Revista Brasileira de Gestão e Desenvolvimento Regional
G&DR. V. 16, N. 1, P. 318-338, jan-abr/2020. Taubaté, SP, Brasil.
ISSN: 1809-239X

Received: 09/05/2019
Accepted: 02/16/2020

IS ECONOMIC COMPLEXITY SPATIALLY DEPENDENT? A SPATIAL ANALYSIS OF INTERACTIONS OF ECONOMIC COMPLEXITY BETWEEN MUNICIPALITIES IN BRAZIL

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Abstract

Even though the world economy has developed over the past century, the divergence has simultaneously led to an increasingly unequal dispersion of wealth. Economists have been fascinated by the underlying mechanisms and determinants; many potential sources of economic development have been scrutinized. Recently, a new theory of economic development has emerged (Hidalgo et al, 2007). Economic complexity emphasizes the importance of the productive structure and disentangles aggregated measures of economic development such as GDP. Whilst it has been applied in explaining growth at the national level with significant results, it has only been sparsely used to explain interregional differences and subnational development. Brazil is infamous for its staggering social and economic regional inequality. This paper applies spatial econometrics to assess whether economic complexity is spatially dependent between Brazilian municipalities in 2010 and evaluates what implications this may have for regional industrial policies. As such it is part of both the diversification versus specialization and of the place-neutral and place-based policy debates. It finds strongly significant and robust evidence of spatial dependence using a series of models and spatial weight matrices at the municipal level.

Keywords: Spatial Econometrics, Economic Complexity, Regional Economics, Productive Structure, Brazil

Introduction

The world economy has experienced unprecedented growth since the end of the Second World War. Simultaneously, the gap between income per capita in advanced and developing countries is widening rapidly (Helpman, 2004). Many potential sources of economic growth and of the recent divergence have been mentioned and empirically studied. It is becoming increasingly recognized that it is not the neo-classical accumulation of capital, or geography, or openness to trade which are the main drivers of improvements in standards of living, but productivity resulting from knowledge, technology, innovation and high quality institutions (Solow, 1956; Helpman, 2004; Rodrik

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et al., 2004; Stiglitz and Greenwald, 2014). Moreover, 'markets and organizations allow the knowledge that is held by few to reach many' (Hausmann et al., 2011: p. 15).

Production has become more complex than it was in the days of Smith. His argumentation is still of major value and the extent of the division of labor is increasing ever more through international developments such as vertical specialization (Hummels et al., 2001; Antràs et al., 2006; Bridgman, 2012; Schwörer, 2013)[3]. This makes his argument even more compelling as well as shows that it may need some updating. Nowadays, production can no longer only be reflected by market transactions. Since many products are produced through large knowledge networks of people, organizations and enterprises, their complexity can no longer accurately be studied using aggregate monetary measurement tools such as GDP. Institutions and capabilities that facilitate the well-functioning of such networks should be incorporated in models that explain or aim to forecast economic development.

A relatively new branch within this field is economic complexity theory, which was introduced by Hidalgo et al. (2007) and combines insights of development economics and the statistical physics of networks. Hausmann et al. (2011) empirically demonstrate that economic complexity outdoes any other existing explanation of economic development. Whereas traditional economic theory uses aggregated measures such as a change in GDP per capita to study economic growth, economic complexity theory emphasizes the importance of the productive structure (Hidalgo, 2009). It stresses the importance of the content of what countries produce rather than how much value its production generates as a whole. Rodrik (2011a: p. 156) summarizes the argument by arguing that 'you become what you produce'. If one is specialized in commodities and raw materials, it will be impossible to escape the periphery of the world economy. Such economies are vulnerable to swings in world markets and institutions are constructed to support the existing ruling class and vested interests of small elites. On the other hand, when an economy is able to diversify away towards 'manufactures and other modern tradable products, you may pave a path toward convergence with the world's rich countries'.

Complexity has not only been applied on models that aim to explain economic growth, but also to explain institutional development and income inequality (Rodrik, 2011a; Hartmann et al., 2015) and the recruitment of experienced workers (Hausmann and Neffke, 2016). There are many issues that remain to be explored in the future. Examples include international and national labor mobility, the environmental impact of complexity and potential positive correlations with environmental perceptions. Furthermore, as economic complexity theory was designed to explain the development of countries, it has only sparsely been used on a subnational level.[4]

This paper assesses whether there are spatial interactions between economic complexity of Brazilian municipalities in 2010 and aims to shed some light on the drivers of economic complexity at the regional level.

Brazil experienced a period of strong economic performance; average Brazilian economic growth between 2000 and 2010 was 3.8 percent (The World Bank, 2015). The spatial impact of this economic development and the role that economic complexity plays within this context can therefore be assessed. Besides, it is a highly diverse country, both with respect to income, to climate, and also with respect to complexity, which allows testing the hypotheses under a large variety of circumstances. Moreover, it is a country of large geographic size. This provides additional opportunities for subnational specialization and diversification, and thus higher complexity at the aggregated national level. Spatial analysis is therefore additionally relevant and the hypotheses can be tested at a relatively large scale with 5565 municipalities. Finally, the available dataset of Brazil allows assessing the impact of potential spatial complexity spillovers at a subnational level in an emerging country context; which is a period of many challenges and possibilities and the choices made will most likely prove to be of crucial importance for its future development.

This paper is organized as follows: it starts with an overview of theoretical and empirical literature, which assesses the theoretical development of economic complexity, examines potential links between government policy and regional development through economic complexity, and will go into detail regarding the Brazilian economy and the current state of affairs with respect to

[3] One should be aware that empirical evidence on the productivity effects of vertical specialisation is not conclusive. The literature suggests multiple conditions to be fulfilled in order to create positive productivity effects. For more on this subject see McMillan and Rodrik (2011a) and Schwörer (2013).

[4] Exceptions are e.g. Oliveira et al. (2016), Poncet and Starosta de Waldemar (2013) who used a Chinese panel data set on complexity and Jarreau and Poncet (2012) who find that highly complex Chinese regions subsequently grow faster.

economic complexity. This theoretical part is followed by a methodology section which amongst others expounds on the spatial econometric method and thereafter continues with a description of data sources. In the fourth part, it starts with some descriptive statistics and then moves to the empirical results and its discussion that includes some remarks on policy implications. The fifth and final part consists of a conclusion with suggestions for further research.

Theoretical framework

What is economic complexity and how to measure it?

According to economic complexity theory, the productive structure of an economy and therefore its complexity is imposed by its capabilities (Hidalgo, 2009). Economies are endowed with capabilities and different products require a certain set of capabilities. The more complex a product, the more capabilities required for its production. Capabilities include physical and human capital, but also institutions, norms, and social networks. Hausmann et al. (2011) use revealed comparative advantage (RCA) to create networks of products and distill the capabilities necessary for their production. RCA is calculated as follows:

$$R_{cp} = [(X_{cp} \;/\; \sum_p X_{cp}) \;/\; (\sum_c X_{cp} \;/\; \sum_{c,p} X_{cp})] \quad (1)$$

where R_{cp} is 'the network connecting countries to the product they export', c is country c, p is product p, and X_{cp} is the matrix of countries' exports (Hidalgo, 2009: p. 5). A country has an RCA in producing a product if $R_{cp} \geq R^*$; where usually $R^* = 1$.

Moreover, if an economy has a large number of capabilities at its disposal, it is considered a complex economy, and it is often diversified and rich. Furthermore, these economies are equipped with rare capabilities that allow them to produce relatively unique products. Together, ubiquity and diversity constitute complexity. If a product's ubiquity is low, only a limited number of countries possess the capabilities necessary for its production. If the diversity of a country is high, it produces many products. It has been empirically demonstrated that economic complexity is strongly correlated with economic performance and that errors in the relationship often predict future growth (Hidalgo and Hausmann, 2009).

The method of reflections is used in order to measure economic complexity and its components diversity and ubiquity (Hidalgo, 2009; Hidalgo and Hausmann, 2011). The weighted network matrix (R_{cp}) is normalized to an unweighted equivalent (M_{cp}). In this unweighted matrix (M_{cp}), values are set equal to one when that product can be produced at RCA (when $R_{cp} \geq R^*$). Using M_{cp}, one can calculate the diversification of country c (k_c) by summing the matrix over products for country c; this gives the number of products country c exports at RCA. A similar method is used to measure the ubiquity of a product; k_p represents the number of countries that exports product p at RCA and is equal to the sum over countries of M_{cp} for product p.

The next step is to iteratively calculate the average value of the previous-level properties of a node's neighbors and is defined as a set of observables. The diversity of a country is therefore calculated as follows:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} k_{p,N-1} \quad (2)$$

where $k_{c,0}$ represents the observed level of diversification of a country, which is the number of products exported by that country. Each of the iterations calculates the number of nodes in the network matrix at distance n from product p. One calculates the average degree of nodes for each country. Iteration 0 equals the number of products c produces; iteration 1 also includes information on how many countries produce these products, etcetera. One continues to add iterations, until the next iteration does not add any information anymore and has the measure converged to its mean.

Diversity is not sufficient to measure the capabilities available in a country. One may produce an equal amount of products as another country, but the number of capabilities necessary to produce these products may be highly divergent. In this case, a country with an export portfolio that requires more capabilities would be more complex, which is not included in the measure. A similar method is therefore used to calculate the ubiquity of the products produced. In this case one sums the number of countries that export a product p as presented in equation 3.

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_c M_{cp} k_{c,N-1}$$
(3)

where $k_{p,0}$ represents the observed ubiquity of a product, which is the number of countries that export that product with RCA. A similar problem as previously described for diversity holds for ubiquity. You may have very low ubiquitous products, but if you only produce a few, you may still only possess a relatively small number of capabilities. The iterations are used for both measures to correct for the bias both diversity and ubiquity inhibit; each subsequent iteration corrects for the bias of the previous one. In the end, after N iterations, one ends up with values for an economy's complexity and product sophistication that converge to their means.

Finally, it is important to stress that a single capability may be used in the production of multiple products. Development through diversification is therefore found to be highly path dependent. This is closely related to the Product Space, which shows the probability of interconnections between products an economy is able to produce (Hidalgo and Hausmann, 2009). According to Hidalgo (2009: p. 3), it 'can be seen as an industrial map of where economic development occurs.' They show that since productive knowledge is hard to acquire, countries can easily produce new products that are 'close' to those they already produce and for which the capabilities are available (Hidalgo, 2009). The more capabilities at one's disposal, the easier it is to diversify even further.

Regional industrial policy and economic complexity

According to Rodrik (2011b), governments have advantageous roles to fulfill in bolstering industrial diversification and upgrading by focusing on market failures with targeted policies. A noteworthy counterintuitive example for neoclassical economists is the fact that government-led diversifying away from initial comparative advantage can lead to economic progress, as was shown by the Asian Tigers. Virtually all present-day successful economies employed intensive government intervention in their productive structure at early stages of development, ranging from the 19th century the United States to China today (Rodrik, 2011a; Stiglitz and Greenwald, 2014). Nevertheless, one should not underestimate the power of market incentives and potential of government failure (Rodrik, 2011b; Stiglitz and Greenwald, 2014).

Hidalgo (2009) proposes different roles for government intervention under differing circumstances. He mentions that copying the reforms China pursued since the late 1970s will not necessarily result in successful outcomes, since China's main concern was not a lack of capabilities but rather a poor incentive structure. His approach therefore underlines the importance of tailor-made industrial policies. Industrial policies are useful and often necessary, as 'markets on their own do not create a learning society' and should foster 'learning and learning spillovers' (Stiglitz and Greenwald, 2014: p. 323). Industrial policies can be defined as a policy aimed at (re)shaping the productive structure of the economy.

Considering the foregoing, one may argue that it is unfortunate that the above-described evolution of complexity theory – and hence of development economics and economic geography – has barely been translated into national and regional industrial and other development policies. Moreover, policymakers still predominantly rely on demand- or supply-side and sectoral dimensions rather than spatial or territorial aspects and attempt to imitate policies that were successful elsewhere, but generally under very different circumstances (Barca et al., 2012). These interventions often ended up aggravating regional inequality, polarisation and with wasted resources and resulted in a subsequent surge of 'a new wave of modern policy thinking' (Barca et al., 2012; Varga, 2015: p. 2). As this paper assesses the potential existence of subnational spillovers of complexity, this section concisely discusses the place-based versus space-neutral debate on development policies and the role complexity may play in improving regional industrial policy.[5]

[5] Another academic debate with respect to regional development and industrial policy is the debate between 'big push' advocates such as Sachs and Solow type of arguments on investment, technological change and productivity (Helpman, 2004). Complexity theory is most easily linked to the latter school. For matters of conciseness, it is not possible to include discussion

Economic complexity and Product Space theory gives insight into the productive structure and capabilities of countries and capability accumulation opportunities, and can do so at subnational levels of regions and municipalities as well.

Proponents of spatially-blind strategies use New Economic Geography (NEG) based arguments and advocate macroeconomic policies and institutional reform aiming at the stimulation of agglomeration, efficiency, and equal opportunities. Space-neutral policies allow factors of production to move where they are most productive. Through this mechanism, aggregate welfare is stimulated optimally and individual lives can be improved (Barca et al., 2012). Lagging regions should be adequately connected with agglomerations through policies directed at decreasing transportation costs to increase their integration with successful regions or cities. Place-based policies aimed at underdeveloped regions lead to a loss in the effective use of resources, as these could also be used to increase agglomeration effects (Varga, 2015).

Place-based strategies, on the contrary, emphasize the significance of geographical context and space, path dependency, and the essence of knowledge and interactions with local groups and different levels of governance in policy intervention (Barca et al., 2012). McCann (2014) e.g. argues that there should be sufficient policy space for the local and regional government to enable them to address local challenges. It stresses the potential of regions and of geographical spillovers after successful development intervention and underscores that a country is constructed out of heterogeneous urban and regional systems. Moreover, a spatially-blind approach regularly has unintentional spatial effects. According to Barca et al. (2012), the place-based school of thought is especially advantageous in times of rapid developments and transition, as choices made today under these circumstances may have a long-run impact for development.

With respect to regional industrial productive structures and policy that aims to technically enhance or diversify them, Neffke et al. (2011) mention the importance of an optimal level of cognitive distance, path dependency at the regional level, and find high technological cohesion in Swedish regions.[6] However, the authors also argue that a 'higher degree of variety among related industries in a region will exhibit more learning opportunities and consequently more local knowledge spillovers' and results in a specific kind of vertical diversification called "regional branching" (2011: p. 241-242). This evidence suggests that diversity between regions is beneficial for development and place-based strategies would probably be best suited to facilitate its development.

According to Boschma and Iammarino (2009), one of the potential channels through which extra-regional knowledge spills over is through interindustry trade. Similarly, Naudé et al. (2010) find evidence for spatial industrial dependence amongst South African regions, albeit using a cross-sectional dataset and only using a spatial error model. This provides additional evidence that spatial interactions between regions are an important source of productive structure development. As mentioned in the introduction, interregional recruitment of human capital by pioneer firms may be other channels through which knowledge and capabilities are transmitted between regions (Hausmann and Neffke's, 2016).

The role of a sufficient absorptive capacity should thus not be disregarded in this context (McCann, 2014; Cortinovis and Van Oort, 2015). Capello and Lenzi (2014) use the Schumpeterian distinction between knowledge and innovation and find that they have a different spatial impact. First, they argue theoretically and find empirically that innovation more easily spills over to neighboring regions than knowledge. Second, they argue that knowledge does not automatically lead to innovation and crucially depends on the commercialization of knowledge and new ideas into innovation which, according to Capello and Lenzi, should actively be supported by innovation policy efforts. They are therefore proponents of a place-based approach.

One may argue that, in light of the above evidence, place-based policies should more regularly be implemented. Regions with related industries can be targeted as a group and knowledge and/or innovation may by virtue of this spillover between them and policies be directed towards higher complexity though related industries to minimize their subsequent exit probability. This is especially important in geographically larger economies such as Brazil with a polycentric nature (Cortinovis and Van Oort, 2015). Neffke et al. (2011), however, also argue governments should

on this topic in this paper. One should, however, realise that there is debate on whether the structural change economic complexity theory and Product Space theory propose, is even necessary to achieve development.

[6] The theoretical concept is highly similar to increasing complexity through nearby capability accumulation in the Product Space.

exercise restraint with respect to industrial policies and only target bottlenecks, as many of these mechanisms often already occur unaided. Furthermore, as mentioned before, there is always the possibility of government failure.

Finally, Varga (2015) stresses the complementarity between the two schools of thought and proposes several methods through which they can be combined. Moreover, he develops a model through which decisions can be made whether either a place-based or spatially-blind approach is preferable under differing circumstances. These methods acknowledge the significance of geographical features of spatial entities that are targeted with these policies as well as the macro effects regional policies may have. Varga's approach may also be applicable for increasing complexity, and the potential impact of spatial spillovers definitively would underline the merit of a significant role for place-based policies in Varga's proposed mix of both approaches.

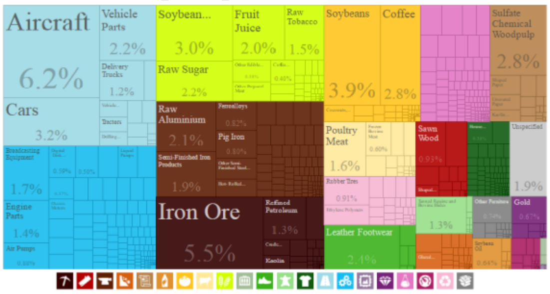
The Brazilian economy and complexity at the municipality level

Brazil has experienced economic development and strongly diversified its export portfolio since the 1970s. Gozgor and Can (2016) argue that low and low-middle income countries should first diversify before specializing again at later stages of development, this may at least partially explain their economic successes. This section discusses some essential characteristics and developments of Brazil's economy. It furthermore discusses some evidence on spatial interactions of economic growth in the Brazilian context and analyses its development regarding economic complexity at the subnational level.

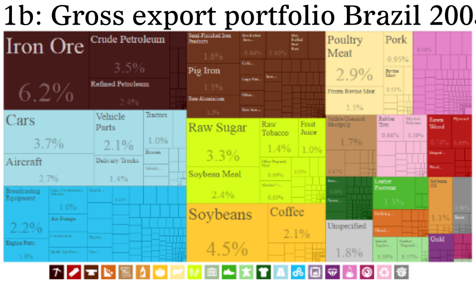
Figure 1 appears that the structure of Brazilian exports underwent considerable changes during the last decades. It is unquestionable that relative to 1965, when half of the Brazilian exports were made of coffee, including green coffee, roasted coffee, and coffee substitutes (Felipe and Hidalgo, 2015), Brazilian exports became more diversified in terms of individual goods' and individual good categories' share of the country's total exports.

Figure 1: Gross export portfolio development Brazil, by sector[7]

1a: Gross export portfolio Brazil 2000

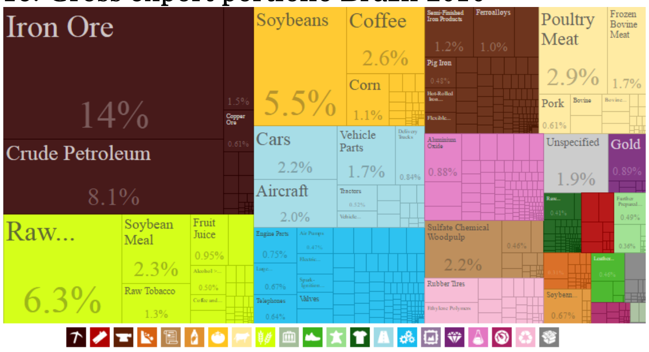


1b: Gross export portfolio Brazil 2005



[7] For more details about the sectors used in this paper, see Appendix 1.

1c: Gross export portfolio Brazil 2010



Source: Fapemig. 2016.

In 2005 and 2010, the structure of Brazilian exports appears to have remained relatively more diversified than in 1965. Similarly, in contrast to 2000 however, Brazilian exports in 2005 and 2010 appear to have, if anything, grown slightly more concentrated. Since 2010, exports of the most exported goods and of goods part of the same product category made up a larger share of total exports. Moreover, it is also worth noting that relative to 2005, the share of exported secondary-goods, seem to have kept declining since 2010.

Figure 2 shows the transition of the top three sectors of the Brazilian export portfolio. The mineral products sector became rapidly more important over the period under scrutiny.

Figure 2: Changing major sectors Brazilian export portfolio

2000	2005	2010
1. Foodstuffs (13%)	1. Mineral products (17%)	1. Mineral products (29%)
2. Machinery/electrical (13%)	2. Machinery/electrical (12%)	2. Foodstuffs (13%)
3. Transportation (12%)	3. Transportation (12%)	3. Vegetable products (11%)

Source: Author's construction based on Harvard's Center for International Development (2014)

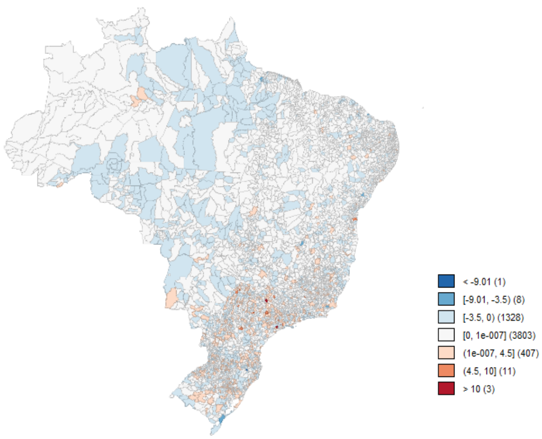
In 2010, this relatively low complexity sector had become even the largest one and the relative importance of the other less complex sectors of foodstuffs and vegetables increased as well. The relatively high complex sectors machinery/electrical and transportation fell to 7 and 8% respectively between 2005 and 2010. This could be one of the explanations of the fact that the country dropped from the 29th in 2000 to the 50th place in 2010 on the ECI rankings.

Looking at a regional perspective, many studies on Brazilian interregional inequality stress the importance of spatial analysis at multiple scale levels, as it shows that spatial effects are of major importance and that the intensity of spatial spillovers differs between different scale levels (Resende, 2011; Özyurt and Daumal, 2013; Cravo and Resende, 2015; Cravo et al., 2015).

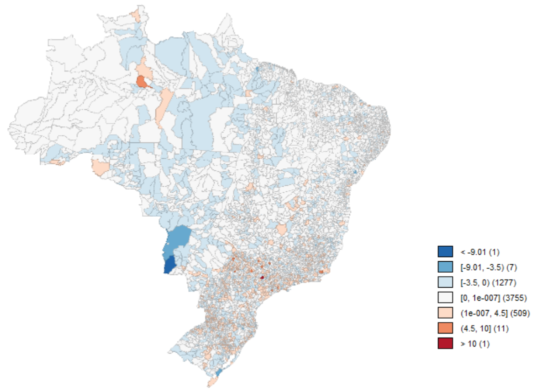
Globally, South-Eastern and Southern municipalities in general are relatively complex, whereas in the North and North-East, the vast majority of municipalities are far less complex. As observed with other variables, also with respect to the spatial dispersion of complexity the South and the North are divided into two strongly divergent groups. With only a few exceptions, where the South is generally developed and complex, the North is lagging behind and the difference is rather dramatic. One of the most notable exceptions is the municipality of Manaus, which is one of the more complex municipalities of Brazil, but it is located in the Amazon rainforest and only has a very limited number of relatively complex municipalities in its neighborhood in both years. This is the result of several decades of successful economic policies and its electronics and chemical industries

(MDIC, 2008). Whether these exceptions only prove the rule of spatial patterns and spillovers is what will be analyzed in the empirical part of this study.

Figure 3: Spatial distribution of economic complexity in Brazil by the municipality



3a: Economic Complexity Index 2002



3b: Economic Complexity Index 2010

Source: Oliveira et al. (2016)

In that sense, we can see that Brazil is a highly heterogeneous and unequally developed country, both on an aggregate and at the interregional level. On the one hand, this may fill one with despair and lead to the expectation that the extent of the differences may obstruct regions to gain from the experience and knowledge of the others. On the other, there is sufficient evidence that knowledge, innovation, and capabilities may spill over between economies and even that the less developed within a country may relatively easily gain from innovation from the most advanced ones. Moreover, there is evidence of spatial gains with respect to economic growth between regions in the Brazilian context. In the second and empirical part, this paper will assess whether economic complexity indeed spills over between municipalities and whether this may form a possible channel through which Brazil's regional inequality is reduced and can be used to do so even further.

Econometrics specification

This paper follows the strategy for setting up a spatial analysis proposed by Anselin (1988), which is the optimal pathway according to Viton (2010), and starts with a simple OLS model and thereafter performs several tests to determine whether a spatial model should be used and if so, what model is most appropriate.

The OLS model is formulated as follows:

$$ECI_{2010} = \beta_0 + \beta_1 ECI_{2000} + X_i'\beta_k + \delta_{n-1}(Reginal\ Dummy)_i + \varepsilon_i \quad (1)$$

Where:

ECI_{2010} is the Economic Complexity Index of 2010 of Brazilian municipalities.

ECI_{2000} is the Economic Complexity Index of 2000.

Regional Dummy is of four out of the five regions of Brazil ($N = 5$).

X_i is the control variables that have been included, which consists of variables measuring population (density), human capital, trade openness, GDP per capita, the share of agricultural income and a variable that measures the share of industrial sector income in GDP, a Gini index, and one to measure social development.

β_k and $\delta_{n\text{-}}1$ are the parameters to be estimated.

ε_i is the idiosyncratic error term.

With respect to the model selection, this study will start with executing a Moran's I and a Lagrange Multiplier (LM) test to test the null hypothesis of no spatial correlation in the error term. If both hypotheses are rejected at the five percent significance level, spatial dependence is traced in the model and spatial weights should be added to the equation. In order to determine whether one should start with using a Spatial Autoregressive (SAR) Model or Spatial Error Model (SEM), an LM spatial lag test is carried out. According to Elhorst (2014), the spatial misspecification robust LM spatial error and lag tests can also be executed and only have to be rejected at the 10 percent level. If this null is also rejected in this case, the SAR model will be the base model. The SEM model will, for transparency, in that case also be presented. Other models will also be calculated to test for spatial interactions through the explanatory variables or combinations of sources of spatial dependency. A model that tests for spatial dependence in the explanatory variables is necessary to test the hypothesis that the determinants of economic complexity a positive spatial spillover effect as well, either through affecting economic complexity in other regions directly or indirectly through the spatial lag that will be added in multiple models.

Univariate Moran's I tests are carried out on all explanatory variables to test for spatial correlation between them. If the null for variables is rejected, spatial weight matrices should be added for these variables. In order to determine which spatial model is the best fit for the question at hand and thus which spatial weights should be added, the likelihood ratio (LR) test can be performed after every model specification has been estimated (LeSage, 2008; Elhorst, 2014). The higher the outcome of the LR test statistic, the better the fit of the model and the weight matrix. Due to data limitations, this paper applies a one-year cross-sectional analysis. Finally, the spatial models are estimated using Maximum Likelihood (ML) estimation, with the exception of the SAC model – as this model can only be executed using Generalised Method of Moments (GMM) estimation.

A final issue with respect to the interpretation of the coefficients found with spatial econometrics when $\rho \neq 0$ is the following. The estimators (β) should not be interpreted in the same way as conventional regression coefficients, and the usual ceteris paribus interpretation does not apply (LeSage, 2008; LeSage and Pace, 2009; Elhorst, 2014). If spatial dependence is found in the dependent variable of the model of this paper ($\rho \neq 0$), a change in economic complexity at one location affects the economic complexity in another through spillovers. The effect of changing values of variables is therefore captured by a combination of β, W, and ρ, θ, or λ; or put differently, by 'a partial derivative interpretation' (Elhorst, 2014: p. 20).

According to LeSage (2008: p. 33), in measuring the partial effect of a change in X on the dependent variable in a model that includes a spatial lag is measured one should distinguish between the direct and indirect effects. The direct effect captures the impact of all explanatory variables (X_i) on the dependent variable ($ECI2010_i$). The indirect effect measures the effect of the explanatory variables of all other municipalities j (X_j) on the spatial lag ($ECI2010_j$), which in turn affects the dependent variable ($ECI2010_i$). Together, these two components sum up to the total effect which measures the actual partial effect. Furthermore, according to LeSage (2008), the feedback effects of spatial coefficients should not be interpreted as immediately occurring, but rather as a long-run evolution to the next steady state.

Data

Our dataset is a cross-section data for all 5565 Brazilian municipalities in the year 2010 and the selection of the variables is based on Daude et al. (2016). With respect to functional form, it should be noted that all variables are included in level form, with the exception of the population of which the natural logarithm is taken to simplify the interpretation of this variable.

The name of all the variables, their hypothesized signs, as well as their descriptions and sources are provided in table 1 below.

Table 1: Description of the variables used in the model.

Variable	Description	Hypothesized sign	Source
ECI	ECI is a scale that uses the theory and calculations for economic complexity to rank countries according to their level of complexity, following Hidalgo and Hausmann (2009).	Positive	Fapemig, DataViva
Natural log of the population (logPOP10)	Natural log of the population in the municipality.	Positive	IPEADATA
EXPGDP	Describes the exports over GDP per municipality (EXPGDP) is included and measures trade openness.	Negative	Author's calculations (Based on IBGE data)
EDU10	This variable describes the percentage of the population that enjoyed high school educated.	Positive	IBGE
EDU1_10	This variable measures the percentage of the population with a university degree.	Positive	IBGE
Shareagric	This variable measures the share of agricultural income in GDP.	Positive	IPEADATA
Shareind	This variable measures the share of industry income in GDP.	Positive	IPEADATA
gdp_percapita	GDP per capita.	Positive	IBGE
GINI	Gini index.	Negative	IPEADATA
IDHM10	Human Development Index.	Positive	IPEADATA
South-East	Dummy variable, 1 if the state is part of the South-East region, 0 otherwise	Positive	Authors
North-East	Dummy variable, 1 if the state is part of the North-East region, 0 otherwise	Negative	Authors
South	Dummy variable, 1 if the state is part of the South region, 0 otherwise	Positive	Authors
North	Dummy variable, 1 if the state is part of the North region, 0 otherwise	Negative	Authors

Source: Author's construction.

Finally, this study uses R (R Development Core Team, 2016) for mapping, creating spatial weight matrices, testing, and regressions. We also use this software to apply the LeSage and Pace (2009) method of the decomposition of the direct, indirect, and total impact measures, and for the estimation of the remaining models.

Results and discussion

Results

In Table 2, we present the estimates for our baseline model that are based on a simple OLS regression, SAR and SEM models using the third order Queen spatial weight matrix.

Table 2: Regression results for OLS, SAR and SEM models

	1	2	3
Variable	OLS	Spatial Lag	Spatial Error
Constant	-0.1143	-0.1090	-0.1152
ECI00	0.7267***	0.7239***	0.7246***
North	-0.0148	-0.0090	-0.0158
North-East	-0.0052	-0.0005	-0.0072
Center-West	-0.0557***	-0.0456**	-0.0555***
South	-0.0141	-0.0078	-0.0156
logPOP10	0.0115**	0.0120**	0.0120**
EXPGDP	-0.0001***	-0.0001***	-0.0001***
EDU10	-0.0017	-0.0017	-0.0018
EDU1_10	0.0040	0.0037	0.0038
gdp_percap	0.0006***	0.0006***	0.0006***
Shareind	0.0278**	0.0289**	0.0335**
Shareagric	0.0722*	0.0807**	0.0779*
GINI	-0.1218	-0.1348*	-0.1246
IDHM10	0.0497	0.0342	0.0496
ρ	--	0.0768***	--
λ	--	--	0.0937**
R2	0.6140	0.6150	0.6145
Log likelihood	-2109.53	-20103.00	-2107.09
Likelihood ratio test	--	13.0649***	4.8872**
Observations	5565	5565	5565

***, **, and * indicate the 1, 5, and 10 percent significance levels.
ρ is the spatial error correlation and spatial lag correlation coefficients
All models use the row standardized 3rd order Queen contiguity matrix
Source: Author's calculation.

After executing the OLS regression, several tests were performed to test for the presence of spatial effects. Most of the test statistics are significant: the LM tests for spatial dependence for the lagged model are both significant at the one percent level, the LM test and the Moran's I for the error are significant at the five percent level. An exception is the robust LM error test, which is insignificant, but nevertheless, the null hypotheses of no spatial dependence in both the spatial lag and the spatial error are rejected in most tests. The spatial error test statistics are somewhat less significant than the ones for spatial lag models, implying that the spatial lag model is the preferred one out of the OLS, SAR and SEM models.[8]

Moreover, the Likelihood ratio test, which allows comparing the fit of spatial econometric models, also clearly indicates that the SAR model of column 2 is the preferred one. The first observation that can be made is the remarkable stability of the model when comparing the different estimation methods and models. The sign of the coefficients stay equal across all columns, and so does their magnitude and significance to a major extent. This is an indication that the model is well-specified.

Second, and most importantly, ρ, or the spatial lag coefficient, is significant at the one percent level using the SAR model. This confirms the main hypothesis of this research that economic complexity is positively spatially dependent. Municipalities (i) can thus learn from or are at least affected by others (j's) through spatial interactions or spillovers. Through which channels municipalities exactly affect the economic complexity of municipality i cannot be determined by the models of table 2.

There is a positive and significant relationship between the level of the economic complexity of the municipality and its previous year. It shows that Brazilian municipalities which had a complex product structure in the previous year could maintain that status during the following year. This

[8] The robust LM error test is not significant, but is known for being vulnerable to type II errors. The LM SARMA test is also significant at the one percent level, suggesting that a Keleijan-Prucha or SAC model may be even better. Often heard critique on the LM SARMA test is, however, that it often is significant if one of the two sources (lag or error) is strongly significant, corrupting the outcome of the SARMA test.

result emphasizes the importance of considering capabilities as a stock that creates a condition to a more complex economy over time. In that sense, as indicated by Hausmann et al. (2011) the economic complexity is positively related to local income level, and it may create some virtuous cycle where complex economies tend to raise the local income level and improving the economic complexity in the future.

Moreover, most of the other control variables have the expected signs, with a few exceptions. First, the regional dummies are negative, as was foreseen. The South-East region dummy was omitted to evade the dummy variable trap and is thus the base region. As it is the most developed of the regions of Brazil, the coefficients on the regional dummies were all hypothesized to be negative. One may find it remarkable that only the Center-West is the only dummy that is constantly significant. One explanation may be that other variables already explain most of the variation between regions, which causes little unexplained variation between regions to be remaining to be picked up by the regional dummies.

Furthermore, *logpop* is statistically significant and positive, as was hypothesized. The trade openness variable (*EXPGDP*) is negative and significant, as was expected based on the export portfolio of Brazil in 2010. It has become more and more focused on less complex products such as petroleum and soybean production. This has probably caused municipalities to import more complex products, reinforcing the effect of specialization towards less complex production. The fact that the estimator is such a small value may be caused by the specification of the variable or simply by the fact that it is not economically significant.

Another expected result is the negative coefficient on *GINI*. Whilst it is only statistically significant according to the conventional significance levels in the SAR model, in the other models it is very close to the 10 percent level with p-values of 0.1151 and 0.1097 in the OLS and SEM models, respectively. A potential reason why this result may be insignificant or only slightly significant may be the opposing effects that inequality of effort and inequality of opportunity may have on economic complexity. Such diverging effects would be in line with the findings of Marrero and Rodríguez (2013) who argue that these two sources of inequality are both part of typical measures of inequality.

The share of the agricultural sector in GDP (*Shareagric*) is positive and significant in all models. A reason why this may be the case may be vertical diversification, which aims to improve the quality of agricultural products such as coffee and thus may include relatively complex products in the agricultural sector. Another potential explanation is that it is relatively more complex than other municipalities that are more specialized in even less complex products such as in the natural resource sectors. The share of the industrial sector in GDP (*Shared*) is positive, but insignificant. This result goes on line with Ferraz et al (2018) who finds similar result to Latin American countries. It may be the case of Brazilian states which still have low participation of the Industry sector and, especially, exporting manufactured goods. This scenario keeps these countries, and this case, the Brazilian states, dependent on commodity exports, which does not necessarily require the improvement of the capacities for a better Human Development (Ferraz, et al, 2018).

The above interpretation of the SAR model estimation is, however, as was mentioned before, not entirely accurate and actually cannot directly be compared with the OLS and SEM results. It is important to distinguish between the direct, indirect, and total effects for SAR models using the LeSage and Pace (2009) methodology. The results and a comparison with the OLS estimation results are shown in table 3.

The results of the total effects of the SAR model in column 5 do not differ with respect to significance, but their magnitude is larger when compared with the OLS results of column 1 and SAR results that were not decomposed into different effects of column 2. This indicates that the exclusion of a spatial lag and failure to use the LeSage and Pace method results in a downward bias. For the purpose of this paper it does not appear to have a strong impact on the results, especially because of the endogeneity concerns at hand that causes that one has to be cautious with making causal claims. Moreover, the results show that the comparison with OLS that was made in the above is still valid. Furthermore, it is also notable that all indirect effects have the same sign as the direct effect and thus reinforce each other.

It is especially interesting that the indirect effects of column 4 of both *ECI00* and *gdp_percap* are positive and significant. On the other hand, the indirect effect of *ECI00* seems to be statistically significant, whereas the effect of *gdp_percap* is less convincing with that respect. The estimates for the other variables are insignificant, which is not in line with what was hypothesized as spatial effects were hypothesized to be also strong for these variables. The effect the other potential determinants of economic complexity have on the complexity in municipalities j does thus not seem to be strong enough to affect the complexity in municipality i through the spatial lag.

Table 3: LeSage and Pace (2009) partial effect calculations

	1	2	3	4	5
			SAR partial effects		
Variable	OLS	SAR original	Direct	Indirect	Total
Constant	-0.1143	-0.1090			-0.1090
ECI00	0.7267***	0.7239***	0.7240***	0.0600***	0.7841***
North	-0.0148	-0.0090	-0.0090	-0.0007	-0.0097
NorthEast	-0.0052	-0.0005	-0.0005	0.0000	-0.0006
CenterWest	-0.0557***	-0.0456**	-0.0456**	-0.0038	-0.0494**
South	-0.0141	-0.0078	-0.0078	-0.0006	-0.0084
logPOP10	0.0115**	0.0120**	0.0120**	0.0010	0.0130**
EXPGDP	-0.0001***	-0.0001***	-0.0001***	0.0000	-0.0001***
EDU10	-0.0017	-0.0017	-0.0017	-0.0001	-0.0019
EDU1_10	0.0040	0.0037	0.0037	0.0003	0.0040
gdp_percap	0.0006***	0.0006***	0.0006***	0.0000**	0.0006***
Shareind	0.0278	0.0289	0.0289	0.0024	0.0313
Shareagric	0.0722*	0.0807**	0.0808**	0.0067	0.0875**
GINI	-0.1218	-0.1348*	-0.1349*	-0.0112	-0.1461*
IDHM10	0.0497	0.0342	0.0342	0.0028	0.0370
ρ	--	0.0768***	--	--	0.0768***
R2	0.6140	0.6150	--	--	0.6150
Likelihood ratio test	--	13.0649***	--	--	13.0649***
Weight matrix	3rd order Queen	3rd order Queen	3rd order Queen		
Observations	5565	5565	5565	5565	5565

***, **, and * indicate the 1, 5, and 10 percent significance levels.
ρ is the spatial error correlation and spatial lag correlation coefficients
All models use the row standardized 3rd order Queen contiguity matrix
Source: Author's calculation.

Since the diagnostics for spatial dependence indicated in most tests that spatial correlations of the error term were also statistically significant, a Kelejian-Prucha or Spatial Autoregressive Confused (SAC) model has been executed.[9] The results, which are reported in table 4, columns 1-3, show that λ is not significant anymore after introducing the spatial lag which confirms the outcomes of the spatial dependence tests that the spatial lag is preferred.

[9] The SAC model is used for an analysis of spatial effects in one model of both a spatial lag and the error term.

Table 4: Kelejian-Prucha / SAC model results

	1		2		3		4		5		6	
Variable	**SEM**		**SAR total effects**		**SAC**		**SEM**		**SAR total effects**		**SAC**	
constant	-0.1152		-0.1090		-0.1377		-0.1179		-0.1057		-0.1370	
ECI00	0.7246	***	0.7239	***	0.7120	***	0.7219	***	0.7847	***	0.7120	***
North	-0.0158		-0.009		0.0165		-0.0176		-0.0005		0.0169	
NorthEast	-0.0072		-0.0005		0.0289		-0.0089		-0.0096		0.0291	
CenterWest	-0.0555	***	-0.0456	**	-0.0420	**	-0.0553	**	-0.0492	**	-0.0416	**
South	-0.0156		-0.0078		-0.0125		-0.0171		-0.0082		-0.0121	
logPOP10	0.012	**	0.012	**	0.0126	**	0.0126	**	0.0130	**	0.0126	**
EXPGDP	-0.0001	***	-0.0001	***	-0.0001	***	-0.0001	***	-0.0001	***	-0.0001	***
EDU10	-0.0018		-0.0017		-0.0022		-0.002		-0.0019		-0.0021	
EDU1_10	0.0038		0.0037		0.0035		0.0039		0.0040		0.0034	
gdp_percap	0.0006	***	0.0006	***	0.0005	***	0.0006	***	0.0006	***	0.0005	***
Shareind	0.0335		0.0289		0.0377		0.0432		0.0312		0.0366	
Shareagric	0.0779	*	0.0807	**	0.1246	***	0.0894	**	0.0877	**	0.1250	***
GINI	-0.1246		-0.1348	*	-0.1755	**	-0.1251		-0.1471	*	-0.1760	**
IDHM10	0.0496		0.0342		0.0240		0.0466		0.0365		0.0228	
ρ			0.0768	***	0.0000	***			0.0780	***	0.0000	***
λ	0.0937	**			0.1924		0.1889	***			0.1907	
R^2	0.6145		0.6150		not available		0.6152		0.6169		not available	
Likelihood ratio test	4.8872	**	13.0649	***	not available		12.2688	***	38.9234	***	not available	
W type	**Q3rd**		**Q3rd**		**Q3rd**		**R3rd**		**R3rd**		**R3rd**	
Observations	5565		5565		5565		5565		5565		5565	

***, **, and * indicate the 1, 5, and 10 percent significance levels.
All models use the row standardised 3rd order Queen contiguity matrix.
λ and ρ are the spatial error correlation and spatial lag correlation coefficients.

Source: Author's calculation.

Since it was hypothesized that the control variables or determinants of economic complexity also may affect economic complexity through spatial interdependence, Spatial Durbin Model (SDM) and Spatial Durbin Error Model (SDEM) were estimated. The results can be found in table 5, 5a (SDM) and 5b (SDEM), but as argued before, the models that include a spatial lag are preferred; therefore the discussion here focuses on the SDM model. Moreover, there are only minor differences between the regression outcomes of the main variables between the two models, so a description of both estimations would result in a duplication of efforts.

Table 5: SDM and SDEM results

5a SDM estimation

	1	2
Variable	SDM Queen	SDM Rook
Constant	0.0444	0.0545
ECI00	0.7226***	0.7220***
North	0.0014	0.0017
NorthEast	0.0166	0.0182
CenterWest	-0.0335	-0.0324
South	-0.4914**	-0.4932**
logPOP10	0.0169***	0.0171***
EXPGDP	-0.0001	-0.0001
EDU10	-0.0032**	-0.0031**
EDU1_10	0.0034	0.0032
gdp_percap	0.0006***	0.0006***
Shareind	0.0589	0.0574
Shareagric	0.1188**	0.1172**
GINI	-0.1410	-0.1452**
IDHM10	0.1625	0.1605
lag.ECI00	0.0343	0.0428
lag.logPOP10	-0.0104	-0.0108
lag.EXPGDP	0.0001	0.0001
lag.EDU10	0.0054	0.0049
lag.EDU1_10	0.0107	0.0125
lag.gdp_percap	-0.0002**	-0.0002**
lag.Shareind	-0.3169***	-0.2986**
lag.Shareagric	-0.1694	-0.1633*
lag.GINI	0.1257	0.1493
lag.IDHM10	-0.4568	-0.4806
ρ	0.0756*	0.0753*
LM test for spatial error	0.3355	1.6261
W type	Q3rd	R3rd
Observations	5565	5565

***, **, and * indicate the 1, 5, and 10 percent significance levels.
ρ is the spatial lag correlation coefficient.
Source: Author´s calculation.

5b SDEM estimation

	1	2
Variable	SDEM Queen	SDEM Rook
Constant	0.0279	0.0395
ECI00	0.7232***	0.7226***
North	0.0024	0.0028
NorthEast	0.0198	0.0216
CenterWest	-0.0369	-0.0359
South	-0.5017*	-0.5045*
logPOP10	0.0169***	0.0171***
EXPGDP	-0.0001***	-0.0001***
EDU10	-0.0032**	-0.0031**
EDU1_10	0.0034	0.0033
gdp_percap	0.0006***	0.0006***
Shareind	0.0565	0.0550
Shareagric	0.1158**	0.1140**
GINI	-0.1412*	-0.1455*
IDHM10	0.1625	0.1612
lag.ECI00	0.0910***	0.0996***
lag.logPOP10	-0.0097	-0.0101*
lag.EXPGDP	0.0001	0.0001
lag.EDU10	0.0053	0.0047
lag.EDU1_10	0.0122	0.0142
lag.gdp_percap	-0.0002*	-0.0002**
lag.Shareind	-0.3276**	-0.3081**
lag.Shareagric	-0.1652*	-0.1581
lag.GINI	0.1434	0.1717
lag.IDHM10	-0.4601	-0.4889
λ	0.0844*	0.0869**
W type	Q3rd	R3rd
Observations	5565	5565

***, **, and * indicate the 1, 5, and 10 percent significance levels.
λ is the spatial error correlation coefficient.
Source: Author´s calculation.

Importantly, ρ remains positive and significant at a comparable magnitude with the other models where it is included. The most notable result when comparing the SDM results to the OLS, SAR, SEM, and SAC regression results in the control variables is especially that *EDU10* became significant. Second, the population coefficient has become strongly statistically significant and has a larger magnitude than in the other models. Even though its lag is insignificant, this coefficient is negative and it thus appears that competition effects of larger neighboring municipalities hamper economic complexity development.

There are multiple other coefficients that provide an identical image with respect to competition effects. The lag variables have a *lag.gdp_percap*, *lag.Shareind*, and *lag.Shareagric* coefficients, which are all negative and statistically significant at the five or one percent level in their lagged form. It seems that potential knowledge spillovers are therefore limited or are overshadowed by the negative effect of competition on economic complexity. Another reason may be a deliberate policy choice to aim for regional municipal heterogeneity, which may result in higher productivity levels at larger geographical scales because of comparative advantage and specialization induced gains. Especially the lagged share of industrial income in GDP is economically significant, which is what one would expect in the light of the above. These negative effects are, however, not in accordance with what was hypothesized with respect to the positive spatial effects of these variables. Other lags are found not to have a significant effect on *ECI2010*. Even though they are insignificant, a final remarkable observation is the positive signs on both lagged education variables. This may be caused by the positive effects of targeted recruitment of human capital, as was found by Hausmann and Neffke (2016).

The spatial lagged dependent variable estimators are strongly significant in all models, implying that spatial spillovers of capabilities and knowledge do seem to affect economic complexity at the Brazilian municipal level in 2010. These results have important policy implications and can be interpreted as support for the place-based policy approach. Furthermore, the existence of strong path dependency with respect to economic complexity is confirmed by the strong economic and statistical significance of the time-lagged ECI variable in all regressions, which provides further evidence in favor of the favourability of place-based policy approaches. Local challenges often differ – this is reflected by the major (spatial) deviations with respect to most variables including economic complexity between Brazilian municipalities in the sample. Municipalities should not only take their own bottlenecks and potential solutions of these challenges into account when designing (industrial) policies, but also the circumstances in their neighborhood or region. Regional policies should take this into account as well and regional cooperation might in certain cases serve as a means to ensure the success of municipal industrial and development policies.

The SDM and SDEM models showed that spatial spillovers occur through economic development (*lag.gdp_percap*), the development of the productive structure (*lag.Shareagric* and *lag.Shareindus*) which is in line with previous empirical evidence of i.a. Boschma and Iammarino (2009) and Naudé et al. (2010), and possibly the population variable that negatively affects economic complexity. These results most likely occur due to competition effects or because of deliberate productivity enhancing regional and municipal specialization or vertical diversification as was suggested by Cortinovis and Van Oort (2015). The evidence may be regarded as a confirmation of potential benefits of a spatially blind analysis, which would allow the maximization of NEG type of agglomeration economies and would be most equitable (Barca et al., 2012). In the end, Varga's (2015) argumentation on the complementarity of both schools might best fit the results of this paper.

Conclusion

This study empirically assessed the possible existence of spatial dependence of economic complexity at the municipality level in Brazil in 2010. It found strong and robust evidence in favor of the hypothesized positive effect of spillovers of complexity, especially in the models that include a spatial lagged dependent variable (SAR, SAC, and SDM). Moreover and more generally, multiple control variables have been found to be strongly spatially correlated using univariate Moran's I tests. As was mentioned in the introduction, the importance of space in economic analysis is increasingly recognized.

The results in all models and specifications are remarkably stable, which suggest that they are quite robust and that the model is well-specified. Moreover, in the introduction it was already mentioned that Brazil is a strongly diverse and polycentric country and one with major regional inequality. Obviously, on the one hand this is an advantage with respect to the generalizability of the results, as was argued in the introduction. On the other, however, even though regional dummies were included in the analysis, economic development is found to be highly idiosyncratic (Neffke et al., 2011) and results may be quite different in individual cases or different parts of the country.

The SDM and SDEM results can further be linked to the diversification versus specialization debate; competition may force municipalities to diversify or specialize away from the comparative advantage of neighbors, hampering capability accumulation and knowledge spillovers. Another possibility might be, once again, an intentional policy strategy that aims for regional municipal heterogeneity to increase aggregate productivity. Positive knowledge spillovers do not seem to exist at the municipal level through these variables, though they may occur directly as the spatial lag of economic complexity (ρ) is found positive and significant in all models and specifications.

Diversification is a historically proven effective potential strategy for economic development, especially at early stages, and it is moreover part of the very foundations of economic complexity theory. Also in this case, a combination of both strands of thought such as the U-shaped approach with respect to diversification and specialization at different stages of development (such as in Cadot et al., 2013 and Gozgor and Can, 2016). The importance of context in determining strategies, as is stressed in McCann, (2014), is most in conformity with the results of this research, as major differences exist regarding development between different Brazilian municipalities, which may have affected the results. This is once again a reason why a place-based policy approach should at the minimum be incorporated in industrial policy formulation.

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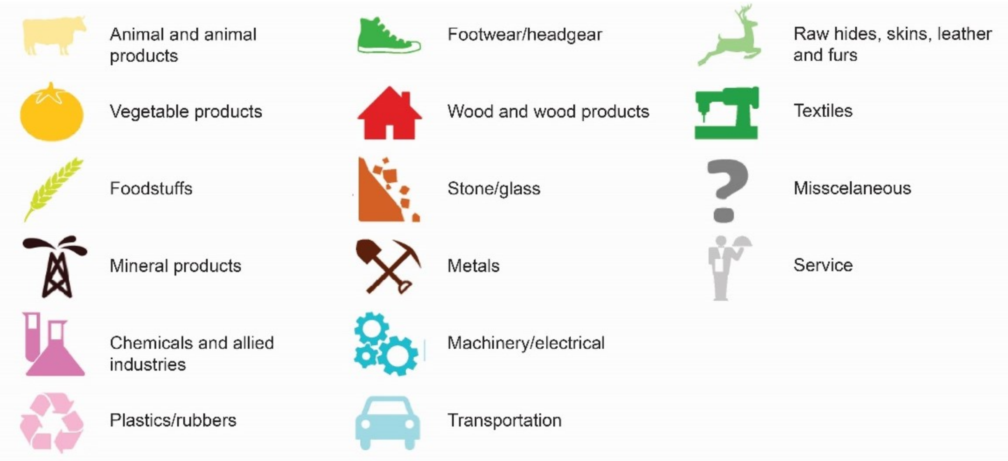
Appendix 1: Key to sector symbols in graphs and figures



Source: own construct based on Harvard's Center for International Development (2014).