Regional Subsidies and Industrial Prospects of Lagging Regions

by

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ABSTRACT

Large and sustained differences in economic performance across regions of developing countries have long provided motivation for fiscal incentives designed to encourage firm entry in lagging areas. Empirical evidence in support of these policies has, however, been weak at best. This paper undertakes a direct evaluation of the most prominent fiscal incentive policy in Brazil, the Fundos Constitucionais de Financiamento (Constitutional Funds). In doing so, we exploit valuable features of the Brazilian Ministry of Labor's RAIS data set to address two important elements of firm location decisions that have the potential to bias an assessment of the Funds: (i) firm "family structure" (in particular, proximity to headquarters for vertically integrated firms), and (ii) unobserved spatial heterogeneity (with the potential to confound the effects of the Funds). We find that the pull of firm headquarters is very strong relative to the Constitutional Funds for vertically integrated firms, but that, with non-parametric controls for time invariant spatial heterogeneity, the Funds provide statistically and economically significant incentives for firms in many of the targeted industries.

JEL Classification: L22, R12, R58

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1. INTRODUCTION

Sub-national disparities in economic performance and living standards are large and often sustained in many countries. Prospects for lagging regions in developing counties are of particular concern as these areas are not just characterized by lower relative incomes and standards of living, but may in fact be home to significant incidence of absolute poverty. Local populations may be stuck in so-called spatial poverty traps, in which poor infrastructure and resource endowments limit access to educational, social, and economic opportunities (Jalan and Ravallion 1997).

Many governments have opted for interventions to offset these disparities, actively intervening to promote capital flows and fiscal transfers designed to support incomes or to subsidize the creation of jobs and the extension of credit. These incentives should offset costs of firm location that may arise due to higher transport and logistics costs, poor infrastructure conditions, factor price differentials, and lower levels of public services and amenities. Tax holidays and interest rate subsidies have been used to develop an autonomous industrial base in the Northeast of Brazil; financial concessions and investment subsidies (along with industrial estates and preferential industrial licensing) were used to stimulate growth in backward regions of India; reductions in import duties, taxes (income, sales, and capital gains), and interest rates were used to move industry out of the largest urban areas in Mexico; and extensive tax holidays were used as an incentive for firms in Thailand to move out of Bangkok into regional cities.

In most countries, there is little evidence that decades of spatially explicit interventions have led to improved economic performance and welfare enhancements in lagging regions. It is even more difficult to demonstrate that regional incentive policies

have enhanced national welfare. Is it welfare enhancing to move a firm from one location to another and then pay for its re-location costs? Do these policies encourage any new entry, or do they simply result in the spatial re-allocation of firms that would have entered anyway? In this paper, we outline a strategy to evaluate the simplest impacts of spatially explicit development programs using data from the Brazilian Constitutional Funds – one of the largest regional incentive policies in the world.

1.1 Regional Disparities in Brazil

Brazil has a long history of regional disparities. The Brazilian Northeast has historically been the poorest region in the country, with regional per capita incomes being about one half of those in the prosperous Southeast (Lall and Shalizi, 2003). Figure 1 describes the 25th, 50th, and 75th percentiles of the Brazilian monthly income distribution by state based on 1991 demographic census data (state abbreviations defined in Table 1). The highest median per capita household income ($79.93 per month in Goias) is nearly four times larger than that of the lowest median per capita household income state ($20.49 per month in Maranhao). Eight states report median per capita household incomes of less than $1 per day, seven of which are located in the country's Northeast region. Of the ten poorest states in the country, eight are in the Northeast, and two in the North region (Azzoni et. al, 2002). These large per capita income differences across regions are, moreover, surprisingly stable over very long periods. Per capita income in the Southeast was 2.9 times that of the Northeast in 1939 and 2.8 times in 1992 (World Bank, 1998).

Beyond purely economic indicators, social indicators in the Northeast region are also considerably worse than the national average. The illiteracy rate is at least three times

higher than that of São Paulo, the child mortality rate is twice as large as that of the Southeast (54.5 per thousand in the Northeast compared to 26.3 per thousand in the Southeast), life expectancy four years shorter, and income inequality is much worse (Ferreira, 2004). Inequality, measured by the Theil coefficient is 0.80 for Ceará, Bahia and Pernambuco, in contrast to 0.55 for the state of São Paulo (Ferreira, 2000). Fifty percent of the Northeast population lives in poverty.

1.2 Regional Development Policies in Brazil

Large regional disparities between the Northeast and the rest of the country (coupled with a severe drought in 1958) stimulated the Brazilian government to develop explicit policies for that region (Baer, 1995). The strategy was to establish an autonomous center of manufacturing expansion by attracting "dynamic" and high-growth industries, such as those in metallurgy, machinery, electrical equipment and paper products (World Bank, 1987). Instruments such as fiscal incentives, transfers, and direct expenditures in the form of industrial land and infrastructure were widely used to attract economic activity (Goldsmith and Wilson, 1991; Markusen, 1994; World Bank, 1987).

Financial outlays from the central government in Brazil to support spatially explicit programs have been estimated to be US $3 to 4 billion per annum in recent years (Ferreira 2004). The estimated cost of tax breaks and associated regional development programs (excluding the Zona Franca de Manaus) in 2002 was estimated at almost US $900 million (Secretaria da Receita Federal, 2003). Tax credits directed to the Zona Franca de Manaus are estimated to be US $1.2 billion in 2003 alone. Investment incentive programs for the North and the Northeast, funded by income tax deductions, averaged more than 600

million dollars a year between 1995 and 2000, before they were shut down over accusations of mismanagement.

The main objective of our paper is to examine the effect of regional subsidies on industrial prospects of lagging regions in Brazil. There have been several reviews of spatially explicit programs in Brazil and also in other countries, with the general conclusion that these initiatives have very small effects. For instance, Ferreira (2004) claims that much of the GDP per capita growth in the Northeast (and convergence with the South and Southeast) can be attributed to out-migration rather than local employment creation, and that welfare gains from these interventions are limited as most of the population that benefited from the jobs created came from other parts of Brazil. He also finds that most of the convergence in per capita incomes across Brazilian regions occurred over the period 1970-1985, before the initiation of the Constitutional Funds. [Ellery and Ferreira (1996)] Maia Gomes (2002) finds that, while GDP did grow throughout Brazil over the period 1960 to the present, it did not grow as fast in the Northeast (the focus of most regional policies) as in the rest of the country. Ferreira (2004) finds similar results focusing only on the period 1990-2000 (i.e., the first decade of the Constitutional Fund program).

Each of these papers looks for indirect evidence of regional policies' impacts on economic outcomes (e.g., GDP or GDP growth rates). The problem with this approach is that these outcomes are affected by a multitude of factors besides regional policy (e.g., macroeconomic shocks), some of which may influence certain parts of the country more than others. The relevant question is not whether the Northeast grew faster than the rest of the country during the Constitutional Fund program, but rather whether it grew faster than

it would have in the absence of the program. This is a very difficult question to answer. In this paper, we instead conduct a more direct evaluation of the impact of the Constitutional Funds. In particular, we address a relatively limited question – did the Constitutional Funds successfully induce entry by firms into Brazil's lagging regions? Answering this question necessarily precedes and motivates further work on measuring the welfare impacts of the policy (which we outline in the conclusion). In addressing this question, we account for two features of the firm location problem that have the potential to bias estimates if ignored. First, we non-parametrically account for regional attributes such as amenities, infrastructure, local public goods, and natural endowments. Since regional incentives are allocated to compensate for inter-regional differentials in local characteristics, it is imperative to adequately account for these factors in examining the contribution of these programs. Otherwise, there is a tendency to systematically understate their value. Second, our empirical analysis makes use of a linked headquarter-branch plant panel data set, which allows us to consider the role of intra-firm considerations in the location decisions of vertically integrated firms. If firms tend to locate branch plants in close proximity to their headquarters, and if those headquarters are disproportionately located in unsubsidized areas, this could be mis-interpreted as a failure of the fiscal incentive. While the empirical application focuses on Brazil, the estimation strategy outlined in the paper has broader applicability and can be used to examine similar issues across countries.

Our main findings are that subsidized credit offered to firms via the CF's has worked in terms of industrialization in the Northeast. At the same time, we find that pull of the headquarters has a much bigger effect on entry than the CF's for the minority of

vertically integrated firms (i.e., with headquarters). This implies that, for vertically integrated industries, firm structure needs to play a part in the CF – i.e., reform to promote entry by headquarter firms into lagging regions. In more footloose sectors, such reforms would not be necessary.

The remainder of this paper is organized into five sections. In Section 2, we discuss the design and allocation of the CF's. Section 3 describes the data, and Section 4 discusses our estimation strategy. Section 5 describes the main findings and Section 6 concludes.

2. ALLOCATION OF BRAZILIAN CONSTITUTIONAL FUNDS

National governments in many countries have a long history of using fiscal incentives to stimulate the growth potential of lagging sub-national regions. These spatially explicit programs are designed to compensate for location specific disadvantages, such as transport and logistics costs, infrastructure conditions, factor price differentials and lower levels of public services and amenities. A detailed discussion on various regional development programs in Brazil is provided in Ferreira (2004) and World Bank (2005). Explicit spatial policies in Brazil include three sets of instruments which target private sector development through various kinds of subsidies: (a) fiscal incentive programs such as those administered by SUDENE, SUDAM, and the Zona Franca de Manaus (Manaus Free Trade Zone); (b) subsidized credit channeled through the CF's, which has become one of the most important instruments of spatial policy in Brazil; (c) and regional development banks, such as Banco do Nordeste do Brazil (BNB).

The focus of our analysis is on the effectiveness of subsidized credit channeled

through the CF's. In 1989, the Brazilian Congress instituted three Constitutional Investment Funds (Fundos Constitucionais de Financiamento) for the Northeast (FNE), the Center-West (FCO), and the North (FNO). The main aim of these funds was to stimulate economic and social development in these regions by extending credit to local entrepreneurs. Preferential treatment was provided to micro- and small-scale agricultural producers and small-scale manufacturing to encourage the use of local raw materials and labor. Sixty percent of the outlays for the CF's were allocated to the Northeast, and 20 percent were allocated to each of the North and the Center West. Funds are transferred from the National Treasury to the Ministry of Integration ("Ministério da Integração"), which later reallocates them to the operating banks – the Banco do Nordeste (FNE), Banco da Amazônia (FNO) and Banco do Brasil (FCO). The CF's are financed by receipts from income taxes and taxes on industrial products.

Interest rate subsidies are the main incentive offered through the CF's. While market interest rates offered to private firms are currently more than 45%, the CF's offer credit at 8.75% to non-agricultural micro firms; 10% to small firms, 12% to medium sized firms; and 14% to large enterprises. Interest rates are even lower for comparable agro producers: 6% for mini-producers, 8.75% for small to average and 10.75% for large ones. These interest rates were negative in real terms in 2002, when inflation was 12.5%. Rates offered to individual producers varied by sector, investment size, and credit record of the borrower. Between 1989 and 2002, more than US $10 billion were provided in subsidized loans, which is about 0.8 % of the total GDP of the 3 regions per year (Ferreria 2004).

3. DATA

We compile a database that maps the spatial entry decisions of new establishments in Brazil, with the goal of learning how the CF's affect those decisions. The main source of information is the RAIS micro data, provided by the Labor Ministry.[1] We study the effects of the CF's on entry by firms in 18 sectors (11 manufacturing and 7 service, which are listed in Table 2) into 265 "urban agglomerations" (see description below) over the years 1993-2001. The RAIS database contains a wide range of information for all economic establishments in the formal sector in Brazil from 1986 onward. For each establishment in this database, we have annual information on the number of employees at the beginning and end of each year; total salaries and wages; in which municipality the company is located; as well as the establishment's economic activity according to several industry classifications. To avoid problems caused by a large number of establishments with very few employees, we limit our analysis to establishments with no fewer than 10 employees. This paper is the first research project to use the RAIS data to study firm geography and the effectiveness of fiscal incentives.

As discussed above, one important piece of information in the estimated models is the composition and location of the "relatives" for each establishment. To uncover the composition of each family of establishments (parent and sibling establishments), which constitutes a firm, we make use of the establishment identification number, hereafter CNPJ. The CNPJ has 14 digits and is the official identification number for all productive units in the formal sector. The first 8 digits of the CNPJ indicate the company (or family) of each establishment. The next 4 digits indicate the position of the establishment in the

[1] The RAIS data was used under a cooperation agreement between the Labor Ministry and the Institute of Applied Economic Research (IPEA).

family. For example, "0001" indicates the first establishment in the company, which is assumed in this paper to be the company headquarters. The other establishments in the company are given sequential codes, so that the second establishment receives "0002", the third establishment receives "0003", and so on. Some of the companies are comprised of a single establishment, which receives the 4-digit code "0001".[2] The last two digits of the CNPJ correspond to the establishment economic sector, and they work more as a confirmation code. Therefore, we use the first 12 digits of the CNPJ to extract the establishment composition of each company.

To summarize, there are three reasons why the RAIS data set is particularly useful for the analysis. These are:

(i) It identifies entry behavior each year, allowing us to build a panel of entry data that we use to control for spatial fixed effects.

(ii) It provides spatial detail on entry decisions (necessary for discussion of policies to promote entry into lagging regions).

(iii) It describes firm family structure (i.e., identifies parent or headquarters, which we find to be a particularly important determinant of entry).

To model spatial entry decisions, we had to select an appropriate geographic unit. Using municipalities creates several problems: (i) there are a large number of municipalities (5,506 in the year 2000), which would significantly increase the computational burden in estimating the location decision model; (ii) many municipalities

[2] The establishment with digits "0001" in positions 9 to 12 is the initial headquarters of the company. However, should the headquarters be transferred to another municipality and the previous establishment be maintained, the new headquarters may receive a four-digit sequence different from "0001" while the previous establishment retains the "0001" four-digit code, even though it is not the headquarters anymore. On the other hand, it may happen that if the headquarters moves to another municipality, it will keep the same CNPJ, and in this case, we still have the headquarter with the "0001" code. Even though we cannot identify these two situations from the data, the econometric results presented in the following sections show evidence of the importance of the "0001" headquarters location, which suggests the validity of our assumptions.

are very small (i.e., with fewer than 5,000 inhabitants) and/or in rural areas with very few establishments in the formal sector; (iii) because of the continuous creation of new municipalities in Brazil, it is necessary to coordinate different municipality maps across the years of study; and (iv) entry into municipalities within the same urban area is likely to be highly correlated. Given these problems, we decided instead to use the concept of "urban agglomerations," defined in a comprehensive urban study developed by IPEA, IBGE and Unicamp (2002), and used by Da Mata, Deichmann, Henderson, Lall and Wang (2005a and 2005b).

Even though RAIS micro data are available from 1986 to 2003, the data from 1993 to 2001 contain fewer missing observations and are considered to be generally more reliable. We therefore use only these years for the analysis. For each year, we identify new establishments with at least 10 employees and record the urban agglomeration in which they entered. If the entering establishment belonged to a multi-establishment firm, we also identify the urban agglomeration of the parent.

As can be noted from Table 1, most parent establishments are located in the Southeast (58.15% in 1993). Note, however, that the percentage of entering parent firms over the period 1993-2001 (i.e., the CF years) falls to 42.7% in the Southeast, but rises to 21.01% in the Northeast (from 12.49% of the parents in 1993). Thus, considering only the spatial distribution of parents (which are footloose by definition), there is some evidence that the CF's were effective. There is also evidence in this table, however, that if branches are closely tied to parents, the CF's have a lot to overcome in vertically integrated industries, given the initial distribution of parent firms in 1993.

How empirically relevant is the "pull" of the parent firm? The answer depends

upon the sector being considered. Table 2 shows percentage of entrants over years 1993-2001 that have headquarters. We would expect proximity to the parent to be particularly important for Metallurgy, Communcations and Electronics, Transportation, Chemicals, and Shoes. Table 2 also shows the average distance branch plants locate from headquarters (conditional on having a headquarters). These numbers are very small, providing further evidence that the pull of the parent is significant.

4. ESTIMATION STRATEGY

Our estimation strategy is designed to answer the following questions: (i) were the CF's effective in inducing firms to locate new establishments in Brazil's lagging regions, (ii) what role does the spatial distribution of a multi-unit firm play in the location decision, and (iii) what local attributes are important factors in firms' location decisions. In answering these questions, we face a number of challenges. First among these is separating the role of idiosyncratic firm characteristics from those of local attributes and CF allocations. In particular, in deciding where to place a new branch plant, a multi-unit firm may take into account proximity to the firm's headquarters. The location of each firm's headquarters will be unique, and it is unclear *a priori* in what direction ignoring this factor would bias our conclusions.[3]

Second, we must separate the role of the CF subsidies from that of unobserved local attributes. The CF is a subsidy to promote entry into lagging regions. Regions with high subsidies are therefore likely to be unattractive for entry in a variety of other

[3] Given that most firms' headquarters were located in the Southeast, our expectation is that failing to account for the pull of parent firms would lead us to overstate the quality of the Southeast region for entry by branch plants. Because this region did not receive any CF support, this would likely have the effect of biasing downward the estimated impact of the CF's.

dimensions. Data to control parametrically for these other factors are incomplete, creating a problem of (negatively) correlated unobservables. We exploit useful features of the RAIS data set to control for this problem with agglomeration fixed effects.

Finally, in determining the role played by other factors in the entry decision (e.g., classical determinants like transportation cost and market size, along with agglomeration effects and other forms of local spillovers), we are confronted with problems of severe multicollinearity. In Brazil, development (as measured by the IDH) is highly correlated with measures of education, infrastructure (e.g., sewage, electrification), and even transport accessibility. This will limit our ability to deduce the separate causal role of many of these factors.

In dealing with these complications, we undertake a two-stage estimation procedure. The following sub-sections describe each of these stages. The next section provides a discussion of the results.

4.1 Stage #1: Maximum Likelihood Entry Model

In the first stage, we recover non-parametric estimates of each agglomeration's overall attractiveness for entry (separately for each sector), taking into account the possibility that a firm might consider the proximity of the new site to its headquarters. *Ceteris paribus*, we should expect firms to dislike locating their plants long distances from the parent. The magnitude (and even sign) of this effect, however, may differ by sector.

We model the payoff to an entering plant i (part of firm k in industry m) from locating in agglomeration j in year t as:[4]

[4] While we estimate separate payoff function parameters for each sector, we do not differentiate between firms of different sizes in the current analysis. Doing so will be important for future work, as previous

(1) $$\Pi^m_{i,j,k,t} = \delta^m_{j,t} + \beta^m_t D_{i,j,k,t} + \eta_{i,j,k,t}$$

where

$\delta^m_{j,t}$ = fixed effect capturing all features of agglomeration j in period t, as perceived by a potential entrant in industry m[5]

$D_{i,j,k,t}$ = distance (km) to the parent of plant i from location j in year t (= 0 if no parent)

$\eta_{i,j,k,t}$ = unobserved idiosyncratic features of location j in year t specific to plant i from firm k

We take the set of all entering firms in each year as given and model their entry decision over the set of all locations.[6] Assuming $\eta_{i,j,k}$ is distributed i.i.d. Type I Extreme Value, the probability that plant i enters agglomeration j in year t is given by:

(2) $$P^m_{i,j,k,t} = \frac{EXP\{\delta^m_{j,t} + \beta^m_t D_{i,j,k,t}\}}{\sum_{l=1}^{J} EXP\{\delta^m_{l,t} + \beta^m_t D_{i,l,k,t}\}}$$

research has found that larger firms may be more responsive to local variables in a model of spatial entry, either because of economies of scale in spatial search or because smaller firms may be more tied to the home of the entrepreneur. (Levinson 1996)

[5] At this stage of the model, $\delta^m_{j,t}$ can be assumed to control for a wide variety of local attributes including (but not limited to) indicators of development (e.g., sewage, electrification, piped water), measures of transportation accessibility (e.g., cost of transporting freight to Sao Paulo), the education and income of the local population (e.g., average education of the population over age 25, illiteracy rate), market size (i.e., population, income), and spillovers with other firms (both within and across sectors).

[6] More specifically, our estimation algorithm uses only the information contained in the *share* of new entrants choosing to locate in each agglomeration, and does not use the total number of new entrants for identification.

The likelihood of the observed data (defined separately for each industry *m* and year *t*) is thus given by:

$$(3) \qquad L_t^m(\overline{D}_t^m; \beta_t^m, \overline{\delta}_t^m) = \prod_{i \in m} \prod_{j=1}^{J} [P_{i,j,k,t}^m]^{\lambda_{i,j,t}}$$

where $\lambda_{i,j,t}$ = 1 if plant *i* sites in urban agglomeration *j* in year *t* (= 0 otherwise). Maximizing this expression yields estimates of β_t^m and $\overline{\delta}_t^m$.[7]

A practical difficulty arises in this stage of the estimation. In particular, some urban agglomerations may not be entered by any plants in an industry in a particular year. The data, therefore, reveal only that these locations are inherently undesirable, but do not indicate just how undesirable. The fixed effects $\delta_{j,t}^m$ are not identified for these locations. This is fundamentally a problem of censored data. Unlike traditional approaches to this problem (which rely on strong distributional assumptions), we solve it by ascribing a very small minimum artificial number of entrants (e.g., 10^{-6}) to each agglomeration – a numerical "patch". Depending upon how small of a patch is assumed, the estimated values of $\delta_{j,t}^m$ for each un-entered agglomeration can be arbitrarily negative. Timmins and

[7] Explicitly maximizing the likelihood function in (3) over the full vector of fixed effects $\overline{\delta}_t^m$ may prove computationally difficult. We therefore employ the contraction mapping proposed by Berry (1994) and used in Berry, Levinsohn, and Pakes (1995) to avoid this problem. Practically, we integrate over entrants *i* in equation (2), yielding expressions for the predicted share of plants in each sector choosing to locate in each agglomeration in each year. Given a guess for the value of β_t^m, these expressions constitute a contraction mapping in the vector of $\delta_{j,t}^m$'s. We use this mapping to find the unique set of $\delta_{j,t}^m$'s that make the shares predicted by the model equal the actual shares within some acceptable level of tolerance. The likelihood function is calculated based on these $\delta_{j,t}^m$'s. The parameter β_t^m is updated in such a way as to increase that likelihood value, and the contraction mapping is repeated in order to recover new $\delta_{j,t}^m$'s. The procedure is complete when the likelihood function is maximized.

Murdock (2006) demonstrate that, as the patch size becomes increasingly small, the estimated values of $\delta^m_{j,t}$ for those urban agglomerations *that are entered* converge to stable values. As long as a majority of agglomerations are entered by each sector, median regression used to recover the determinants of $\delta^m_{j,t}$ will be unaffected by the artificially assumed number of entrants in un-entered agglomerations.[8]

4.2 Stage #2: Median Regression and the Role of the Constitutional Funds

In order to evaluate the role of the CF's in promoting entry, we use median regression on the panel of data (defined over J = 265 agglomerations and T = 9 years) for each industry.[9]

(4) $$\delta^m_{j,t} = \gamma^m + \overline{YEAR'}_t\theta^m + \overline{AGG'}_j\phi^m + \psi^m CF_{j,t} + u^m_{j,t}$$

where

$\overline{YEAR}_t$ = vector of dummy variables indicating year t = 1994, …, 2001 (1993 excluded)

$\overline{AGG}_t$ = vector of dummy variables indicating agglomeration j = 2, …, 265 (agglomeration j = 1 excluded)

$CF_{j,t}$ = average CF allocation per employee in year t in the state containing agglomeration j[10]

[8] See Koenker and Basset (1978) and Koenker and Hallock (2001) for comprehensive discussions of median regression.

[9] Note that estimating this equation via median regression requires explicit estimation of all fixed effects – differencing the data is not equivalent to fixed effect estimation in the median regression context.

[10] In particular, we take the *ex post* contracted allocation of CF's in each state in each year and divide by the number of entering plants. Doing so controls for the fact that attractive states experiencing more entry will, by definition, receive more CF allocations. The size of the entering firms will also have an effect on the overall allocation each state receives (bigger firms will receive larger subsidies than small firms). We therefore divide by the average firm size (i.e., employees per firm) amongst entrants in each state in each

$u_{j,t}^{m}$ = unobservable determinant of entry quality in agglomeration *j* for firms in sector *m* in year *t*

The vector of year dummies is included to account for the fact that an arbitrary normalization underlies the vector of $\bar{\delta}_t^m$ in each year *t* (in particular, these fixed effects have no natural scale, so we normalize them so that their average values equal zero in each year for each industry).

The vector of agglomeration dummies plays an especially important role in this regression. In particular, CF's are allocated in a remedial fashion (i.e., with more funds being allocated toward locations that are less attractive for entry).[11] A regression of $\delta_{j,t}^{m}$ on only year dummies and CF allocations therefore suffers from an omitted variable bias – in particular, a bias towards finding that the CF's had no impact (or even an adverse impact) on entry behavior. With only cross-sectional data, one would be forced to deal with this fact by including as many agglomeration attributes in the model as possible. While such data exist, they will necessarily be incomplete. With our panel data (obtained by using annual entry behavior observed in the RAIS), we are able to control non-parametrically for any features of each agglomeration that do not change over time. This

year. This converts our measure of CF's into the average contracted allocation *per employee* in each state, which we treat as an exogenous measure of the state's attractiveness in terms of the CF. Controlling for the sectoral composition of entering firms on our measure of the CF's as well has no effect on the results that we report. Note one remaining potential source of bias – firms with better credit ratings will receive higher CF subsidies (conditional upon size). If firms with better credit ratings disproportionately locate in sites with desirable unobservables, the error in our CF measure will be correlated with those unobservables, biasing our results towards finding positive effects of the CF's. We demonstrate below, however, that this potential source of bias is not a concern in interpreting our results.

[11] This is apparent when one considers that the Funds were only made available to firms entering in the Northeast, North, and Center-West regions, in order to help draw them away from the more affluent South and Southeast.

takes care of the most important differences between agglomerations, and leaves us with the variation in CF allocations over time with which to identify their impact.

5. RESULTS

5.1 The Role of Parent Location in Entry

Table 3 reports the results of our first stage estimates of β_t^m for each of eighteen sectors.[12] In every instance, firms exhibit a statistically significant preference for siting their new plants close to their headquarters. In recovering these effects, Stage #1 of our estimation strategy non-parametrically controls for everything about agglomerations that varies by sector and year and that might be a determinant of firm entry. This should control for the most important confounding factors (i.e., for any factor that makes it attractive to put any firm from a particular sector – headquarters or otherwise – in the agglomeration). It cannot distinguish, however, between distance effects and the effect of idiosyncratic unobservables.[13]

While providing evidence of statistical significance, the parameter estimates in Table 3 do not, however, allow us to judge the economic significance of the "pull" of the firm headquarters in plant location decisions. In particular, in each of the maximum likelihood procedures underlying the estimates reported in Table 3, there is a vector of fixed effects normalized so that their average value equals zero. This normalization is arbitrary, and makes direct comparison of parameter estimates across years or industries impossible. More can be learned about the way in which these firm headquarters influence

[12] Estimates of $\delta_{j,t}^m$ are not reported for the sake of brevity, but will be used in the following sub-section to explore the role of the CF's.

entry behavior by way of simulation. In particular, it is possible to simulate how entry patterns would have differed by sector and region if firms did not care about proximity to headquarters. Assuming that the values of $\delta_{j,t}^{m}$ are not affected by this counterfactual assumption,[14] we simply "turn off" the distance-to-parent coefficient in the entry model, and simulate new entry patterns in each year. Table 4 reports the percent change in the distribution of entry (i.e., between actual and predicted under this counterfactual assumption), across regions and aggregated over the years 1993-2001. The biggest differences are seen in the North (i.e., where relatively few headquarters were in place in any sector, but which sees the biggest gains when distance-to-parent effects are taken out) and in the Southeast (i.e., the home to the majority of headquarters, which sees the largest drop in entry). The Northeast, Center-West, and South see mixed effects that vary by sector, although the general trend is for entry to increase in these sectors when we make all plants "footloose".

5.2 The Effectiveness of the Constitutional Funds

Table 5 describes our decomposition of the fixed effects, $\delta_{j,t}^{m}$. Columns describe the results of median regressions that (i) exclude agglomeration fixed effects, using only year fixed effects and annual CF contracts per employee, (ii) use year fixed effects and annual CF contracts per employee along with a collection of covariates describing

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[13] For example, the model would interpret a case in which an entrepreneur has a strong preference for a particular agglomeration and locates all of his plants and headquarters there as a distaste for locating branch plants far from the headquarters.

[14] If entry by firms in one year makes a region more attractive for entry by firms in the same and other sectors in later years, this assumption implies that we will understate the impact of removing parent effects on lagging regions.

observable agglomeration attributes,[15] and (iii) use year fixed effects, agglomeration fixed effects, and annual CF allocations. In the table, we report only the coefficient on the CF variable. Without any controls for agglomeration heterogeneity in column (i), we find significant (both economically and statistically) negative effects of the CF on entry. This result corresponds to that found in previous work (Ferreira 2004) and likely reflects the fact that the CF's are allocated in a remedial fashion. Including covariates in column (ii) to control for local attributes does little to change these results.

Time-invariant forms of heterogeneity are non-parametrically controlled for by the introduction of agglomeration fixed effects. These are included in the specification described in column (iii), where we find significant positive effects of the CF's on entry for five out of the eleven manufacturing industries, and positive but insignificant effects for all but paper and publishing and metallurgy (where effects are negative and insignificant).

While the fixed effects succeed in alleviating the downward bias in the CF parameters that is evident in columns (i) and (ii), keep in mind that there still may be some remaining downward bias caused by time varying forms of local heterogeneity that are negatively correlated with CF allocations. We are less concerned with the potential for bias introduced by the mis-measurement of CF allocations resulting from the non-random siting of plants according to their credit rating (see footnote 12). In particular, we would expect that firms with more talented entrepreneurs would have better credit ratings and that these entrepreneurs would be more likely to site plants in locations with desirable

[15] In particular, we use the average of the 1990 and 2000 Human Development Indices, populations, and average years of education of those over the age of 25, along with the 1995 transportation cost to Sao Paulo. For further description of the variables used, refer to Da Mata, Deichmann, Henderson, Lall and Wang (2005a and 2005b).

unobservable attributes. This would tend to bias the coefficient on CF in our median regressions upward. This source of bias should go down, however, when we introduce agglomeration fixed effects to account for time-invariant forms of unobserved heterogeneity. It is precisely when we introduce these fixed effects, however, that the sign of most of our CF effects changes dramatically, switching from negative to positive. Clearly, if there had been an upward bias in the absence of these fixed effects, it was not very big and was swamped by the bias introduced by the correlation between CF and undesirable unobservable local attributes.

Of the non-manufacturing sectors, only retail, transportation and communication, and hotel and food services show positive effects from the CF's. Non-manufacturing sectors are generally not covered by the CF's, so we should not expect to see the positive effect here that we saw in the case of most manufacturing industries. Entry in the retail sector, however, may quickly follow manufacturing entry and, hence, exhibit a positive correlation with CF. In addition, the CF's have been used to promote tourism related activities, which may influence firm entry in the hotel and food services and transportation and communication sectors (Ferreira 2004).

6. CONCLUSIONS

We learn two things from this analysis. First, (contrary to previous work) we find that the CF allocations have, in fact, been successful in inducing entry into lagging regions, conditioning on the location of firms' headquarters. This result however, can be easily lost among the confounding effects of local unobservables that are negatively correlated with CF allocations. It is hard to capture these determinants of entry with available data

describing agglomeration attributes, and without properly accounting for these factors, there is a bias toward finding a negative effect of the CF's on entry. The RAIS data, which describe spatial entry behavior on an annual basis, provide a unique opportunity to overcome this problem non-parametrically.

Second, we learn that, while the CF's were successful, headquarter proximity is a significant determinant of entry behavior (conditional upon having a parent) that works to offset this success. Simply "turning-off" the effect of parent firm location significantly raises overall entry into lagging regions. These effects are, moreover, likely a lower bound on the effect of removing the pull of firm headquarters if we believe that there are positive spillovers between entrants.

The conclusions of this paper for policy-makers are, unfortunately, limited. While we find that the CF's were successful in inducing firms to locate in Brazil's lagging regions (and that the CF's may yield more "bang for the buck" if they are used to induce entry by firms' headquarters into those regions), we are unable to determine with available data whether the CF's were good policy or not. In further research, we plan to move from the limited (but important) question of "do subsidies affect firm location decisions" to the more policy-relevant question of "are these subsidies welfare enhancing". In answering that question, it will be crucial to determine (i) whether the CF's induced new entry into lagging regions or simply re-allocated entry away from the South and Southeast regions, and (ii) what was the productivity effect on re-located firms.[16] Answering these questions was not possible with the data used in this paper, but may require new efforts in collecting

[16] In addition to informing us on the value of the CF's, this latter point will speak to the question of whether or not there is generally a tradeoff between regional distribution objectives and national economic growth. This question has broad implications beyond the current study.

survey data from entrepreneurs about what motivated their entry decisions, and about their inputs and outputs conditional upon those decisions.

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Table 1
Spatial distribution of Firm Headquarters in 1993

State		Distribution of Parent Firms (1993)		Entry by Parent Firms (1993-2001)	
		Firm Count	%	Firm Count	%
Rondonia	RO	157	0.71	195	1.33
Acre	AC	49	0.22	33	0.23
Amazons	AM	211	0.95	194	1.33
Roraima	RA	24	0.11	39	0.27
Para	PA	304	1.38	248	1.70
Amapa	AM	47	0.21	42	0.29
Tocantins	TO	124	0.56	41	0.28
North		916	4.14	792	5.42
Maranhao	MA	172	0.78	224	1.53
Piaui	PI	145	0.66	122	0.83
Ceara	CE	494	2.23	509	3.48
Rio Grande do Norte	RN	177	0.80	218	1.49
Paraiba	PB	136	0.62	219	1.50
Pernambuco	PE	612	2.77	609	4.17
Alagaos	AL	135	0.61	153	1.05
Sergipe	SE	127	0.57	122	0.83
Bahia	BA	763	3.45	895	6.12
Northeast		2761	12.49	3071	21.01
Minas Gerais	MG	2064	9.34	1339	9.16
Espirito Santo	ES	472	2.13	301	2.06
Rio de Janeiro	RJ	2673	12.09	1101	.53
Sao Paulo	SP	7648	34.59	3499	23.94
Southeast		12857	58.15	6240	42.70
Parana	PR	1400	6.33	1026	7.02
Santa Catarina	SC	957	4.33	871	5.96
Rio Grande do Sul	RS	1700	7.69	746	5.10
South		4057	18.35	2643	18.09
Mato Grosso do Sul	MS	220	1.00	207	1.42
Mato Grosso	MG	325	1.47	549	3.76
Goias	GO	534	2.42	614	4.20
Distrito Federal	DF	439	1.99	498	3.41
Center-West		1518	6.87	1868	12.78
Brazil		22109	100.00	14614	100.00

Table 2
Entrant Descriptive Statistics
% Entrants with Parent Firms and Average Distance
to Parent Firm After Entry (Conditional on Having Parent)

IBGE Sector	Percent Entrants with Parent	Avg. Distance to Parent (km)
Metallurgy	15.15	48.41
Machinery	1.56	143.50
Communications and Electronic Equipment	15.81	38.80
Transportation Equipment	16.04	119.83
Wood and Furniture	1.59	80.11
Paper and Publishing	2.86	99.18
Rubber, Tobacco, and Skins	0.99	68.95
Chemicals, Pharmaceuticals, Veterinary & Perfumes	13.47	80.08
Textiles	1.24	67.00
Shoes	14.22	104.07
Food, Beverages, and Alcohol	0.99	79.07
Retail	2.33	94.86
Credit Institutions & Insurance	41.63	52.81
Real Estate	16.71	123.26
Transportation & Communication	2.51	107.73
Hotel and Food	2.65	56.98
Medical, Veterinary, and Dentistry Services	14.40	29.22
Education	61.63	134.96

Table 3 (a)
First Stage Parameter Estimates – Disutility of Distance from Firm Headquarters
(standard errors in parentheses)

	Metallurgy	Mechanical	Comm. & Electrical Equipment	Transport Equipment	Wood & Furniture	Paper & Publishing	Rubber, Tobacco, & Skins	Chemical, Pharmaceutical, Veterinary, & Perfumes	Textiles
1993	-4.633	-1.023	-3.517	-4.117	-0.003	-0.745	-1.529	-2.251	-3.637
	(0.061)	*(0.091)*	*(0.586)*	*(0.249)*	*(0.156)*	*(0.242)*	*(0.252)*	*(0.366)*	*(0.351)*
1994	-4.777	-1.027	-2.268	-2.065	-2.361	-2.319	-2.238	-1.247	-2.633
	(0.055)	*(0.098)*	*(0.302)*	*(0.097)*	*(0.244)*	*(0.359)*	*(0.498)*	*(0.221)*	*(0.248)*
1995	-4.197	-1.312	-7.136	-2.911	-2.316	-1.748	-1.771	-0.598	-2.772
	(0.047)	*(0.101)*	*(0.853)*	*(0.104)*	*(0.262)*	*(0.379)*	*(0.522)*	*(0.189)*	*(0.256)*
1996	-4.379	-1.550	-0.9575	-1.990	-2.215	-1.124	-1.672	-1.791	-3.782
	(0.044)	*(0.092)*	*(0.202)*	*(0.092)*	*(0.250)*	*(0.532)*	*(0.296)*	*(0.272)*	*(0.258)*
1997	-4.660	-1.374	-2.662	-2.126	-2.734	-1.923	-1.569	-2.544	-2.031
	(0.052)	*(0.105)*	*(0.302)*	*(0.085)*	*(0.263)*	*(0.358)*	*(0.304)*	*(0.321)*	*(0.219)*
1998	-4.666	-0.9885	-2.282	-1.123	-2.105	-1.664	-0.473	-0.704	-3.331
	(0.051)	*(0.090)*	*(0.334)*	*(0.080)*	*(0.326)*	*(0.310)*	*(0.283)*	*(0.293)*	*(0.263)*
1999	-4.444	-1.246	-3.663	-1.526	-1.740	-0.896	-0.828	-0.570	-2.830
	(0.049)	*(0.102)*	*(0.309)*	*(0.090)*	*(0.252)*	*(0.226)*	*(0.205)*	*(0.212)*	*(0.261)*
2000	-3.780	-0.907	-4.836	-1.882	-3.322	-0.495	-1.317	-1.458	-2.844
	(0.039)	*(0.092)*	*(0.370)*	*(0.095)*	*(0.402)*	*(0.255)*	*(0.300)*	*(0.252)*	*(0.205)*
2001	-4.211	-1.502	-5.994	-1.520	-1.666	-0.843	-1.057	-2.139	-2.330
	(0.047)	*(0.104)*	*(0.652)*	*(0.079)*	*(0.252)*	*(0.315)*	*(0.218)*	*(0.263)*	*(0.219)*

Table 3 (b)
First Stage Parameter Estimates – Disutility of Distance from Firm Headquarters
(standard errors in parentheses)

	Shoes	Food, Beverage & Alcohol	Retail	Credit Institutions & Insurance	Real Estate	Transpor-tation & Communica-tion	Hotel, Food, Repair & Publishing Services	Medical, Veterinarian & Dentistry Services	Education Services
1993	-1.617	-3.514	-3.392	-1.618	-3.519	-1.532	-2.703	-5.121	-0.702
	(0.178)	*(0.235)*	*(0.296)*	*(0.210)*	*(0.263)*	*(0.078)*	*(0.083)*	*(0.330)*	*(0.079)*
1994	-0.795	-2.403	-5.207	-1.467	-1.449	-0.835	-2.776	-2.501	-0.724
	(0.123)	*(0.164)*	*(0.503)*	*(0.121)*	*(0.197)*	*(0.080)*	*(0.080)*	*(0.134)*	*(0.075)*
1995	-1.367	-5.366	-2.932	-2.095	-1.547	-0.712	-3.090	-2.816	-0.947
	(0.161)	*(0.257)*	*(0.244)*	*(0.183)*	*(0.242)*	*(0.060)*	*(0.070)*	*(0.096)*	*(0.082)*
1996	-1.773	-6.043	-3.245	-1.497	-0.650	-1.214	-3.192	-4.031	-0.276
	(0.154)	*(0.394)*	*(0.318)*	*(0.123)*	*(0.159)*	*(0.076)*	*(0.073)*	*(0.146)*	*(0.06)*
1997	-1.915	-4.268	-2.644	-1.947	-2.493	-0.979	-3.344	-3.138	-0.936
	(0.139)	*(0.198)*	*(0.253)*	*(0.343)*	*(0.416)*	*(0.060)*	*(0.079)*	*(0.112)*	*(0.08)*
1998	-1.022	-2.552	-2.290	-2.530	-1.577	-1.054	-3.178	-3.240	-1.002
	(0.152)	*(0.171)*	*(0.254)*	*(0.193)*	*(0.257)*	*(0.069)*	*(0.091)*	*(0.129)*	*(0.070)*
1999	-2.029	-5.888	-2.425	-1.518	-0.963	-1.531	-3.104	-4.145	-0.730
	(0.164)	*(0.423)*	*(0.320)*	*(0.206)*	*(0.156)*	*(0.074)*	*(0.073)*	*(0.154)*	*(0.073)*
2000	-1.468	-4.492	-1.770	-1.324	-1.139	-1.272	-3.262	-4.384	-0.501
	(0.127)	*(0.251)*	*(0.255)*	*(0.176)*	*(0.172)*	*(0.072)*	*(0.073)*	*(0.172)*	*(0.064)*
2001	-1.250	-1.184	-2.587	-2.035	-3.002	-1.287	-3.162	-4.747	-0.313
	(0.122)	*(0.140)*	*(0.239)*	*(0.243)*	*(0.309)*	*(0.060)*	*(0.065)*	*(0.138)*	*(0.070)*

Table 4
Percent Change in Predicted Entry With and
Without "Distance to Parent" Effects (1993-2001)

IBGE Sector	North	Northeast	Southeast	South	Center-West
Metallurgy	0.17	-0.05	-0.05	0.03	0.08
Machinery	0.06	0.02	-0.03	0.02	0.01
Communications and Electronic Equipment	0.26	-0.09	-0.24	-0.01	0.04
Transportation Equipment	0.22	0.03	-0.13	-0.05	0.02
Wood and Furniture	0.06	0.04	-0.02	0.03	0.03
Paper and Publishing	0.08	0.05	-0.02	0.05	0.04
Rubber, Tobacco, and Skins	0.06	0.02	-0.01	-0.02	0.01
Chemicals, Pharmaceuticals, Veterinary & Perfume Products	0.10	0.08	-0.03	0.04	0.05
Textiles	0.07	0.05	-0.02	0.03	0.04
Shoes	0.13	0.06	-0.04	0.05	0.05
Food, Beverages, and Alcohol	0.05	-0.01	-0.01	0.01	0.02
Retail	0.09	-0.02	-0.06	0.00	0.02
Credit Institutions, Insurance, & Capitalization	0.54	-0.31	-0.47	-0.12	-0.15
Real Estate	0.07	-0.06	-0.08	0.00	-0.10
Transportation & Communication	0.10	0.05	-0.03	0.03	0.03
Hotel and Food	0.10	0.02	-0.04	0.04	0.06
Medical, Veterinary, and Dentistry Services	0.17	0.08	-0.08	0.04	0.04
Education	0.41	0.17	-0.27	-0.05	-0.09

Table 5
Second Stage Constitutional Fund Coefficient Estimates
(t-statistics in parentheses)

	(i)	*(ii)*	*(iii)*
Manufacturing Sectors			
Metallurgy	-0.653	-0.656	-0.006
	(-12.95)	*(-13.03)*	*(-1.01)*
Machinery	-0.555	-0.572	0.055
	(-6.70)	*(-6.91)*	*(4.22)*
Communications and Electronic Equipment	-0.250	-0.250	0.015
	(-1.76)	*(-1.76)*	*(0.85)*
Transportation Equipment	-0.660	-0.659	0.032
	(-8.70)	*(-8.69)*	*(3.80)*
Wood and Furniture	-2.684	-2.694	0.024
	(-18.53)	*(-18.61)*	*(2.25)*
Paper and Publishing	-4.157	-4.157	-0.002
	(-20.68)	*(-20.69)*	*(-0.13)*
Rubber, Tobacco, and Skins	-4.574	-4.662	0.011
	(-23.91)	*(-24.48)*	*(0.62)*
Chemicals, Pharmaceuticals, Veterinary & Perfume Products	-4.125	-4.154	0.013
	(-23.16)	*(-23.33)*	*(0.71)*
Textiles	-3.452	-3.455	0.054
	(-23.57)	*(-23.59)*	*(2.40)*
Shoes	-1.458	-1.440	0.003
	(-10.02)	*(-9.90)*	*(0.14)*
Food, Beverages, and Alcohol	-2.968	-2.969	0.039
	(-24.71)	*(-24.72)*	*(2.70)*
Non-Manufacturing Sectors			
Retail	-0.573	-0.580	0.047
	(-6.95)	*(-7.04)*	*(3.91)*
Credit Institutions, Insurance, & Capitalization	0.024	0.030	0.042
	(0.32)	*(0.40)*	*(1.22)*
Real Estate	-0.115	-0.121	-0.054
	(-3.10)	*(-3.28)*	*(-8.78)*
Transportation & Communication	-0.776	-0.785	0.022
	(-10.20)	*(-10.33)*	*(2.17)*
Hotel and Food	-0.722	-0.716	0.009
	(-12.66)	*(-12.57)*	*(1.12)*
Medical, Veterinary, and Dentistry Services	-0.372	-0.396	-0.026
	(-6.55)	*(-6.97)*	*(-1.58)*
Education	-0.184	-0.182	-0.036
	(-4.98)	*(-4.91)*	*(-7.51)*
Year Fixed Effects	Yes	Yes	Yes
Local Covariates	No	Yes	No
Agglomeration Fixed Effects	No	No	Yes

Figure 1: Brazilian Monthly Per Capita Income Distribution