIP) is a natural extension of the Poisson specification in Eq. (2) and is given by:

$$y_i = 0, \quad \text{with probability } P_i \tag{3}$$

[8] Although convenient, a restriction of the Poisson model is that λ_i is both the mean and variance of y_i. Failure of this restriction has consequences similar to those for heteroscedasticity in the ordinary least-squares framework: parameter estimates are consistent, but variances are inconsistently estimated, leading to invalid hypothesis tests. We also estimated a negative binomial model, which allows the variance of the process to differ from the mean. The probability distribution of the negative binomial model is given by:

$$\mathrm{Prob}(Y = y_i|u) = \frac{\exp((-\lambda_i \exp(u_i))\lambda_i^{y_i}}{y_i!} \tag{a}$$

where $\exp(u)$ has a gamma distribution with mean 1 and variance α. The negative binomial model has an additional parameter, α, but allows a natural form of overdispersion given by:

$$\mathrm{Var}[y_{ij}]/E[y_{ij}] = 1 + \alpha_j E[y_{ij}] \tag{b}$$

Given that α_j is insignificant in each regression model that converged, we present only Poisson estimates below.

[9] The intuition is similar to Schmenner's (1977) market area penalty variable, which represents an initial indication of whether a county is suitable for location.

$$y_i \sim \text{Poisson}(\lambda_i), \quad \text{with probability } 1 - P_i \tag{4}$$

where $\ln\ \lambda_i = \beta' X_i$, and, therefore:

$$\text{Prob}[y_i = 0] = P_i + [1 - P_i]R_i(0) \tag{5}$$

$$\text{Prob}[Y = y_i | Y > 0] = [1 - P_i]R_i(\text{not } 0) \tag{6}$$

P_i represents the state probability and R_i is the Poisson distribution for y_i.

The formulation of the state probability, P_i, used to estimate the location decision is given by:

$$P_i \sim \text{Logistic}(z_i) \tag{7}$$

where z_i is defined as:

$$z_i = \varphi\beta' X_i \tag{8}$$

which defines a single new parameter, φ. Under this formulation, the ancillary probability, P_i, is determined by a logistic scalar of $\beta' X_i$, or, likewise, the splitting phenomenon is determined by a single parameter, φ; implying county characteristics included in Stage 2 regressions (X_i) identically overlap with exogenous variables (X_i) included in the Stage 1 logit model.

A final nuance of zero inflated models is that the changed probability induces a divergence between the mean and variance of the distribution, even in the absence of heterogeneity. Consequently, zero inflated models induce overdispersion; the more likely the zero state, the greater is the overdispersion. Since the ZIP model is not nested within the Poisson model, testing for this phenomenon cannot be carried out using normal techniques. Vuong (1989), however, has proposed a test statistic for non-nested models that has powerful statistical properties. The Vuong statistic is directional and therefore if $|V| < 1.96$ the test supports neither model at the 5% level (e.g. ZIP vs. standard Poisson). Whereas, if the test statistic is positive and larger than 1.96, the zero inflated model is favored, while large negative values support the unaugmented, or standard model.

2.2. The data

We have collected data on new foreign firm births in manufacturing for counties in California in 1983–1992. We focus on counties in California for several reasons. First, California has attracted the largest number of FDI occurrences since the mid-1970s. Second, California remains one of the major players in the FDI area as its total FDI in the early 1990s has been nearly double that of the next state (New York). Third, as described below, California's counties vary significantly in terms of important local attributes such as wages, pollution regulatory intensity, and agglomerations, making California a practical choice for a county-level firm location analysis.

Data on FDI are from the International Trade Administration's (ITA) annual publication *Foreign Direct Investment in the United States*. Annually, the ITA summarizes information from publicly available sources (such as public files from government agencies) to classify FDI according to type of investment, the 4-digit SIC of the investment, the investing country, location of the investment, and in some cases the total cost of the completed investment. The ITA classifies investment type into six categories: new plant, merger and acquisition, equity increase, joint venture, plant expansion, and real property purchase. Instead of focusing on all six forms of investment, we analyze factors that affect the location of new plants for two primary reasons. First, new plants constitute the most important and coveted type of FDI because they create jobs (Friedman et al., 1992). Furthermore, Figlio and Blonigen (1998) find that new foreign firms tend to increase local wages much more than new domestic producers, which serves to raise the stakes in the race to attract new FDI plants. Second, new plants must consider all spatial factors when making the location decision, such as complying with existing county-level environmental regulations, whereas other forms of investment may allow the existing plant to be grandfathered into less stringent regulations.

Although these FDI data may appear to be a perfect measure of total investment from foreign entities into the US, they are deficient in at least one important aspect: the level of investment for each FDI occurrence is not available. Ideally, we would like to model the total value of the completed foreign investment as a function of the exogenous variables, but for the most part these figures are available for less than 50% of the new plant investment reported in the ITA publication. Consequently, we use a second best approach and count the number of FDI occurrences in a given year. For example, if a foreign firm completes construction of a new plant in December of 1988 in county i, county i is credited with one occurrence of FDI in 1988, whether the dollar amount was 5 million or 50 million. This technique is a familiar one as previous location studies using ITA data have also opted for this approach (see, for example, Coughlin et al., 1991; Friedman et al., 1992; Woodward, 1992).

Since firms of varying pollution intensity may be affected differently by environmental regulations, we analyze data for all manufacturing industries together as well as separately for two subsamples — a pollution-intensive subsample and a non-pollution-intensive subsample. We note that many facets of the complex pollution process need to be considered when labeling SICs as pollution or non-pollution-intensive. To carry this task out, we: (1) analyzed firm-level pollution abatement operating expenditures to abate the media air, water, and solid/contained waste from the Current Industrial Report's *Pollution Abatement Costs and Expenditures* (PACE); (2) examined actual emissions, by industry, of the five criteria air pollutants from 1980 and 1990 from the *National Air Pollutant Emission Trends* (1900–1994) published by the Environmental Protection Agency (EPA); and (3) reviewed the appropriate literature (e.g.

Levinson, 1996 and Jaffe et al., 1995), to establish our two groupings. In the end, we included SIC 26, 28, 29, 32, 33, 34 and 37 in the pollution-intensive group and the remaining manufacturing industries were placed in the non-pollution-intensive group.[10] Columns 2 and 3 of Table 1 provide an overview of the spatial location patterns of pollution-intensive and non-pollution-intensive plants in 1983–1992. In sum, 67 occurrences of new plant FDI were identified from the ITA listing. Of this total, 19 occurrences were in pollution-intensive industries and 48 occurrences were in non-pollution-intensive industries. Table 1 also indicates that only 18 of the 58 California counties attracted a positive number of new foreign plants in 1983–1992, further supporting use of the ZIP model.

2.3. The regressors

In estimation of Eqs. (3)–(8), we follow previous studies of firm location (see, for example, Woodward, 1992; Levinson, 1996; List and Kunce, 1999) and analyze how exogenous variables in 1982 affect location decisions in 1983–1992. Exogenous variables included in vector X_i are traditional regressors hypothesized to be arguments in the firm's profit function, and include measures of, or proxies for, agglomerations, pollution regulatory intensity, market size and accessibility, and other characteristics of the county, such as wages and the tax climate.

2.3.1. Agglomerations

A key tenet of most regional growth theories are the agglomeration economies that can accrue to firms locating in close proximity to one another. Availability of market information, technology transfers, access to a skilled labor pool, and networking with immediate suppliers of essential materials are all potential positive externalities associated with dense areas of manufacturers. Although previous studies have analyzed the effects of agglomeration at the state level, agglomeration economies are better analyzed within smaller geographic areas, such as counties, since proximity to other manufacturers is better controlled within a county-level regression model (Woodward, 1992). To measure agglomerations (Agglo.), we use the ITA data set described above. More specifically, we sum the count of all investment in the six categories: new plant, merger and acquisition, equity increase, joint venture, plant expansion, and real property purchase in 1974–1982 for each county.[11] Our agglomeration variable, therefore, captures the historical trend of past foreign entrants into the California market. As such, the

[10] We would have liked to split the data into even finer categories (e.g. 4-digit SIC levels), but data limitations precluded our efforts as zero investment was made in many industries in the sample period.

[11] We are limited to using 1974–present data since 1974 was the first year the ITA issued these data.

Table 1
Counts of new plant FDI per California county (1983–1992)

County	Total	Pollution intensive	Non-pollution intensive	No. of pollutants out-of-attainment
Alameda	7	4	3	2
Alpine	0	0	0	0
Amador	0	0	0	0
Butte	0	0	0	2
Calaveras	0	0	0	0
Colusa	2	1	1	0
Contra Costa	1	1	0	2
Del Norte	0	0	0	0
El Dorado	0	0	0	1
Fresno	4	1	3	2
Glenn	0	0	0	0
Humboldt	0	0	0	0
Imperial	0	0	0	1
Inyo	0	0	0	0
Kern	0	0	0	3
Kings	0	0	0	1
Lake	0	0	0	0
Lassen	0	0	0	0
Los Angeles	15	8	7	4
Madera	0	0	0	1
Marin	0	0	0	3
Mariposa	0	0	0	1
Mendocino	0	0	0	0
Merced	1	0	1	1
Modoc	0	0	0	0
Mono	0	0	0	0
Monterey	0	0	0	2
Napa	0	0	0	3
Nevada	0	0	0	0
Orange	8	1	7	4
Placer	1	0	1	1
Plumas	0	0	0	0
Riverside	1	1	0	3
Sacramento	0	0	0	3
San Benito	0	0	0	1
San Bernardino	4	0	4	4
San Diego	7	1	6	3
San Francisco	1	0	1	2
San Joaquin	0	0	0	3
San Luis Obispo	0	0	0	2
San Mateo	1	0	1	3
Santa Barbara	0	0	0	3
Santa Clara	10	0	10	3
Santa Cruz	1	0	1	1
Shasta	0	0	0	0
Sierra	0	0	0	0

Table 1 (continued)

County	Total	Pollution intensive	Non-pollution intensive	No. of pollutants out-of-attainment
Siskiyou	0	0	0	0
Solano	0	0	0	3
Sonoma	0	0	0	3
Stanislaus	1	0	1	2
Sutter	0	0	0	1
Tehama	0	0	0	0
Trinity	0	0	0	0
Tulare	0	0	0	1
Tuolumne	0	0	0	0
Ventura	1	0	1	2
Yolo	1	1	0	2
Yuba	0	0	0	1
Total	67	19	48	–

agglomeration regressor may also help to control for unobservable county-level characteristics that are left uncontrolled in our regression framework. We expect the coefficient on (Agglo.) to be positive and significant, implying prospective foreign firms tend to locate in close proximity to other foreign firms.

2.3.2. Intensity of pollution regulations

In the US, responsibility for regulating air polluters rested almost exclusively with the states until the early 1960s. Indeed, from the first city smoke ordinances in 1855 until the early 1970s, the federal government did not concern itself greatly with environmental matters. Disappointed with outcomes associated with decentralized control of the environment, federal authorities began to take a more active role in environmental regulation with the passage of the National Environmental Policy Act and the first Clean Air Act Amendments (CAAA) in 1970.[12] Federal organizations, such as the Environmental Protection Agency and the Council on Environmental Quality, were soon created to administer and enforce these statutes. As environmental authority was being shifted to Washington, DC, technological and political changes made industry more geographically mobile, potentially intensifying and promoting interjurisdictional competition (see Tannenwald, 1997, and the references cited therein). Coupling these temporal changes in firm mobility with confusion about how states should implement the new regulations of the CAAA of 1970, the federal government passed important provisioning rules via the 1977 Clean Air Act Amendments.

[12] The original Clean Air Act was passed in 1963.

As per the 1977 CAAA, starting in 1978 every county in the US is designated annually as being in attainment or out of attainment (non-attainment) of national air quality standards in regards to five criteria air pollutants: carbon monoxide, sulfur dioxide, total suspended particulates, ozone, and nitrogen oxide (other pollutants, such as particulate matters, have subsequently been added).[13] For those counties not in attainment of federal standards, each state is required to submit comprehensive plans that will lead to attainment status in the near future (State Implementation Plans, SIP). If standards are not met in due time, states are subject to decreased federal monies that help to fund state-level public goods and services. If a new plant chooses to locate in a non-attainment designated county, it is subject to Lowest Achievable Emission Rate (LAER) standards on installed equipment, *regardless of cost*, which can potentially run into the millions of dollars. As Gray (1997a,b) notes, difficulties may also arise when the firm attempts to secure construction permits, due either to delays in permit issuance or to uncertainty about whether the permit will be issued at all. In contrast, the primary means to regulate polluters in attainment counties is a policy known as Prevention of Significant Deterioration (PSD). New plants that wish to locate in attainment counties must install the Best Available Control Technology (BACT) before commencing production activities. Regulatory requirements are commonly understood to be more lax in attainment counties compared to non-attainment counties. In sum, the CAAA of 1977 served to add significant spatial differentials in air quality regulation across counties within states.

Within any of the five criteria air pollutant categories, county status may range from attainment of the primary standard to non-attainment, with partial and secondary standards in between these two polar cases. Because a county can be out of attainment in several air pollutant categories, and many heavy polluters emit numerous pollutants, we follow Henderson (1997) and index the attainment variable as the summation of criteria air pollutants for which the county is not in full attainment in 1982 (Non-Attain.). Thus, we make use of the variation in county attainment status to allow the attainment variable to vary cross-sectionally. The attainment variable can therefore take on values from 0 to 5, depending on the extent that the county is out of attainment.

Column 4 in Table 1 presents a county-by-county breakdown of attainment status. Although no counties are out of attainment for all five pollutant types, traditional county pollution havens such as Los Angeles, Orange and San Bernardino are out of attainment of federal air quality standards for four of the five pollutant types (they are each within NO_x limitations). Although casual observation of the statistics in Table 1 provides anecdotal evidence of the relationship between site choice and county attainment status, all manner of variables could be playing a part in the patterns exhibited in Table 1. To sort this out requires the

[13] For California, the data are located in the Federal register Title 40 CFR Part 81.305.

econometric specification provided above. When estimating the ZIP model above, since environmental regulations represent a firm-level constraint, we expect to uncover a significant negative relationship between county non-attainment status (Non-Attain.) and firm entry rates, particularly in the pollution-intensive subsample.

2.3.3. Other control variables

Although markets are continual integrating, positive transportation costs provide local producers with an advantage in serving local consumer markets. Consistent with this notion, many previous studies have included market size and accessibility as control variables in the location equation. We include population density (Pop.den. = population/land area) to control partially for market size and accessibility. Population density, taken from the *Current Population Reports,* appears to be a powerful explanatory variable as it potentially captures effects ranging from public good expenditures, such as infrastructure and park and recreation budgets, to market size. Consequently, we expect (Pop.den.) to be directly related to new firm births.[14]

We also include average manufacturing wage rates (Wage), a control for county-level taxes (Tax), and county land area (Land) in the regression equation. County-level wage rates are taken from *County Business Patterns* and represent a control for factor input prices. We expect (Wage) to be negatively related to new firm location. We use per capita property tax figures from the US Bureau of Census to control for the tax climate in a county. While it is true that counties often provide tax incentives to new plant investors, and that property taxes paid by individuals may not accurately reflect the actual taxes paid by FMNC's, we believe this figure to be a reasonable proxy for the tax climate specific to each county (see, for example, Woodward, 1992 who uses a similar measure). We expect higher taxes (Tax) to deter new firm investment. Finally, we include county land area (Land) to test if ''Bartik's dartboard theory'' holds across California counties. As the premise suggests, larger counties should attract more new firms than smaller counties, ceteris paribus. Table 2 contains a further description of all variables and their sources as well as some descriptive statistics.

3. Empirical results

Table 3 presents empirical estimates from the standard Poisson model described in Eq. (3) as well as the zero-inflated model described in Eqs. (4)–(8) for each of

[14] Note that our agglomeration variable also captures market size, as (Agglo.) and population have a correlation coefficient greater than 0.60.

Table 2
Description of variables[a]

Variable	Mean (S.D.)	Definition and source
New plants		Actual count of new plants entering the county in 1983–1992;
Total	1.16 (2.8)	Foreign Direct Investment in the US: Transactions compiled by the International Trade Administration (ITA)
Pollution-intensive	0.33 (1.2)	Firms labeled as having production activities that are pollution intensive; SIC 26, 28, 29, 32, 33, 34, 37
Non-pollution intensive	0.83 (2.0)	Firms labeled as having production activities that are non-pollution intensive; SIC 20–25, 27, 30, 31, 35, 36, 38, 39
Agglomerations (Agglo.)	0.21 (0.97)	Summation of the count of all foreign investment from 1974–1982; Foreign Direct Investment in the US: Transactions compiled by the International Trade Administration (ITA)
Attainment status (Non-Attain.)	1.38 (1.31)	Intensity of pollution regulations measured as the number of criteria air pollutants for which the county is out of attainment of federal standards in 1982; Federal register Title 40 CFR Part 81.305
Wage rate (Wage)	20085 (3983)	Total annual manufacturing payroll divided by the number of employees by county; County Business Patterns (1982)
Population density (Pop.den.)	497 (1950)	Population divided by land area; Current Population Reports, US Bureau of Census (1982)
Land area (Land)	2694 (3105)	County land area, US Bureau of Census (1982)
Tax rate (Tax)	343.4 (128.6)	Per capita property tax, US Bureau of Census (1982)

[a] Data are for the 58 California counties.

Table 3
Empirical estimates of the determinants of county-level FDI[a]

Ind. var.	Model type					
	Entire sample		Pollution-intensive industries		Non-pollution-intensive industries	
	Poisson	ZIP	Poisson	ZIP	Poisson	ZIP
ln(Agglo.)	0.21	0.42	0.01	0.03	0.18	0.30
	(0.06)	(0.02)	(0.74)	(0.94)	(0.07)	(0.02)
Non-Attain.	−0.05	−0.14	−0.05	−0.05	0.04	−0.05
	(0.57)	(0.41)	(0.13)	(0.91)	(0.61)	(0.75)
ln(Wage)	−0.59	−0.87	−0.21	−0.22	−0.25	−0.51
	(0.01)	(0.10)	(0.03)	(0.77)	(0.25)	(0.20)
ln(Pop.den.)	0.27	0.42	0.09	0.09	0.13	0.25
	(0.005)	(0.02)	(0.04)	(0.82)	(0.12)	(0.04)
ln(Land)	0.31	0.50	0.09	0.09	0.15	0.31
	(0.002)	(0.002)	(0.06)	(0.82)	(0.08)	(0.02)
ln(Tax)	0.36	0.53	0.16	0.18	0.05	0.24
	(0.24)	(0.34)	(0.40)	(0.55)	(0.85)	(0.60)
Pseudo-R^2	0.85	–	0.64	–	0.80	–
Log-likelihood	−51.9	−48.9	−22.0	−24.4	−47.9	−44.5
$\chi^2(df)$	166.2(6)	–	63.9(6)	–	109.3(6)	–
Vuong (V)	–	2.64	–	0.56	–	3.04
φ	–	−2.25	–	−0.49	–	-2.06
		(0.19)		(0.82)		(0.16)

[a] Dependent variable is the count of FDI new plants in 1983–1992. Independent variables are measured in 1982. p values in parentheses under marginal effects estimates. Coefficient estimates are marginal effects computed at the sample means. Marginal effects are derivatives of the conditional mean function with respect to the attribute vector ($\mathrm{d}E(y|x)/\mathrm{d}x = \lambda_i \beta$). First-stage regression results are available upon request. When taking the log of (Agglo.) we added one to each county's value to avoid taking the natural logarithm of 0.

the three samples — all manufacturing, pollution intensive, and non-pollution intensive. Also contained in Table 3 are pseudo-R^2 values, log-likelihood values, χ^2 statistics for testing the hypothesis that the slopes are jointly equal to zero, Vuong statistics (V), and estimated splitting parameters (φ).[15] In terms of overall model significance, the χ^2 statistics, each distributed with six degrees of freedom, indicate all three models are significant at $p<0.01$. In addition, the pseudo-R^2 values, ranging between 0.64 and 0.85, suggest our relatively parsimonious

[15] The splitting parameter estimates (φ) provide intuition into the magnitudes of the factors that affect whether a county attracts any FDI. The parameters in the splitting equation are the same proportion, φ, of their counterparts in the second regression. We also tried to estimate the model without restricting the coefficients in the splitting model to be a constant multiple of those in the regression model. Although convergence was not achieved in all model types, the models that did converge yielded qualitatively similar results as the restricted models.

specifications capture a significant portion of the variation in firm location patterns. Since a unique set of regressions is used for each subsample, the discussion will begin with estimates from the sample including all manufacturing and proceed to the other two subsamples.

Columns 1 and 2 in Table 3 present empirical estimates from regressions using data on all manufacturers. An important first issue regards which of the Poisson models is appropriate. Log-likelihood values suggest the ZIP specification is preferred, but as previously mentioned, the models are non-nested and, therefore, log-likelihood values are not directly comparable. The Vuong statistic $V=2.64>1.96$, however, clearly suggests that the zero inflated model is more appropriate than the unaugmented model, indicating an improvement is made by using the ZIP model. Hence, we will focus attention on these estimates.

Response coefficients presented in Table 3 are marginal effects estimates, or derivatives of the conditional mean function with respect to the attribute vector measured at the overall sample means — ($\partial E(y|x)/\partial x = \lambda_i \beta$). Estimated marginal effects are elasticities when regressors are in logarithmic form and provide intuition into the factors that influence firm location patterns. For example, in the pooled model, estimates from the ZIP model (p values shown below the marginal effects estimates) imply that counties which experienced a large influx of FDI in 1973–1982 (Agglo.) also enjoyed a much better chance of attracting new foreign firms in 1983–1992. Estimates suggest that a one standard deviation increase in 1973–1982 FDI occurrences (≈462% change from the mean, see Table 2) increased the probability of attracting a new foreign plant by 194% in 1983–1992. This finding supports the premise that unobserved heterogeneity in counties is important, and that flows of FDI are attracted to locations selected by previous foreign entrants.

To provide a more thorough indication of the estimated impact of the regressors on new firm location patterns, we present marginal effects computed at the sample mean as well as at plus/minus one standard deviation [$(\bar{X}+\sigma)$ and $(\bar{X}-\sigma)$] from the sample mean for the appropriate model type in Table 4. These estimates reveal that the marginal impact of the regressors varies quite substantially over the distribution of values. For the pooled manufacturing sector, estimates in Column 1 suggest when the regressors are one standard deviation below their means, $\bar{X}-\sigma$, the estimated elasticity of our agglomeration measure is 0.08. Alternatively, a 1% increase in 1973–1982 FDI measured at $\bar{X}+\sigma$ induces a 2.26% increase in the expected conditional mean of new foreign firms in 1983–1992.

Other parameter estimates in Column 2 of Table 3 are mostly intuitive and largely support previous findings — namely that higher wages deter new firm investment (at the 10% significance level), and larger, densely populated counties have significantly higher expected inflows of new foreign entities, ceteris paribus. Besides statistical significance, these variables also have economically significant impacts. For instance, the estimated marginal effect of wage levels implies that foreign entrants are highly sensitive to intercounty wage differentials — at the

Table 4
Marginal effects of the determinants of county-level FDI[a]

Ind. var.	Model type								
	ZIP Entire sample			Poisson Pollution-intensive industries			ZIP Non-pollution-intensive industries		
	$\bar{X}-\sigma$	$\bar{X}$	$\bar{X}+\sigma$	$\bar{X}-\sigma$	$\bar{X}$	$\bar{X}+\sigma$	$\bar{X}-\sigma$	$\bar{X}$	$\bar{X}+\sigma$
ln(Agglo.)	0.08	0.42	2.26	0.01	0.01	1.01	0.02	0.30	1.49
Attain.	−0.02	−0.14	−0.73	−0.01	−0.05	−1.76	−0.01	−0.05	−0.22
ln(Wage)	−0.07	−0.87	−4.45	−0.01	−0.21	−6.53	−0.03	−0.51	−2.11
ln(Pop.den.)	0.04	0.42	2.13	0.01	0.09	2.73	0.01	0.25	1.08
ln(Land)	0.06	0.50	2.59	0.01	0.09	2.86	0.02	0.31	1.35
ln(Tax)	0.02	0.53	2.64	0.02	0.16	4.94	0.02	0.24	0.90

[a] Marginal effects are calculated from the most appropriate model type in Table 3. Marginal effects are calculated at the sample mean ($\bar{X}$), as well as plus ($\bar{X}+\sigma$) and minus ($\bar{X}-\sigma$) one standard deviation from the sample mean.

mean a one standard deviation increase in wages (≈20%) decreases the conditional mean of new foreign plants by approximately 17%. Referring to Table 4, we see that the wage effect is magnified (diminished) for relatively large (small) values of the independent variables. A somewhat surprising result in Table 3 is that property tax rates (Tax) are an insignificant determinant of foreign investment flows. Nonetheless, this result is consistent with previous studies (see, for example, Woodward, 1992), and adds to the controversy surrounding the effects of higher tax rates on foreign firms — despite a substantial amount of research, tax effects remain largely unresolved.

Finally, empirical estimates suggest that environmental regulations (Non-Attain.) are an insignificant determinant in the foreign firm location process ($p=0.41$). Although this result is in accordance with the majority of previous empirical studies of domestic firm location (see, for example, Bartik, 1988; McConnell and Schwab, 1990; Duffy-Deno, 1992; Garafolo and Malhotra, 1995, Levinson, 1996), it may be due to a pooling effect. By grouping industries of varying pollution intensity we may be masking the effect that environmental regulations have on some industries (perhaps heavily polluting industry) by pooling them with other industries that are most likely not influenced by stringent pollution regulation (lesser pollution-intensive industry). In light of the descriptive statistics in Table 1, the results in Column 2 are most assuredly averaging over a number of non-pollution-intensive firms and a few pollution-intensive firms; and as a whole the effect of environmental regulation is insignificant. Consequently, there may be omitted variable bias in the regression equation since we are treating pollution-intensive firms and non-pollution-intensive firms similarly. To test this premise, we analyze results from pollution-intensive and non-pollution-intensive industries separately.

Columns 3 and 4 in Table 3 contain empirical results from the pollution-intensive subsample. Diagnostics in Columns 3 and 4 suggest that a model more sophisticated than the standard Poisson model may be unnecessary. For example, log-likelihood values are lower in the standard Poisson model (−22.0 vs. −24.4), and the Vuong statistic (0.56) does not provide compelling evidence in favor of the augmented model. Furthermore, large coefficient standard errors indicate the inappropriateness of the zero inflated model. We therefore focus on empirical estimates from the standard Poisson specification in Column 3 of Table 3, and provide additional marginal effects estimates for the Poisson model in Table 4.

Perusal of Table 3 reveals that most coefficients have intuitive signs and are significant at conventional levels. In certain respects, empirical estimates indicate that pollution regulations influence the location patterns of pollution-intensive foreign firms. Parameter estimates suggest, at the 13% level, pollution-intensive firms are deterred from locating in non-attainment counties. Although statistically significant, the effect is minute — at the mean, a one unit increase in the non-attainment status of a county decreases the expected count of new foreign plants by 0.05 in 1983–1992. Measured at other data points, the marginal effects reach much higher levels — at $\bar{X} + \sigma$, estimates in Table 4 imply that a one unit increase in the non-attainment status of a county decreases the expected flow of new foreign plants by about 1.76 in 1983–1992.

Interestingly, the estimated marginal effect computed at the variable means is much smaller than comparable estimates in Henderson (1996), which used an econometric model similar in spirit to the ZIP approach. Numerous factors may potentially explain this finding, but the most apparent is sample composition. Two distinct differences exist between our sample and Henderson's. First, Henderson examines highly pollution-intensive subsectors — SIC 282, 286, 291, 307, 331 — whereas we use data from SIC 26, 28, 29, 32, 33, 34 and 37. Second, Henderson's estimates average over a number of domestic entrants and a few foreign entrants, while our sample is comprised of purely foreign firms. If this latter difference is important, it provides an indication that foreign entrants are less sensitive to pollution regulations than their domestic counterparts. There may be important reasons why these different location patterns occur — perhaps foreign firms are less informed about the rules and codes of local US environmental regulations. Anecdotal evidence to support this conjecture is plentiful. For example, Hyundai recently located a semiconductor firm in Eugene, Oregon, and its construction was delayed for more than a year with wetlands permit disputes. While this evidence is purely anecdotal, coupling it with the findings above provides an indication that foreign entrants may be less sensitive to pollution regulations than domestic firms.

Other significant parameter estimates in Column 3 of Table 3 are intuitive and imply that pollution-intensive firms are attracted to large, densely populated counties with low wages. For instance, at the mean a one standard deviation increase in wages ($\approx$20%) decreases the probability of attracting a new pollution-intensive foreign plant by approximately 4%. Again, this estimate is greatly magnified or diminished if one considers the impact at larger or smaller regressor values, as per Table 4. Unintuitive estimates include an insignificant effect of both agglomeration economies and property taxes. These results imply that other area-specific attributes are more important in the foreign firm's location decision.

Columns 5 and 6 in Table 3 contain Poisson and ZIP empirical estimates for non-pollution-intensive industries. Diagnostics in Columns 5 and 6 suggest the augmented model is appropriate — e.g. log-likelihood values and the Vuong statistic $V=3.04>1.96$ both indicate the appropriateness of the augmented model. Therefore, we will focus attention on the ZIP estimates in Table 3 and present various marginal effects estimates for the augmented model in Table 4. For non-pollution-intensive firms it appears that agglomeration economies are extremely important — a one standard deviation increase in the number of previous FDI occurrences leads to a 139% increase in the conditional mean function. In Table 4, we see that this marginal effect estimate is magnified five-fold when computed at $\bar{X} + \sigma$ — verifying the importance of agglomeration economies to the entering non-pollution-intensive foreign firm. Other parameter estimates are according to extant findings, as larger, densely populated counties attract foreign entrants, and wages weakly deter entry. Again, we find that taxes are an insignificant determinant of location patterns of foreign firms.

Concerning environmental regulations, we find that ex ante intuition is supported as more stringent environmental regulations have negligible effects on non-pollution-intensive foreign entrants ($p=0.75$). This result, coupled with parameter estimates from the pollution-intensive sector, indicates that environmental regulations have heterogeneous effects on industries of varying pollution intensities. Although evidence from the pollution-intensive subsample is relatively weak in terms of statistical significance, the mere fact that heterogeneity exists in the investment decision is important since previous studies have largely ignored this possibility.

4. Concluding remarks

Cognizant of the recent surge in foreign direct investment, policymakers have expended considerable effort to attract FDI. Although a plethora of anecdotal evidence, from newspapers to policymakers, suggests there is a tradeoff between the environment and jobs, little has been done to test whether FDI is influenced by pollution regulations. We use a two-step empirical approach to examine which county-level variables are important to new foreign entities. Empirical estimates from models of count data suggest that previous counts of FDI, market size and accessibility, and land area are positively related to FDI occurrences, while higher wage rates and more stringent environmental regulations weakly deter new firm entry. The effects of more stringent environmental regulations, however, are found to be quite heterogeneous across sectors — prospective new plants in pollution-intensive sectors are weakly deterred by more stringent pollution regulation while new plants in non-pollution-intensive sectors are not effected.

More work needs to be done in this area. Although our empirical estimates suggest foreign firms are less sensitive to pollution regulations than their domestic counterparts, comparisons are made across studies that use different empirical models, control variables, and sampling populations. A study that analyzes the effects of environmental regulations across domestic and foreign firms would be invaluable. If our anecdotal evidence is supported, it would be worthwhile to investigate the country-level welfare implications of allowing heterogeneous environmental regulations across domestic and foreign firms.

Acknowledgements

I would like to thank Robert Masson and two anonymous reviewers for helpful comments. Bruce Blonigen and Craig Gallet provided thoughtful comments on an earlier version of this paper. Alan Williams provided invaluable research assistance. The usual caveats apply.

References

Bartik, T.J., 1988. The effects of environmental regulation on business location in the United States. Growth and Change 19, 22–44.

Blonigen, B., 1996. Firm-specific assets and the link between exchange rates and foreign direct investment. American Economic Review 87, 447–465.

Blonigen, B., Feenstra, R., 1997. Protectionist threats and foreign direct investment, Working Paper No. 5475, NBER.

Coughlin, C., Terza, J., Arromdee, V., 1991. State characteristics and the location of foreign direct investment within the United States. The Review of Economics and Statistics 73, 675–683.

Duffy-Deno, K.T., 1992. Pollution abatement expenditures and regional manufacturing activity. Journal of Regional Science 32, 419–436.

Figlio, D., Blonigen, B., 1998. The effects of direct investment on local communities, Working Paper, University of Oregon.

Friedman, J., Gerlowski, D., Silberman, J., 1992. What attracts foreign multinational corporations? Evidence from branch plant location in the United States. Journal of Regional Science 32, 403–418.

Garafolo, G., Malhotra, D., 1995. Effect of environmental regulations on state-level manufacturing capital formation. Journal of Regional Science 35, 201–216.

Gerking, S.D., List, J.A., 1999. Spatial economic aspects of the environment and environmental policy. In: Folmer, H., Gabel, L., Gerking, S.D., Rose, A. (Eds.), Frontiers of Environmental Economics, Elgar Publishing, London, in press.

Gray, W., 1997a. Discussion of state regulatory policy and economic development, New England Economic Review, Proceedings of the Symposium on the Effects of State and Local Public Policies on Economic Development, March–April, 99–103.

Gray, W., 1997b. Plant location: Do different industries respond differently to environmental regulation? Mimeo, Clark University.

Greene, W., 1994. Accounting for excess zeros and sample selection in Poisson and negative binomial regression models, Working Paper No. EC-94-10, New York University.

Greenstone, M., 1998. The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufacturers, Working Paper No. 408, Princeton University.

Heilbron, D., 1989. Generalized linear models for altered zero probabilities and overdispersion in count data, Technical Report, Department of Epidemiology and Biostatistics, University of California, San Francisco.

Henderson, V., 1996. Effects of air quality regulation. American Economic Review 86, 789–814.

Henderson, V., 1997. The impact of air quality regulation on industrial location. Annales d'Economie et de Statistique 45.

Jaffe, A., Peterson, S., Portney, P., Stavins, R., 1995. Environmental regulation and the competitiveness of US manufacturing: What does the evidence tell us? Journal of Economic Literature XXXIII, 132–163.

Kogut, B., Chang, S.J., 1991. Technological capabilities and Japanese FDI in the US. Review of Economics and Statistics 73, 401–413.

Lambert, D., 1992. Zero-inflated Poisson regression, with an application to defects in manufacturing. Technometrics 34, 1–14.

Levinson, A., 1996. Environmental regulations and manufacturers' location choices: Evidence from the Census of Manufacturers. Journal of Public Economics 62, 5–29.

List, J.A., Kunce, M., 1999. Environmental protection and economic growth: What do the residuals tell us? Land Economics, in press.

List, J.A., Shogren, J.F., 1998. Deadweight loss of Christmas: Comment. American Economic Review 88, 1350–1355.

McConnell, V., Schwab, R., 1990. The impact of environmental regulation on industry location decisions: The motor vehicle industry. Land Economics 66, 67–81.

Papke, L., 1991. Interstate business tax differentials and new firm location. Journal of Public Economics 45, 47–68.

Schmenner, R., 1977. Urban industrial location: An evolutionary model. Journal of Regional Science 17, 179–194.

Tannenwald, R., 1997. State regulatory policy and economic development, New England Economic Review, Proceedings of a Symposium on the Effects of State and Local Public Policies on Economic Development, March–April, 83–97.

Vuong, Q., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica 57, 307–334.

Woodward, D., 1992. Locational determinants of Japanese manufacturing start-ups in the United States. Southern Economic Journal 58, 690–708.