IDB WORKING PAPER SERIES No. IDB-WP-475

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October 2013

Inter-American Development Bank
Office of Evaluation and Oversight

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Inter-American Development Bank
2013

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Industrial clusters and economic performance in Brazil / Jose Claudio Pires, Tulio Cravo, Simon Lodato, Caio Piza.
p. cm. — (IDB Working Paper Series ; 475)
Includes bibliographic references.
1. Industrial clusters—Brazil. 2. Brazil—Economic conditions. I. Pires, José Claudio Linhares. II. Cravo, Tulio. III. Lodato, Simon. IV. Piza, Caio. V. Inter-American Development Bank. Office of Evaluation and Oversight. IV. Series.
IDB-WP-475

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# Industrial Clusters and Economic Performance in Brazil

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## Abstract

Industrial clusters, which are commonly targeted to receive financial support allocated to locally based development projects, are seen as an effective industrial policy tool for improving productivity and generating employment. Nevertheless, identifying clusters and assessing their economic performance is a challenge for policymakers. This paper aims to address this challenge by identifying the location of clusters based on neighbor relationships and specialization in Brazil and providing some insights on their effects on employment generation. The paper uses both Location Quotient and Local Indicator of Spatial Association to identify potential clusters in 27 industrial sectors in 5564 Brazilian municipalities. In addition, it uses annual municipal panel data for 2006-2009 to assess whether the presence of potential clusters is correlated with employment generation. The results show that clusters located in municipalities whose neighbors have similar industrial structures perform better than those that present industry specialization only.

JEL Classification: C0, R11, R12.
Keywords: Industrial cluster, regional economic development, spatial dependence.

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## 1. Introduction

The financial support allocated to firms and projects in industrial clusters—also known as *industrial districts* and *local production systems*—is commonly justified by the increased social welfare that is expected to result from the improved coordination such clusters allow. Martin et al. (2011), for instance, argue that the governments of Germany, Japan, South Korea, Spain, and Brazil promote clusters to foster development. Cluster policies have been widely adopted as part of local economic development programs, and multilateral organizations, such as the Inter-American Development Bank (IDB) and United Nations Industrial Development Organization (UNIDO), and numerous national and regional development agencies provide generous financial support for cluster programs.[1] Nevertheless, despite the popularity of the concept, identifying, designing and evaluating cluster projects is still a challenge for policymakers.[2]

The difficulty begins with the definition of a cluster. There must be a cluster or a potential cluster to justify a cluster-based development project; and projects should be framed and evaluated as clusters only when they have certain characteristics.

Porter (1998) introduced the concept as “geographic (co-location) concentrations of interconnected companies and institutions in a particular field.” However, as Martin and Sunley (2003) point out, such a broad and vague definition could shape even a nationwide cluster. In fact, most cluster-based development programs work with the definition of “sizeable agglomeration of firms in a spatially delimited area,” set out by Altenburg and Meyer-Stamer (1999).[3]

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1 For instance, from 1994-2009 UNIDO cluster and network development initiatives approved financial support for 64 projects in more than 20 countries, amounting to US$31.4 million. The IDB has approved US$270 million to support cluster projects since 2002. These organizations use cluster projects to pursue such development-related objectives as poverty reduction; see UNIDO (2004, 2010).

2 Most of the evaluations of cluster projects are focused on developed countries. For an evaluation of cluster policies in Brazil, see Garone et all (2012)

3 This definition is also more similar to the concept of industrial districts (e.g., Markusen, 1996) or local production systems (e.g., Martin et al.. 2011; Belussi, 1999). Altenburg and Meyer-Stamer (1999) also argue that most definitions of clusters add extra characteristics to the basic notion of spatial agglomeration, which makes the precise definition cumbersome.

Cluster identification is particularly important in Brazil, where cluster-based development programs are seen as appropriate tools for reducing the well-known regional inequalities within the country (Ferreira, 2000; Azzoni, 2001; Laurine et al., 2005; Cravo, 2010a; Resende, 2011).

This paper follows Carroll et al. (2008) and uses a two-way classification to identify potential clusters in Brazil: the traditional Location Quotient (LQ) alongside a measure of Local Indication of Spatial Association (LISA) that takes into account spatial dependencies. It is worth noting that the use of measures of spatial autocorrelation is particularly necessary in Brazil, whose regions exhibit strong spatial dependence (e.g., Silveira-Neto and Azzoni, 2006; Cravo, 2010b; Resende, 2011).

In addition, the paper draws on Spencer et al. (2010) to evaluate whether clusters are related to better economic performance and whether municipalities that have industrial clusters perform better in terms of employment generation than those that do not. Thus, the aim of this paper is to (a) provide a rigorous approach for policymakers to identify clusters in Brazil, and (b) offer preliminary evidence on whether clusters are correlated with employment generation.[4]

The paper is organized as follows: Section 2 presents the methodology to identify clusters and a brief description of the data, Section 3 assesses whether municipalities that have industrial clusters perform better than those that do not have clusters, and Section 4 concludes.

## 2. Data and Identification of Clusters

### *2.1 Data*

The identification of potential clusters uses the RAIS[5] database, a comprehensive administrative census data set of the formal economy collected annually by the Brazilian Ministry of Labor, covering approximately 44 million workers as of the end of 2010. The information in RAIS can be retrieved according to various regional and sectoral levels.

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[4] The paper also follows up on initial research by the authors on cluster identification in Brazil (Pires at al., 2011).

[5] RAIS stands for *Relação Anual de Informações Sociais* [Social Information Annual Report].

This paper uses information on formal employment in manufacturing for all 5564 Brazilian municipalities to calculate the LQs and LISA and identify clusters in Brazil.[6] The municipal geographic scale offers some advantages over larger ones as it provides more territorial units to perform the analysis. Also, since spatial dependence is stronger at finer regional scales (Resende, 2011), the use of municipalities reduces the risk of missing a self-contained cluster in a larger scale.

The paper also uses complementary municipality-level data from IPEADATA[7] to examine the relationship between clusters and economic performance.

### *2.2 Identification of Clusters*

There are unique challenges in the systematic identification and measurement of clusters (Spencer et al., 2010). Because employment data are readily available, the use of LQs is widespread in economics and geography to identify regions' specialization in a given industry; and, according to Billings and Johnson (2012), the LQ remains the metric of choice for detecting industrial specialization. The LQ compares the sectoral employment shares in a region with a larger geographical area of reference, such as a state or country. When the LQ is greater than 1 for a sector, it indicates relative specialization of this sector in a region.[8]

However, the LQ only captures the nature of the concentration of employment in a region without considering the characteristics of the surrounding area. LISA complements the LQ to provide a better geographical delimitation of a potential cluster, as in Feser et al. (2005) and Carroll et al. (2008). LISA detects concentrations of cluster activities across regional boundaries,

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6 As in Carroll et al. (2008), this paper used the 3-digit level CNAE classification (*Classificação Nacional de Atividades Econômicas*, or Brazilian National Classification of Economic Activities) to capture some cross-specialization that would be lost using more detailed sectoral codes.

7 Institute of Applied Economic Research Database.

8 The LQ is given by the following expression: $LQ = \frac{E_j^i}{E_j} \Big/ \frac{TE^i}{TE}$, where $E_j^i$ represents the stock of employment in sector $i$ in the municipality $j$, $E_j$ is the total employment in the municipality $j$, $TE^i$ represents the total employment in sector $i$ in the country, and $TE$ stands for the total employment in the country.

rather than just within them, by taking into account the similarity of adjacent regions. A cluster is classified as such when the value of sectoral employment at a location is more similar to its neighbors than it would be under spatial randomness. LISA allows for the identification and assessment of the significance of local spatial clustering around an individual location, and for the identification of pockets of spatial nonstationarity (Anselin, 1995). LISA is expressed as follows:

$$I_i = \frac{z_i \sum_j w_{ij} z_j}{\sum_i z_i^2}$$

where $Z$ is the vector of a given variable in deviation from its mean and $W$ is the spatial weight matrix. This index gives a formal indication of the association between the original vector of variables $Z$ and its spatially lagged transformation $WZ$. Local spatial clusters can be identified as those locations where high-high values of LISA are significant. This index yields the so-called "Moran significance map," showing the regions with significant LISA and indicating by a color code the quadrants they belong to in the Moran scatterplot.[9]

To assess the existence of spatial effects, the first task is to quantify the spatial structure for Brazilian microregions through a spatial weight matrix. As Le Gallo and Ertur (2003) noted, the choice of the spatial matrix can have a substantive effect on results and should be made with caution. The construction of the spatial structure should reflect the fundamental theorem of regional science, "distance matters." Therefore, the strength of spatial dependence should decline with the geographical distance between observations.[10]

This paper uses the concept of *k*-nearest neighbors, calculated from the distance between regions' centroids, to construct the row-standardized spatial weights, as in LeGallo and Ertur (2003):

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[9] For more details, see Anselin, 1995; Anselin, 1996; Anselin and Bao, 1997.

[10] This is the expression of the first law of geography (e.g., Tobler, 1970), where everything is related to everything else but near things are more related than distant ones. Thus, the choice of a spatial weight is usually guided by the reasonable assumption that the spatial dependence declines with distance.

$$W = \begin{cases} w_{ij}^*(k) = 0 \text{ if } i = j \\ w_{ij}^*(k) = 1 \text{ if } d_{ij} \leq d_i(k) \text{ and } w_{ij}(k) = w_{ij}^*(k) \Big/ \sum_j w_{ij}^*(k) \\ w_{ij}^*(k) = 0 \text{ if } d_{ij} > d_i(k) \end{cases}$$

where $d_i(k)$ is a critical cut-off distance defined for each region *i*. It is the *k*-th order smallest distance between regions *i* and *j* in a manner that each region *i* has exactly *k* neighbors. In other words, a value of 1 is assigned to each of the *k*-nearest neighbors of each region.[11]

The use of the LQ together with LISA gives rise to a two-way classification, as Carroll et al. (2008) suggest. In this identification process, regions that simultaneously present a relatively high LQ (L>2) and significant LISA are classified as *potential cluster regions* (PCRs). Regions that are relatively specialized in a given industry but are relatively isolated and not significantly similar to their neighbors are labeled *specialized regions* (SRs).[12] Finally, regions located in the neighborhood of the PCR, which have significant LISA and low LQ, are classified as *periphery regions* (PRs). Table 1 summarizes the two-way classification of clusters.

**Table 1. Two-Way Classification of Clusters**

| ***Cluster*** | ***LQ*** | ***LISA*** |
|---|---|---|
| PCR | L>2 | High |
| SR | L>2 | -- |
| PR | L<2 | High |

*Note:* A region is classified as having "high" LISA when it is located in the first quadrant of Moran's I and has a significant LISA.

11 This paper uses a spatial weight matrix based on the 100 *k*-nearest neighbors. Alternative spatial weights based on 20, 50, and 500 *k*-nearest neighbors were also used and generate similar qualitative results. All versions of spatial weight matrices are row-standardized. The spatial weight matrices were created using the software GeoDa, a free software program for spatial data analysis that can be downloaded at http://geodacenter.asu.edu/software.

12 The paper uses LQ>2 as a threshold to classify a municipality as relatively specialized. This criterion is used in, for example, Suzigan et al. (2004).

The paper used this two-way classification of clusters to identify clusters in 27 industrial sectors in Brazil. As an example, the results for LQ for CNAE Division 29 are plotted in Figure 1. The figure shows 159 out of 5564 municipalities that are relatively specialized in "Manufacture of motor vehicles, trailers and semi-trailers" (CNAE Division 29). Nevertheless, as Carroll et al. (2008) argue, LQ only captures the nature of the concentration of employment and does not consider the characteristics of the surrounding area.

Figure 2 plots the high-high significant values of the LISA map for employment in the CNAE division 29.[13] It shows that 116 municipalities are significantly similar to neighboring regions in terms of CNAE Division 29 activity. Interestingly, only municipalities in the south and southeast regions of Brazil are identified in the LISA map. This suggests that this industry presents spatial dependence only in these regions; municipalities that are close to each other are more likely to have a similar industry composition.

13 The paper uses the spatial weight based on the 100 *k*-nearest neighbors as this weighting presents the largest number of significant high-high values; Carroll et al. (2008) also use the criterion of largest number of clusters generated.

**Figure 1. Specialized Municipalities**

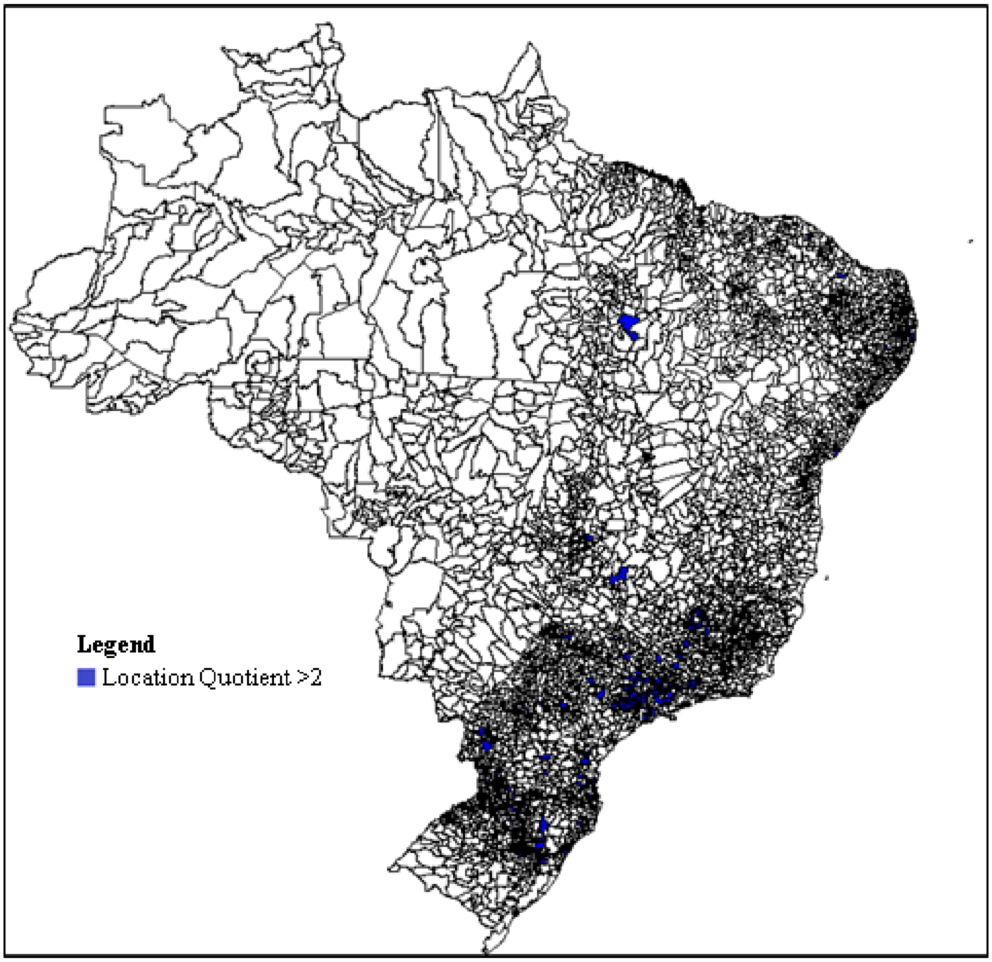
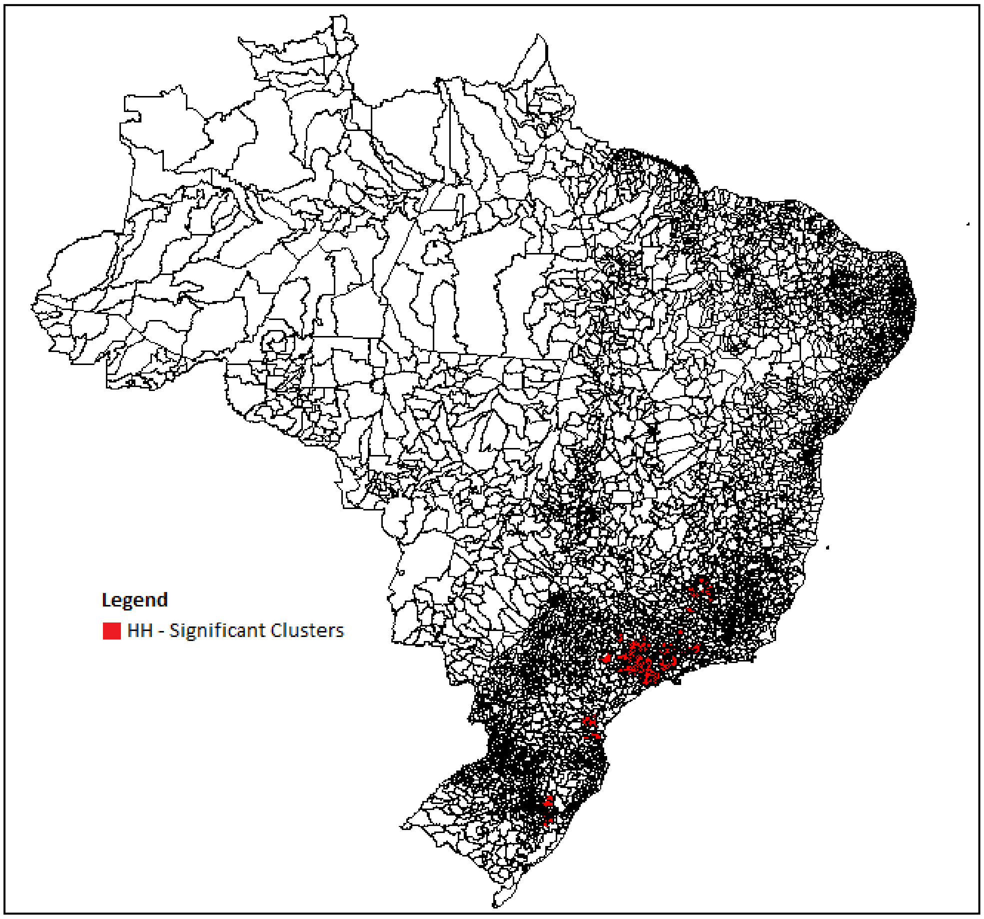


**Figure 2. LISA High-High MAP**

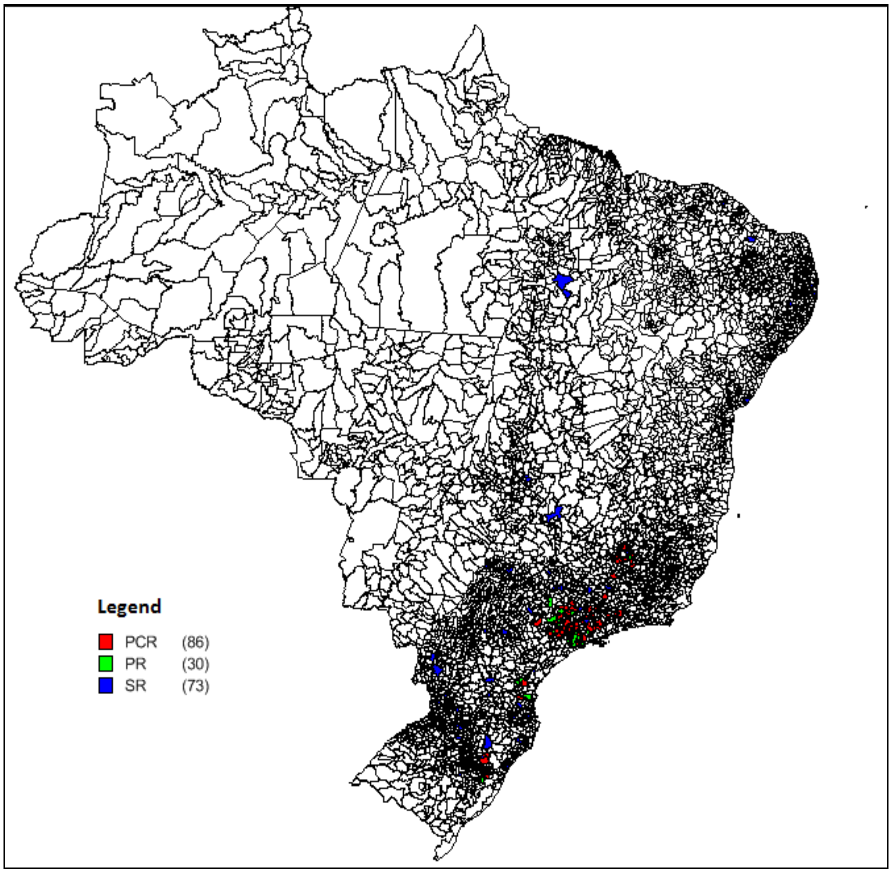



Finally, Figure 3 combines the two previous figures. Regions that simultaneously present a relatively high LQ and significant LISA clusters are classified as PCRs and are coded in red. Regions that are relatively specialized in a given industry but are isolated and not significantly similar to their neighbors are labeled as SRs and are coded in blue. Finally, regions located in the PCR neighborhood with significant LISA values and low LQ are classified as PRs and shown in green.[14] This exercise is repeated for each of the other 25 industrial sectors of the 3-digit level

[14] An LQ greater than 2 combined with a significant LISA does not necessarily indicate clusters, since the share of interconnected firms, an important cluster characteristic, is unknown. It does not imply that agglomerations of non-interconnected firms should be excluded from cluster-based development project. In this case, the project and expected results should be adjusted to this reality, aiming at promoting links among firms. In Figure 3, 86 municipalities are classified as PCRs, 30 are PRs, and 73 are SRs.

sectoral classification of the Brazilian CNAE classification. The results are summarized in Table 2.

**Figure 3. Core of the Potential Cluster Region**




Taking into account specialization and spatial dependence, academics and policymakers could use the two-way procedure to improve the effectiveness of cluster-based development projects. As Spencer et al. (2010) argue, it can also be complemented by qualitative analysis to help understand the complexity of intangible qualities and relationships that underlie cluster dynamics.

**Table 2. Potential Clusters by Sector in Brazil**

| *Sector* | *Total* | *PCR* | *SR* | *PR* |
|---|---|---|---|---|
| 10-Manufacture of food products | 870 | 189 | 592 | 89 |
| 11-Manufacture of beverages | 342 | 64 | 240 | 38 |
| 12-Manufacture of tobacco | 64 | 12 | 48 | 4 |
| 13-Manufacture of textiles | 377 | 90 | 249 | 38 |
| 14-Manufacture of wearing apparel | 739 | 57 | 646 | 36 |
| 15-Manufacture of leather and footwear | 369 | 84 | 275 | 10 |
| 16-Manufacture of wood products | 988 | 267 | 655 | 66 |
| 17-Manufacture of paper and paper products | 308 | 125 | 146 | 37 |
| 18-Printing and reproduction of recorded media | 157 | 22 | 105 | 30 |
| 19-Manufacture of coke and refined petroleum products | 206 | 89 | 107 | 10 |
| 20-Manufacture of chemicals and chemical products | 333 | 77 | 217 | 39 |
| 21-Manufacture of basic pharmaceutical products | 87 | 29 | 48 | 10 |
| 22-Manufacture of rubber and plastics products | 332 | 103 | 185 | 44 |
| 23-Manufacture of other nonmetallic mineral products | 1032 | 125 | 809 | 98 |
| 24-Manufacture of basic metals | 248 | 83 | 126 | 39 |
| 25-Manufacture of fabricated metal products (metallurgy) | 379 | 99 | 228 | 52 |
| 26-Manufacture of computer, electronic, and optical | 108 | 41 | 45 | 22 |
| 27-Manufacture of electrical equipment | 184 | 56 | 96 | 32 |
| 28-Manufacture of machinery and equipment | 348 | 108 | 203 | 37 |
| 29-Manufacture of motor vehicles, trailers and semi-trailers | 189 | 86 | 73 | 30 |
| 30-Manufacture of other transport equipment | 81 | 19 | 51 | 11 |
| 31-Manufacture of furniture | 546 | 113 | 370 | 63 |
| 32-Other manufacturing | 292 | 64 | 184 | 44 |
| 33-Repair and installation of machinery and equipment | 268 | 62 | 152 | 54 |
| 62-Computer programming, consultancy and related | 56 | 14 | 27 | 15 |
| 63-Information service activities | 126 | 15 | 83 | 28 |

## 3. Clusters and Economic Performance in Brazil

This section has two objectives. First, drawing on Spencer et al. (2010), it examines whether municipalities that belong to clusters are more correlated with economic indicators. Second, it analyzes whether there is a positive association between cluster and employment.

### *3.1.Clusters and Overall Performance Indicators*

Table 3 shows that, compared with non-cluster municipalities, municipalities with potential clusters have larger establishments, and their workers earn higher wages, work more hours per week, and have longer job tenure. In addition, per capita GDP is higher in municipalities with potential clusters, and these municipalities have a better development index.[15]

Table 4 presents performance indicators of the different types of potential clusters identified.[16] Most of the industrial employment—3.2 million workers—is located in PCRs, the regions characterized by industrial specialization with spatial similarity. The other types of clusters, PRs and SRs, each have about 1.5 million workers. The average establishment size varies substantially among different types of clusters: industries that form a PCR cluster have on average 199 employees per establishment, while industries that are only specialized have on average 49 employees per firm, and industries in PR regions average only 27 employees per establishment. The difference in the average size of the establishment is important, as this factor might influence productivity and employment growth; small manufacturing plants located in regions where their own industry is dominated by a few large firms may be less able to capture the benefits of agglomeration economies than plants in regions with less concentrated industrial structure (Drucker and Feser, 2012). For instance, the average wage is higher in PR regions where the average establishment is smaller.

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[15] Table 3 compares municipalities that have any potential clusters in any sector against municipalities that do not have any potential cluster. The table provides initial evidence on whether municipalities with potential clusters have better municipal level indicators.

[16] The numbers presented in Table 4 are based on the information of establishments and employment within the sectors identified as a given type of clusters in a given municipality. Furthermore, one municipality can have clusters of different sectors so that the sum of occurrences of potential clusters exceeds the number of municipalities with clusters as indicated in Table 3.

**Table 3. Performance Indicators: Potential Clusters versus Non-clusters**

| *Indicator* | *Cluster* | *Non-cluster* | *%* |
|---|---|---|---|
| Average establishment size | 32.70054 | 4.449061 | 734.99 |
| Average wage | 993.6657 | 481.9343 | 206.18 |
| Average hours worked (weekly) | 43.565 | 26.84524 | 162.20 |
| Average number of months at work | 36.88642 | 20.84215 | 176.97 |
| IFDM (Municipal Development Index) | 0.673184 | 0.5789099 | 116.28 |
| Population | 46,333.71 | 13,994.64 | 331.08 |
| GDP | 411,551.00 | 50,795.98 | 810.20 |
| GDP per capita | 6.482266 | 3.575722 | 181.28 |
| GDP growth (2006-2009) | 0.030311 | 0.038129 | 79.496 |
| *Municipalities (n)* | *3378* | *2186* | |

**Table 4. Performance Indicators of Potential Clusters, by Type**

| *Indicator* | *SR* | *PR* | *PCR* |
|---|---|---|---|
| Total cluster employment | 1,670,443 | 1,473,896 | 3,245,703 |
| Average establishment size | 49.17102 | 27.05406 | 199.443 |
| Average wage | 941.6412 | 1420.126 | 1324.087 |
| Average number of months at work | 35.99235 | 43.0629 | 42.89421 |
| Average hours worked (weekly) | 43.61837 | 43.56428 | 43.4923 |
| *Clusters (n)* | *3000* | *213* | *972* |

As the analysis in Tables 3 and 4 is based on descriptive statistics only, a correlation analysis of different types of clusters can help explain the level of association between the type of agglomeration and economic performance. To this end, Table 5 shows simple correlations analyzing whether there is a positive association between cluster and employment generation. The share of local employment in clusters is used to examine whether a higher prevalence of cluster employment is correlated with dependent variables that capture municipality-level economic performance. Thus, Table 5 provides initial evidence about the general relationship between employment in clusters and municipality performance, as in Spencer et al. (2010), but also provides the analysis for different types of clusters identified in Section 2, following the typology of Carroll et al. (2010).

**Table 5. Correlation between Clusters and Performance Indicators (2006 - 2009)**

| ***Cluster type*** | ***GDP per capita*** | **Bolsa Familia *per capita*** | ***Municipality Development Index*** | ***Employment total*** | ***Employment manufacturing*** | ***Wage per employee*** |
|---|---|---|---|---|---|---|
| (a) Cluster Total | 0.2726* | -0.4662* | 0.4179* | 0.0177 | 0.1256* | 0.3028* |
| (b) Cluster PCR | 0.2356* | -0.2974* | 0.2819* | 0.0242*** | 0.1386* | 0.2532* |
| (c) Cluster PR | 0.2011* | -0.193* | 0.288* | 0.3081* | 0.4485* | 0.2597* |
| (d) Cluster SR | 0.121* | -0.3299* | 0.2698* | -0.0265** | -0.0059 | 0.1402* |

Note: ***** Statistically significant at 1%, 5%, and 10%, respectively.***

Table 5 reports the correlation between cluster and some performance indicators for municipalities identified as cluster and for each type of cluster separately. The first row (a) of Table 5 indicates that cluster is positively related to wages, employment in manufacturing, municipal development and GDP per capita. The correlation between total employment and cluster is also positive, but not statistically significant. Clusters also seem to be related to less need of conditional cash transfer programs: the relationship between cluster and the percentage of participant households in the Brazilian conditional cash transfer program *Bolsa Familia* is negative.

Table 5 also presents the results for each type of cluster separately—an exercise to shed light on how different types of clusters might influence economic performance in Brazil. The results for municipalities identified as being part of PCRs are in line with the overall results (row (b) of Table 5): cluster in PCR municipalities is positively related to wages, employment, municipal development, and GDP per capita and negatively related to the percentage of participants in *Bolsa Familia*.

Row (c) presents the results for PR municipalities, which are significantly similar to their neighbors and might benefit from spatial spillovers generated by the presence of similar economic activity in the neighboring municipalities. Once again, the results suggest that cluster in PR municipalities is positively related to wages, employment, municipal development, and GDP per capita and negatively related to the percentage of people receiving *Bolsa Familia*. However, it is interesting to note that the PR municipalities' correlations for employment in manufacturing and total employment are stronger than those for PCRs and Cluster Total (rows (a) and (b)).

Thus, the initial correlation analysis presented in Table 5 suggests that overall clustering is positively related with employment generation. Nevertheless, when different types of clustering are considered separately, the results suggest that municipalities in SRs are negatively associated with employment generation, and clusters of municipalities with neighbors that have similar industrial structure (PRs and PCRs) perform better than those that only present industry specialization (SRs) and are not close to similar municipalities. In other words, the results suggest that proximity and spatial similarity are more strongly associated with employment generation than specialization is.

### *3.2. Clusters and Employment Generation*

This paper uses first difference estimator to provide initial evidence on the effect of different types of clusters on the formal employment rate at the municipality level in Brazil. This estimator was chosen because it accounts for time-invariant covariates and municipality fixed effects. Annual panel data of Brazilian municipalities between 2006 and 2009 are used, a model to test the effect of clusters on employment rate could take the following specification:[17]

$$\Delta Y_{it} = \alpha + \beta cluster_i + \phi T + \Delta \varepsilon_{it} \tag{1}$$

where $Y_{it}$ is the formal employment rate in municipality *i* in year *t*; $cluster_i$ is a dummy variable—1 if a municipality belongs to a cluster region and 0 otherwise; *T* is a vector of time dummies; and $\varepsilon_{it}$ is the error term that is assumed to be strictly exogenous. The regressions are also run for the three types of clusters—PCRs, PRs, and SRs.

Since other factors of municipal economies are likely to affect municipalities' formal employment rate, variables such as GDP per capita at municipal level, the proportion of households that benefit from *Bolsa Familia* (BF),[18] and the index IFDM (*Índice Firjan de Desenvolvimento Municipal*)[19] are added as control variables. Thus, the model is respecified and estimated as follows:

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17 The period of analysis is defined according to comparable sectoral data availability. This study uses the sectoral classification based on CNAE 2.0, which is available from 2006 onward. The last year of the analysis is 2009, the latest time for which GDP per capita at municipality level is available.

18 This variable is used as a proxy for poverty incidence at the municipal level.

19 The IFDM index aims to capture each municipality's level of development.

$$\Delta Y_{it} = \alpha + \beta cluster_i + \phi T + \gamma_1 \Delta \ln GDPpc + \gamma_2 \Delta BF + \gamma_3 \Delta IFDM + \Delta \varepsilon_{it} \quad (2)$$

where variables $Y_{it}$, $cluster_i$, and $T$ are defined as in Equation (1). De Vor and de Groot (2010) use a similar approach to analyze the relation between agglomeration and employment growth.

A second step consists of decomposing the employment rate into two components: the employment rate inside industrial cluster sectors and the employment rate outside such sectors. This exercise aims to capture potential spillover effects of cluster regions on jobs not directly related to the cluster itself. This is an interesting approach, since agglomerations of firms are very likely to have general equilibrium effects on the labor market.

### 3.3. Results

This section presents the estimates of the effect of cluster on the three formal employment rates under consideration. Table 6 shows the effect of cluster based on the broadest definition, considering all definitions of clusters together.

**Table 6. Effect of Cluster on Formal Employment Rate**

| ***Variable*** | ***Δ share of formal employment*** | ***Δ share of formal employment inside industrial sector*** | ***Δ share of formal employment outside industrial sector*** |
|---|---|---|---|
| Cluster | 0.0034*** | 0.0019*** | 0.0015*** |
| | (5.56) | (3.43) | (5.27) |
| Δ% beneficiaries of BF | 0.15*** | -0.030 | 0.18*** |
| | (7.71) | (-1.13) | (4.81) |
| Δ Municipality Development Index (IFDM) | 0.039*** | 0.024* | 0.015* |
| | (6.10) | (1.96) | (1.76) |
| Δln(GDP per capita) | 0.025*** | 0.011*** | 0.014** |
| | (4.49) | (4.19) | (2.18) |
| Observations | 16686 | 16686 | 16686 |
| $R^2$ | 0.06 | 0.01 | 0.03 |

*Note:* ***, **, * Statistically significant at 1%, 5%, and 10%, respectively. The estimates use standard errors clustered at state level and include time dummies.

According to the estimates, being in a cluster area implies, all other things being equal, an average increase in the employment rate of 0.34 percentage points (pp). The coefficients of the control variables are highly significant, and GDP growth has the expected sign and positively influences employment generation. The coefficient is also significant in economic terms as it represents about 140,000 extra jobs in the total stock of workers.[20]

The second column of the table shows the cluster area effect on employment rate inside industrial sectors—about 0.2 pp. The coefficients of all control variables have the expected sign. In absolute terms the point estimate represents 77,900 jobs.

Finally, the third column sheds some light on potential spillover effects of cluster, showing the effect that a municipality's being in a cluster area has on the employment rate outside industrial sectors. The effect is relatively lower but still statistically significant: about 62,000 jobs (50% of the 120,000 extra jobs) were created outside clustered industrial sectors. The similarity between job creation inside and outside clustered sectors suggests that the spillover effects of agglomeration economies may be large and positive for the local economy.

Table 7 mimics Table 6 but report results that are specific for each type of cluster. These complementary results test whether the effect of cluster on employment rate is sensitive to the way cluster is identified.

Using the PCR definition (columns 1 to 3), the point estimate increases for total employment rate and employment rate inside industrial sectors and remains very much the same for employment rate in other sectors as shown in Table 6. This indicates that employment creation in PCR clusters are mostly influenced by employment creation inside the cluster sector.

[20] Annex A illustrates the effect of being in a cluster area in terms of absolute employment.

**Table 7. Effect of Cluster on Formal Employment Rate: PCR, PR and SR**

| | *PCR* (1) | *PCR* (2) | *PCR* (3) | *PR* (4) | *PR* (5) | *PR* (6) | *SR* (7) | *SR* (8) | *SR* (9) |
|---|---|---|---|---|---|---|---|---|---|
| ***Variable*** | *Δ share of formal employment* | *Δ share of formal employment inside industrial sector* | *Δ share of formal employment outside industrial sector* | *Δ share of formal employment* | *Δ share of formal employment inside industrial sector* | *Δ share of formal employment outside industrial sector* | *Δ share of formal employment* | *Δ share of formal employment inside industrial sector* | *Δ share of formal employment outside industrial sector* |
| Cluster (PCR/PR/SR) | 0.0046*** | 0.0032*** | 0.0014** | 0.0062*** | 0.00065*** | 0.0056*** | 0.0020*** | 0.00087** | 0.0011** |
| | (6.75) | (3.30) | (2.67) | (8.34) | (3.59) | (7.69) | (5.52) | (5.61) | (3.88) |
| Δ% beneficiaries of BF | 0.15*** | -0.034 | 0.18*** | 0.15*** | -0.032 | 0.18*** | 0.15*** | -0.031 | 0.18*** |
| | (7.73) | (-1.21) | (4.75) | (7.61) | (-1.19) | (4.78) | (7.73) | (-1.13) | (4.81) |
| Δ Municipality Dev.Index (IFDM) | 0.039*** | 0.024* | 0.015* | 0.038*** | 0.023* | 0.015* | 0.038*** | 0.023* | 0.015* |
| | (6.05) | (1.95) | (1.72) | (6.06) | (1.94) | (1.77) | (6.15) | (1.96) | (1.72) |
| Δln(GDP per capita) | 0.026*** | 0.012*** | 0.014*** | 0.025*** | 0.011*** | 0.014** | 0.025*** | 0.011*** | 0.014** |
| | (4.47) | (4.13) | (2.17) | (4.39) | (4.11) | (2.17) | (4.44) | (4.15) | (2.17) |
| Observations | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 |
| R2 | 0.06 | 0.01 | 0.03 | 0.06 | 0.01 | 0.03 | 0.06 | 0.01 | 0.03 |

*Note:* ***, **, * Statistically significant at 1%, 5%, and 10%, respectively. The estimates use standard errors clustered at state level and include time dummies.

The largest effect on total employment rate is observed when we use the PR definition (columns 4 to 7). Interestingly, the largest effect on employment rate outside industrial sector is also observed in PR clusters. This might indicate that positive externalities that affect sectors outside potential clusters are larger in PR clusters, suggesting that PR cluster impact employment generation mostly due to employment creation outside cluster sectors. Nevertheless, the point estimate for employment rate inside the industrial sector is very small although statistically significant.

Columns 7 to 9 in Table 7 report results for potential clusters that have only sector specialization. These estimates show that the smallest effect on employment rate is observed for SR clusters.

These results are in line with the initial descriptive results presented in the previous section, as they indicate that clusters are overall positively related to employment generation. However, results vary according to the definition of clusters used. PR clusters affect employment generation the most, followed by PCR clusters and SR clusters.

The robustness tests, depicted in Annex B, control for cluster sectors and are in line with the baseline results (Table B.1). Additional robustness tests are provided in Table B.2 and include all types of clusters in the same regressions. The results remain in line with baseline regressions. Overall, clusters are positively related with employment generation, while proximity and spatial similarity seem to be more strongly associated with employment generation than specialization, as evidenced by a greater magnitude of the coefficients of PCR and PR reported in Table B.2. PR cluster seems to impact employment generation mostly due to employment creation outside cluster sectors as PCR clusters appear to affect total employment because of employment creation inside the cluster sectors. As in the baseline regressions, the smallest effect on employment is observed for SR clusters.

The establishment of causal links is difficult when using the first difference estimator, as this method does not address endogeneity bias and concerns of reverse causation.[21] To mitigate endogeneity bias, results for the system GMM (Blundell and Bond, 1998) estimators are also provided in Annex B (Tables B.3 and B.4). The results are again in line with the view that specialization and spatial similarity seem to be more strongly associated with employment generation; PCR clusters present a strong and significant association with employment generation. Table B.4, which includes all types of clusters in the same regressions, also suggests that while PR clusters impact employment creation outside cluster sectors, PCR clusters impact employment creation inside the cluster sectors. Nonetheless, the Hansen tests for the validity of instruments indicate that internal instruments are invalid and results still suffer from endogeneity bias.[22]

The results are consistent with Spencer et al. (2010), who indicate that clusters affect employment generation positively. This paper complements the Spencer et al. analysis, providing initial results on how different types of clusters might affect municipal-level economic performance in industrial and non-industrial sectors and also influence employment generation.

Nevertheless, further efforts are necessary to shed light on the causal link between clusters and economic performance. For example, Acceturo and Blasio (2012) and Martin et al. (2011) used quasi-experimental technique to estimate the treatment effect of the agglomeration on the outcomes of interest. An ongoing evaluation based on microdata is designed to complement this work and provide more evidence on how industrial clusters influence firm and regional performance.

[21] The consistency of the first difference estimates depends on the strict exogeneity condition, which is unlikely to hold in this case; the agglomeration dynamics are affected by the dependent variable, and municipalities in the cluster areas have more in common than their counterparts outside these areas, meaning that independent variables are likely correlated with the error term. The system GMM (Blundell and Bond, 1998) estimator (GMM-SYS) can be used to take this endogeneity into account.

[22] The values for the diagnostic Hansen test, presented at the bottom of Table B.3 are the *p*-values for the joint validity of the instruments under the null that the instruments are valid.

### 4. Conclusion

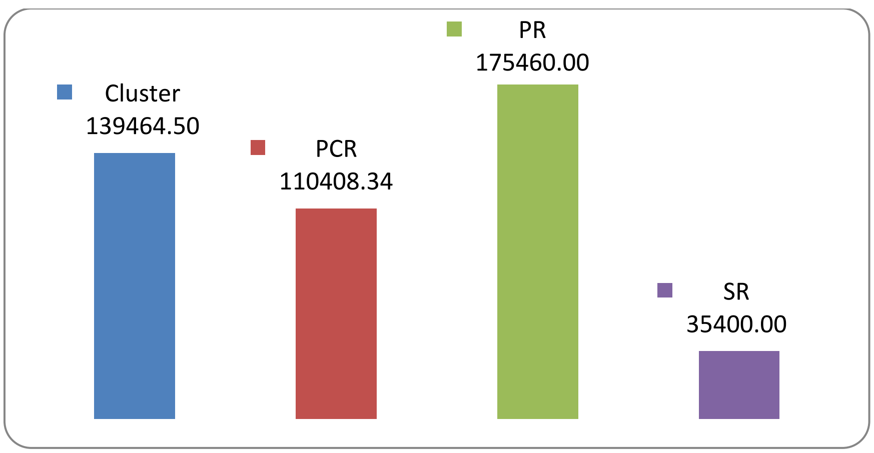
This paper applies for the first time a two-way methodology to identify clusters in manufacturing sectors in Brazil. Considering both industrial specialization and geographic dependency, the paper examines the relationship between clusters and economic performance, particularly employment generation. Overall, the results suggest that clusters are positively correlated with economic performance. Different definitions of clusters seem to influence economic performance differently. Clusters that encompass specialized municipalities that present spatial similarity perform better than clusters defined only by relative specialization.

An adequate identification of clusters is the crucial first step in every effort to measure the effect of cluster policy on regional development. The results obtained can contribute to a deeper discussion about better strategies to promote locally based development and employment generation.

### Annex A. Job Creation Estimates

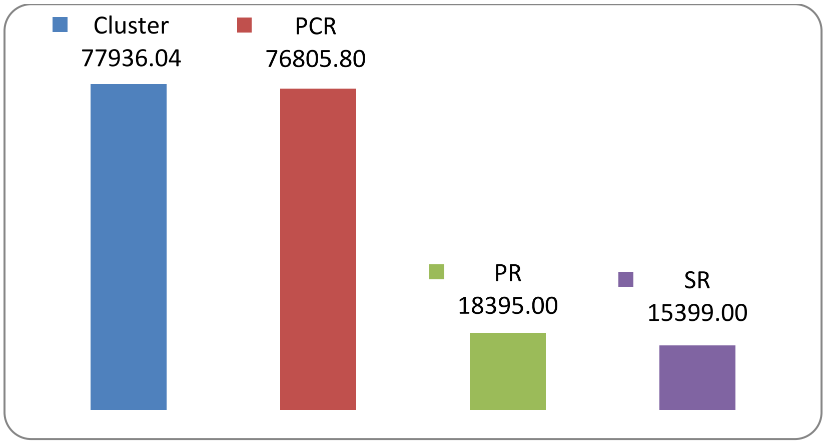
Figures A1 to A3 illustrate the effect of cluster on job creation for the four cluster definitions, based on the regression coefficients and data on formal employment provided by RAIS.

**Figure A.1. Effect of Cluster on Creation of Formal Employment**




The effect on total employment is highest for PR clusters. The significant heterogeneity between the numbers suggests that the evidence on the impact of cluster on employment might be sensitive to the way cluster is identified. Estimates indicate that the difference between the numbers of job created in cluster regions varies by more than 200 percent, depending on the measure used.

**Figure A.2. Effect of Cluster on Creation of Formal Employment in Industrial Sectors**




The heterogeneity is also present when the impact of cluster is measured inside industrial sectors. The huge disparities in the numbers of job created reinforce the evidence that the effect of cluster may be sensitive to the way cluster is defined.

**Figure A.3. Effect of Cluster on Creation of Formal Employment Outside Cluster Regions**

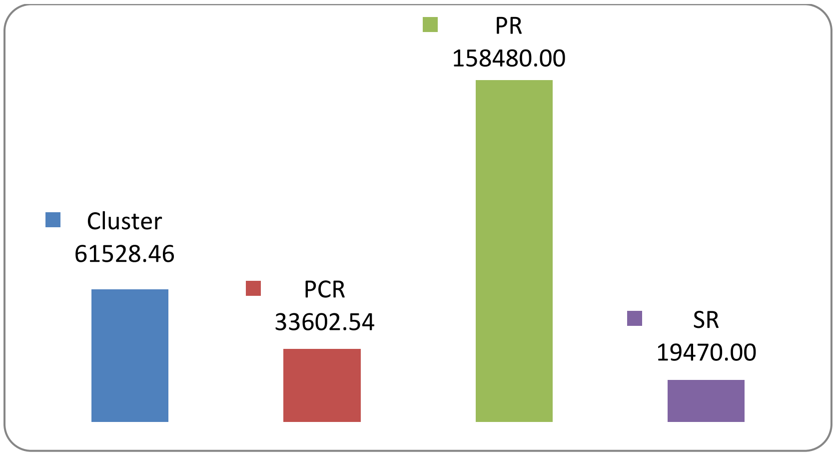



Figure A.3 suggests that the effect of cluster may go beyond the sectors directly affected by the agglomeration itself. A substantially higher "spillover" effect emerges for PR clusters than for the other three indicators.

## Annex B. Robustness Checks: Sectoral Dummies, Pooled Cluster Effects and GMM Estimations

**Table B.1. Effect of Cluster on Formal Employment Rate (Cluster Sector Dummies)**

| ***Variable*** | ***Cluster (1)*** | ***Cluster (2)*** | ***Cluster (3)*** | ***PCR (1)*** | ***PCR (2)*** | ***PCR (3)*** | ***PR (1)*** | ***PR (2)*** | ***PR (3)*** | ***SR (1)*** | ***SR (2)*** | ***SR (3)*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | 0.0028*** | 0.0024*** | 0.00047 | 0.0051*** | 0.0053*** | -0.00017 | 0.0041** | 0.00015 | 0.0040** | 0.0014** | 0.00072 | 0.00066 |
| | (5.05) | (4.81) | (0.80) | (5.57) | (6.60) | (-0.17) | (2.33) | (0.10) | (2.14) | (2.54) | (1.52) | (1.15) |
| Δ% beneficiaries of BF | 0.15*** | -0.027* | 0.18*** | 0.15*** | -0.029* | 0.18*** | 0.15*** | -0.033** | 0.18*** | 0.15*** | -0.028* | 0.18*** |
| | (8.96) | (-1.80) | (9.99) | (8.84) | (-1.96) | (9.99) | (8.58) | (-2.16) | (9.94) | (8.93) | (-1.86) | (10.01) |
| Δ Municipality Development Index (IFDM) | 0.040*** | 0.024*** | 0.016*** | 0.039*** | 0.024*** | 0.015*** | 0.038*** | 0.023*** | 0.015*** | 0.039*** | 0.024*** | 0.015*** |
| | (13.18) | (9.13) | (4.94) | (13.08) | (9.19) | (4.81) | (12.79) | (8.84) | (4.83) | (13.03) | (9.03) | (4.89) |
| Δln(GDP per capita) | 0.025*** | 0.011*** | 0.014*** | 0.025*** | 0.011*** | 0.014*** | 0.025*** | 0.011*** | 0.014*** | 0.025*** | 0.011*** | 0.014*** |
| | (17.05) | (8.73) | (8.94) | (16.96) | (8.72) | (8.87) | (16.95) | (8.70) | (8.91) | (16.97) | (8.68) | (8.91) |
| Observations | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 |
| R2 | 0.06 | 0.01 | 0.03 | 0.06 | 0.02 | 0.03 | 0.06 | 0.01 | 0.03 | 0.06 | 0.01 | 0.03 |

*Note:* (1) Share of formal employment, (2) Share of formal employment inside industrial sector, (3) Share of formal employment outside industrial sector. *t* statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

**Table B.2. Effect of Cluster on Formal Employment Rate: SR, PCR and PR (Pooled cluster effects)**

| | (1) *Δ share of formal employment* | (2) *Δ share of formal employment inside industrial sector* | (3) *Δ share of formal employment outside industrial sector* | (4) *Δ share of formal employment (with sector dummies)* | (5) *Δ share of formal employment inside industrial sector (with sector dummies)* | (6) *Δ share of formal employment outside industrial sector (with sector dummies)* |
|---|---|---|---|---|---|---|
| SR | 0.0018*** | 0.00063*** | 0.0012*** | 0.0019*** | 0.0011*** | 0.00080** |
| | (5.15) | (3.98) | (3.75) | (3.56) | (3.37) | (2.11) |
| PR | 0.0040*** | -0.0015* | 0.0055*** | 0.0031** | -0.0013** | 0.0044*** |
| | (4.14) | (-1.75) | (7.82) | (2.38) | (-2.56) | (4.54) |
| PCR | 0.0037*** | 0.0034*** | 0.00033 | 0.0030*** | 0.0037*** | -0.00066 |
| | (5.37) | (2.85) | (0.45) | (5.40) | (2.88) | (-0.68) |
| Δ % beneficiaries of BF | 0.15*** | -0.032 | 0.18*** | 0.15*** | -0.029 | 0.18*** |
| | (7.89) | (-1.17) | (4.77) | (7.69) | (-1.11) | (4.73) |
| Δ Municipality Development Index (IFDM) | 0.040*** | 0.024* | 0.016* | 0.040*** | 0.024* | 0.016* |
| | (6.12) | (1.96) | (1.79) | (6.16) | (1.96) | (1.77) |
| Δ ln(GDP per capita) | 0.026*** | 0.012*** | 0.014** | 0.026*** | 0.011*** | 0.014** |
| | (4.50) | (4.15) | (2.18) | (4.45) | (4.14) | (2.15) |
| Observations | 16686 | 16686 | 16686 | 16686 | 16686 | 16686 |
| R2 | 0.06 | 0.01 | 0.03 | 0.06 | 0.01 | 0.03 |

*Note:* ***, **, * Statistically significant at 1%, 5%, and 10%, respectively. The estimates use standard errors clustered at state level and include time dummies.

**Table B.3. Robustness Checks GMM Estimations**

| *Variable* | *Cluster (1)* | *Cluster (2)* | *Cluster (3)* | *PCR (1)* | *PCR (2)* | *PCR (3)* | *PR (1)* | *PR (2)* | *PR (3)* | *SR (1)* | *SR (2)* | *SR (3)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | 0.0170*** | 0.0157*** | 0.00308 | 0.0569*** | 0.0519*** | 0.00890*** | 0.0263*** | -0.0193*** | 0.0409*** | 0.00301 | 0.00369* | -0.00228 |
| | (4.96) | (6.70) | (1.36) | (12.64) | (16.28) | (3.09) | (2.67) | (-3.76) | (5.27) | (0.91) | (1.85) | (-0.99) |
| ln GDP per capita | 0.0586*** | 0.0130*** | 0.0480*** | 0.0611*** | 0.0145*** | 0.0494*** | 0.0627*** | 0.0166*** | 0.0495*** | 0.0616*** | 0.0156*** | 0.0494*** |
| | (11.00) | (4.54) | (11.53) | (12.00) | (5.80) | (12.12) | (11.90) | (6.01) | (12.18) | (11.48) | (5.39) | (11.84) |
| % beneficiaries of BF | -0.163*** | -0.0591** | -0.0731** | -0.169*** | -0.0508** | -0.0830** | -0.207*** | -0.0783*** | -0.0975*** | -0.188*** | -0.0718** | -0.0812** |
| | (-2.96) | (-2.13) | (-2.00) | (-3.25) | (-2.07) | (-2.32) | (-3.69) | (-2.79) | (-2.66) | (-3.27) | (-2.50) | (-2.16) |
| IFDM | 0.0630*** | -0.00496 | 0.0562*** | 0.0652*** | -0.00344 | 0.0563*** | 0.0727*** | -0.00000852 | 0.0603*** | 0.0694*** | -0.000699 | 0.0579*** |
| | (3.83) | (-0.71) | (4.58) | (4.06) | (-0.53) | (4.62) | (4.24) | (-0.00) | (4.83) | (4.00) | (-0.09) | (4.56) |
| Observations | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 | 22256 |
| AR 1 | 0.00500 | 0.233 | 0.144 | 0.00435 | 0.233 | 0.143 | 0.00343 | 0.232 | 0.142 | 0.00385 | 0.232 | 0.142 |
| M2 | 0.170 | 0.240 | 0.0697 | 0.163 | 0.243 | 0.0680 | 0.156 | 0.250 | 0.0676 | 0.160 | 0.247 | 0.0679 |
| Hansen | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Sargan | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

*Note:* (1) Share of formal employment, (2) Share of formal employment inside industrial sector, (3) Share of formal employment outside industrial sector, all regressions include sector dummies. *t* statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The m2 statistic is the autocorrelation test under the null that differenced errors are not serially autocorrelated. Hansen statistics are distributed as chi-squared with degrees of freedom equal to the number of over-identifying restrictions, under the null that instruments are valid. In all GMM-SYS instrumented estimations, all employment determinants are treated as potentially endogenous using the instrument set containing all available lagged values of the variables in the model. The ml statistic for the l-lag order correlation proposed by Arellano and Bond (1991) is given by the following expression: $m_l = \frac{\hat{v}'_{-l}\hat{v}}{\sqrt{\hat{v}}}$ , where $\hat{v}$ represents the estimated residuals of GMM estimations. The ml order statistic is standard normal distributed and test the null that differenced errors are not l-order serially autocorrelated. The Hansen statistic is given by $J = \hat{v}'Z(\sum_{i=1}^{N} Z_i'\hat{v}_i\hat{v}_i'Z_i)^{-1}Z'\hat{v}$, where $\hat{v}$ represents the two-step residuals in this case. This statistic becomes the Sargan statistic when we believe errors are homoscedastic and use the first-step residuals (see Arellano and Bond, 1991, page 282). Sargan and Hansen statistics are distributed as chi-squared with degrees of freedom equal to the number of over-identifying restrictions. The null hypothesis is $E[Z'v] = 0$, under the null that instruments are valid.

**Table B.4. Robustness Checks GMM Estimations: SR, PCR and PR (Pooled cluster effects)**

| | (1) Δ share of formal employment | (2) Δ share of formal employment inside | (3) Δ share of formal employment outside industrial sector |
|---|---|---|---|
| PCR | 0.0814*** | 0.0650*** | 0.0273*** |
| | (7.11) | (8.36) | (4.00) |
| SR | 0.0144*** | 0.0103*** | 0.00382 |
| | (4.45) | (5.39) | (1.60) |
| PR | 0.0262** | -0.0191*** | 0.0410*** |
| | (2.32) | (-3.51) | (4.90) |
| ln GDP per capita | 0.0562*** | 0.0118*** | 0.0464*** |
| | (10.82) | (4.52) | (11.41) |
| % beneficiaries of BF | -0.117** | -0.0325 | -0.0606* |
| | (-2.34) | (-1.36) | (-1.71) |
| IFDM | 0.0575*** | -0.00831 | 0.0562*** |
| | (3.84) | (-1.44) | (4.81) |
| Observations | 22250 | 22250 | 22250 |
| AR 1 | 0.00609 | 0.233 | 0.145 |
| M2 | 0.181 | 0.236 | 0.0720 |
| Hansen | 0.0000 | 0.00733 | 0.0000 |
| Sargan | 0.0000 | 0.0000 | 0.0000 |

*Note:* All regressions include sector dummies. *t* statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01. The m2 statistic is the autocorrelation test under the null that differenced errors are not serially autocorrelated. Hansen statistics are distributed as chi-squared with degrees of freedom equal to the number of over-identifying restrictions, under the null that instruments are valid. In all GMM-SYS instrumented estimations, all employment determinants are treated as potentially endogenous using the instrument set containing all available lagged values of the variables in the model. The ml statistic for the l-lag order correlation proposed by Arellano and Bond (1991) is given by the following expression: $m_l = \frac{\hat{v}'_{-l}\hat{v}}{\sqrt{\hat{v}}}$ , where $\hat{v}$ represents the estimated residuals of GMM estimations. The ml order statistic is standard normal distributed and test the null that differenced errors are not l-order serially autocorrelated. The Hansen statistic is given by $J = \hat{v}'Z(\sum_{i=1}^{N} Z'_i\hat{v}_i\hat{v}'_iZ_i)^{-1}Z'\hat{v}$, where $\hat{v}$ represents the two-step residuals in this case. This statistic becomes the Sargan statistic when we believe errors are homoscedastic and use the first-step residuals (see Arellano and Bond, 1991, page 282). Sargan and Hansen statistics are distributed as chi-squared with degrees of freedom equal to the number of over-identifying restrictions. The null hypothesis is $\mathrm{E}[Z'v] = 0$, under the null that instruments are valid.

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