Infrastructure and the Location of Foreign Direct Investment A Regional Analysis [φ]

Lucio Castro [ξ]
Paulo Regis [ψ]
Daniel Saslavsky [ς]

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Abstract

In the 1990's, Argentina became a top destination for FDI to developing countries. The geographical distribution of FDI inflows was, however, highly uneven. In parallel, the spatial allocation of public infrastructure greatly mirrored these regional disparities. What were the determinants of FDI location? What was the role of public infrastructure? This paper attempts to answer these questions using spatial econometric techniques for a panel of regional and FDI data of the Argentine provinces. Results suggest that space matters for FDI location, indicating some competition effects in FDI inflows between neighbouring provinces. Paved roads seem also matter but other proxies of infrastructure do not seem to be that important. According to our results, a 10% increase in paved roads per capita augments FDI between 17% and 33% in the average host regional economy and extending the network of paved roads in neighbouring regions would increase FDI between 12% and 14%.

Key words: Foreign Direct Investment, Infrastructure, Spatial Econometrics, Economic Geography

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[ξ] Corresponding author: Lucio Castro, Department of Economics, University of Sussex; Arts Building E, Falmer, Brighton, BN1 9SN; l.castro@sussex.ac.uk
[ψ] Paulo Regis, Department of Economics, University of Nottingham, lexpjr@nottingham.ac.uk
[ς] Daniel Saslavsky, Centro de Implementación de Políticas para la Equidad y Desarrollo (CIPPEC); dsaslavsky@cippec.org

"Everything is related to everything else, but near things are more related than distant things"

Tobler (1979)

1. Introduction

From 1991 to 2001 Argentina received an annual average of U$S 6,813 millions of Foreign Direct Investment (FDI) inflows, becoming one of the top destinations for trans-national companies' (TNCs) investment not only in Latin America and the Caribbean but also of all developing countries. According to Sacroisky (2006), Argentina attracted 6 percent of the total FDI directed at developing countries, becoming the fourth most important developing country of destination for TNCs' investment. The spatial or geographical distribution of these FDI inflows across the Argentine regions was, however, highly uneven. For instance, Buenos Aires province and Buenos Aires city -the country's capital- attracted more than half of the total accumulated foreign direct investment inflows. In parallel, the allocation of public expenditure in infrastructure across provinces to a great extent mirrored these regional disparities with, for example, 120 lines per thousand inhabitants in Buenos Aires city, and less than 5 in Formosa.

What are the determinants of the location of FDI across provinces? What is the role of public infrastructure in determining the geographical distribution of FDI in Argentina? What policy lessons can be drawn from the Argentine experience to be applied to the rest of the Latin American region? To provide an answer to these questions, we apply recently developed econometric procedures for spatial analysis to a sample of firm-level FDI inflows, combined with a detailed regional dataset for the Argentine provinces for 1991-2001. As Blonigen, Davies, Waddell and Naughton (2005) point, not controlling for the presence of spatial or geographical correlation may introduce severe omitted biases in empirical FDI studies and thereby spatial econometric techniques are required when using panel datasets.

In fact, recent international studies have found significant spatial effects in FDI location. Using data on U.S. outward FDI to developed countries, Bloniguen et. al. (2005) find a negative coefficient of spatially lagged FDI. Examining U.S. FDI localization patterns across Chinese provinces, Coughlin and Segev (2000) identify a positive endogenous spatial lag of FDI. Head, Ries and Swenson (1995) findings points to agglomeration effects between neighbouring U.S. states in their analysis of Japanese foreign affiliates' investment.

In principle, public infrastructure should have a significant influence on foreign firms' costs and revenues and hence on their location decisions. Using state level data, Coughlin et. al. (1991) found a statistically significative correlation between FDI in the United States and several measures of infrastructure. Head and Ries (1996) found similar results for Chinese cities. Cheng and Kwan (2000) similarly report that good infrastructure, among other factors, positively influenced the location decisions of foreign investors in China from 1985 to 1995. In a cross-country study, Kumar (2001) found that infrastructure availability does contribute to the relative attractiveness of a country as a location site for FDI inflows. Shepotulylo (2006) was, however, not able to find any correlation between a measure of infrastructure stock and the pattern of geographical location of FDI in 24 transition countries. Similarly, Bronzini (2004) did not find any significant impact of public infrastructure on the spatial distribution of foreign direct investment inflows across Italian regions. Thus, it is possible to say that the empirical evidence on the influence of public infrastructure on the location of FDI inflows is not conclusive and the matter is still open for debate.

Our results suggest that space matters for FDI location. The analysis of the determinants of the spatial location of aggregate FDI inflows shows some substitution or competition effects between neighbouring provinces. According to our results, a 10% increase in FDI to neighbouring regions, reduces FDI inflows into the host provincial economy by 3.3%. Paved roads seem also matter for FDI location but other proxies of public infrastructure do not seem to be that important. Our results suggest that a 10% increase in per capita paved roads boost FDI in the average host province between 17% and 33%. Less dramatically, increasing paved roads in geographically close provinces would augment FDI inflows between 12% and 14%, although the results are not so robust. Finally, measured either by GPP or population, the size of neighbouring provincial markets seems also to be an important determinant for FDI location in line with recent research for other countries.

The remainder of the paper is organized as follows. Section 2 presents some stylized facts of the characteristics of FDI inflows and public infrastructure within Argentina in the 1990s. Section 3 sets out the theoretical background guiding our econometric estimations. Since spatial analysis is not standard in the econometric literature, section 4 provides some discussion about spatial econometric techniques, and particularly, the econometrics of spatial lags and FDI. Section 5, presents our empirical strategy, describing the data used and discussing some econometric issues. Section 6 summarizes and interprets our main results. Finally, section 7 concludes drawing some conclusions and setting an agenda for future research.

2. Stylized facts

After the hyperinflationary crisis of 1989, Argentina embraced a comprehensive structural reform program characterized by privatization of state-owned assets, capital account liberalization, and unilateral tariff reductions. Partly as a result of higher openness to foreign trade and investment induced by the structural reforms, the nineties were characterized by persistent foreign direct investment inflows which totalled more than U$S 70 billions for 1990-2001 (See Figure 1). Around 56% of this amount represented M&A operations, and more than 40% were explained by Greenfield investment and other capitalization schemes within these firms.[1]

Consequently, throughout the nineties inward FDI stock grew annually by 25%. In terms of GDP, the stock of FDI increased sixfold (from 5% to 30%) between 1990 and 2001 (see Figure 2). However, as a result of the collapse of the currency board (commonly known as 'Convertibility') in late December 2001, this percentage plunged to 18%. The consequences of the Convertibility breakdown on FDI inflows into Argentina are well beyond the scope of this paper.[2] Therefore, we concentrate here in describing the main trends and patterns of regional, sectoral and aggregate FDI between 1990 and 2001.

In terms of the absolute FDI spatial or geographical distribution between provinces, Figure 3.A applies a graphic approach to illustrate existing disparities. As expected, most

[1] UNCTAD (2006)

[2] See Sacroisky (2006) and Bezchinsky et. al (2007) for detailed overviews of the evolution and characteristics of FDI inflows to Argentina in the post-currency board period.

densely populated and economically important provinces stand out from the rest, such as Buenos Aires and Buenos Aires city (depicted in dark grey); and followed by a second tier of mid-size provinces such as Cordoba, Santa Fe, Mendoza and Nequen (depicted in light grey).

When calculating the geographical distribution of FDI inflows in per capita terms, as shown in Figure 3.B, regions endowed with natural resources (oil, gas and minerals) stand out. Southern provinces, like Santa Cruz, only marginal in absolute terms become extremely important (dark grey) due to their scarce population. In the case of Neuquen (dark grey), the effect is twofold. Not only low population density affects the ratio of per capita FDI (as is the case of Santa Cruz), but also the magnitude of FDI inflows, which are relatively important thanks to its abundance in natural resources such as oil and gas. Catamarca, a northern province (light grey) becomes second in importance according to the used scale, mainly due to its large mining industry. Finally, when calculating FDI as percent of GPP, the picture is relatively similar to the case just mentioned.

When looking at the sectoral distribution of FDI inflows, both at the national and provincial level (see Figures 4 and 5), a number of distinct features emerge. First of all, FDI directed to the Services sector represents the bulk of foreign direct investment, with more than 45% of accumulated flows between 1990 and 2001. In contrast, tradable sectors like Industry (20%) and Agriculture, Mining and Forestry (10%) account for another 30%, while Oil and Infrastructure held the remaining 25%. Secondly, when observing FDI distribution by province, Buenos Aires and Buenos city accounted for half of the total foreign direct investment inflows. Even more, 60% of this percentage was directed towards the non-tradable sector, which in turn represented 30% of all FDI inflows between 1990 and 2001.

Figure 6 plots Lorenz curves for different points in time to measure potential changes in FDI spatial concentration patterns. While the 1990, 1994 and 1998 estimates indicate a clear pattern of progressive geographical deconcentration in FDI inflows, it is harder to draw conclusions from the 2001 estimations. Whilst “smaller” FDI beholders seemed to be worse-off, medium sized provinces were able to secure a higher share in total foreign direct investments, so the overall distribution effect is uncertain.

When looking at the infrastructure indicators at hand, we only focus on public expenditure in infrastructure by type and province, and some infrastructure stock variables, namely fixed telephones, energy production capacity, and roads, all expressed in per capita terms. In the first place, Buenos Aires' share of expenditure in infrastructure as percent of national infrastructure expenditure is almost 20% (see Figure 7.A). In other words, Buenos Aires' expenditures in infrastructure is four times larger than its next four followers.

In terms of its destination sector or use, 16% of infrastructure expenditures were oriented to Housing purposes, while Transport & Telecommunications (16%), Energy and Oil (9%), Primary Sector (7%), Water (5%) and Industry (0.9 %) accounted for the rest. On the other hand, some of the "core" indicators of investment in infrastructure are usually those included in Figure 7.B. Telecommunication infrastructure shows substantial disparities among provinces, with almost 120 lines per thousand inhabitants in the case of Buenos Aires city (capital city), and less than 5 in Formosa. This result is possibly driven by the location and agglomeration bias commonly found in capital cities. In turn, energy production capacity also shows a substantial degree of concentration. This result is caused by some provinces' –such as Neuquen- abundant in natural resources that specialize in the production of hydroelectric energy, gas and oil. Finally, road infrastructure is probably the less concentrated of all indicators introduced here, even though there are significant differences between regions. While La Pampa province holds almost 120km of roads per inhabitant, Buenos Aires only has 11.

Figure 8 presents the concentration of selected measures of provincial public expenditures in infrastructure. These indicators vary greatly depending on its sectoral use, measured by the Gini index. Two different points in time (1990 and 2001) were estimated in order two obtain a sense of its evolution throughout the past decade. Clearly, only public expenditures in energy and oil suffered from substantial deconcentration between 1990 and 2001. For its part, transport and telecommunications public expenditures remained almost invariant, whereas the Gini index in water and housing increased only in marginal terms.

3. Theoretical background

Following some recent theoretical models of economic geography that attempt to explain the spatial location of FDI,[3] we assume that the decision of a TNC on which province to locate investment depends on a set of characteristics of the host province affecting either foreign firms' revenues or costs such as factor endowments, market size, income per capita, skilled labor, and the availability of public infrastructure, among others.

Focusing our attention on the effects of public infrastructure, we interpret public infrastructure as comprising "any facility, good or institution provided by the state which facilitates the juncture between production and consumption".[4] In short, the presence of quality public infrastructure is seen as reducing any type of costs that may be affecting the amount of output that reaches the consumer, commonly known in the international trade literature as "iceberg" costs.[5] This characterization not only captures the key role played by transport infrastructure but also by other types of public infrastructure that may have an effect on output costs such as telecommunications networks or electricity. In line with earlier literature,[6] we also adopt as a simplifying assumption that public infrastructure is only supplied by or through the government.

The presence of quality public infrastructure is likely to affect the location decisions of foreign firms in multiple ways depending on the motivation of FDI. First, as mentioned, the presence of a good infrastructure can significantly reduce firms' output costs, providing a *positive* incentive for *vertical* foreign direct investment or investment where transnational firms base their location decisions purely on a cost basis.[7] Second, an improved public infrastructure could, in contrast, provide a *negative* incentive for the location of *horizontal* FDI inflows or investment motivated by avoidance of transport or other output costs.[8] In this case, foreign companies may choose to supply the provincial

[3] Head and Mayers (2001) and Amiti and Wei (2005)
[4] Martin and Rogers (1995)
[5] See Krugman (1990)
[6] See Arrow and Kurtz (1970), Barro (1990) and Martin and Rogers, op. cit.
[7] Markusen (1984) set out the seminal general-equilibrium model where foreign investment is motivated by market access reasons.
[8] Helpman (1984) was the first to develop a general equilibrium model where FDI arises from the desire of TNCs to access cheaper factor inputs abroad.

economy from a subsidiary located in other province instead of locating a plant, thereby reducing FDI inflows into the host economy with an improved domestic infrastructure. Further, Martin and Rogers (1995) suggest that in the presence of economies of scale public expenditure in *domestic* infrastructure may have different impacts on the geographical distribution of FDI inflows than expenditure in *regional* infrastructure, or public infrastructure aimed at enhancing market access to neighbouring provinces. In such setting, foreign firms would tend to locate in provinces with the best *domestic* infrastructure in order to take advantage of the presence of economies of scale.[9] In contrast, regional infrastructure may influence the sensitivity of foreign firms' investment location decisions to infrastructure differentials and hence actually *reduce* FDI in the provinces with poor domestic infrastructures. The overall effect of regional infrastructure is therefore ambiguous a priori as depends on the existing stock of domestic infrastructure in each host province. Third, public infrastructure could also enhance access to intermediate goods suppliers in neighbouring provinces, providing a *positive* incentive for *complex* FDI location strategies, where transnational companies locate different production activities in separate geographic regions.[10] Summing up, theory does not suggest an unambiguous and unique effect of a reduction in transportation or other output costs caused by improvements in public infrastructure on the spatial location of FDI.

Thus, given the multiplicity of channels of influence presented by the theory, disentangling the effects of public infrastructure on the geographical distribution of FDI primarily remains as an empirical issue. In the next sections, we provide an empirical approximation to the effects of public infrastructure expenditure on the geographical location of FDI in Argentina in the 1990s applying spatial econometric techniques.

[9] Head et.al. (1995, 1999); Hansen (1987); Head and Ries (1996); Guimaraes et.al (2000) and Crozet et.al. (2004) provide empirical evidence on the importance of these agglomeration effects for FDI location at the sub-national level. Agglomeration effects in the location of FDI may be countered by the presence of geographically constrained factor endowments. Beyond certain level of concentration, the attractiveness of other locations for the location of FDI will increase as labor cost will rise, infrastructure will be congested and the prices of intermediate inputs will go up. (Guanzhou Hu and Owen, 2005)

[10] See Baltagi, Egger and Pfaffermayr (2004) for a formal model of 'complex' FDI location strategy.

4. Spatial Econometrics

The use of spatial techniques is an area of econometrics that has recently experienced significant improvements. Whilst Cliff and Ord (1973, 1981) is the standard reference for spatial models, it was only in the second half of the 1990s when new econometrical developments made available computationally simple estimators for large samples and no symmetric spatial weights and presented Montecarlo evidence contrasting their properties in small samples. Alongside to these theoretical contributions, there is an increasing number of applied contributions that focus on empirical analysis of spatial issues, taking advantage of the development of the new spatial estimation methods.

The spatial regression analysis is based on two different models: the spatial error model and spatial lag model. The spatial error model includes spatial correlation in the disturbance term; violating OLS assumptions since the error term depend on the error term of the other cross-sectional units. The spatial lag model introduces a spatial lag of the dependent variable which is typically correlated with the disturbance term so, again, OLS is not consistent.[11]

The traditional approach to estimate these models requires the use of maximum likelihood (ML) estimators. However, some recent studies have proposed an alternative three-step procedure that is computationally simpler, has similar performance in small samples to ML and has no distributional assumption. Kelejian and Prucha (1999) departs from the spatial error model for a cross-section which controls for spatial correlation introducing a spatial lag in the error term. Since the disturbance term is assumed to be spatially autoregressive (SAR), it may be called the SAR model. The second step procedure presents a new generalized moment (GM) estimator of the spatial lag parameter in the error term. Once the second step provides a consistent estimate of the spatial autoregressive parameter, FGLS can be performed to obtain consistent estimates of the right hand side variables' coefficients.

An additional complication may be introduced if the spatially lagged dependent variable is introduced as a regressor. The new source of spatial correlation generates an endogeneity bias that makes the three step procedure for the SAR model inconsistent.

[11] An in-depth review of the spatial econometric literature can be found in Anselin and Bera (1998).

Kelejian and Prucha (1998) suggest an instrumental variable estimation procedure based on the GM estimator of the spatial autoregressive process, which is analogous to the GM procedure for the SAR previously described. Instrumental variables estimates are obtained by 2SLS and the procedure could be referred as generalized spatial two-stage least squares (GS2SLS).

New contributions deal with further augmentations of these two alternative procedures for panel data. Kapoor, Kelejian and Prucha (2006) generalises the estimators proposed in Kelejian and Prucha (1999) to consider spatially and time-wise autocorrelation as well as controlling for heteroskedasticity. Also, this new procedure increases the moment conditions of the second step GM estimator from three to six. Finally, Kelejian and Prucha (2004) generalises Kelejian and Prucha (1998) to a simultaneous system of cross-sectional sections. Then, additional spatial lags for each dependent variable may be introduced in the system. When considering only one equation, the procedure is the GS2SLS with new spatially lagged variables, in addition to the dependent variable. If we define all the equations of the system and use the full system information, consistent estimates are yielded by 3SLS and the procedure using this full information estimator may be called GS3SLS.

4.1 The Econometrics of Spatial Lags and FDI

The estimation of spatial models requires defining spatial lags which may arise in the error term, the dependent variable or one of the independent variables. The inclusion of a spatial lag in the error term controls for any bias due to omitted variables which may be spatially correlated with the dependent variable. However, the interpretation of the spatial correlation coefficient is not clear. That is why the inclusion of a generic spatial lag in the error term (or spatially autocorrelated error term) is desirable to avoid biases but it may be obscure about the sources of the correlation.

Other types of spatial lags are more informative since the interpretation is more straightforward. Once the spatial correlation is associated with a particular variable, the spatial coefficient measures the impact of its spatial distribution in the dependent variable. In the FDI and spatial analysis literature, the sign of the spatial lag of the dependent variable (i.e. FDI) is one of the primary concerns. The coefficient of this spatial lag can be interpreted differently, depending on its sign. The other coefficient of interest in this literature is the one for the 'regional market' effect –usually proxied by a distance weighted measure of the GPP or population in neighbouring regions- which is commonly associated with the idea that host economies surrounded by larger markets tend to attract more FDI.

The signs of the spatially lagged dependent variable and the 'regional market' effect coefficients are of interest since different theories of FDI motivation predict different signs.[12] In the case of *horizontal* FDI or investment motivated by avoidance of transport costs no spatial relationship between FDI into neighbouring markets is expected as multinational companies make independent decisions about how to serve the host market. If transport costs between geographically close markets are low enough, the multinational firm will chose to invest in a selected platform market and serve other markets through sales. This kind of *regional sales-platform* foreign direct investment[13] implies a *negative* spatial lag in FDI as foreign investment to the platform province substitutes for FDI to other regional markets. Additionally, the size of the FDI going into the sales-platform region will depend on the economic size of neighbouring markets it will be serving through sales. Therefore, we expect to find a negative spatial lag and a positive sign for the spatially weighted market size of neighbouring regions. In the case of FDI motivated purely by factor cost-minimization reasons or *vertical* FDI, a *negative* spatial lag coefficient is expected as the FDI into the host economy is at expense of foreign investment into other regional economies. The regional market effect, in turn, should not be significant. Finally, the presence of FDI motivated by the fragmentation of production activities across separate regions of *complex* vertical FDI is expected to generate both positive spatial lag and regional market coefficient as the presence of vertical suppliers in neighbouring regions is likely to increase FDI into a particular host economy.

[12] The discussion in the next discussion follows closely the one presented in Bloniguen et.al. (2005).
[13] In a cross-country setting, this type of FDI is usually labelled as 'export-platform FDI'.

5. Empirical Specification

This paper provides some spatial analysis results for a panel of twenty one Argentine provinces for 1990-2001, when Argentina was one of the most important developing country destinations for FDI inflows. In Annex B we provide a description of our dataset and some summary statistics in Annex C.

We utilize two alternative spatial econometric models: the Spatial Autoregressive (SAR) model and a model that introduces a spatial lag in the right hand side of the regression term or spatial lag model (SL). Although the literature on the spatial analysis of FDI usually chooses only one of these two spatial models, we present estimates for both. The two alternative models should provide an extra sensitivity analysis for the spatial correlation results which may prove fructiferous. However, we should be aware of the different nature of the data generation processes in each case.

The simpler of the two models is the (Cliff-Ord type) first order SAR, which is presented by the following expressions

$$FDI = X^{'}\beta + u \qquad (1)$$

$$u = \rho Wu + \varepsilon \qquad (2)$$

where FDI inflows are a function of a $1xk$ vector of observations of k exogenous variables and the regression disturbance term (u). All variables are introduced in logarithmic transformations and dummies variables for each province is introduced to control for fixed effects. The disturbance term (u) is modelled as a weighted average of disturbances of other cross-sectional units, plus an iid white noise (ε) with variance σ^2_{ε}. The weighted average depends on a set of time invariant weights, grouped in the matrix W, and the parameter ρ, which is the main parameter of interest for spatial analysis.

Consistent estimates are obtained from the three-step SAR procedure. In the first step, equation (1) is estimated by OLS. The residuals of the first step are utilized in the second step to estimate ρ and σ^2_{ε} by the GM estimator described in Kelejian and Prucha (1999, 2006)[14]. In the third step, the GM estimate for ρ is used to account for the spatial correlation in the disturbance, using a Cochran-Orcutt-type transformation, a standard transformation in spatial analysis. The SAR estimator for β is obtaining by estimating the transformed model by OLS.

The second model considers a second type of spatial correlation: the dependent variable weighted average of the neighbour cross sectional units. This weighted average represents the spatial lag of the dependent variable. Then, equation (1) is replaced by

$$FDI = \lambda W\, FDI + X^{'} \beta + u \qquad (3)$$

where λ is a scalar, which is multiplied by the weighting matrix W and the dependent variable[15]. Then, our spatial lag model or SL model consist of equations (2) and (3), which has two scalar spatial autoregressive parameters (ρ and λ). Again, we have a three-step procedure, similar to the previous procedure, modified to introduce an instrumental variable approach. To deal with the endogeneity of $WFDI$, the first and third step OLS of the SAR procedure are replaced by 2SLS, and the new estimator is called GS2SLS.

The spatial lag model does not require spatial autocorrelation in the error term. Most of the literature of the traditional ML approach prefers to confront the two models, highlighting their different interpretation of the spatial dimension of the data generation process. If the error SL were not included, estimation procedure would be simpler, requiring only the fist step 2SLS estimation, that is, a 2SLS estimate of equation (3). However, the omission of equation (2) would ignore any other source of spatial correlation. Therefore, we opt to include ρ, making the final specification more general. Likewise, when the ρ second step estimate is zero, the GS2SLS procedure provides the same estimates and standard deviation than the 2SLS estimate of (3).

[14] The GM estimator exploits three moment conditions similar to Kelejian and Prucha (1999), except that we use panel data rather than a single cross-section, and Kelejian and Prucha (1999), if serial correlation is eliminated from this model.

[15] It is possible the two weighting matrices in the error spatial lag of equation (1) and the FDI spatial lag in (3) are different but it is not the case.

The spatial weights matrix W is calculated as the inverse of the distance of host province i's to the neighbouring provinces, or formally:

$$W_y = \begin{bmatrix} 0 & w_y\left(d_{i,j}^{-1}\right) & w_y\left(d_{i,k}^{-1}\right) \\ w_y\left(d_{j,i}^{-1}\right) & 0 & w_y\left(d_{j,k}^{-1}\right) \\ w_y\left(d_{k,i}^{-1}\right) & w_y\left(d_{k,j}^{-1}\right) & 0 \end{bmatrix} \tag{4}$$

where the simplest functional form for elements of the weight matrix is assumed. Even though it is feasible to define different weighting matrices in the spatial lag model for the disturbance term and the dependent variable, we avoid this complication since we find no sensitive reason to make any relevant distinction between the two weighting average transformation.

The vector X completes the final specification for our empirical analysis, including some variables that may affect FDI: infrastructure, market size, public expenditure composition and factor endowments. These variables were selected following the theoretical background presented in section 3 and previous empirical research on the determinants of FDI inflows. Infrastructure includes two alternative proxies for road network (total roads length and paved roads) and electricity (installed power capacity and gross generation). Host market size was proxied with Gross Provincial Product (GPP) while factor endowment proxies are the share of construction in GPP -as a proxy for investment- and per capita primary and secondary school enrolment –as proxies for unskilled and skilled labor, respectively-.

GPP is expected to be positive for FDI inflows, and therefore we anticipate that its coefficient should have a positive sign. Economic geography models and empirical studies of FDI determinants suggest that larger economies tend to attract more investment because there is more potential market demand. Usually, market size is also often proxied by population and thereby we should also expect a positive coefficient. However, Blonigen et. al. (2005) suggest that, holding GPP constant, a rising population may reduce per capita GPP and therefore FDI inflows, as GPP per capita proxies the average purchasing power in the host market. We are thereby a priori agnostic about the sign of the coefficient on population.

Provincial factor endowments are also expected to have a positive impact, particularly on foreign investment horizontal inflows, except for unskilled labor since FDI is usually correlated with some minimum threshold of human capital.[16] Labor market conditions are also likely to be an important determinant for FDI location. Specifically, provincial unemployment rates – our proxy – are expected to be positively correlated with foreign direct investment inflows as lower (higher) utilization rates usually imply diminished (increased) real salaries and hence lower (higher) labor costs for foreign firms in the host province. The level of education of the labor force is also another important factor in determining the spatial distribution of FDI inflows within a country or region. The presence of a skilled labor force is usually associated with increased FDI inflows in the host province and thereby we expect a positive coefficient.

In addition, we control for public expenditure composition. Instead of introducing an aggregate measure of the size of provincial public sector, we break down public expenditure by component as we expect they may have differential effects on FDI location. A priori, it is likely that some productive public expenditure is more relevant to foreign investment than general public expenditures which as are normally associated merely with government size. This may be the case of spending in productive sectors and infrastructure such as public expenditure in economic development (and its four components: transport and communications, agriculture, energy and industry), housing and sanitary services (water, henceforth).[17] Further, public expenditure in education may enlarge human capital endowment, having a positive impact on FDI. More general and unproductive public expenditure may include general public services, defence and security, public health (and health in general which includes public health and sanitary services) and social security and social services. Similar to general health, housing and social security and social services can be aggregated to social welfare public expenditure.

6. Estimation results

Table 1 commence our empirical analysis exploring whether the data presents any spatial relationship in the FDI location patterns and whether controlling for the presence

[16] See Borenztein et. al. (1997)
[17] See Annex A: Data description.

of spatially correlated errors with the SAR estimator and the inclusion of spatial lags with the GS2LS estimator affects the standard determinants of FDI included in our base model, namely GPP, investment, factor endowments –proxied by primary and secondary schooling-, population, and factor utilization –proxied by unemployment-.

Column (1) presents OLS results without controlling for spatially correlated disturbances or including a spatially lagged term. In columns (2) and (3), we control for the presence of serial correlation by running an autoregressive model (AR) and a two-stage least square (2LS) estimator respectively. Column (4) presents the SAR estimates and Column (5) provides the GS2LS estimates which includes a spatial lag on FDI. Standard errors are in parentheses and significance levels are indicated by stars, as usual, with *** p<0.01, ** p<0.05, and * p<0.1. All variables are expressed in logarithms.

Several observations can be made from results in Table 1. First, population and GPP seem to be the most important determinants of FDI location in our base model, presenting mostly positive and significant coefficients at least at 5% across all the estimators. Other explicative variables like Investment, Unemployment and Education (primary and secondary schooling) are, however, not robust across different econometric techniques. Second, the relatively poor results the base model yields when running 2LS, and particularly AR estimators, suggest that serial correlation is not a particularly serious concern in our panel dataset. Finally, when controlling for the presence of spatially correlated errors as in column (4) or including a spatially lagged term as in column (5), most of the explanatory variables in our base model turn out significative and with the expected signs, providing evidence that not controlling for the presence of spatial correlation could lead to a significant omitted bias in our dataset.

Tables 2 and 3 present the complete results for SAR and GS2SLS estimators. Table 2 includes all variables in equation (1) and an extra row where we can find the GM estimates of ρ from equation (2), including its level of significance. The spatial autoregressive model provides a valid standard deviation for the error spatial lag and an observable statistic to contrast the significance of the parameter. Tables 3 presents the estimates for equation (3) and the second-step GM estimate for ρ. However, the three-step procedure does not provide with standard deviation of the error spatial lag. In this case, the coefficients are displayed in italics to stress the fact we cannot established whether is statiscally significant..

The variables included in the SAR and GS2SLS are the same and can be grouped in three categories: base model (i.e. market size and purchasing power, factor endowment, and factor utilization), public expenditure composition and infrastructure stock (roads and electricity). The first two columns only include the basic variables. Then, we include infrastructure in the next four columns while the last four columns adds public expenditure composition. Only the components that show any significance are included. Some times, total expenditure is included since it is more significant that any subcomponent of public spending.

Table 2 shows GPP is always highly significant and positively correlated with FDI. Population's coefficient is negative and usually significant at least at 5%, except when paved roads is included in the regression when becomes not significant. Investment (proxied by the construction to GPP ratio) is usually significant at 5% (except in columns 7 and 9). Primary and secondary school are always significant at least at 5 and 10% respectively, with opposite sign. Our proxy of unskilled labour has a negative sign while skilled labour (secondary school) has a positive sign and it is significant at 5% in the first six columns although it is only significant at 10% when the public expenditure composition is included. Unemployment shows a highly significant positive coefficient which is the expected sign. One of our proxies for infrastructure stock, paved roads, is significant at 5% with the expected positive sign but the other infrastructure variables are never significant. Public expenditure composition shows that general expenditure is highly significant and positive for FDI but social security, if any, has a negative effect on FDI but it is only significant at 10% in columns (8) and (10).

Our estimates for the spatial autoregressive parameter ρ show a consistent highly significant positive coefficient of around 0.5. This is strong evidence of spatial correlation in the error term of the OLS results of equation (1). The omission of a proper methodology to deal with spatial issues is a potential source of biases for the other rest of the factors that affect FDI.

On the other hand, Table 3 show some results that suggests the interdependence among the spatial units that arises in FDI is more complex than the one previously described When the spatially weighted average of FDI is introduced, it is consistently significant at least at 5% but its sign is negative, contrary to the sign of the error spatial lag in Table 2. Further, the error spatial lag revert its sign in table 3. Even though we are not able to establish if it is statistically significant, the magnitude of the coefficient is consistently close to one third, a magnitude which cannot be easily discharged as irrelevant. This also indicates that inclusion of equation (2) in the spatial lag model may be pertinent.

The interpretation of the negative coefficient of the FDI spatial lag is straightforward: FDI is substitutive so foreign investment located in neighbouring provinces reduces inflows to the local economy. There are important changes in the other determinants of FDI as well. GPP still has a strongly significant positive coefficient but now population is not longer negative and is always significant at 1%. Further, unemployment is not longer significant at 5% except for the simplest model in column 1. Certainly, it is more difficult to find any significant correlation between FDI and investment, skilled and unskilled labour endowment. None of these variables is significant at 5% when public expenditure composition and infrastructure is considered. Primary school is significant at 5% only in the first six columns. Secondary school is significant at 5% in column 1 and investment is significant at 5% in columns 4 and 6. General public spending is still highly significant but social welfare is replaced by housing (one of the components of social welfare) which has now a positive coefficient and it is significant at 5%. Infrastructure shows similar results than before or even higher correlation with FDI since paved roads is significant at 1% and electricity (power capacity) is significant at 10% in columns (6) and (10).

Table 4 looks at explaining the sources of spatial correlation in the SAR and Spatial lag models introducing spatially weighted averages of Population and Paved Roads into the independent variable matrix (X). The model with total roads is discharged here since paved roads showed to be a better proxy for road networks. Both SAR and GS2SLS present levels of significance of at least 5% for the spatial lag of Population while Paved Roads lag is only significant in the SAR model. This suggests both Population and the spatial distribution of Population are important for FDI but only SAR find strong evidence for the spatial distribution of Roads. Also, the difference in sign for Population disappears. Now, both models display positive coefficients (although not significant in columns 3 and 4). In connection to Population's Spatial Lag, our results suggest the presence of a dominant 'regional market' effect on FDI inflows in line with international literature.[18] [19] Other proxies of public infrastructure (i.e. Roads, Electricity Generation and electricity Capacity) and spatially lagged variables are not significant.

Further, a contradicting sign in the error spatial lag persist but the GS2SLS ρ estimates are much closer to zero (always below 0.04), indicating Population spatial correlation was partly causing this puzzling result. Finally, Secondary Schooling and Social Security Expenditure are not significant even for SAR while Primary Schooling never significant in the GS2SLS estimator. Likewise, substitution effects in FDI to neighbouring provinces in table 4, columns 5 to 8 are not as robust as in table 3. While the sign of the FDI Spatial Lag coefficient is still negative, it is not significant in column (6) and the level of significance drops significantly in the remaining columns.

Introducing spatially lagged independent variables allow us to disentangle the motivations behind the geographical distribution of FDI according to the theoretical discussion presented in sections 3 and 4.1. The presence of statistically significant spatial coefficients suggests that FDI location patterns go beyond simple horizontal FDI motivations. The presence of a negative spatial lag on FDI provides evidence on the prevalence of either vertical or sales-platform strategies in foreign investment into the host provincial economies. The positive coefficient in our proxies for 'regional market effects' (i.e. the geographically weighted average of Population in neighbouring regions) and domestic and regional public infrastructure (i.e. Paved Roads and spatially weighted Paved Roads, respectively) provides some additional evidence on the importance of vertical motivations in FDI.

It is worth noting that overall our preferred estimator is the SAR model as most of the 'gravity' variables traditionally employed to explain the location of FDI are statistically

[18] Regressions including a spatial lag on our other proxy for 'market size' effects –i.e. GPP- yielded counterintuitive and relatively poor results and therefore are not presented here but are available upon request to the authors.

[19] See, for example, Bloniguen et.al. (2005)

significant and with the expected signs as well as indicate that there is a large 'market size' effect, in line with previous literature. In the case of the GS2LS estimator, once we allow for spatial lags in the independent variables, the spatially lagged FDI is not anymore relevant. These results suggest that studies that only include a spatial lag in the dependent variable may not be explaining the real sources of spatial correlation in FDI inflows that could be arising from geographically determined relationships in some of the regressors.

7. Conclusions

With two alternative spatial models, we found evidence that favours the introduction of spatial correlation in the analysis of FDI location. Whilst some results are difficult to interpret, we can conclude that space matters for FDI. Not tackling this issue could generate misspecifications in some form of omitted variable biases.

When choosing a spatial lag model, the analysis of aggregate FDI inflows shows substitution effects between neighbouring provinces, favouring a "competition for FDI" explanation for the geographical location pattern of FDI flows.[20] Results suggest that an increase in 10% of FDI into neighbouring regions would reduce FDI inflows into the host province by 3.3%. The presence of positive spatially lagged FDI and 'regional market' effect coefficients also point the prevalence of either complex vertical or sales-platform motivations in the geographical distribution of FDI in Argentina during the 1990s. However, the results in table 4 shows that the substitution effect of FDI is not so strong when spatial lags of the other variables are included.

Paved roads seem also matter for FDI location but other proxies of infrastructure do not seem to be that important. More precisely, our results suggest that increasing by a 10% the number of kilometres of paved roads per capita in the average province would lift up FDI in the host province between 17% and 33%. In contrast, the influence of regional infrastructure -proxied by the weighted average of paved roads in neighbouring provinces- is not so clear cutting. While estimates from the SAR model seem to suggest that extending the network of paved roads in geographically close provinces would increase foreign investment into the host economy by between 12 and 14%, the GS2LS

[20] See Blonigen et.al. (2005)

estimator only yields extremely poor results. Beyond these differences in the results produced by the estimators, the positive coefficient in both paved roads and geographically weighted average paved roads in neighbouring provinces provides additional evidence on the presence of vertical or sales-platform strategies in the location of foreign investment across the Argentine provinces.

Further, public expenditure in infrastructure and other productive sectors show a depreciative effect on FDI location. From the public expenditure components that may be more related to infrastructure or productive expenditure, only housing shows some significance. Public sector expenditure usually has a positive effect on FDI, except for public welfare and health which are negatively associated with FDI. Specially, general spending shows a strong correlation with the dependent variable. The fact that productive spending is not significant makes this result difficult to interpret.

In line with the findings of the literature, there is also a significant and robust 'home market' or domestic 'market size' effect,[21] pointed by a positive and significant coefficient for GPP in most of the regressions in the SAR and spatial lag models. Labor market conditions seem also to be important when the SAR model is preferred.

Generally, our results emphasize the importance of including spatial lags of the independent variables in the econometric analysis of the determinants of FDI location. Only including geographically weighted averages of the dependent variable (i.e. FDI) may be omitting extremely influential sources of spatial correlation highlighted by the theoretical literature on FDI motivations. Particularly, results point to the influence of 'regional size' effects (in our case proxied by distance-weighted averages of population in neighbouring provinces) and domestic and regional public infrastructure (i.e. paved roads) in determining FDI spatial distribution.

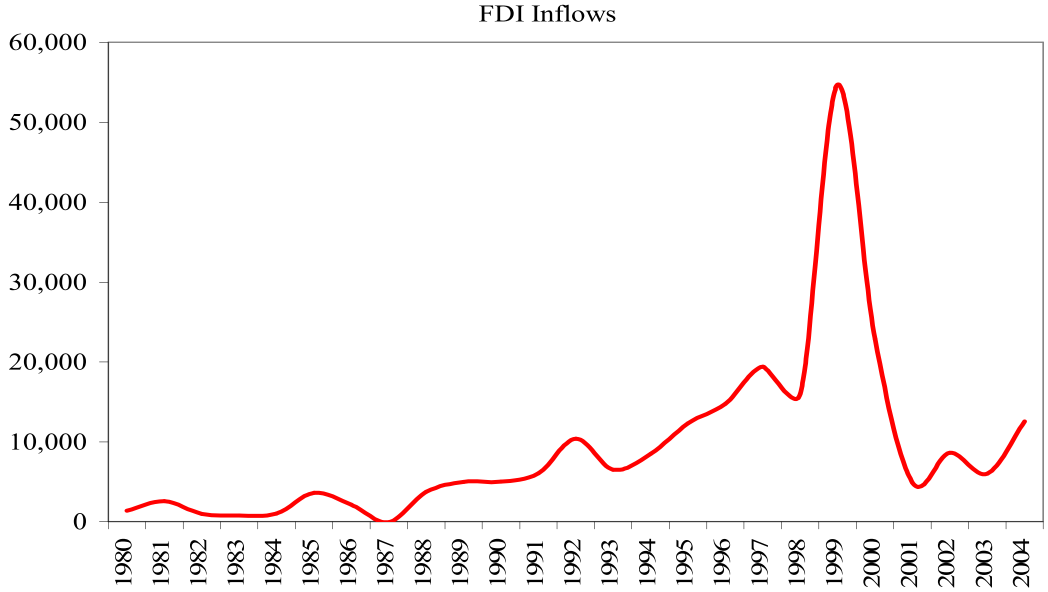
Finally, whilst our research is only focused on the geographical patterns of FDI location in Argentina during the 1990s, we believe our results provide interesting lessons for other countries in Latin America. While limited to paved roads, the presence of a quality infrastructure not only in the host economy but also in neighbouring regions seems to be a relatively significant determinant in the attraction of FDI inflows. Our

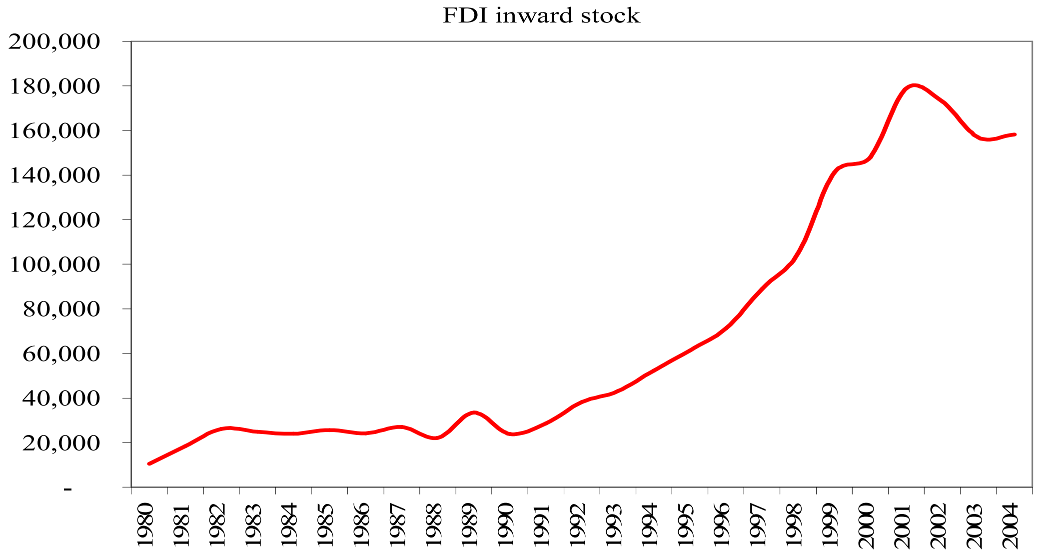
[21] See Davis and Weinstein (1999) and Head and Mayer (2004).

results also suggest that the presence of large markets and vertical suppliers in geographically close economies provides a positive influence for the location of FDI in the host economy.

Tables and figures

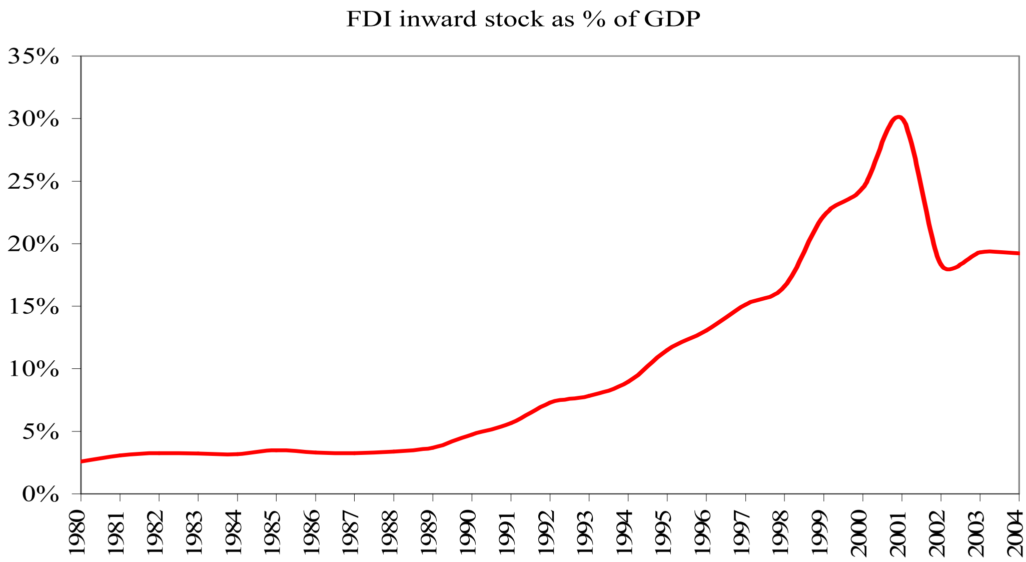
Figure 1: FDI inflows and inward stock in Argentina (millions of $ 2004), 1980-2004





Source: own calculations based on UNCTAD (2007)

Figure 2: FDI inward stock in Argentina (as percent of GDP), 1980-2004



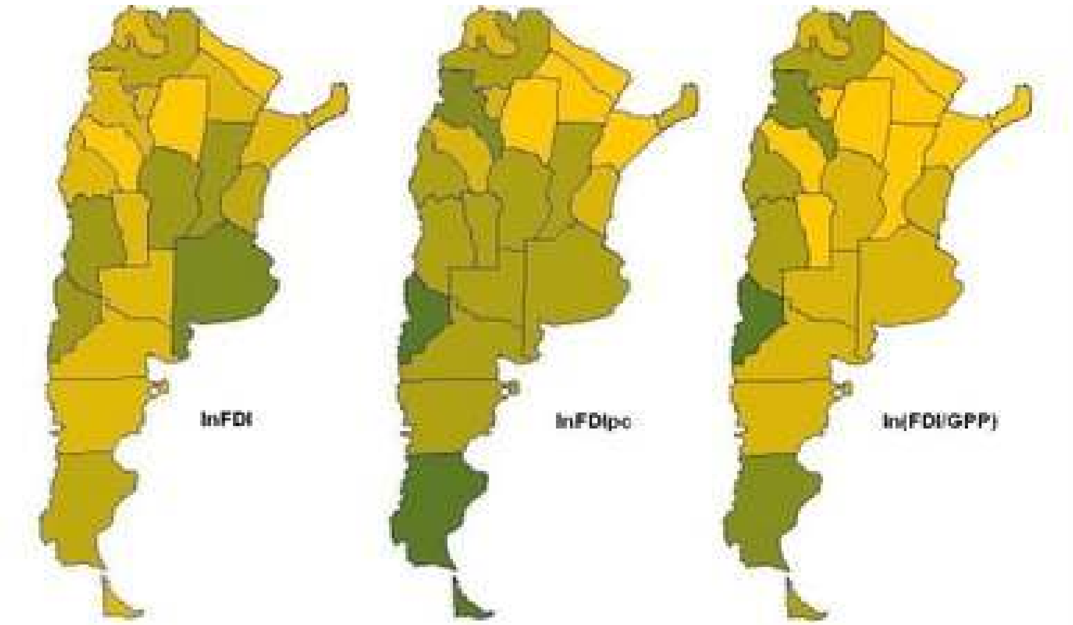
Source: own calculations based on UNCTAD (2007) and Ferreres (2006)

Figure 3: FDI location across provinces, 2001

(A) Log FDI

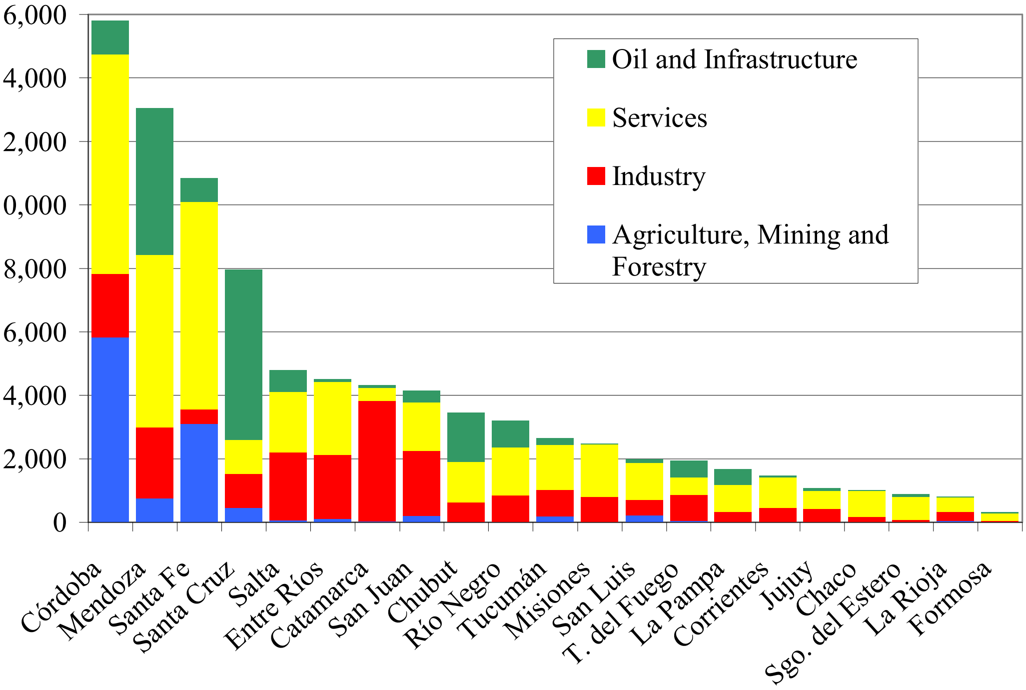
(B) Log provincial per capita FDI

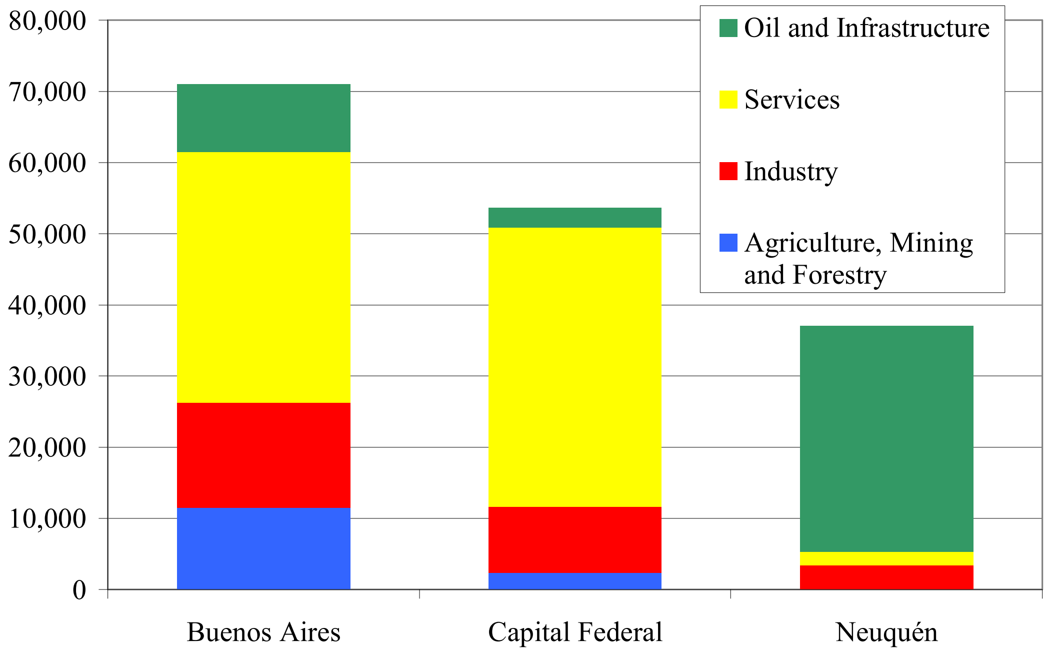
(C) Log FDI as % of GPP



Note: Figures are in 2004 pesos
Sources: own calculations based on Ministry of Interior - Provinfo.

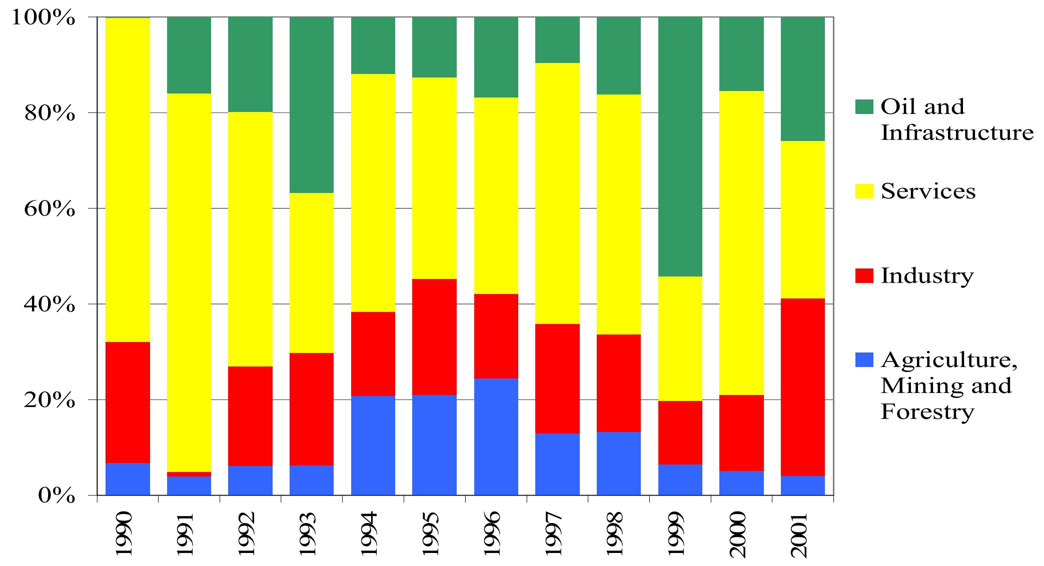
Figure 4: Sectoral FDI by province, Accumulated 1990-2001





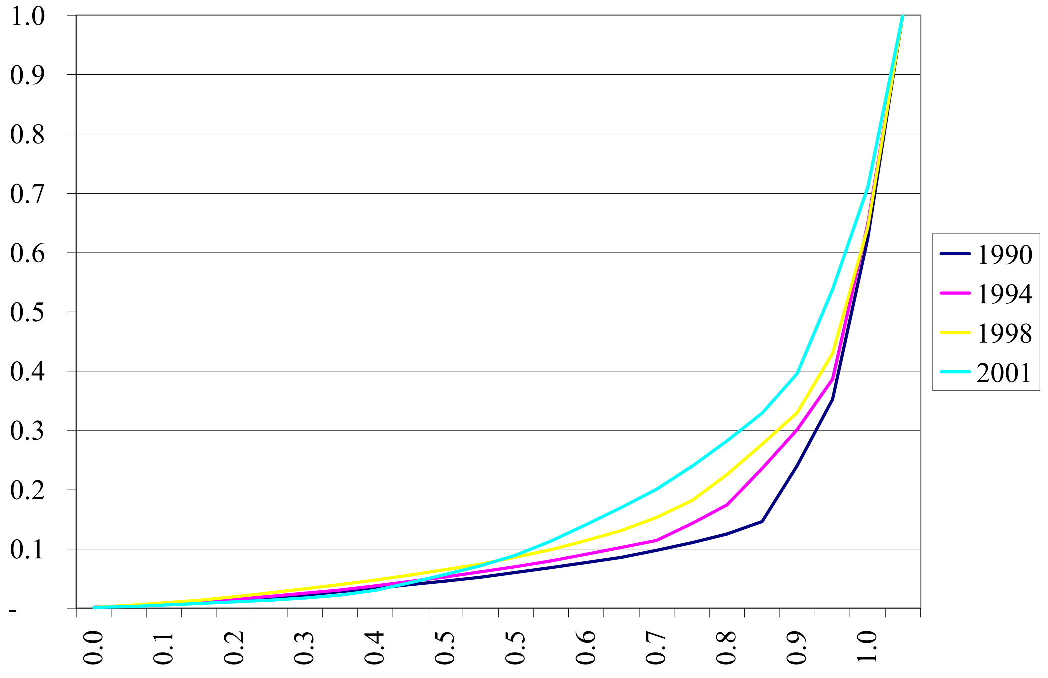
Sources: own calculations based on Ministry of Interior - Provinfo.

Figure 5: Sectoral FDI, as Percent of Total FDI, Accumulated 1990-2001



Sources: own calculations based on Ministry of Interior - Provinfo.

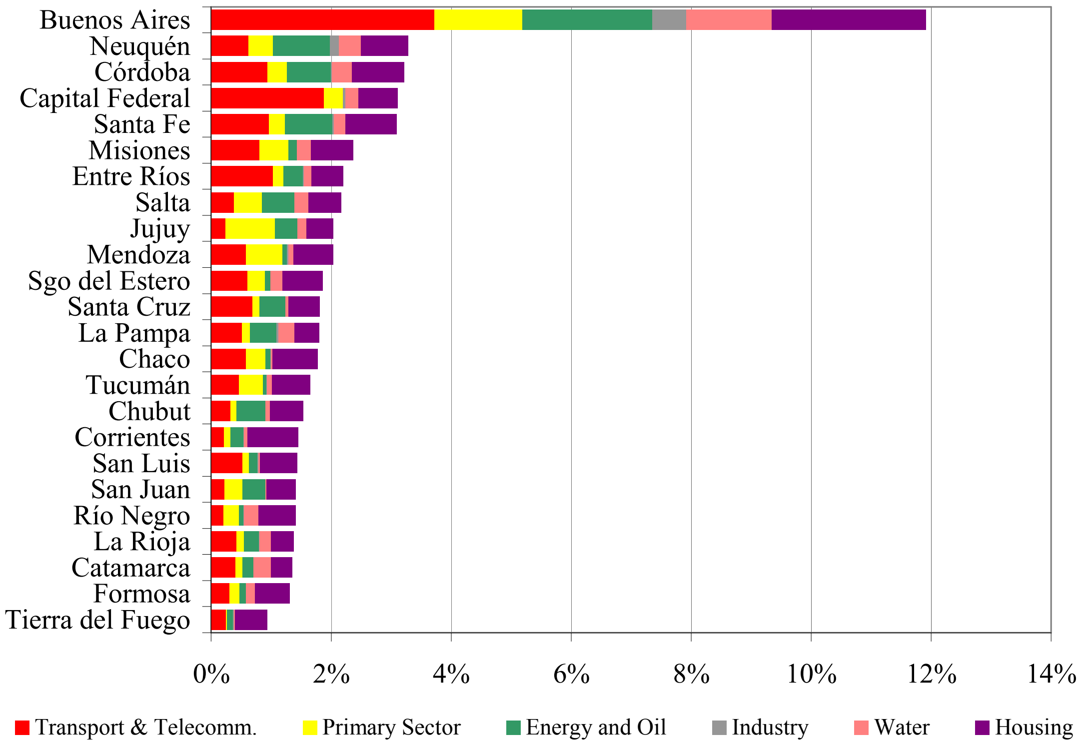
Figure 6: FDI inflows regional concentration curves, selected years



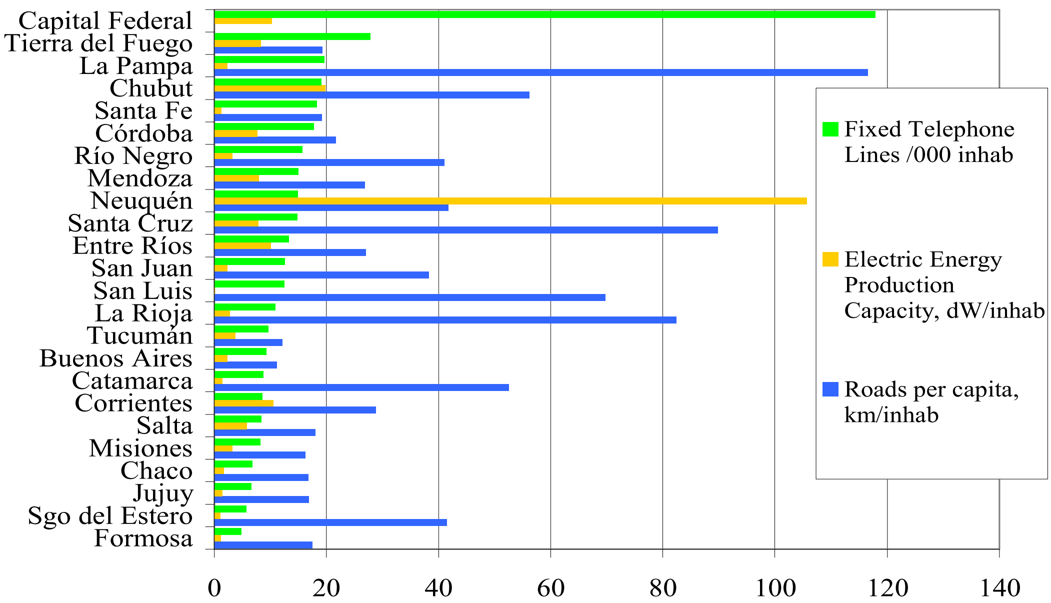
Sources: own calculations based on Ministry of Interior - Provinfo.

Figure 7: Infrastructure expenditure and stock by province and sector, as percent of total infrastructure expenditure, 2001

(a) Expenditure

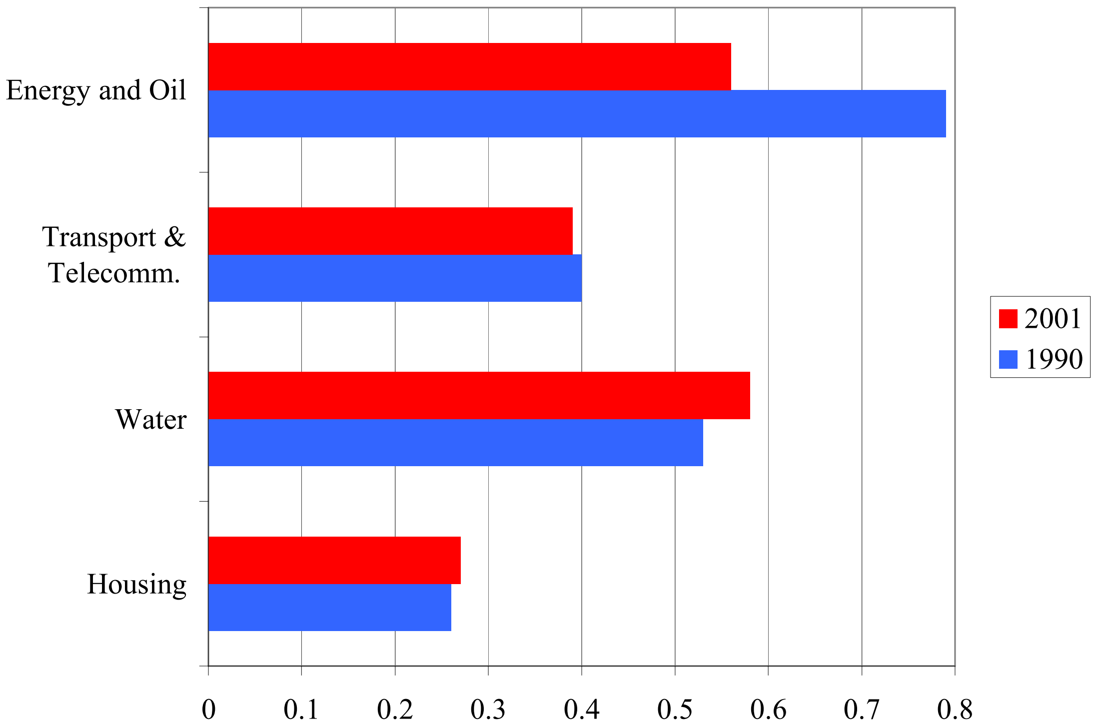


(b) Stock



Source: own calculations based on regional database

Figure 8: Concentration of Provincial Public Infrastructure Expenditure, Gini Index 1990/2001



Source: own calculations based on Regional database

Table 1: Spatial Analysis of FDI location – Alternative Models

	(1) OLS	(2) AR	(3) 2SLS	(4) SAR	(5) GS2SLS
GPP	1.649***	1.449**	0.603	1.853***	2.686***
	(0.50)	(0.60)	(0.83)	(0.37)	(0.48)
Investment	0.596*	0.555	0.816*	0.989***	0.475
	(0.33)	(0.35)	(0.47)	(0.36)	(0.33)
Primary School	-0.213	1.060	0.788	-4.379***	-2.91***
	(0.85)	(0.77)	(1.03)	(0.89)	(0.80)
Secondary School	0.232	-0.290	-0.751	1.712**	1.274*
	(0.62)	(0.72)	(0.90)	(0.75)	(0.67)
Population	9.300***	9.474***	2.703	-1.367***	2.212***
	(1.22)	(1.49)	(4.26)	(0.50)	(0.64)
Unemployment	0.0412	0.0781	0.0933	0.562***	0.314**
	(0.14)	(0.15)	(0.16)	(0.15)	(0.15)
FDI Time Lag			0.731**		
			(0.37)		
FDI Spatial Lag					-0.28**
					(0.11)
AR		*0.397*			
Observations	252	252	231	252	252

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Spatial Auto-Regressive Error Model (SAR) for FDI flows

	(1) SAR	(2) SAR	(3) SAR	(4) SAR	(5) SAR	(6) SAR	(7) SAR	(8) SAR	(9) SAR	(10) SAR
GPP	1.917***	1.853***	1.855***	1.343***	1.859***	1.308***	2.674***	2.131***	2.710***	2.107***
	(0.38)	(0.37)	(0.41)	(0.47)	(0.41)	(0.49)	(0.44)	(0.49)	(0.44)	(0.51)
Investment	1.214***	0.989***	1.022***	1.145***	1.013***	1.137***	0.554	0.701**	0.565	0.715**
	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
Primary School	-5.322***	-4.379***	-4.305***	-3.862***	-4.349***	-3.874***	-2.360**	-1.913**	-2.391***	-1.877**
	(0.88)	(0.89)	(0.90)	(0.92)	(0.90)	(0.92)	(0.92)	(0.92)	(0.92)	(0.93)
Secondary Sch.	2.657***	1.712**	1.776**	1.712**	1.806**	1.689**	1.275*	1.238*	1.325*	1.220*
	(0.72)	(0.75)	(0.76)	(0.75)	(0.76)	(0.75)	(0.72)	(0.71)	(0.72)	(0.71)
Population	-1.299**	-1.367***	-1.273**	-0.296	-1.297**	-0.259	-1.784***	-0.840	-1.834***	-0.771
	(0.51)	(0.50)	(0.64)	(0.73)	(0.65)	(0.78)	(0.61)	(0.69)	(0.61)	(0.73)
Unemployment		0.562***	0.569***	0.587***	0.585***	0.589***	0.385***	0.401***	0.394***	0.395***
		(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)	(0.15)	(0.15)
General Pub. Exp							1.644***	1.642***	1.620***	1.627***
							(0.29)	(0.29)	(0.29)	(0.28)
Social Security							-0.325	-0.373*	-0.317	-0.362*
							(0.21)	(0.20)	(0.21)	(0.20)
Roads			0.163		0.165		0.358		0.340	
			(0.42)		(0.42)		(0.41)		(0.41)	
Paved Roads				1.067**		1.085**		1.201**		1.254**
				(0.52)		(0.54)		(0.48)		(0.51)
Electr. Generat			-0.0515	-0.0309			0.0145	0.0370		
			(0.056)	(0.056)			(0.054)	(0.054)		
Electr. Capacity					-0.131	-0.0289			-0.0331	0.0832
					(0.14)	(0.14)			(0.13)	(0.14)
Error spatial lag (rho)	0.500***	0.500***	0.510***	0.512***	0.507***	0.511***	0.509***	0.513***	0.506***	0.512***
Observations	252	252	252	252	252	252	252	252	252	252

Table 3: Spatial Lag Model for FDI flows

COEFFICIENT	(1) GS2SLS	(2) GS2SLS	(3) GS2SLS	(4) GS2SLS	(5) GS2SLS	(6) GS2SLS	(7) GS2SLS	(8) GS2SLS	(9) GS2SLS	(10) GS2SLS
FDI Spatial Lag	-0.33***	-0.28**	-0.31***	-0.42***	-0.31***	-0.43***	-0.26**	-0.36***	-0.25**	-0.36***
	(0.095)	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)
GPP	2.639***	2.686***	2.656***	1.868***	2.642***	1.804***	3.316***	2.542***	3.310***	2.503***
	(0.48)	(0.48)	(0.48)	(0.49)	(0.48)	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)
Investment	0.504	0.475	0.405	0.796**	0.441	0.879***	0.004	0.433	0.0499	0.524*
	(0.33)	(0.33)	(0.34)	(0.33)	(0.33)	(0.33)	(0.33)	(0.32)	(0.33)	(0.32)
Primary School	-2.25***	-2.91***	-2.75***	-2.04**	-2.74***	-1.89**	-1.51*	-0.78	-1.51*	-0.67
	(0.76)	(0.80)	(0.81)	(0.80)	(0.82)	(0.81)	(0.83)	(0.81)	(0.84)	(0.82)
Secondary Sch.	1.354**	1.274*	1.186*	0.886	1.168*	0.818	0.873	0.597	0.885	0.576
	(0.62)	(0.67)	(0.68)	(0.66)	(0.68)	(0.66)	(0.66)	(0.64)	(0.66)	(0.64)
Population	5.128***	2.212***	2.823***	4.664***	2.648***	4.694***	2.191***	3.912***	1.969***	3.885***
	(0.79)	(0.64)	(0.78)	(0.84)	(0.77)	(0.84)	(0.73)	(0.79)	(0.72)	(0.79)
Unemployment		0.314**	0.278*	0.187	0.279*	0.156	0.204	0.104	0.215	0.0842
		(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)
General Pub Exp							1.242***	1.274***	1.247***	1.267***
							(0.27)	(0.25)	(0.27)	(0.25)
Housing Pub Exp							0.298**	0.298**	0.302**	0.304**
							(0.15)	(0.14)	(0.15)	(0.14)
Roads			0.390		0.371		0.694		0.670	
			(0.47)		(0.47)		(0.46)		(0.45)	
Paved Roads				3.234***		3.358***		3.323***		3.392***
				(0.73)		(0.73)		(0.68)		(0.68)
Electr. Generation			0.0333	0.0590			0.0463	0.0749		
			(0.056)	(0.055)			(0.054)	(0.053)		
Electr. Capacity					0.107	0.245*			0.0948	0.233*
					(0.15)	(0.15)			(0.14)	(0.14)
Error spatial lag (rho)	*-0.306*	*-0.316*	*-0.299*	*-0.318*	*-0.312*	*-0.334*	*-0.306*	*-0.324*	*-0.323*	*-0.343*
Observations	252	252	252	252	252	252	252	252	252	252

Table 4: Spatial Lags in Independent Variables

	(1) SAR	(2) SAR	(3) SAR	(4) SAR	(5) GS2SLS	(6) GS2SLS	(7) GS2SLS	(8) GS2SLS
FDI Spatial Lag					-0.252*	-0.219	-0.278**	-0.246*
					(0.14)	(0.14)	(0.13)	(0.13)
GPP	1.647***	1.614***	2.268***	2.239***	1.678***	1.721***	2.321***	2.366***
	(0.44)	(0.45)	(0.47)	(0.48)	(0.52)	(0.51)	(0.55)	(0.54)
Investment	0.882**	0.886**	0.592*	0.612*	0.650**	0.724**	0.413	0.486
	(0.34)	(0.34)	(0.34)	(0.34)	(0.33)	(0.33)	(0.33)	(0.33)
Primary School	-3.245***	-3.234***	-1.851**	-1.812**	-0.254	-0.261	-0.0665	-0.0777
	(0.87)	(0.87)	(0.89)	(0.90)	(0.84)	(0.84)	(0.83)	(0.84)
Secondary Sch.	0.968	0.951	0.793	0.780	0.412	0.461	0.425	0.479
	(0.72)	(0.72)	(0.69)	(0.70)	(0.62)	(0.62)	(0.61)	(0.62)
Population	2.663***	2.691***	1.396	1.439	9.561***	9.213***	8.311***	8.021***
	(0.87)	(0.89)	(0.86)	(0.88)	(1.26)	(1.24)	(1.38)	(1.37)
Unemployment	0.354**	0.351**	0.260*	0.252*	-0.0492	-0.0421	-0.0561	-0.0511
	(0.15)	(0.15)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)
Gen. Pub. Expenditure			1.324***	1.311***			0.595**	0.589**
			(0.29)	(0.29)			(0.29)	(0.29)
Social Security			-0.260	-0.250				
			(0.20)	(0.20)				
Housing Pub Exp							0.323**	0.339**
							(0.14)	(0.14)
Roads				1.66***				
				(0.54)				
Paved Roads	1.452**	1.503**	1.557**	1.658**	1.391*	1.591*	1.801**	1.999**
	(0.70)	(0.74)	(0.67)	(0.71)	(0.81)	(0.85)	(0.83)	(0.87)
Electr. Generation	0.00164		0.0473		0.100**		0.0938*	
	(0.053)		(0.052)		(0.050)		(0.049)	
Electr. Capac.		0.0283		0.108		0.193		0.187
		(0.14)		(0.13)		(0.14)		(0.13)
Pop. Spatial Lag	3.161***	3.157***	2.392***	2.377***	0.928***	0.633**	0.863***	0.578**
	(0.58)	(0.58)	(0.58)	(0.58)	(0.28)	(0.27)	(0.26)	(0.27)
Paved Roads Spat. Lag	1.352**	1.373**	1.168*	1.211*	0.464	0.402	0.458*	0.381
	(0.64)	(0.65)	(0.62)	(0.63)	(0.28)	(0.27)	(0.27)	(0.26)
Error spatial lag (rho)	0.542***	0.544***	0.548***	0.550***	*-0.001*	*-0.027*	*-0.010*	*-0.039*
Observations	252	252	252	252	252	252	252	252

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Annex A: Data description

In this Annex we present a short description of the data utilized in the analysis of regional infrastructure and FDI, including available sources. Whilst most of the series present some availability restrictions, we constructed a fairly complete dataset for the period 1990-2001 for which data on the dependent variable (FDI) is available. The variables included in the dataset have three main components.

First, the dependent variable is foreign direct investment (FDI) inflows. We extended the existing Provinfo database[22] of FDI inflows by province produced by the Ministry of Interior with firm-level investment data collected by the Centro de Estudios de la Produccion (CEP) of the Ministry of the Economy of Argentina for 1991-2005. This highly disaggregated dataset allows us to differentiate FDI inflows and destination province, as well as destination industry/sector. This level of detail is (to our knowledge) rarely accessible for a limited number of developed nations, and even less so for the developing countries.

Second, we include several proxies for public infrastructure. We completed partial time series previously collected by Regis and Andres (2006) from several sources on infrastructure stock for the two sectors: roads (total and paved roads) and electricity (gross generation and installed capacity).

Third, public expenditure composition is introduced from provincial government functional classifications which are only available from 1991 onwards. These series provides provincial expenditure for some infrastructure sectors like water and sewerage, transport and communication, and energy.

Additional variables include Gross Provincial Product (GPP), with the aggregate and breakdown by sector; provincial population extracted from national censuses; and the unemployment rate by province from the Permanent Household Surveys (Encuesta Permanente de Hogares). We used as a proxy for provincial investment construction as a component of GPP which is around 60% of total investment, according to national government figures.

It is noteworthy that we have included only twenty one provinces –out of twenty four- in our sample. From the twenty four subnational autonomous districts of Argentina, we exclude three due to severe data limitations. The Federal District has no road network since it is considered as a city and not as a province while Tierra de Fuego road network is very small and not comparable with other provinces. Likewise, San Luis was dropped from the sample

[22] http://www.mininterior.gov.ar/provinfo/inicio.asp

since the province relies heavily on other provinces as source of electricity. Therefore, the electricity installed capacity and gross generation is null for most of the years.

Annex C: Summary Statistics

Description	Gross Provincial Product, Million (2004 pesos)		Primary schooling, % province population		Secondary schooling, % province population		Population, in Million		Unemployment, %		Total expenditure, as % of GPP	
Province	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Buenos Aires	96,300	7,384	13.8%	1.0%	6.9%	0.9%	13.11	0.42	14.0%	5.4%	9.0%	2.0%
Cordoba	20,492	2,350	13.9%	0.9%	7.0%	0.2%	2.89	0.10	11.4%	5.0%	11.5%	1.5%
Capital Fed.	67,467	7,984	9.6%	1.2%	7.3%	0.3%	2.86	0.08	9.6%	3.6%	4.3%	0.3%
Catamarca	1,406	423	18.2%	0.9%	7.8%	0.4%	0.29	0.02	12.0%	3.9%	36.2%	5.8%
Chaco	2,841	164	18.7%	0.9%	6.5%	0.6%	0.90	0.05	10.5%	3.1%	31.9%	7.9%
Chubut	4,201	464	16.9%	1.0%	8.0%	0.4%	0.38	0.02	11.5%	3.8%	13.2%	1.6%
Corrientes	2,919	117	19.4%	1.0%	6.7%	0.8%	0.85	0.05	11.7%	5.4%	23.8%	3.4%
Entre Ríos	5,334	580	15.6%	1.1%	7.1%	0.2%	1.08	0.05	10.7%	3.4%	20.6%	3.5%
Formosa	915	62	21.0%	1.3%	7.5%	0.4%	0.44	0.03	8.3%	2.5%	74.7%	6.7%
Jujuy	1,675	76	18.9%	1.5%	9.8%	0.5%	0.55	0.03	11.9%	5.5%	40.1%	5.3%
La Pampa	2,412	196	14.8%	0.7%	6.9%	0.5%	0.28	0.01	8.1%	3.9%	20.0%	4.1%
La Rioja	2,006	194	17.6%	1.0%	8.0%	1.1%	0.25	0.02	9.2%	2.7%	28.3%	3.5%
Mendoza	7,100	370	15.2%	0.8%	6.9%	0.4%	1.48	0.06	6.6%	2.6%	18.4%	4.6%
Misiones	4,245	377	19.8%	1.2%	5.9%	0.4%	0.86	0.06	6.6%	1.1%	17.7%	3.3%
Neuquen	4,257	973	18.1%	1.1%	8.1%	0.3%	0.42	0.03	12.0%	3.0%	23.5%	3.3%
Rio Negro	4,012	164	17.7%	0.9%	7.6%	0.3%	0.52	0.02	...	...	18.4%	2.9%
Salta	3,782	220	18.1%	1.0%	8.8%	0.5%	0.95	0.07	12.6%	3.9%	22.4%	2.7%
San Juan	2,715	252	16.2%	1.1%	7.3%	0.5%	0.57	0.03	9.9%	3.1%	25.2%	4.0%
San Luis	4,260	262	15.5%	1.3%	6.6%	0.9%	0.32	0.03	8.0%	2.5%	10.1%	2.9%
Santa Cruz	2,619	324	16.4%	1.1%	8.4%	0.4%	0.18	0.01	4.1%	1.6%	22.7%	4.0%
Santa Fe	21,558	1,676	14.5%	1.1%	6.8%	0.5%	2.88	0.07	14.1%	4.8%	10.6%	1.1%
Sgo.del Estero	1,378	123	19.1%	0.9%	5.6%	0.4%	0.73	0.04	7.1%	3.9%	50.0%	4.5%
Tierra del Fuego	1,389	218	17.0%	2.1%	8.3%	0.7%	0.08	0.01	9.6%	2.1%	26.2%	7.6%
Tucuman	4,486	392	16.0%	1.1%	6.2%	0.4%	1.23	0.07	15.2%	3.6%	21.3%	3.1%
All	*11,240*	*1,056*	*16.8%*	*1.1%*	*7.3%*	*0.5%*	*142.1%*	*5.8%*	*10.2%*	*3.5%*	*24.2%*	*3.7%*

(Cont.)

Description	Greneral Purpose Expenditure, as % of GPP		Soc.Security Expenditure, as % of GPP		Housing Expenditure, as % of GPP		Health Expenditure, as % of GPP		Education Expenditure, as % of GPP	
Province	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Buenos Aires	2.3%	0.4%	0.9%	0.2%	0.2%	0.0%	1.1%	0.2%	2.8%	0.9%
Cordoba	3.3%	0.6%	1.3%	0.2%	0.3%	0.1%	1.3%	0.3%	3.2%	0.8%
Capital Fed.	0.7%	0.1%	0.7%	0.1%	0.1%	0.0%	1.2%	0.1%	1.3%	0.1%
Catamarca	9.1%	1.3%	5.3%	2.7%	1.9%	1.0%	4.6%	1.2%	9.0%	2.9%
Chaco	9.7%	2.5%	3.4%	0.5%	2.0%	0.4%	3.2%	0.6%	8.7%	2.0%
Chubut	2.9%	0.4%	1.5%	0.3%	1.0%	0.3%	1.7%	0.2%	3.2%	0.4%
Corrientes	6.3%	1.0%	3.3%	0.8%	2.1%	0.8%	2.3%	0.1%	6.6%	1.5%
Entre Ríos	4.9%	0.9%	2.5%	0.6%	0.7%	0.2%	2.4%	0.6%	5.6%	0.9%
Formosa	19.8%	2.4%	8.1%	1.7%	4.7%	1.7%	7.6%	1.0%	15.2%	2.7%
Jujuy	9.8%	2.5%	3.7%	1.0%	2.0%	0.5%	4.6%	0.9%	9.9%	2.7%
La Pampa	4.5%	0.8%	2.2%	0.5%	1.3%	0.4%	3.1%	0.7%	4.6%	1.0%
La Rioja	10.1%	1.1%	3.5%	1.0%	1.4%	0.4%	3.1%	0.7%	5.6%	1.5%
Mendoza	4.9%	1.1%	1.7%	0.3%	0.7%	0.1%	1.8%	0.3%	4.9%	1.5%
Misiones	4.3%	0.7%	1.8%	0.4%	1.2%	0.3%	1.9%	0.2%	4.4%	0.9%
Neuquen	5.3%	0.7%	2.5%	1.0%	1.4%	1.1%	3.1%	0.5%	5.9%	1.0%
Rio Negro	4.6%	0.9%	2.0%	0.3%	1.1%	0.3%	2.2%	0.5%	4.7%	0.7%
Salta	5.9%	1.2%	2.4%	0.4%	1.0%	0.1%	3.4%	0.4%	5.1%	1.0%
San Juan	6.7%	1.4%	3.7%	1.0%	1.3%	0.5%	2.9%	0.5%	5.9%	1.4%
San Luis	1.9%	0.8%	1.7%	0.8%	1.1%	0.5%	1.2%	0.3%	2.6%	1.0%
Santa Cruz	5.5%	0.6%	3.5%	1.2%	1.5%	0.9%	2.1%	0.5%	5.1%	0.9%
Santa Fe	3.0%	0.5%	1.3%	0.2%	0.3%	0.1%	0.9%	0.1%	3.3%	0.6%
Sgo.del Estero	13.2%	1.2%	5.4%	2.2%	3.5%	1.3%	6.3%	1.3%	13.8%	2.5%
Tierra del Fuego	8.1%	2.3%	4.7%	1.6%	2.8%	1.1%	2.9%	0.9%	5.7%	1.2%
Tucuman	6.5%	1.5%	2.6%	0.7%	1.0%	0.1%	2.2%	0.2%	5.7%	1.1%
All	***6.39%***	***1.12%***	***2.90%***	***0.82%***	***1.44%***	***0.51%***	***2.80%***	***0.51%***	***5.95%***	***1.30%***

(Cont.)

Description	Roads per capita, km per habitant		Paved roads per capita, km per habitant		Annual prod. of electricity, per capita MWh		Installed electrical generation capacity, per capita MW	
Province	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Buenos Aires	31.3	0.8	11.2	0.3	814.6	117.4	228.2	49.5
Cordoba	80.1	5.6	21.7	0.2	2,598.9	253.5	771.5	19.3
Capital Fed.	...	...			3,735.4	677.8	1,023.2	294.5
Catamarca	183.1	10.0	52.6	4.5	227.2	120.7	145.8	9.2
Chaco	74.0	1.0	16.8	0.3	40.2	57.1	166.8	30.3
Chubut	243.3	23.1	56.2	1.1	9,577.9	1,115.5	1,984.2	79.2
Corrientes	80.7	3.7	28.8	1.5	3,253.5	3,045.4	1,056.9	771.9
Entre Ríos	115.1	5.0	27.0	0.6	4,541.3	1,230.4	1,014.9	166.5
Formosa	93.0	6.2	17.5	1.4	31.9	28.9	120.7	49.9
Jujuy	80.8	4.8	16.9	1.6	155.1	121.5	148.2	7.3
La Pampa	339.0	14.8	116.5	6.2	488.8	488.7	230.5	89.3
La Rioja	154.0	35.5	82.4	9.2	193.0	198.6	275.0	98.7
Mendoza	106.4	10.9	26.9	0.6	2,039.5	563.7	793.0	35.0
Misiones	43.0	1.7	16.3	2.1	593.1	184.7	322.9	74.5
Neuquen	138.9	8.6	41.8	3.0	31,620.6	11,649.1	10,563.8	2,092.4
Rio Negro	162.3	2.0	41.0	0.5	638.9	383.2	325.3	115.8
Salta	89.7	4.6	18.0	0.5	2,010.0	636.9	578.8	227.5
San Juan	95.4	4.9	38.3	1.6	743.7	201.4	238.9	10.6
San Luis	234.5	31.4	69.7	2.0	1.8	4.3	19.2	21.9
Santa Cruz	497.0	17.7	89.8	5.1	2,396.2	338.6	789.3	66.3
Santa Fe	55.6	1.8	19.2	0.3	250.6	98.9	127.7	10.5
Sgo.del Estero	190.6	52.7	41.5	0.7	366.9	121.5	114.6	9.8
Tierra del Fuego	130.6	10.8	19.2	7.5	1,829.8	388.3	829.5	128.2
Tucuman	21.6	1.1	12.2	0.4	1,572.6	1,259.4	371.9	220.7
All	***140.9***	***11.2***	***38.3***	***2.2***	***2905.1***	***970.2***	***926.7***	***195.0***