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No. 1628 | June 2010

Web: www.ifw-kiel.de

Kiel Working Paper No. 1628 | June 2010

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Abstract:
This paper analyzes the determinants of the location choices made by foreign investors at the district level in India to gauge the relative importance of economic geography factors, local business conditions, and the presence of previous foreign investors. We employ a discrete-choice model and Poisson regressions to control for the potential violation of the assumption of Independence of Irrelevant Alternatives. Our sample includes about 19,500 foreign investment projects approved in 447 districts from 1991-2005. We find that foreign investors strongly prefer locations where other foreign investors are. They are also attracted to industrially diverse locations and those with better infrastructure. We conclude that the concentration of FDI in a few locations could fuel regional divergence in post-reform India.

Keywords: FDI, economic geography, location choice, infrastructure

JEL classification: F23; R12

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I. Introduction

The stock of foreign direct investment (FDI) in India soared from less than US$ 2 billion in 1991, when the country opened up to world markets, to US$ 123 billion in 2008 (UNCTAD 2009). Policymakers in India as well as external observers attach high expectations to FDI. According to the (former) Minister of Finance, P. Chidambaram, "FDI worked wonders in China and can do so in India" (Indian Express, November 11, 2005). Bajpai and Sachs (2000: 1) claim that FDI brings "huge advantages with little or no downside." However, the Chinese evidence also suggests that FDI contributed to widening income gaps between prospering coastal regions and provinces in the hinterland (e.g., Fujita and Hu 2001; Zhang and Zhang 2003).

Sachs, Bajpai and Ramiah (2002) argue that the reform-mindedness of Indian states has rendered them more attractive to FDI. However, the concentration of FDI in a few relatively advanced regions may prevent FDI effects from spreading across the whole economy. To the extent that greater openness to FDI leads to further agglomeration, FDI may fuel regional divergence, rather than promoting convergence. According to the Schumpeterian growth model of Aghion et al. (2005), more FDI promotes growth in relatively advanced regions, while leaving growth almost unaffected in poorer regions. Indeed, FDI is clearly concentrated at the level of Indian states (e.g., Purfield 2006). Maharashtra accounted for more than a quarter of the amount of approved FDI in all-India in 2001-2005, followed by Delhi and Karnataka, which together contributed another quarter. Preliminary evidence also points to strong FDI clustering within large Indian states (Nunnenkamp and Stracke 2008).

For less advanced regions to share the benefits of FDI, it is thus important to gain insights into the location choices of foreign investors. We estimate count and discrete choice models using project-specific FDI data to assess the determinants of location choices at the level of Indian districts. The focus is on the post-reform period of 1991-2005. In addition to various factors reflecting the local business environment, we account for economic geography factors, including distance-weighted market potential, as well as previous location choices by foreign investors.

In the next section, we discuss how the present analysis relates to the previous literature and we derive our hypotheses for the case of post-reform India. We describe the data and introduce the estimation approach in Section III. Key findings are presented in Section IV, while Section V carries out robustness checks. Section VI concludes with a discussion of major contributions and limitations.

II. Hypotheses and related literature

A fairly strong concentration of FDI in relatively few locations can be observed both across and within host countries. The small group of developed countries persistently absorbed more than two-thirds of worldwide FDI stocks.[1] Among developing countries, the 20 top performers account for more than 80 per cent of total FDI stocks. At the level of particular host countries, FDI in the United States has been shown repeatedly to be located primarily in a few large and relatively advanced states.[2] At the finer level of US economic areas, almost one third of the FDI transactions used by Chung and Alcácer (2002) fall into just four major metropolitan areas (out of 170 economic areas). Coastal areas in China absorbed about 90 percent of overall FDI inflows during the period 1986-1998 (Zhang and Zhang 2003). Likewise, the spatial distribution of new greenfield FDI in Portugal in 1982-1992 was biased heavily towards urban and coastal locations, especially around the largest cities of Lisbon and Porto (Guimaraes, Figueiredo and Woodward 2000). FDI in India, too, is strongly concentrated both across and within states (see Section III).

Models of location choice by foreign investors have addressed various factors that may help explain the concentration of FDI across and within host countries. The theoretical starting point typically is that foreign firms decide on a particular location based on expected profitability. Consequently, location choices depend on how the characteristics of one particular spatial unit and its geographic environment affect firms' profits relative to the characteristics of other spatial units. Major factors shaping these choices include expected demand for a firm's products, the supply of required inputs, factor costs, and the quality of infrastructure. In addition, previous location choices by peers and competitors figure prominently on the list of FDI determinants and have received particular attention in the recent empirical literature.

[1] See: http://stats.unctad.org/FDI

[2] For instance, just two US states – California and New York – account for a quarter of the sample of manufacturing firms underlying the analysis of Coughlin, Terza and Arromdee (1991). See Coughlin and Segev (2000b) for an analysis at the level of US counties.

A priori considerations on more specific hypotheses involve considerable ambiguity depending on the level of regional disaggregation and the type of FDI (Alegría 2006; Blonigen et al. 2007). For instance, it may seem obvious that the size and purchasing power of local markets induce more foreign investors to enter a location. This hypothesis is most plausible in a cross-country context and as long as FDI is purely horizontal.[3] The motive of market access may also shape the distribution of horizontal FDI across fairly large spatial units in major host countries such as US or Indian states. Local demand should matter less, however, when location choices relate to smaller spatial units such as Indian districts, or when FDI is motivated by vertical specialization. Conversely, the *surrounding* market potential might become more important with smaller spatial units being analyzed.

Similar ambiguity prevails with regard to the costs of production. The relevance of wage costs, on which previous literature focuses, is “highly sensitive to small alterations in the conditioning information set” in cross-country studies according to the Extreme Bounds Analysis of Chakrabarti (2001). But even if higher wages discourage (vertical) FDI flows at the host country level, location choices by foreign investors within low-wage countries such as India are less likely to be affected. Regional wage disparity is small compared to average wage gaps between the host and source countries.[4] As a result, the concentration of FDI within low-wage countries is unlikely to be reversed by wage increases in its economic centres.

Availability of sufficiently skilled labour, which is the input of major interest in various studies, is likely to be a local pull factor attributing to the concentration of FDI within host countries such as India. According to the World Bank’s Investment Climate Assessment, survey respondents complained about serious skill shortages in various Indian states (World Bank 2004). Majumder (2008) stresses persistent regional disparities with respect to education. Majumder also provides extensive evidence on substantial variation in the regional quality of infrastructure, particularly

[3] This type of FDI essentially duplicates the parent company’s production at home in the host countries of FDI. Market access motivations dominate over cost considerations. By contrast, vertical FDI provides a means to allocate specific steps of the production process to where the relevant cost advantages can be realized.

[4] See Alegría (2006) for a similar line of reasoning. In the case of India, average labour costs (per worker and day worked in 2003-04) differed by a factor of less than two between relatively rich states such as Maharashtra (Rs. 438) and relatively poor states such as Bihar (Rs. 237) (Government of India 2006).

with regard to financial infrastructure. Regional disparities in the quality of infrastructure appear to have widened in the post-reform era.

Local skills and efficient infrastructure can be expected to be important regional pull factors of FDI even though FDI-related outsourcing may primarily involve labour that is relatively low skilled from the country of origin's point of view. Feenstra and Hanson (1997) have clearly demonstrated that the corresponding labour demand of foreign investors qualifies as relatively high skilled in lower-income host countries such as or India. Even as early as the second half of the 1990s, UNCTAD had argued that foreign investors were increasingly pursuing so-called complex integration strategies. And that accordingly, host countries would have to offer "an adequate combination of the principal locational determinants …. important for global corporate competitiveness" (UNCTAD 1998: 112), including sufficiently skilled labour, adequate infrastructure facilities and specialized support services. Specifically related to India, UNCTAD (2004: 172-3) expects that services outsourced to India are moving towards higher value-added levels, thereby giving rise to fiercer competition for skilled local labour.

Regional disparities in India, in combination with increasingly complex integration strategies of firms, may strengthen the incentives of foreign investors to cluster in economic centres.[5] It is thus of particular interest to assess the self-reinforcing effects of FDI on current location choices. Existing clusters of FDI may attract subsequent FDI by allowing for knowledge spillovers as well as offering a wider range of intermediate inputs. According to Bobonis and Shatz (2007), an additional one percent of FDI stock from a particular source country in a particular US state boosts the value of subsequent FDI from that source country in that state by 0.11 to 0.15 percent. Head, Ries and Swenson (1995; 1999) use count data on location choice of Japanese FDI in manufacturing industries of US states. The likelihood of a state being chosen by a subsequent investor in a particular industry increases by 5-6 percent for states where the count of previous Japanese investments in this industry is 10 percent higher. By contrast, Guimaraes, Figueiredo and Woodward (2000) find the self-reinforcing effects of previous location choices by foreign investors to be rather weak in Portugal. Compared to the aforementioned studies on FDI at the level of US

[5] Several studies suggest that regional inequality has increased in post-reform India, including Sachs, Bajpai and Ramiah (2002) and Kochhar et al. (2006). According to Lall and Chakravorty (2005), this also holds at the level of Indian districts.

states, Guimaraes et al. analyze location choices at a much finer regional level, namely the 275 (fairly small) Portuguese *conselhos*, similar to our focus below on Indian districts.

Among developing host countries, China has received most attention with regard to the self-reinforcing effects of FDI. Head and Ries (1996) estimate a model of self-reinforcing FDI using data on the distribution of 931 foreign ventures across 54 Chinese cities in 1984-1991. Cheng and Kwan (2000: 379) consider FDI in 29 Chinese provinces in 1985-1995, finding "a strong self-reinforcing effect of FDI on itself."[6]

Recent contributions to the literature have refined the tools of accounting for economic geography and self-reinforcing FDI effects. Until recently, it was common to apply a simple form of geographic relationship among spatial units, i.e., setting a dummy variable equal to one for adjacent countries or regions.[7] By contrast, distance-related weighting schemes have been introduced by Blonigen et al (2007) as well as Baltagi, Egger and Pfaffermayr (2007) to model more complex spatial effects, notably the surrounding market potential and the self-reinforcing effects of existing FDI clusters. Few studies have employed these tools so far at the regional level to assess location choices of foreign investors within particular host countries, or a group of host countries. For example, Alegría (2006) includes the external market potential, weighted by inverse distances, as an economic geography factor driving 4,800 instances of intra-EU FDI in the period 1998-2005. Ledyaeva (2009) assesses FDI determinants in Russian regions, accounting for external market potential and the spatially lagged dependent FDI variable.[8] Likewise, Crozet, Mayer and Mucchielli (2004) include external market potential and spatially lagged dependent variables, both weighted according to inverse distances in their study on FDI in France. The latter study resembles the present analysis of FDI in FDI in two respects: (i) the number of foreign investors deciding on where to locate is relatively large (almost

[6] Coughlin and Segev (2000a) also use provincial FDI data for addressing the dependence among Chinese provinces by estimating a spatial error (autocorrelation) model. Increased FDI in a province has positive effects on FDI in neighbouring provinces.

[7] Studies applying this concept of binary contiguity include: Head, Ries and Swenson (1995), Coughlin and Segev (2000a), and Bobonis and Shatz (2007).

[8] As we do in the subsequent analysis, Ledyaeva (2009) performs several cross-section estimations for sub-periods of the whole period under consideration (1996-2005). Ledyaeva is mainly interested in whether FDI determinants and the type of FDI changed after the 1998 financial crisis in Russia.

4,000 observations over ten years), and (ii) location choices relate to narrowly defined spatial units (92 French *départements*), rather than large regions such as US states.

III. Data and estimation

a. FDI data

We draw on a detailed account of FDI approvals in India during the period 1991-2005. The unpublished data were kindly made available by the Department of Industrial Promotion and Policy (DIPP) of the Ministry of Commerce and Industry. The dataset covers about 19,500 FDI projects, providing project-specific information on approved amounts, the home country of the foreign investor, as well as the state and district in India where the project is located. Non-resident Indians are included as a distinct source of FDI. It is also possible to distinguish FDI projects by foreign equity shares, making it possible to assess whether FDI determinants differ between minority and majority owned subsidiaries in India. Moreover, information on planned activities allows for a classification of FDI projects into broad sectors, notably a distinction between FDI in manufacturing and services.[9]

Approved FDI amounts may deviate considerably from realized FDI. However, it does not seriously constrain the subsequent analysis that the regional distribution of realised FDI in India is not available.[10] We focus on the counts of FDI projects, rather than approved amounts. While it cannot be ruled out that some approved FDI projects are not carried out at all, the count measure is unaffected by the typical gap between approved and realised amounts for particular projects. Changes in approval procedures after India's reform program of 1991 should not pose a major problem either. So-called automatic route approvals are included in the database until October 2004, according to information received from the Ministry of Commerce and Industry. Hence, our estimations are not distorted by the progressive extension of the list of FDI projects subject to the automatic approval route.

[9] The sector structure of FDI in India has changed considerably since the early 1990s. FDI in services accounted for about 60 percent of all approved FDI projects in recent years. In sharp contrast, FDI in manufacturing clearly dominated in the first half of the 1990s. FDI in the primary sector remained marginal throughout the period of observation. Chakraborty and Nunnenkamp (2008) observed similar shifts for realized FDI stocks.

[10] It may also be noted that aggregate data on realized FDI in India is not perfect either. It is only since 2000 that the Reserve Bank of India reports a revised series of realized FDI inflows that includes reinvested earnings and debt transactions between related entities (to be counted as FDI according to international standards).

FDI in India is strongly concentrated at the state level. Maharashtra, Delhi and Karnataka accounted for more than half of the amount of approved FDI in all-India in 2001-2005 (Nunnenkamp and Stracke 2008). Figure 1 shows that FDI is also spatially concentrated within states, i.e. at the district level. The maps reveal the density of FDI project applications; the size of the circles is proportional to the number of applications within the district. The left-hand side map illustrates that whilst some districts in the country potentially attract a lot of FDI activity, others are virtually empty. Of the possible 604 districts, FDI seems to be attracted to only 320 districts over the period of 1991-2005. Of these, 50 percent of all FDI is drawn to only six districts. The right-hand side map replicates the same exercise, but after controlling for district population. FDI applications increase in districts in the southern and western parts of the country, and activity in districts around Delhi and Mumbai is better highlighted.

b. Econometric model

The two most popular models of location choice are conditional logits (or nested logits) and Poisson regressions.[11] The use of a discrete choice framework to model location behaviour stretches back to the 1970s, when Carlton (1979) adapted and applied McFadden's (1974) Random Utility Maximisation framework to firm location decisions.

In line with the discrete choice framework, we start with positing a general profit function to explain the location behaviour of foreign investors choosing a location (here district) in India. Following McFadden (1974) it is assumed that an investor i choosing to locate in district j will derive a profit of π_{ij}:

$$\pi_{ij} = U_{ij} + \varepsilon_{ij} \tag{1}$$

where U_{ij} is the deterministic part and ε_{ij} represents the random variable. District j will be preferred by the investor i if

$$\pi_{ij} > \pi_{ik}\ ,\ \forall k, k \neq j$$

[11] See Appendix table 1 for a summary of studies employing these models.

The stochastic nature of the profit function implies that the probability that location j is selected by the investor i equals:

$$P_{ij} = \Pr ob(\pi_{ij} > \pi_{ik}), \; \forall k, k \neq j$$

It is assumed that the *i*th firm will choose district *j* if $\pi_{ij} > \pi_{ik}$ for all k where k indexes all the possible location choices to the *i*th firm. Under the assumption of independent and identically distributed error terms ε, with type I extreme-value distribution, the probability of choosing district j becomes:

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{k=1}^{n} \exp(U_{ik})} \qquad (2)$$

The above equation expresses the conditional logit formulation. If we further assume that the systematic part of profit is affected by a set of m regressors, we can estimate the effects these have on location decisions. Typically, it is assumed that U_{ij} is a linear combination of the explanatory variables:

$$U_{ij} = \beta_1 X_{ij}^1 + \beta_2 X_{ij}^2 + \ldots\ldots.. + \beta_m X_{ij}^m$$

The simplicity of the conditional logit model (CLM) allows first insights into the behaviour of foreign investors across different districts within the country. For instance, it is possible that a foreign investor may consider large urban agglomerations in different states as possible alternatives. In other words, an investor may consider Kota in the state of West Bengal and Pune in Maharashtra as possible alternatives since they serve as satellite towns to larger cities (Kolkata and Mumbai, respectively).

In practice, however, the implementation of the conditional logit model in the face of a large set of spatial alternatives is very cumbersome.[12] The CLM is also characterised by the assumption of Independence of Irrelevant Alternatives (IIA). Consequently the ratio of the logit probabilities for any two alternatives j and k does

[12] Guimaraes, Figueiredo and Woodward (2003) provide an overview of the problems and how different researchers have attempted to deal with them in the past.

not depend on any alternatives other than j and k. More formally this implies that the ε_{ij} are independent across individuals and choices; all locations would be symmetric substitutes after controlling for observables. This assumption could be violated if districts within particular states are closer substitutes than others outside of the state boundary. To effectively control for the IIA assumption, one would need to introduce a dummy variable for each individual choice. This would amount to a specification of the following type:

$$\pi_{ij} = U_{ij} + \varepsilon_{ij} = \delta_j + \beta' z_{ij} + \varepsilon_{ij} \tag{3}$$

where δ_j s are the alternative specific constants introduced to absorb factors that are specific to each particular choice. In this case all explanatory variables (observable or unobservable) that only change across choices are absorbed by the alternative specific constants. However, in the presence of a large dataset this implementation would be impractical because of the large number of parameters to be estimated.

As an econometric alternative, Guimaraes, Figueiredo and Woodward (2003) show that the implementation of conditional logit models yields identical results to Poisson regression models when the regressors are not individual specific. They demonstrate how to control for the potential IIA violation by making use of an equivalence relation between the CLM and Poisson regression likelihood functions. In a separate paper, Guimaraes, Figueiredo and Woodward (2004) provide an empirical demonstration. In this model the alternative constant is a fixed-effect in a Poisson regression model, and coefficients of the model can be given an economic interpretation compatible with the Random Utility Maximisation framework. Since using both models yield identical parameter estimates, we will use Poisson regressions to generate coefficients.

Let n_{ij} be the number of investments in region j. Based on the profit function in Equation (3), the probability of investor i selecting location j would then become:

$$P_{ij} = \frac{\exp(\delta_j + \beta' z_{ij})}{\sum_{j=1}^{J} \exp(\delta_j + \beta' z_{ij})} \tag{4}$$

The parameters of equation (4) can then be estimated by maximising the following log-likelihood:

$$\ln L_{cl} = \sum_{j=1}^{J} n_{ij} \log P_{ij} \qquad (5)$$

Guimaraes, Figueiredo and Woodward (2003) show that Equation (5) is equivalent to that of a Poisson model that takes n_{ij} as the dependent variable and includes a set of location-specific explanatory variables. The same results will be obtained if we assume that η_{ij} follows a Poisson distribution with expected value equal to

$$E(n_{ij}) = \lambda_{ij} = \exp(\alpha' d_j + \beta z_{ij})$$

That is, the above problem can be modelled as a Poisson regression where we include as explanatory variables d_j (which vary across locations) and z_{ij} (which vary across groups of investors and locations); n_{ij} is the number of investments in j.

More recently, Schmidheiny and Brulhart (2009) have shown that the elasticities of the conditional logit and Poisson models establish the boundary values at polar ends. In other words, they observe that the Poisson model implies more elastic responses by, here, investment counts, to given changes in own-region characteristics than the conditional logit model. Also, unlike in the conditional logit model, in the Poisson model, one region's change in locational attractiveness has no impact on the number of investments located among any of the other regions. We will exploit the features of both, conditional logits and Poisson, models to compute the two extremes for the elasticities, i.e. the percentage change in the expected number of firms in a region (or a neighbouring region) with respect to a unit change in the locational characteristics of the region.[13]

[13] The conditional logit model implies a zero-sum allocation process of a fixed number of investments over the J locations. In the Poisson model, by contrast, new investments are non-rivalrous, in the sense that we are in a positive-sum economy and one region's gain is not another region's loss.

c. Specification of variables

In the conditional logit model the dependent variable is a binary variable taking the value of one if the investor chooses to invest in a district and zero otherwise. In the Poisson model the dependent variable is the count of new foreign investment projects approved in a district. As noted above, the overall sample includes about 19,500 foreign investment projects approved in 447 districts belonging to 35 states and union territories. Whilst we have annual FDI observations for the period 1991-2005, data on district-level location variables are available for only a few years. This restricts our analysis to three cross-sections: 1991, 1996 and 2001. Our focus is on the fully specified model for 2001, while the more limited estimations for the two earlier years serve as robustness tests.

The independent variables include characteristics of the district that can affect the profits of the investor. We classify these variables into those with an economic geography dimension, those that reflect business conditions in the district (notably, the availability of complementary factors of production and the quality of infrastructure), and those that relate to the behaviour of previous investors within the district as well as in other districts of the same state. A brief description of major variables follows.[14]

The economic geography variables in our model are represented by the Herfindahl index, market access, and population to indicate the size of the local market. We use the Herfindahl index to measure the degree of economic diversity in each region. HI_j is the sum of squares of employment shares of all industries in region *j*:

$$HI_j = \sum_k \left(\frac{E_{jk}}{E_j} \right)^2$$

Unlike measures of specialisation, which focus on one industry, the diversity index considers the industry mix of the entire regional economy. The largest value for HI_j is one when the entire regional economy is dominated by a single industry. Thus higher values signify lower levels of economic diversity.

[14] See also Appendix table 2 for definitions and sources; Appendix table 3 presents summary statistics.

Access to larger markets should provide a stronger incentive for investors to pick particular locations. For instance, investors in satellite towns, for instance Gurgaon, would also have access to larger neighbouring markets, say Delhi. The classic gravity model, which is commonly used in the analysis of trade between regions and countries, states that the interaction between two places is proportional to the size of the two places (as measured by population, employment or some other index of social or economic activity), and inversely proportional to some measure of separation such as distance. We use the formulation proposed initially by Hanson (1959) that states that the accessibility at point 1 to a particular type of activity at area 2 (say, employment) is directly proportional to the size of the activity at area 2 (say, number of jobs) and inversely proportional to some function of the distance separating point 1 from area 2. Accessibility is thus defined as the potential for opportunities for interaction. Thus, market accessibility is defined as:

$$MA_j = \sum_j \frac{S_m}{d^b_{j-m}}$$

where MA_j is the accessibility indicator estimated for location *j*, S_m is a size indicator at destination *m*, d_{jm} is a measure of distance between origin *j* and destination *m*,[15] and *b* describes how increasing distance reduces the expected level of interaction.[16] The accessibility measure is constructed using population as the size indicator and distance as a measure of separation; it is estimated without exponent values. The market access measure is constructed by allowing transport to occur along the straight line connecting any two districts. Instead of calculating the distance between any pair of districts across the country, we restrict the links to districts within a 500-kilometre radius.

Turning to district characteristics reflecting business conditions, we use non-agricultural hourly wage rates as an indicator of labour costs. We also account for education (higher-secondary education or middle-higher schools) as a proxy of the qualification of the workforce, which is traditionally considered to be an important complementary factor of production. In addition, we employ various proxies for the

[15] We are grateful to Eckhardt Bode for providing us with the syntax for computing the great circle (orthodormic) distance calculations.
[16] In the original model proposed by Hanson (1959), b is an exponent describing the effect of the travel time between the zones.

availability and quality of district-level infrastructure, including power (electricity), communications (telephone), transport (access to buses or roads), financial (bank branches) and health (access to health centres) infrastructure.

Finally, following Crozet, Mayer and Mucchielli (2004), we include a variable to account for previous investment choices by foreign investors. In particular, we assess whether foreign investors are attracted to locations that attracted other foreign investors before, and whether this effect is stronger for investors from the same country of origin. We include a count variable to take account of all foreign firms within a district and in all districts within the state, weighted by their distance. Formally stated, we include:

$$FA_j = Count_j + \sum_{j \in s} \frac{Count_m}{d_{j-m}} \quad \text{and} \quad FS_j = Count_j + \sum_{j \in s} \frac{Count_m}{d_{j-m}}$$

where FA_j and FS_j refer, respectively, to all foreign and all same-country foreign firms in location j. The value of FA is computed for all years leading up to the year for which the cross-section is carried out.

Without convincing instruments, it is difficult to control for possible endogeneity. In particular, location choices by previous investors may be jointly determined with our dependent variable resulting in an omitted variable bias. The limited availability of district-level data for a continuous set of years prevents us from addressing endogeneity concerns by performing panel estimations. Rather, we estimate three cross-sections to fully exploit the available data. Although, this does not allow us to control for endogeneity concerns, it does reduce the possibility of bias. There is also little reason to be concerned about reverse causality running from our regressors to firm-specific location choices. Note also that we lag our regressors by assessing their impact on location choices in the concurrent and the two subsequent years, in order to mitigate possible endogeneity problems.

IV. Results and discussion

We illustrate the key characteristics of the data and the subsequent modelling choices, by using the 2001 cross-section as an example. One of the key characteristics of the data is that it is over-dispersed. In Table 1, the mean number of investments per district is around 11, while the standard deviation is over 90, i.e. over eight times the mean. A Poisson model implies that the expected count, or mean value, is equal to the variance. This is a strong assumption, and does not hold for our data.

A frequent occurrence with count data is an excess of zeroes compared to what would be expected under a Poisson model. This is indeed a problem faced by our data – the mean number of investments is about 35 when excluding zeros and the standard deviation is 161, i.e. around 4.6 times the mean. Also note that 369 out of 533 districts did not receive any investments in 2001-2003.[17] This implies that we would need to take into account, both, over-dispersion and the excess of zeroes in the data, when selecting a model to fit the data.

Another way to reiterate the unsuitability of the Poisson model in this case is to show that such a model is unable to predict the excess zeroes found in our data. In Table 1, “obs” refers to actual observations in the data, and fitp, fitnb and fitzip refer to the predictions of the fitted Poisson, negative binomial and zero-inflated Poisson models respectively. While 69.23% of the locations in the sample received no investments, the Poisson model predicts that only 58.35% would get no investments. Clearly the Poisson model underestimates the probability of zero counts. The negative binomial model, which allows for greater variation in the count variable than that of a true Poisson, predicts that 63.85% of all districts will receive no investments, much closer to the observed value.

One way to account for the excess zeroes would be to assume that the data comes from two separate populations, one where the number of investments is always zero, and another where the count has a Poisson distribution. The distribution of the outcome is then modelled in terms of two parameters – the probability of always zero and the mean number of investments for those locations not in the always zero group. The zero-inflated Poisson model (fitzip) predicts that 64.84% of all locations will receive no investments, marginally better than the predictions of the negative binomial model.

An alternative approach to deal with an excess of zeroes would be to use a two-stage process, with a logit model to distinguish between the zero and positive counts, and then a zero-truncated Poisson or negative binomial model for the positive counts. In our case this would imply using a logit model to differentiate between

[17] Although there are a total of 604 districts in India, we exclude all districts for which we do not have data for the regressors.

districts that receive no investments and those that do, and then a truncated model for the number of districts that receive at least one investment. These models are referred to as "hurdle models" – a binary probability model governs the binary outcome of whether a count variable has a zero or positive realisation; if the realisation is positive, the 'hurdle' is crossed and the conditional distribution of the positives is governed by a truncated-at-zero count model data model (McDowell 2003).[18]

Against this backdrop, Table 2 reports the results of the 2001 cross-section based on alternative models. The response variable is 'count', i.e. the number of investments received by a district. The Poisson regression models the log of the expected count as a function of the predictor variables. More formally, $\beta = \log(\mu_{x+1}) - \log(\mu_x)$, where β is the regression coefficient, μ is the expected count and the subscripts represent where the regressor, say x, is evaluated at x and x+1 (here implying a unit percentage change in the regressor).[19] Since the difference of two logs is equal to the log of their quotient, i.e. $\log(\mu_{x+1}) - \log(\mu_x) = \log(\frac{\mu_{x+1}}{\mu_x})$, we could also interpret the parameter estimate as the log of the ratio of expected counts. In our case, the count refers to the 'rate' of investments per district. We report exponentiated coefficients[20], i.e. incidence rate ratios. The incidence rate ratios can be interpreted as follows: if education (i.e. the proportion of the population with a high-school degree) was to increase by a percentage unit, the rate ratio for count would be expected to increase by a factor of 1.28, i.e. by 28 percentage points. As mentioned earlier, the conditional logit and the Poisson models establish the range for the odds ratios of the analysis. We also present the results of the conditional logit estimation in the last column of Table 2, commonly referred to as 'odds ratios'. The odds ratio can be interpreted as follows: a unit percentage increase in education would be associated with a 57 percent increase in the odds of receiving an investment in a district. An incidence rate or odds ratio greater than one implies a positive effect; less than one implies a negative effect, and equal to one means that changes in the predictor variable leave the dependent variable unaffected.

[18] We were unable to achieve convergence for the zero-inflated and the zero-truncated negative binomial models when using all regressors. We report the results of these models when convergence is achieved using limited regressors.

[19] This is because the regressors are in logarithms of the original independent variables.

[20] The unexponentiated coefficient results can be made available on request.

In order to select the preferred model, Table 2 also presents the Bayesian information criterion (BIC) and Akaike's information criterion (AIC). Since the models are used to fit the same data, the model with the smallest values of the information criteria is considered superior. By these criteria the negative binominal models generally perform better than the Poisson models. Note that this holds not only for the 2001 cross-section but also for the cross-sections for 1996 and 1991 reported in Appendix tables 4 and 5 as robustness tests.

The presentation and interpretation of results focuses on the 2001 cross-section as the data situation is clearly superior compared to earlier years. Apart from the health-related variable on infrastructure, the full set of explanatory variables is available for 2001 (see also Appendix table 2). By contrast, two variables of major interest – the Herfindahl index on economic diversity and labour costs – are lacking for earlier years. Moreover, the data is available for most Indian districts in 2001, whereas coverage of districts is limited in 1991 and 1996. Nevertheless, the results for the two earlier cross-sections offer some valuable insights on the robustness of several variables driving the location choices of foreign investors in post-reform India.

The dependent count variable used for 2001 cross-section actually includes FDI projects approved during the three-year period 2001-2003. In this way we make use of a larger part of the FDI database introduced in Section III above. At the same time, the consideration of three years as regards approvals smoothes cyclical FDI fluctuations.[21] As a first result, it should be noted that we find a strong tendency of foreign investors to go where other foreign investors are already present. The preferred binominal models reveal a particularly strong clustering of FDI; but even the Poisson models suggest that a percentage increase in the value of FA (which includes investors within the same district and in neighbouring districts) would result in a 40 percent increase in the expected rate of FDI counts. Whenever available[22] the coefficient is statistically significant at the 0.1 percent level. As shown in Appendix table 4, the high statistical significance of FA and its strong quantitative impact also holds in the earlier cross-section for 1996.[23] This invites the conclusion that regional clustering of FDI prevailed throughout most of the period under consideration. In

[21] Similarly, we use FDI approvals in 1996-1998 for the 1996 cross-section and, respectively, approvals in 1991-1993 for the 1991 cross-section.
[22] Since convergence could not be achieved with the full set of predictor variables within zero-truncated models, the coefficients for the dropped variables could not be computed.
[23] FA does not enter the cross-section for 1991 in Appendix table 5 as 1991 is the first year covered in the FDI database.

other words, insofar as India's reform program initiated in the early 1990s resulted in more FDI, it is likely to have contributed to regional disparities in India by exacerbating the concentration of FDI.

Turning to the economic geography variables, population consistently has a positive effect and, typically, is highly significant at the one percent level. In the zero-inflated negative binominal models, the quantitative effect is about 39 percent if population increases by one percentage point. Similar results are achieved for the two earlier cross-sections, even though the level of significance and the quantitative impact vary somewhat over time and across models. Recalling the discussion on horizontal FDI in Section II, population is surprisingly robust as a relevant driving force of FDI at the district level. This finding qualifies the popular view held in various source countries that the boom of FDI in post-reform India is mainly associated with vertical, i.e. cost-cutting FDI; it rather appears that FDI is horizontal, i.e. closely associated with the size of the local market.

In contrast to population in the district where FDI locates, distance-weighted population in other districts - representing our proxy of market access (MA) - does not appear to impact positively on FDI. In the preferred negative binominal models in Table 2, MA does not differ significantly from zero; the Poisson models even suggest a negative effect as the IRR are significantly below one.[24] This is in conflict with the hypothesis that districts in the neighbourhood of large metro areas are likely to benefit, in terms of attracting more FDI, from having easier access to these markets than remote Indian districts. Rather, it appears that large metro areas divert FDI projects away from neighbouring districts, thereby perpetuating or even widening the urban-rural divide.[25] Conversely, the sharp urban-rural divide in India implies limited market potential surrounding the metro areas, which further weakens any positive effects MA may have on FDI.

HI seems to have a negative relationship (i.e. the IRR<1) with FDI projects. Recall that this variable is a measure of the level of industrial diversity within the

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[24] MA also proves to be insignificant in the negative binominal models run for the earlier cross-sections. By contrast, the Poisson models often result in significantly positive results for MA in Appendix tables 4 and 5. The latter finding applies especially to the cross-section for 1996. Recall however that the reliability of the results for 1996 suffers from a drastically reduced number of observations.

[25] It should be noted in this context that, for instance, almost 90 percent of approved FDI projects in Karnataka went to Bangalore; Kolkata accounted for 70 percent of projects approved in West Bengal (Nunnenkamp and Stracke 2008).

district. A higher HI implies higher employment concentration by one industry and lower industrial diversity. Thus, the negative coefficient for HI is evidence of a positive association between more industrial diversity and more FDI. This could be since foreign investors are increasingly pursuing complex integration strategies, as noted by UNCTAD (1998). Consequently, they rely on a diverse set of intermediate inputs from various industries, giving locations a competitive edge where these inputs are easily available. Our finding on HI is in line with Kathuria (2002), according to whom the degree of vertical integration of FDI projects has declined in post-reform India. Unfortunately, owing to lack of data we are unable to test this relationship further for other cross-sections.

It is not only greater industrial diversity that attracts FDI to Indian districts. The same applies to districts with a better-qualified workforce, as reflected in IRRs typically being greater than one for our variable on education. With the exception of the zero-truncated negative binominal model, education proves to be statistically significant throughout in the cross-section for 2001, at the five per cent level or better. The findings for education are somewhat weaker, both in terms of statistical significance and quantitative impact, in the earlier cross-section for 1991 (Appendix table 5). This may indicate that the availability of sufficiently qualified labour in Indian districts has become more important over time as a complementary factor of production. However, this conclusion can only be tentative, recalling that the specification of our variable on education differs slightly between the cross-sections due to data limitations.

While better-educated workers attract FDI, higher labour costs could be expected to discourage FDI. However, the evidence for 2001 is ambiguous and we are unable to make any comment for earlier years.[26] The negative effect is highly significant at the 0.1 percent level as well as quantitatively important in the three Poisson models. By contrast, the negative binominal models – preferred because of lower AIC and BIC statistics – reveal wage effects that do not differ significantly from one, implying no change in the incidence rate ratios. As will be shown below, the impact of wages on FDI differs considerably across sectors.

Finally, Table 2 reveals somewhat ambiguous findings concerning the relationship between infrastructure and FDI at the district level. On the one hand,

[26] As noted above, wage data at the district level are not available for the earlier cross-sections.

electricity enters with a highly significant and strongly positive coefficient irrespective of the choice of model. On the other hand, telephone connections – our proxy of communication infrastructure – typically remain insignificant. The evidence varies across models with respect to financial infrastructure and transport infrastructure (proxied by bus services in Table 2). This ambiguity resembles previous findings at the level of Indian states. As a matter of fact, the role of infrastructure as a determinant of FDI in India has remained disputed. While the World Bank (2004) claims that deficient infrastructure represents an important bottleneck to investment even in relatively advanced states such as Maharashtra and Gujarat, Chakravorty (2003) finds that infrastructure had little influence in determining the location or quantity of new industrial investment. Nunnenkamp and Stracke (2008) show that the impact of infrastructure on state-level FDI depends on the specific indicator chosen.

V. Robustness checks

As a first robustness check, we differentiate between FDI in the secondary and the tertiary sector and re-run the cross-section regressions for the year 2001 to observe if the effect of the predictor variables varies across these two sectors. Although we carried out the regressions using Poisson and zero-inflated and zero-truncated methods as well, we only report the results of the simple negative binomial specifications.[27] This is to facilitate comparison, but more importantly because the negative binomial model exhibited the best goodness-of-fit statistics. As before, the coefficients are reported as Incidence Rate Ratios for ease of interpretation.

In several respects, the results for the manufacturing and services sub-samples in Table 3 closely resemble the corresponding negative binominal model results for the overall FDI sample in column 2 of Table 2 above. For both sub-samples, there appears to be a strong tendency to locate where other foreign investors have chosen to locate.[28] We find, as before, that population has a positive effect on FDI projects. While the tendency to follow previous investors appears to be slightly stronger in the manufacturing sector, population has a somewhat stronger impact of FDI projects in

[27] Results from the models are available on request.

[28] We estimated FA for the total of projects within the same district and in neighbouring districts; i.e., this variable is not further disaggregated by the type of sector. This is because we would like to capture the effect of FDI drawn to locations for reasons of intra-industry advantages, but also for buyer-supplier linkages across sectors.

the services sector. This is in line with economic intuition, in which services industries usually benefit more than manufacturing industries from being close to where people are situated. As before for the overall sample, our measure of industrial diversity (HI) is still not significantly different from one if the negative binominal model is estimated for sector-specific FDI.[29]

Yet we find some interesting differences between FDI in manufacturing and FDI in services. Most notably, the costs of local labour discourage FDI only in the services sector. Here, the effect of wages is significant at the one percent level, and quantitatively important with a one percentage point increase in wages resulting in a decline by more than 40 percent in the expected count of FDI projects. The striking contrast in wage effects between sectors invites the conclusion that vertical FDI, which is mainly motivated by cost considerations, is largely restricted to India's services sector, whereas FDI in its manufacturing sector continues to be horizontal, i.e., local market seeking.[30] This could also be because certain services sectors rely on access to cheap and abundant labour (for instance, call centres) and they would then be theorised to be more sensitive to wage increases. However, since we are unable to disaggregate the data down to the two-digit industry level, we cannot be certain which specific industries within these sectors maybe driving the results. Moreover, the sector-specific perspective adds to the ambiguity concerning infrastructure. The effect of electricity proves to be strongly significant for FDI in manufacturing only, while the presence of banking facilities at the district level encourages FDI in the services sector at the five percent level of significance.

The next robustness test distinguishes between majority and minority foreign owned joint ventures (JVs). We use foreign equity shares as presented in the DIPP database to group all FDI projects into these two categories.[31] This distinction may be relevant as higher foreign equity shares tend to be associated with a relatively strong bargaining position of foreign investors (e.g., Asiedu and Esfahani 2001) which, in turn, may imply that location choices are more strongly determined by the preferences of foreign investors than those of the host government. Nevertheless, Table 3 reveals

[29] The IRR for our variable on education appears to be of similar size for FDI in manufacturing and services. In contrast to the corresponding estimation for the overall sample, however, this variable turns statistically insignificant at the five percent level for sector-specific FDI, although it remains significant at the 10 percent level.

[30] Agarwal (2001) suspects FDI in India to be still domestic market seeking.

[31] Information on the foreign equity share is missing for various FDI projects, which results in a considerably reduced number of observations.

few significant differences between majority and minority owned JVs with respect to the determinants of location choices. Local market size, as reflected by population, as well as financial infrastructure appears to matter more for minority owned JVs. This is plausible given that majority owned JVs may turn primarily to international capital markets for financing, and may also be more export oriented than minority owned JVs.

Similar to minority owned JVs, smaller FDI projects appear to be more reliant on local markets and local financing than larger FDI projects. This is revealed by our third robustness test when considering the median of the value of foreign equity as the dividing line between small and large FDI projects. In most other respects, however, our results are hardly affected by distinguishing between small and large projects.

Finally, we re-run the CLM included in Table 2 above by separately accounting for previous investment choices by foreign investors of the same country of origin (FS).[32] We find that foreign investors tend to locate where investors from the same country of origin located before; the corresponding odds ratio is significantly higher than one, at the 0.1 percent level. However, the tendency to follow investors from the same country of origin does not appear to be stronger than the tendency to follow other foreign investors. This is broadly in line with the findings of Crozet, Mayer and Mucchielli (2004) for FDI in French *départements*. The results for almost all other variables are robust to the inclusion of FS when comparing the last columns in Tables 2 and 3.[33]

VI. Concluding remarks

This paper contributes to the empirical literature relating to the geography of foreign direct investment in a number of ways. Although there is some previous research on the behaviour of foreign investors in emerging countries like China, to our knowledge this is the first paper that analyses location decisions for over 19,500 FDI projects in India. We differentiate between economic geography factors, such as the presence of existing FDI, access to neighbouring markets and industrial diversity, and factors

[32] This robustness test can only be performed for the CML as the choices of foreign investors need to be matched on a one-to-one basis with those belonging to the same country. This matching exercise is not possible to carry out when investments are grouped as a count variable.
[33] The only exception refers to education that turns insignificant in Table 3.

relating to the local business conditions including the quality of infrastructure at the level of districts. The difference between these two sets of factors is of obvious policy relevance: Whilst public policy may be in a position to influence the level and quality of infrastructure within a lagging region, its ability to affect economic clustering is limited.

Indeed, we find that path dependence tends to constrain the influence of regional policymakers. Foreign investors strongly prefer locations that already host other foreign investors. This effect is significantly positive and robust across different years, sectors and different types of FDI. Moreover, foreign investors tend to follow previous investors from the same country of origin, but also investors from other countries of origin. We also find that the degree of economic diversity within a location attracts FDI, but we are unable to check this result for different years. More surprisingly, districts in the neighbourhood of large metro areas do not benefit, in terms of attracting more FDI, from having easier access to these markets than remote Indian districts. On the contrary, our results suggest that large metro areas divert FDI projects away from neighbouring districts, thereby perpetuating or even widening the urban-rural divide.

However, geography is not destiny. It is in several respects that local business conditions matter for the location choices of foreign investors at the level of districts. For instance, the presence of an educated population is a significant factor drawing FDI projects to a location. This clearly reveals that FDI in post-reform India is attracted not only by lower labour costs but also by the availability of sufficiently skilled labour as an important complementary factor of production. Providing adequate schooling and training thus appears to be an important policy tool for regional policymakers.

Investing in infrastructure represents another option to attract FDI. Access to power, transport and financial infrastructure – factors that the World Bank often classifies as ‘investment climate’ – clearly matters for location decisions of foreign investors. However, the evidence is more ambiguous when it comes to the question of which aspect of infrastructure is particularly relevant for FDI in particular sectors. For instance, the presence of bank services within a location seems to be an important factor driving location choices for FDI in services, but less so for FDI in manufacturing. The opposite pattern turns out for power supply. This ambiguity may render it difficult for policymakers to decide on investment priorities in the area of infrastructure.

Future research may help overcome a few shortcomings once additional data are made available by Indian authorities. Data limitations with respect to FDI determinants at the district level do not permit us to estimate panel regressions, which would allow us to better deal with endogeneity concerns. Additional insights might also be gained if all FDI projects were differentiated between industrial sectors at a disaggregated level. Industry-specific estimations could reveal whether the location choices of foreign investors and the relative importance of economic geography and local business conditions differ across industries. For instance, computer or financial services would probably require different levels and types of labour skills than retail or transport services. Finally, even though the FDI data offer various details on the characteristics of joint ventures in India, it would be desirable to match this dataset with data on the foreign parent company. Its size, age, productivity and technological sophistication may shape location decisions, in addition to district characteristics, considering that such firm characteristics influence the relative bargaining position of foreign investors vis-à-vis regional authorities competing for FDI.

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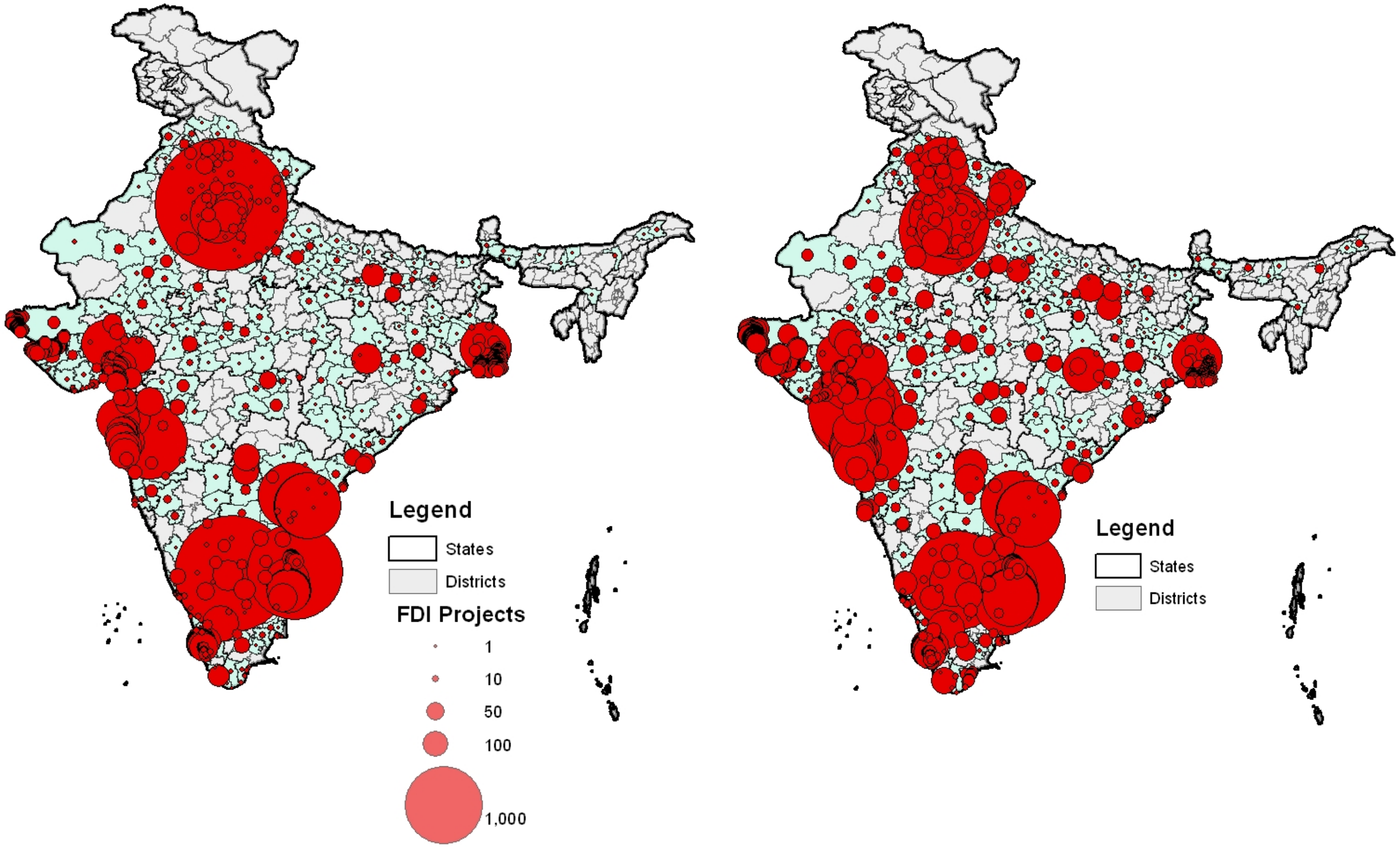
Figure 1: Spatial Distribution of FDI Projects



Source: Department of Industrial Promotion and Policy, Ministry of Commerce and Industry

Table 1: Characteristics of the Data (2001 cross-section)

Variable	#	Mean	Std. Dev.	Min.	Max.
count	533	10.96	90.91	0	1289
count>0	164	35.64	161.52	1	1289
obs	533	0.6923	0.4619	0	1
fitp	423[1]	0.5835	0.3498	0	0.9996
fitnb	423	0.6385	0.3225	2.62E-06	0.9998
fitzip	423	0.6484	0.3241	0.0014	0.9999

[1] The number of observations is less than the number of cases in the dataset owing to missing values for some variables in the model.

Table 2: Incidence Rate Ratios (2001 cross-section)

Variable				Zero-inflated		Zero-truncated	
	Poisson	Negative Binomial	Zero-inflated Poisson	Negative Binomial	Zero-truncated Poisson	Negative Binomial	Odds ratios
Count							
HI	0.489***	1.04	0.693***	1.084	0.641***	0.89	0.8467***
MA	0.788***	1.082	0.712***	0.886	0.648***	1.14	0.3917***
Population	1.087***	1.641***	1.057**	1.388**	1.903***	1.435	0.8933**
Electricity	2.059***	1.557**	1.711***	2.565***	3.310***	1.812	1.1432**
Telephone	0.981	1.128	0.954	1.194	0.830***	1.908	0.8737***
Education	1.287***	1.401*	1.189***	1.318*	1.602***	1.397	1.5700***
Buses	1.184***	1.269	1.124***	1.274	1.105***	3.883**	1.4244***
Banks	1.419***	1.325	1.363***	1.003	1.605***	-	1.4267***
Wages	0.372***	0.929	0.491***	0.978	0.455***	-	0.6889***
FA	1.409***	3.447***	1.424***	2.285***	-	-	2.1047***
#	401	401	401	401	145	151	648810
AIC	4736.6	1158.6	3413.8	1094.4	4767.6	829.3	26527.5
BIC	4780.5	1206.5	3501.6	1186.2	4797.4	856.4	26641.3

Exponentiated coefficients
* p<0.05, ** p<0.01, *** p<0.001

Table 3: Robustness Checks

Variable *Count*	Secondary *IRR*	Tertiary *IRR*	Equity>50% *IRR*	Equity<50% *IRR*	Less than median *IRR*	More than median *IRR*	Including FS *Odds Ratio*
HI	1.078	0.805	1.061	0.778	0.884	0.924	0.695***
MA	1.39	0.936	0.793	0.882	0.695*	0.842	0.605***
Population	1.549***	1.969***	1.129	1.526**	1.358*	1.188	0.852***
Electricity	1.766**	1.498	1.155	1.275	0.949	1.234	1.488***
Telephone	1.073	1.193	1.149	0.905	1.25	1.039	0.948
Education	1.296	1.445	1.241	0.86	1.111	1.25	1.279***
Buses	1.311	1.226	0.992	1.045	0.963	0.916	1.225***
Banks	1.18	1.523*	1.146	1.640***	1.412*	1.179	1.283***
Wages	1.036	0.584**	0.714*	0.486***	0.647**	0.644**	0.479***
FA	2.924***	2.529***	1.808***	1.396***	1.519***	1.637***	1.416***
FS							1.237***
#	371	341	89	55	72	91	309914
AIC	904.7	694.9	492.1	278.3	450.3	444.2	22113.8
BIC	951.7	740.9	521.9	302.4	477.7	474.4	22230.9

Exponentiated coefficients
* p<0.05, ** p<0.01, *** p<0.001

Appendix table 1: Summary of Empirical Literature

Study	Country	Sample	Methodology	
			clogit	*poisson*
Carlton (1983)	USA	528 new firms; 1967-1971	x	
Papke (1991)	USA	8.3 million establishments; 1975-1982		x
Head, Ries and Swenson (1995)	USA	751 new firms; 1980-1987	x	
Becker and Henderson (2000)	USA	641 new births; 1963-1992		x
Guimaraes, Figueiredo and Woodward (2000)	Portugal	758 greenfield investments; 1982-1992	x	
List (2001)	California, USA	67 greenfield investments; 1983-1992		x
Head and Mayer (2004)	EU	452 firms; 1984-1995	x	
Crozet, Mayer and Mucchielli (2004)	France	3,902 firms; 1985-1995	x	
Guimaraes, Figueiredo and Woodward (2004)	USA	65,158 firms; 1989-1997		x
Holl (2004)	Spain	122,000 new plants; 1980-1994		x
Duranton, Gobillon and Overman (2006)	UK	21,813 new firms; 1984-1989		x
Brulhart, Jametti and Schmidheiny (2007)	Switzerland	13,768 new firms (1999-2002), and 12,465 new firms (2001-2002)		x
Devereux, Griffith and Simpson (2007)	UK	79,337 greenfield investments; 1986-1992	x	
Arzaghi and Henderson (2008)	New York county	502 new advertising firms; 1992-1997		x
Davis and Henderson (2008)	USA	11,990 new HQ firms; 1977-1997		x
Coeurdacier, De Santis and Aviat (2009)	EU	73% of all M&As; 1985-2004		x

Appendix table 2: Explanatory Variables – Description and Sources

	Variable	Indicator	Source(s)	Availability		
				1991	1996	2001
Economic geography	HI	Economic diversity	NSSO			✓
	MA	Market access	Census/ Orthodromic distance calculations	✓	✓	✓
	Population	Total population	Census data	✓	✓	✓
Business environment/ Infrastructure	Wages	Non-agricultural hourly wage rates	NSSO			✓
	Electricity*	Proportion of villages with access to electricity	NSSO/CMIE	✓	✓	✓
	Telephone*	Proportion of villages with access to telephone connections	NSSO/CMIE	✓	✓	✓
	Education*	Middle-higher schools per 1 lakh population	CMIE/NSSO	✓	✓	✓
	Buses	Proportion of villages with bus services	Census data			✓
	Roads	Road length per 100 square kilometre	CMIE	✓	✓	
	Banks	Banking branches per 1 lakh population	CMIE	✓	✓	✓
	Health	Primary health centres per 1 lakh population	CMIE	✓		
Previous FDI	FA	Clustering of previous FDI	Ministry of Commerce and Industry	NA	✓	✓
	Cumulative	Total FDI projects in (t-1)	Ministry of Commerce and Industry	NA	✓	✓

Notes:
*For 2001: Electricity, Telephone and Education refer to the proportion of population with access to electricity, with a telephone connection and with a higher-secondary education (Source: NSSO);
1 Lakh = 100,000
NSSO: National Sample Survey Organisation
CMIE: Centre for Monitoring of the Indian Economy

Appendix table 3: Descriptive Statistics

Variable	Expected sign	# 1991	1996	2001	Mean 1991	1996	2001
Investment decisions* (new/cumulative)		1,234	1,669	1,905	-	4,634	12,927
HI	-			533			0.34
MA	+	434	423	530	224,984	240,099	231,256
Population	+	406	408	533	1,982,719	2,075,529	1,926,232
Wages	-			454			89.54
Electricity	+	334	350	533	0.84	0.88	0.56
Telephone	+	126	117	533	0.46	1.12	0.09
Education	+	231	305	533	0.17	0.22	0.06
Buses	+			533			0.50
Roads	+	207	184		61.25	69.30	
Banks	+	393	418	415	7.60	7.32	6.95
Health	+	167			2.59		
FA	+		244	530		25.06	32.84

*Reference years: 1991, 1992, and 1993 (for 1991); 1996, 1997, and 1998 (for 1996); 2001, 2002, and 2003 (for 2001).

Note: # refers to the number of districts for which there are observations.

Appendix table 4: Incidence Rate Ratios (1996 cross-section)

Variable *Count*	Poisson	Negative Binomial	Zero-inflated Poisson	Zero-inflated Negative Binomial	Zero-truncated Poisson	Zero-truncated Negative Binomial	Odds ratios
MA	1.961*	0.74	1.961*	0.74	1.984*	-	3.0312*
Population	1.756***	1.721*	1.756***	1.721*	1.778***	-	1.9187***
Electricity	2.715**	1.281	2.715**	1.281	2.754**	-	5.1181*
Telephone	0.0759***	0.171	0.0759***	0.171	0.0716***	-	0.0552***
Education	1.481***	1.453	1.481***	1.453	1.489***	-	1.2828***
Roads	2.525***	1.465	2.525***	1.465	2.587***	-	2.6852***
Banks	1.025	1.041	1.025	1.041	1.027	-	1.0828
FA	2.269***	2.662***	2.269***	2.662***	2.277***	-	1.9400***
#	38	38	38	38	38		43464
AIC	309.6	250.3	327.6	268.3	308.8		5288.8
BIC	324.4	266.7	357.1	299.4	323.6		5358.3

Exponentiated coefficients
* p<0.05, ** p<0.01, *** p<0.001

Appendix table 5: Incidence Rate Ratios (1991 cross-section)

Variable *Count*	Poisson	Negative Binomial	Zero-inflated Poisson	Zero-inflated Negative Binomial	Zero-truncated Poisson	Zero-truncated Negative Binomial	Odds ratios
MA	1.254***	2.417	1.114	-	1.115	156.6	1.1127*
Population	1.562***	1.285	1.398***	-	1.409***	0.672	1.3929***
Electricity	2.543***	1.896*	2.788***	-	2.524***	1.948	2.1139***
Education	1.180*	1.14	1.203**	-	1.179*	2.774	1.1590*
Roads	1.032	1.152	1.103**	-	1.093*	1.527	1.1000**
Banks	1.436***	1.566	1.190*	-	1.205*	1.432	1.1896*
Health	1.046	0.939	1.012	-	1.017	0.32	1.0284
#	110	110	110	-	63	38	27532
AIC	845.2	470.1	708.3	-	584.4	213.3	3234.4
BIC	866.8	494.4	751.5	-	601.5	228	3291.9

Exponentiated coefficients
* p<0.05, ** p<0.01, *** p<0.001