The spatial concentration of high-skilled workers and city productivity: the case of Latin America

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Abstract

The aim of this study is to cast light on the relationship between the spatial concentration of high-skilled workers and the productivity of cities in Latin America. The relationship is not clear at first sight. On the one hand, the segregation of high-skilled workers should create agglomeration economies and give rise to positive spillovers amongst the most advantaged, offsetting productivity losses that result from the existence of ghettos of low-skilled workers. On the other hand, it may well be that these spillovers are not enough to compensate for the loss of productivity in the worse-off groups, so that aggregate productivity is negatively affected. We analysed this segregation for a group of Latin America's largest cities and found a negative and significant relationship between the productivity of cities and the segregation of high-skilled workers. However, we also found evidence of a quadratic relationship between segregation and productivity.

Keywords

Skilled workers, productivity, cities, segregation, geographical distribution, labour productivity, measurement, economic development, Latin America

JEL classification

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I. Introduction

The purpose of this study is to investigate the effects that the segregation of high-skilled workers, understood as residential segregation, has on the productivity of Latin American cities. This relationship is not clear at first sight. On the one hand, the spatial concentration of high-skilled workers yields agglomeration economies and positive spillovers among the most advantaged that could offset productivity losses resulting from the existence of ghettos of the worse-off. On the other hand, these spillovers might not be enough to compensate for those productivity losses, resulting in the city's aggregate productivity being negatively affected.

To achieve this goal, we use census data from Latin American countries to calculate segregation indices for high-skilled groups. Census information was obtained from the University of Minnesota Population Center's Integrated Public Use Microdata Series (IPUMS) for two dates, the first around the year 2000 and the second around the year 2010. We use individual education levels as a proxy for skills. As a productivity measure, we consider cities' labour productivity, deflating this measure by the Big Mac index for comparability. We collect this information for the countries' largest cities, in several cases more than one per country. Our empirical approach uses cities' productivity as the dependent variable and well-off groups' segregation as the explanatory variable, plus a group of controls. We run pooled regressions and a first difference model, the latter to deal with the contamination of results by omitted variables bias. Using two segregation indices and more than one productivity measure for robustness, we found segregation to have a significant and negative effect upon cities' productivity. We also found evidence of a U-shaped relationship between segregation and productivity. According to this finding, a low level of segregation of the high-skilled has a negative impact, but after a certain threshold has been reached this effect changes and becomes positive. Intuition tells us that below that threshold the segregation level is not capable of generating spillovers big enough to offset the productivity losses due to the isolation of the low-skilled group. Moreover, the analysis shows that there is a relationship between productivity, segregation and sectoral specialization. The segregation of high-skilled workers has a negative effect on the productivity of cities where most employment is generated by primary and secondary sectors. The same segregation could have a positive effect on productivity in cities where the bulk of employment is in tertiary sectors.

II. Literature review

A great deal of academic effort has gone into trying to understand the effects that segregation might have on the performance of individuals and cities alike. For a long time, the general view was that segregation had negative consequences only. More recently, a slew of articles have indicated that this phenomenon can affect households in a positive way. Regarding either type of effect, positive or negative, empirical research must deal with a serious problem of identification, and this is particularly true of segregation based on income. The question that has to be answered is: is a household poor because it is segregated, or segregated because it is poor? As a way of dealing with this endogeneity problem, the United States Department of Housing and Urban Development's Moving to Opportunity for Fair Housing (MTO) programme was designed as an experiment, providing randomly selected low-income families living in some of the most disadvantaged urban areas of the United States with the chance, through the provision of housing vouchers, to move to private sector housing in much less distressed communities. After 11 years of empirical research using the MTO data, the Department reached a striking conclusion: segregation had negligible effects on individuals' well-being except in the area of mental health. This finding reopened the discussion on the topic, and new research has been carried out to look at the effects of segregation on well-being from other angles. For instance, Cuttler and Glaeser (1997), Anas (2002), Conejeros and Vargas (2012) and Corvalan and Vargas (2015) look for macro effects of segregation, while Bjerk (2010) investigates segregation effects on different types of crime, finding evidence that segregation increases violent crime, but not crime in the aggregate. Similarly, Kessler and others (2014) and Ludwig and others (2012 and 2013) investigate the impact of segregation on self-reported life satisfaction and mental health. A significant number of these new papers have found that segregation does have effects, but not necessarily in the areas that the traditional literature has identified. In particular, they indicate that segregation has no consequences for an individual's ability to be economically independent. More recently, Chetty, Hendren and Katz (2016) have found an answer to this puzzle: segregation has irreversible effects, which is why all previous studies using MTO data were not able to find significant consequences. These authors study the consequences for individuals who were very young when their families received vouchers under the MTO programme and find that exposure to a better neighbourhood has no impact on individuals' outcomes if it occurs after the age of 13.

Despite its importance, however, little has been said about segregation of the better-off and its consequences for society as a whole.[2] Probably the most important studies to have addressed this issue are Benabou (1993 and 1996) and Oltmans (2011). According to these, the segregation of high-income groups can have either positive or negative consequences. For instance, if higher levels of income are correlated with greater human capital, then the agglomeration of these groups produces positive spillovers. If these spillovers are enough to compensate for the loss of productivity faced by worse-off households owing to the existence of ghettos of low-skilled workers, aggregate city productivity will be greater because of segregation. However, if these spillovers are not enough to compensate for the productivity losses of the worse-off, then the aggregate effects will be negative. Given the relevance of these studies to the present research, the following subsection will discuss Benabou (1993) and Oltmans (2011) in more detail.

1. Segregation of the high-skilled and the outcomes for cities

Benabou (1993) develops a theoretical model for understanding how the segregation of the high-skilled might affect outcomes for cities. In this model, agents decide the skill level they want to achieve (high, low or none) and their residential location. If agents decide that their skill level is to be zero, they will be out of the labour market. An important assumption of this model is that the labour market embraces the whole city. Meanwhile, education is a local public good. In every neighbourhood, whether high-skilled or low-skilled, the more agents invest in education, the easier it is for them to obtain skills, but it is less easy in low-skilled neighbourhoods than in high-skilled ones. This asymmetry makes high-skilled agents bid for land in neighbourhoods inhabited by high-skilled workers, which will affect the city's economic surplus owing to the mix of abilities and the cost of educating the labour force. In consequence, education costs will grow faster in those communities with a high concentration of low-skilled workers. Hence, in their desire to live among peers, high-skilled workers will transform other communities into unproductive ghettos. A key element of this model is the relationship between local and global interactions, i.e. between educational spillovers, which are local to the neighbourhood level, and neoclassical production complementarities, which work at the city level. The segregation of high-skilled workers results in low-skilled workers' ghettos being left outside the labour market, because in these

[2] Since Piketty and Saez (2003), interest in top income analysis has grown very quickly. Given the high level of inequality in Latin America, this sort of analysis can be of great interest and yield numerous important policy implications for the region (see, for instance, Williamson, 2010).

ghettos education costs will be so high that agents will choose to have no skills at all and will therefore be left outside the labour market. Thus, the more easily high-skilled workers can isolate themselves, the higher unemployment will be. When perfect segregation is attained, the productive sector will collapse because the city's production function needs both inputs: high- and low-skilled workers. Therefore, the segregation of high-skilled workers will harm city productivity, because although the segregated high-skilled workers will more easily obtain better qualifications, segregation will deprive them of the low-skilled workers they need to work with.

Local complementarities operate in different ways. The most obvious is a fiscal externality: if schools are financed by local resources and if they provide an input that supplements individual effort, the return on education will be higher in communities with a high concentration of high-skilled workers because they earn higher wages. This mechanism would work through pure human capital externalities as well. These include peer effects in educational and social networks which decrease the cost of getting a job or provide role models for young people, whom the presence of high-skilled workers in the neighbourhood will teach about the importance of education. Lastly, an alternative explanation is provided by the negative externalities and disruptive influence created by some unemployed and low-skilled workers in the form of crime or drug abuse.

A different possibility is suggested by Oltmans (2011), who seeks to cast light on the causal role that racial segregation may play in urban poverty and inequality. The study is empirical and tests this causal role by examining the historical great migration of African Americans and the pattern of railways within cities. To establish a framework of ideas, she presents a very simple model, some of whose main features will now be discussed. First, there are two cities, one integrated C_I and one segregated C_s, that exist for two generations. The proportion of black inhabitants in each city is β and therefore the proportion of white inhabitants is 1-β. The average human capital for black and white inhabitants is μ_{HB} and μ_{HW}, respectively. From the historical record it is inferred that $\mu_{HB} < \mu_{HW}$. Consider the following human capital production function:

$$E[\lambda_2] = f(\lambda_1)\mu_{HI}^{\alpha} \tag{1}$$

Where $E[\lambda_2]$ is the expected value of the human capital of an individual's offspring, λ_1 is the individual's human capital, α_{HI} is the average human capital of the individual's neighbourhood and $\alpha \geq 0$. In C_I, black and white inhabitants are exposed to the same average human capital, $\beta\mu_{HB} + (1-\beta)\mu_{HW}$, while in C_s, white inhabitants are exposed to higher average human capital than black inhabitants, as $\mu_{HB} < \mu_{HW}$. If $\alpha < 1$, then personal human capital and average neighbourhood human capital are substitutes in the production of the next generation's human capital level, so that integration will produce higher human capital than segregation. If a>1, then personal human capital and average neighbourhood human capital are complements, so that segregation will produce higher levels of human capital than integration. The main finding of this work is that segregation increases black poverty and inequality between white and black inhabitants but reduces white poverty and inequality among white inhabitants. This an important study because of the identification strategy used, which makes it possible to isolate the impact of exogenous segregation on an individual's human capital.

Combining the findings of Benabou (1993) and Oltmans (2011) in relation to the segregation of high- and low-skilled workers, we can identify the following line of argument regarding the connection between segregation of high-skilled workers and urban productivity: the segregation of more advantaged individuals generates positive spillovers for them by reducing the costs of acquiring human capital. This process reduces inequality within the most advantaged population but increases inequality between the more advantaged groups and the less advantaged ones. In Oltmans (2011), these groups are white and black inhabitants, while in Benabou (1993), and in the present article as well, they are high-skilled and low-skilled workers. Benabou (1993) points out that since the city production function needs both types of workers, segregation of high-skilled workers will have a negative effect on a city's production because it will raise the cost of acquiring human capital to the extent that low-skilled workers will prefer not to have any education at all, which in turn will cause the city's production to collapse, as it needs both types of workers. But what would happen if the city did not specialize in sectors that needed high-skilled and low-skilled workers as inputs, e.g. if the city specialized in technology or financial services, and consequently the degree of complementarity between high-skilled and low-skilled workers was very low? In this case, it is not clear that segregation would damage city productivity. Indeed, in the extreme case where a city does not need low-skilled workers at all, segregation of high-skilled workers will have a positive effect on its productivity. The empirical answer to this question will depend mainly on the following factors: first, the extent of specialization in industries that do not need low-skilled workers or the share of high-skilled workers in the city production function and, second, the productivity differences between high-skilled and low-skilled workers. The combination of these factors will tell us whether segregation of high-skilled workers will have a positive or negative impact on the city's productivity and will determine the equilibrium level of high-skilled workers' share of the city's total population.

On the basis of these concepts, we expect, other things being equal, to find the following possible relationship between the productivity of Latin American cities and the segregation of high-skilled workers:

(i) Segregation of high-skilled workers will have a negative effect on productivity in cities specializing in primary and secondary sectors.

(ii) Segregation of high-skilled workers will have a positive effect on productivity in cities specializing in tertiary and quaternary sectors.

Therefore, cities specializing in primary and secondary sectors where high-skilled workers are highly segregated should exhibit a low level of productivity, other things being equal, but cities specializing in the same sectors where high-skilled workers are not very segregated will have a high level of productivity. If a city specializes in tertiary or quaternary sectors, the relationship will be exactly the opposite of the one just described.

III. Methodology

1. A reduced form model

To identify which of the situations prevails in Latin American cities, the effect of segregation on productivity is captured in the following reduced form:

$$y_{i,t} = \alpha + \beta_1 s_{i,t} + X_{i,t}\beta_2 + \mu_{i,t}$$

Where $y_{i,t}$ represents productivity, $s_{i,t}$ is residential segregation and $X_{i,t}$ are control variables for city i during period t.

We calculate residential segregation based on education as a proxy for highly-skilled workers in Latin American cities. Specifically, we calculate segregation of household heads with a university degree. Then we obtain cities' productivity and regress productivity against traditional controls and segregation. Lastly, we use an econometric specification capable of dealing with potential endogeneity issues due to omitted variables bias.

2. Segregation measures

(a) The Duncan Segregation Index

This index can be obtained from the Lorenz curve. It represents the maximum vertical distance between the Lorenz curve and the diagonal line representing complete evenness. When the group under study is small in comparison with the number of geographical subareas (such as census districts), the Duncan Segregation Index is heavily affected by the deviation from evenness and is not sensitive to redistribution between geographical subareas where the proportion of the group under study is smaller than the same group's proportion of the city as a whole. With this index, just moving people belonging to the group under study from the geographical subareas where they are overrepresented to geographical subareas where they are underrepresented can affect the level of residential segregation (Massey and Denton, 1988).

The functional form of the Duncan Segregation Index is:

$$D = \sum\nolimits_{i=1}^{n} \left[\frac{t_i}{p_i} - \frac{P}{2TP(1-P)} \right] \tag{2}$$

where t_i and p_i are the total population and minority population of areal unit i, and T and P are the population size and minority proportion of the whole city.

(b) The Gini coefficient

As Massey and Denton (1988) explain, another measure of evenness is the Gini coefficient. Like the Duncan Segregation Index, it can be derived from the Lorenz curve and varies between 0.0 and 1.0, with 1.0 indicating maximum segregation. The Gini coefficient corresponds to the mean absolute difference between minority proportions weighted across all pairs of subareas, expressed as a proportion of the maximum weighted mean difference.

$$Gini = \frac{\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} t_i t_j p_i - p_j}{2T^2 P(1-P)} \tag{3}$$

Where t_i and p_i are the total population and minority population of areal unit i, and T and P are the population size and minority proportion of the whole city.

(c) City productivity

The *Competitive Cities in the Global Economy* report of the OECD Territorial Reviews series (OECD, 2006) shows that most Organisation for Economic Co-operation and Development (OECD) metro regions have higher productivity and growth than the average for the countries they are in. The report says that "...most OECD metro-regions have a higher GDP per capita than their national average (66 out of 78 metro-regions) and higher labour productivity (65 out of 78 metro-regions) and many of them tend to have faster growth rates than their countries" (OECD, 2006). Cities are centres of economic activity. As such, they are the main platforms for business, commerce and trade. This concentration of activity is at the root of the agglomeration economies which have been identified in the economic literature as the main source of productivity gains. The first sources of positive agglomeration effects were described by Marshall (1920), who argued that having an industry located in one place resulted in labour market pooling, input sharing and knowledge spillovers that fostered the continued growth of that industry. In contrast to Marshallian specialization, Jacobs (1969) stresses the importance of urban diversity for the cross-fertilization of ideas. Strange and Rosenthal (2004) describe three sources of agglomeration economies that go beyond Marshall's and Jacobs' descriptions: the home market effect, consumption and rent-seeking. The home market effect described by Krugman (1980) comes from the interaction between internal scale economies in production and transport costs. This interaction leads to expansion of the home market in a self-reinforcing process of agglomeration. Consumption and rent-seeking are sources of agglomeration economies that work through mechanisms unrelated to productivity. On the empirical side, various studies have tried to measure the impact of agglomeration economies on the productivity of cities. Looking at the manufacturing sector, Fogarty and Garofalo (1978) find the elasticity of productivity to city size to be about 0.05 for a sample of 13 large metropolitan areas from 1957 to 1977. This means that the total factor productivity (TFP) of the manufacturing sector increases by 10% when the size of the city is doubled. Tabuchi (1986), using labour productivity, finds this elasticity to be about 0.02 for Japanese cities in 1980. These studies show the positive relationship between agglomeration economies and productivity in cities.

Whether agglomeration economies derive from city size or industry size is relevant for metropolises in Latin American. Most of the economies in Latin America are dependent on primary commodities which are produced close to small cities. The abundance of nearby natural resources creates conditions favourable to the production of such commodities. In these cities, the industry is large, which means that productivity is high relative to bigger cities. Antofagasta in Chile is a good example of a small city with a large mining industry. Although the copper is produced in rural areas, the sector that supplies services to the mining industry operates mainly in the city, and its productivity is high. Sveikauskas, Gowdy and Funk (1988) show that in these cases city productivity is high because of the large volume of natural resources in the area, suggesting that industry concentration is not enough to obtain high productivity.

Different measures can be used to compute the productivity of an economy. TFP is a legacy of the neoclassical literature (Solow, 1957) and one of the most widely used measures. An economy increases its productivity when it produces more with the same amount of labour and capital. Computing the TFP of a city requires calculation of its stock of capital and the number and characteristics of its workers. Although employee numbers are available, data on capital stock are not for most Latin America cities. In OECD (2006), labour productivity, computed as the ratio between GDP at purchasing power parity (PPP) and employment, is used as the primary measure for the productivity of metro-regions. Sveikauskas (1975) uses labour productivity in a set of manufacturing sectors as a proxy for city productivity. This measure is widely employed in the literature as presented by Eberts and McMillan (1999). Labour productivity has the advantage of being easy to calculate because the information requirements are low.

Following this literature, and in view of the poor availability of information for Latin American cities, labour productivity will be used as a proxy for city productivity. The labour productivity of a city c is computed as:

$$y_c = \frac{Y_c}{L_c} \tag{4}$$

Where Y_C and L_C are, respectively, value added and the total number of workers in city c. City value added is computed as:

$$Y_c = \sum_{i=1}^{n} \frac{l_{i,c}}{L_{i,N}} Y_i^N \tag{5}$$

Where Y_i^N is the value added by sector i in the national economy, l_{ic} is the number of employees working in sector i in city r, and $L_{i,N}$ is the total number of workers in the sector in the national economy. Using this specification to compute productivity involves the assumption that the technology employed to produce at the city and country level is the same in each economic sector. The specificity of the city is captured by the specificity index. This means that agglomeration affects the proposed productivity measure through the self-selection of economic sectors in each city. Cities have more workers in sectors where agglomeration has a greater effect.

IV. Data

1. Segregation data

As mentioned above, we use census samples from the Integrated Public Use Microdata Series (IPUMS). The information has been gathered for metropolitan areas. To obtain consistent and comparable information is a considerable challenge. To achieve this, we have sacrificed accuracy and granularity in some metropolitan areas. For instance, samples for metropolitan areas in Brazil have very detailed information down to the stratum level, but samples from other countries do not have the same level of detail. Consequently, for the calculation of segregation indices, we have used municipalities as the sub-areal unit. We have proceeded in this way in order to maintain consistency between all the indices calculated for each city, which enables us to make comparisons between metropolitan areas and provides a reasonable number of observations for the empirical analysis. We calculate segregation indices for 49 metropolitan areas around the year 2000 and 49 around the year 2010. We calculate 23 indices for each metropolitan area, but in view of the high level of correlation that they exhibit we have used only the Duncan and Gini indices for the analysis here. To calculate segregation, we define high-skilled individuals as household heads with a university degree. The metropolitan areas considered are shown in table 1. The specific metropolitan areas for each country and year are:

Argentina: In the case of Argentina, the cities are Greater Buenos Aires, Córdoba, Mendoza and Rosario. Greater Buenos Aires includes the Autonomous City of Buenos Aires and the Province of Buenos Aires. In the cases of Córdoba, Mendoza and Rosario, the provinces of Córdoba, Mendoza and Santa Fe, respectively, were considered.

Brazil: For Brazil, we collect information on the 10 biggest metropolitan regions: São Paulo, Rio de Janeiro, Salvador, Fortaleza, Belo Horizonte, Curitiba, Porto Alegre, Goiânia, Recife and Belém.

Bolivia (Plurinational State of): Information on the departments of La Paz, Cochabamba and Santa Cruz is collected for the metropolitan areas of the same names.

Chile: Instead of IPUMS data, information from the National Socioeconomic Survey (CASEN) for 2000 and 2009 is used to calculate segregation indices for Greater Santiago, Antofagasta, Viña del Mar-Valparaíso, Concepción and La Serena-Coquimbo in Chile. Greater Santiago consists of 30 municipalities belonging to the Santiago metropolitan area, while the metropolitan areas of Antofagasta, Viña del Mar-Valparaíso, Concepción and La Serena-Coquimbo consist of the provinces of Antofagasta, Valparaíso, Concepción and Elqui, respectively.

Colombia: The Colombian cities covered are Medellín, Bogotá and Barranquilla. The department of Antioquia is used as a proxy for the Medellín metropolitan area, the departments of Bogotá and Cundinamarca for the Bogotá metropolitan area and the department of Atlántico for the Barranquilla metropolitan area.

Costa Rica: Information on the province of San José is used as a proxy for the San José metropolitan area.

Dominican Republic: The Santo Domingo metropolitan area comprises the province of Santo Domingo.

Ecuador: The cities included are Guayaquil, Quito, Cuenca and Santo Domingo, and data were collected for the provinces of Guayas, Pichincha, Azuay and Santo Domingo, respectively.

Mexico: The metropolitan area of Valley of Mexico is made up of 76 municipalities (*delegaciones*), 11 belonging to Mexico City, 59 to Mexico State and 1 to Hidalgo State. The other metropolitan areas are Guadalajara, Monterrey, Puebla, Toluca, Tijuana, Ciudad Juárez, Laguna, San Luis de Potosí and León. All meet the definition of a metropolitan area given by the Mexican National Institute of Statistics and Geography.

Panama: The province of Panamá was used as a proxy for the Panama City metropolitan area.

Paraguay: The Asunción metropolitan area is made up of two districts, Capital and Central.

Peru: The Peruvian metropolitan areas considered here are Lima/Callao, Chiclayo, Arequipa and Trujillo, with the provinces of Lima and Callao, Lambayeque, Arequipa and La Libertad, respectively, being used as proxies.

Uruguay: In the case of Uruguay, the information is for the department of Montevideo.

Table 1

Latin America (13 countries): cities included in the sample for the study of segregation

Country	Cities	Country	Cities
Argentina	Greater Buenos Aires	Dominican Republic	Santo Domingo
	Córdoba	Ecuador	Guayaquil
	Mendoza		Quito
	Rosario		Cuenca
Bolivia (Plurinational State of)	La Paz		Santo Domingo
	Cochabamba	Mexico	Mexico City
	Santa Cruz		Guadalajara
Brazil	São Paulo		Monterrey
	Rio de Janeiro		Puebla
	Salvador		Toluca
	Fortaleza		Tijuana
	Belo Horizonte		Juárez
	Curitiba		Laguna
	Porto Alegre		Querétaro
	Goiânia		San Luis de Potosí
	Recife		León
	Belém	Panama	Panama City
Colombia	Medellín	Paraguay	Greater Asunción
	Bogotá	Peru	Lima
	Barranquilla		Chiclayo
Costa Rica	San José		Arequipa
Chile	Greater Santiago		Trujillo
	Antofagasta	Uruguay	Montevideo
	Viña del Mar-Valparaíso La Serena-Coquimbo		Concepción

Source: Prepared by the authors.

Tables 2 and 3 present segregation rankings based on the Duncan and Gini indices, respectively. On both measures, the Chilean capital Santiago was by far the most segregated metropolitan area in 2000 and 2010. In the Duncan Segregation Index rankings, Brazil had 4 cities among the 10 most segregated in 2000 and 2010 (Porto Alegre, Belo Horizonte, Curitiba and Rio de Janeiro). Bolivian cities (Santa Cruz and La Paz) were also among the most segregated. Montevideo is another city which exhibits high levels of segregation on both the Duncan and Gini indices.

Table 2
Latin America (13 countries): segregation rankings of cities based on the Duncan Segregation Index, 2000 and 2010

Ranking in 2000			Ranking in 2010		
Country	City	Duncan index value	Country	City	Duncan index value
Chile	Santiago	0.4758	Chile	Santiago	0.5237
Brazil	Porto Alegre	0.4264	Bolivia (Plurinational State of)	Santa Cruz	0.4092
Bolivia (Plurinational State of)	Santa Cruz	0.4092	Uruguay	Montevideo	0.3869
Uruguay	Montevideo	0.3869	Brazil	Porto Alegre	0.3864
Brazil	Belo Horizonte	0.3845	Bolivia (Plurinational State of)	La Paz	0.3834
Bolivia (Plurinational State of)	La Paz	0.3834	Paraguay	Asunción	0.3825
Paraguay	Asunción	0.3825	Brazil	Belo Horizonte	0.3444
Brazil	Curitiba	0.3496	Brazil	Curitiba	0.3404
Brazil	Rio de Janeiro	0.3346	Brazil	Rio de Janeiro	0.3143
Argentina	Buenos Aires	0.3317	Colombia	Medellín	0.3114
Argentina	Mendoza	0.3222	Argentina	Buenos Aires	0.3108
Colombia	Medellín	0.3114	Argentina	Mendoza	0.3071
Peru	Trujillo	0.2954	Mexico	Toluca	0.3024
Mexico	Toluca	0.2898	Peru	Trujillo	0.2954
Argentina	Córdoba	0.2852	Mexico	Mexico City	0.2927
Ecuador	Cuenca	0.2818	Ecuador	Cuenca	0.2818
Colombia	Barranquilla	0.2787	Colombia	Barranquilla	0.2787
Bolivia (Plurinational State of)	Cochabamba	0.2763	Bolivia (Plurinational State of)	Cochabamba	0.2763
Mexico	Mexico City	0.2715	Brazil	Recife	0.2594
Mexico	Monterrey	0.268	Chile	Concepción	0.2565
Costa Rica	San José	0.2579	Argentina	Córdoba	0.2514
Brazil	Fortaleza	0.2493	Brazil	Fortaleza	0.2408
Dominican Republic	Santo Domingo	0.2362	Mexico	Puebla	0.2383
Argentina	Rosario	0.2294	Mexico	Monterrey	0.2379
Mexico	Laguna	0.224	Costa Rica	San José	0.2326
Chile	Concepción	0.2202	Argentina	Rosario	0.2322
Mexico	Puebla	0.215	Mexico	Guadalajara	0.2261
Brazil	Recife	0.2148	Dominican Republic	Santo Domingo	0.2161
Ecuador	Guayaquil	0.213	Ecuador	Guayaquil	0.213
Brazil	São Paulo	0.2055	Mexico	Querétaro	0.1837
Mexico	Guadalajara	0.186	Brazil	São Paulo	0.1832
Brazil	Belém	0.1805	Colombia	Bogotá	0.1788
Colombia	Bogotá	0.1788	Brazil	Belém	0.1757
Chile	La Serena-Coquimbo	0.172	Peru	Arequipa	0.1705
Peru	Arequipa	0.1705	Chile	Viña del Mar-Valparaíso	0.1606
Peru	Chiclayo	0.1517	Mexico	Laguna	0.1596
Panama	Panama City	0.1494	Brazil	Salvador	0.1543
Ecuador	Quito	0.1489	Peru	Chiclayo	0.1517
Brazil	Salvador	0.1364	Ecuador	Quito	0.1489
Mexico	Querétaro	0.1334	Panama	Panama City	0.1404
Mexico	San Luis Potosí	0.1302	Mexico	Juárez	0.1389
Mexico	León	0.118	Mexico	León	0.1126
Ecuador	Santo Domingo	0.111	Ecuador	Santo Domingo	0.111
Mexico	Juárez	0.0892	Mexico	San Luis Potosí	0.1087
Chile	Viña del Mar-Valparaíso	0.0809	Peru	Lima	0.0754
Peru	Lima	0.0754	Chile	La Serena-Coquimbo	0.07
Mexico	Tijuana	0.0479	Chile	Antofagasta	0.0651
Chile	Antofagasta	0.0366	Brazil	Goiânia	0.0557
Brazil	Goiânia	0.0335	Mexico	Tijuana	0.0225

Source: Prepared by the authors.

Table 3
Latin America (13 countries): segregation rankings of cities based on the Gini coefficient, 2000 and 2010

Ranking in 2000			Ranking in 2010		
Country	City	Gini	Country	City	Gini
Chile	Santiago	0.6323	Chile	Santiago	0.6547
Uruguay	Montevideo	0.5224	Uruguay	Montevideo	0.5224
Bolivia (Plurinational State of)	Santa Cruz	0.4871	Bolivia (Plurinational State of)	Santa Cruz	0.4871
Brazil	Porto Alegre	0.4675	Paraguay	Asunción	0.4642
Paraguay	Asunción	0.4642	Brazil	Porto Alegre	0.4304
Argentina	Mendoza	0.4375	Mexico	Mexico City	0.4144
Argentina	Buenos Aires	0.4335	Argentina	Mendoza	0.4063
Brazil	Belo Horizonte	0.4049	Bolivia (Plurinational State of)	La Paz	0.3877
Bolivia (Plurinational State of)	La Paz	0.3877	Brazil	Belo Horizonte	0.3859
Mexico	Mexico City	0.3807	Colombia	Medellín	0.3678
Colombia	Medellín	0.3678	Mexico	Toluca	0.3646
Mexico	Monterrey	0.3661	Argentina	Buenos Aires	0.3635
Brazil	Rio de Janeiro	0.3659	Brazil	Curitiba	0.3561
Brazil	Curitiba	0.3582	Mexico	Monterrey	0.3497
Costa Rica	San José	0.3576	Brazil	Rio de Janeiro	0.3455
Mexico	Toluca	0.3504	Chile	Concepción	0.3326
Argentina	Córdoba	0.3307	Costa Rica	San José	0.3306
Peru	Trujillo	0.3237	Peru	Trujillo	0.3237
Dominican Republic	Santo Domingo	0.3016	Mexico	Guadalajara	0.3044
Chile	Concepción	0.294	Argentina	Córdoba	0.3021
Colombia	Barranquilla	0.2927	Dominican Republic	Santo Domingo	0.2965
Ecuador	Cuenca	0.2837	Brazil	Recife	0.2963
Bolivia (Plurinational State of)	Cochabamba	0.2836	Colombia	Barranquilla	0.2927
Mexico	Guadalajara	0.267	Mexico	Querétaro	0.2883
Argentina	Rosario	0.2587	Ecuador	Cuenca	0.2837
Brazil	Recife	0.2547	Bolivia (Plur. State of)	Cochabamba	0.2836
Brazil	Fortaleza	0.2516	Argentina	Rosario	0.2677
Ecuador	Guayaquil	0.243	Mexico	Puebla	0.2574
Brazil	São Paulo	0.2374	Brazil	Fortaleza	0.2449
Mexico	Puebla	0.2374	Ecuador	Guayaquil	0.243
Mexico	Laguna	0.237	Brazil	São Paulo	0.21
Chile	La Serena-Coquimbo	0.1948	Chile	Viña del Mar-Valparaíso	0.2088
Brazil	Belém	0.1862	Colombia	Bogotá	0.1862
Colombia	Bogotá	0.1862	Brazil	Belém	0.1843
Peru	Arequipa	0.173	Mexico	Laguna	0.179
Panama	Panama City	0.1573	Peru	Arequipa	0.173
Peru	Chiclayo	0.1518	Brazil	Salvador	0.1584
Ecuador	Quito	0.1501	Peru	Chiclayo	0.1518
Brazil	Salvador	0.1417	Panama	Panama City	0.1512
Mexico	Querétaro	0.1412	Ecuador	Quito	0.1501
Mexico	San Luis Potosí	0.1302	Mexico	Juárez	0.1389
Ecuador	Santo Domingo	0.126	Ecuador	Santo Domingo	0.126
Mexico	León	0.1207	Mexico	León	0.1154
Chile	Viña del Mar-Valparaíso	0.1148	Mexico	San Luis Potosí	0.1087
Mexico	Juárez	0.0892	Chile	La Serena-Coquimbo	0.0924
Peru	Lima	0.079	Peru	Lima	0.079
Mexico	Tijuana	0.0485	Chile	Antofagasta	0.0654
Chile	Antofagasta	0.0368	Brazil	Goiânia	0.0561
Brazil	Goiânia	0.0335	Mexico	Tijuana	0.0227

Source: Prepared by the authors.

Among the least segregated cities are Antofagasta and Valparaíso in Chile, Goiânia in Brazil, Tijuana and León in Mexico, Lima in Peru and Santo Domingo in Ecuador. We have also calculated the segregation of household heads without any qualifications. Table 4 shows descriptive statistics for both types of segregation. As can be appreciated, segregation is greater in the case of high-skilled workers and is relatively constant in both cases.

Table 4
Latin America (13 countries):[a] descriptive statistics for segregation by skill groups, 2000 and 2010

Variable	Mean	Standard deviation	Minimum	Maximum
Duncan Segregation Index high-skilled, full sample	0.2310194	0.1066767	0.0225	0.5237
Duncan Segregation Index high-skilled, 2000	0.2314388	0.1083908	0.0355	0.4758
Duncan Segregation Index high-skilled, 2010	0.2306	0.1060564	0.0225	0.5237
Duncan Segregation Index low-skilled, full sample	0.1791367	0.0849578	0.0151	0.3958
Duncan Segregation Index low-skilled, 2000	0.1799375	0.0827937	0.0359	0.3888
Duncan Segregation Index low-skilled, 2010	0.1779898	0.0886876	0.0151	0.3958

Source: Prepared by the authors.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

If these results are compared with those of cities in more developed countries, it transpires that segregation values are not much different. For instance, table 5 presents the evolution of high-income and low-income segregation in the United States between 1970 and 2009. Segregation levels are very similar to those in Latin American cities, although not quite as high. It can be observed that segregation of the better-off is systematically higher in Latin American cities as well. However, mean values have increased in the United States while holding more or less steady in Latin America.

Table 5
United States: average segregation by income groups, 1970–2009

	1970	1980	1990	2000	2007	2008	2009
Segregation of poverty	0.112	0.124	0.153	0.146	0.158	0.163	0.163
Segregation of affluence	0.173	0.156	0.189	0.185	0.195	0.202	0.200

Source: Prepared by the authors.

2. Productivity data

Data-gathering for this project involved three main challenges. First, the information had to be collected from countries that have different models for constructing their statistical information. Second, there is no agreement between countries on what defines a city. Third, there are large differences in data availability between Latin American countries. In order to reduce the sources of variability, most of the data used to compute the indices of segregation and employment were collected from IPUMS-International. This is an effort by the Minnesota Population Center at the University of Minnesota to inventory, preserve, harmonize and disseminate census microdata from around the world. The information on the sectoral value added of each country was obtained from OECD input-output tables (OECD, 2021). Lastly, when harmonized data were lacking, information from the national institutes of statistics and central banks of each country was used. Two criteria were applied to select the metropolises to be included in the regressions, namely the importance of the city within a country and the availability of data for the city. The importance of a city was mainly measured by its population relative to the national population. Following these criteria, 49 cities in 13 countries are presented. In many cases, lack of information from the countries means that the information cannot be computed for specific years (table A1.1 itemizes data availability for each city around the initial and final year). When the demographic information does not match the value added information, the demographic data are updated in accordance with the population growth rate reported by each country during the period. In order to compare the productivity of city c at time t with that of another city in a different country or in the period ($t + 1$), all productivity figures were converted using the Big Mac index. In addition, productivity converted to PPP dollars and updated using the dollar inflation rate was used to compare productivity across countries. Table 6 provides abbreviated city rankings by productivity per worker at PPP in 2000 and 2010. It can be seen that the positions of the most productive cities changed considerably over the 10-year period. However, the ranking is more static where the bottom-ranked five cities are concerned (table A1.2 in annex A1 gives full city rankings based on the Big Mac index).

Table 6

Latin America (6 countries): rankings of cities by productivity, 2000 and 2010

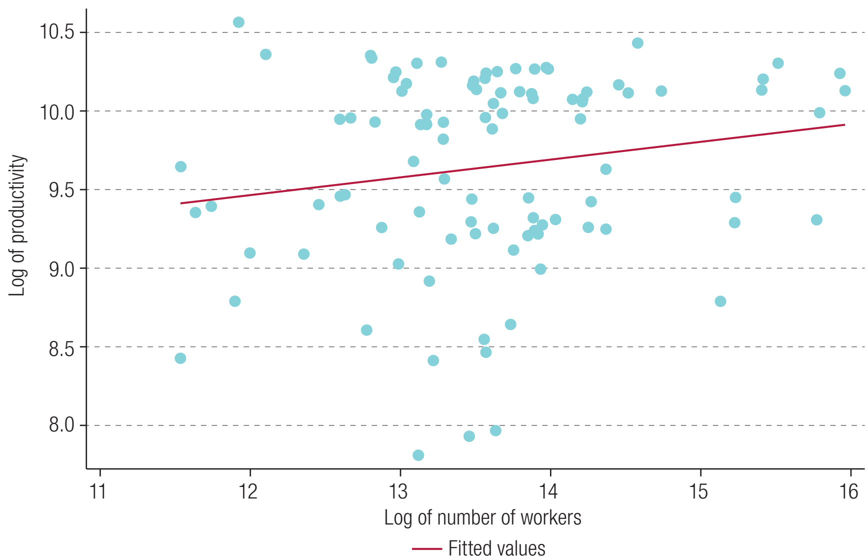
Ranking in 2000	Ranking in 2010	Country	City
18	1	Chile	Antofagasta
19	2	Chile	Santiago
23	3	Chile	La Serena-Coquimbo
20	4	Chile	Viña del Mar-Valparaíso
21	5	Chile	Concepción
13	6	Uruguay	Montevideo
1	7	Argentina	Buenos Aires
2	8	Argentina	Mendoza
45	45	Paraguay	Asunción
42	46	Ecuador	Santo Domingo
47	47	Bolivia (Plurinational State of)	La Paz
48	48	Bolivia (Plurinational State of)	Santa Cruz
49	49	Bolivia (Plurinational State of)	Cochabamba

Source: Prepared by the authors.

Figure 1 is a scatter chart plotting the number of workers in each city against the city's productivity. The line shows that there is a positive relationship, suggesting the presence of economies of agglomeration. In the upper-left corner are two small cities with high productivity. These are Antofagasta and La Serena-Coquimbo in Chile, where the mining sector is influential.

Figure 1

Latin America (13 countries):[a] agglomeration economies in selected cities, 2000 and 2010



Source: Prepared by the authors.

[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

V. Empirical analysis and results

The first empirical exercise that we perform is a pooled regression. The reason is that while collecting consistent and comparable information for 49 cities in Latin America is a challenging task, for the purposes of empirical analysis this is still only a small sample. Using information for 2000 and 2010 in a pooled regression increases the sample to 98 observations, which is a more suitable number for econometric analysis. The additional controls used for this regression are the proportion of high-skilled workers in the metropolitan area, the per capita GDP in PPP of the country concerned, a year dummy and city population. The dependent variables used are productivity deflated by the Big Mac index and productivity in PPP terms, as explained earlier. Descriptive statistics for these variables are shown in table 7. As can be appreciated, the mean of all these variables increased during the period 2000–2010. It can also be observed that the continent is quite heterogenous and unequal.

Table 7
Latin America (13 countries):[a] descriptive statistics of variables for empirical analysis of segregation in selected cities, 2000 and 2010

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
2000					
Big Mac index	49	6 260.575	2 894.455	1 090.809	11 166.74
Productivity	49	13 592.87	6 724.517	2 465.228	26 984.03
Per capita GDP	49	8 574.673	2 445.306	3 497	13 188
Proportion of high-skilled workers	49	0.1024776	0.0324008	0.0318	0.1661
Population	49	1 187 125	1 565 015	102 183	7 210 874
2010					
Big Mac index	49	6 627.128	3 221.966	1 208.268	11 618.85
Productivity	49	22 534.07	8 384.848	4 502.31	38 739.53
Per capita GDP	49	13 292.18	3 637.439	5 289	1 8249
Proportion of high-skilled workers	49	0.1244531	0.0436779	0.0318	0.2298
Number of workers	49	1 441 099	1 820 342	112 930	8 545 510

Source: Prepared by the authors.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Intuition says that these correlations should all be positive: the most productive cities should have higher average income per worker and income per capita and should attract more people to work there, drawing in a more educated labour force. Figure 2 presents scatter plots showing the unconditional relationship between these variables and productivity (log of the Big Mac index). As expected, all these variables have a positive effect on productivity. The clearest impact is from per capita GDP and income per worker, but the proportion of high-skilled workers can be seen to have a similar effect. The relationship between productivity and the number of workers in a city is weaker, albeit still positive. Of course, these are just correlations, and it should be borne in mind that there is a major issue with endogeneity between the variables.

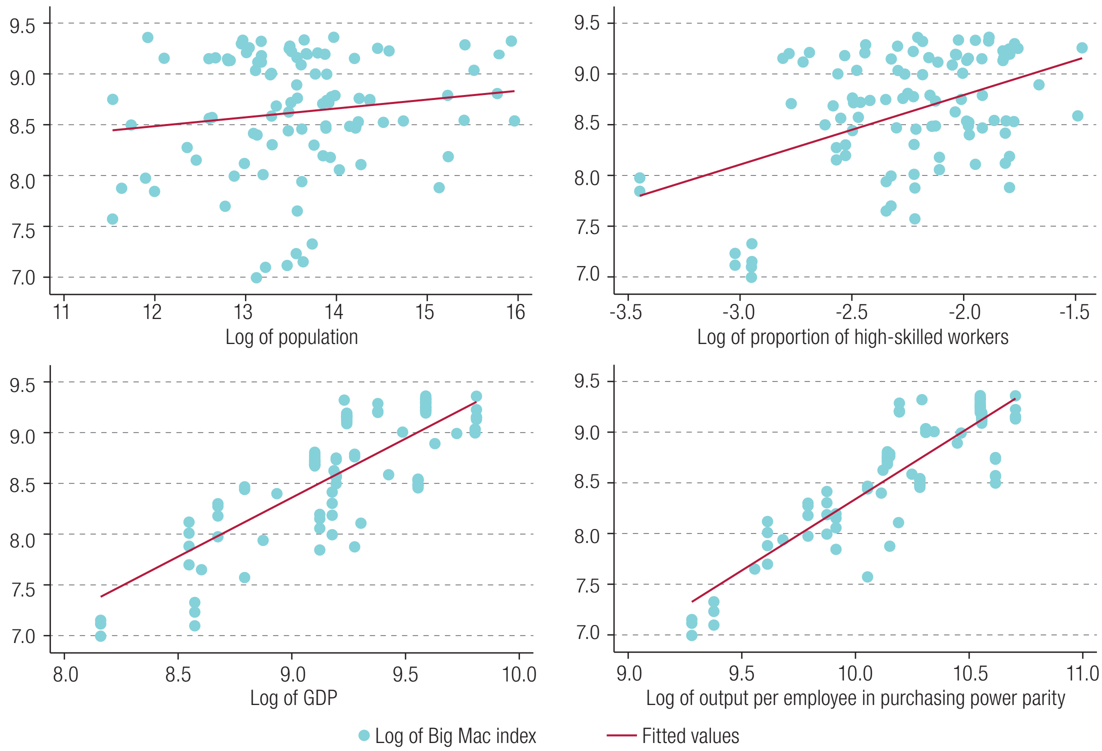
For robustness we have conducted four regressions using as the dependent variables productivity measured in PPP terms and deflated by the Big Mac index and segregation as measured by the Duncan and Gini indices. Standard errors are clustered by country. Table 8 shows the results of these four pooled regressions.[3] Segregation is not significant in any of them, but the sign of the relevant parameters is always negative. However, this regression is most certainly affected by an omitted variable bias problem. As Oltmans (2011, p. 3) explains: "…some unmeasured economic, political, or other attribute may lead certain cities to have both more segregation and more negative characteristics than other cities. For example, cities such as Detroit are highly segregated and their residents have poor economic outcomes, but other characteristics, such as political corruption or the legacy of a manufacturing economy, may

[3] We have performed multicollinearity tests for this set of regressions and those that will be presented below, namely the variance inflation factor (VIF), square root of the VIF, tolerance and R-squared tests. Results are presented in table A1.4. In none of the cases analysed is there any evidence of multicollinearity.

be a cause of both. Failure to entirely capture such attributes will cause omitted variable bias in OLS estimates of the relationship between segregation and population characteristics."

Figure 2

Latin America (13 countries):[a] unconditional relationship between productivity and population, high-skilled workers, total GDP and per capita income in selected cities, 2000 and 2010



Source: Prepared by the authors.

[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Table 8

Latin America (13 countries):[a] pooled regressions from empirical analysis of segregation in selected cities, 2000 and 2010

	(1)	(2)	(3)	(4)
	Log of productivity	Log of productivity	Log of Big Mac index	Log of Big Mac index
Duncan Segregation Index	-0.100		-0.240	
	(0.186)		(0.254)	
Proportion of high-skilled workers	1.519*	1.548*	1.620**	1.677**
	(0.560)	(0.550)	(0.441)	(0.433)
Log of GDP	1.481***	1.486***	1.554***	1.564***
	(0.0616)	(0.0620)	(0.0551)	(0.0568)
Log of number of workers	0.0190	0.0166	0.0231	0.0191
	(0.0443)	(0.0444)	(0.0590)	(0.0592)
Year dummy	-0.141	-0.143	-0.673	-0.677
	(0.0899)	(0.0890)	(0.0761)	(0.0748)
Gini coefficient		-0.0296		-0.110
		(0.150)		(0.212)
Constant	-4.363***	-4.388***	-5.823***	-5.887***
	(0.751)	(0.785)	(0.832)	(0.905)
N	98	98	98	98
R-squared	0.895	0.895	0.837	0.836

Source: Prepared by the authors.

Note: Standard errors are in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.

[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Given the characteristics of our sample, we have opted for a first difference approach which allows us to address the omitted variable problem because it uses repeated observations over time to remove time-invariant omitted variables. As Wooldridge (2001) explains, if we have an omitted variable in the following set of equations:

$$y_{it} = x_{it}\beta + c_i + u_{it}, \quad t = 1, \ldots, T \tag{6}$$

$$y_{i,t-1} = x_{i,t-1}\beta + c_i + u_{it}, \quad t = 1, \ldots, T \tag{7}$$

Then by differencing the two equations we get:

$$\Delta y_{it} = \Delta x_{it}\beta + \Delta u_{it}, \quad t = 2, \ldots, T \tag{8}$$

Which removes the omitted variable c_i. As first differences and fixed effects estimators are numerically equivalent when T=2, we have used a panel data fixed effects model to implement the first differences regressions. As before, standard errors are clustered by country. The results are displayed in table 9.

Table 9
Latin America (13 countries):[a] first differences from empirical analysis of segregation in selected cities, 2000 and 2010

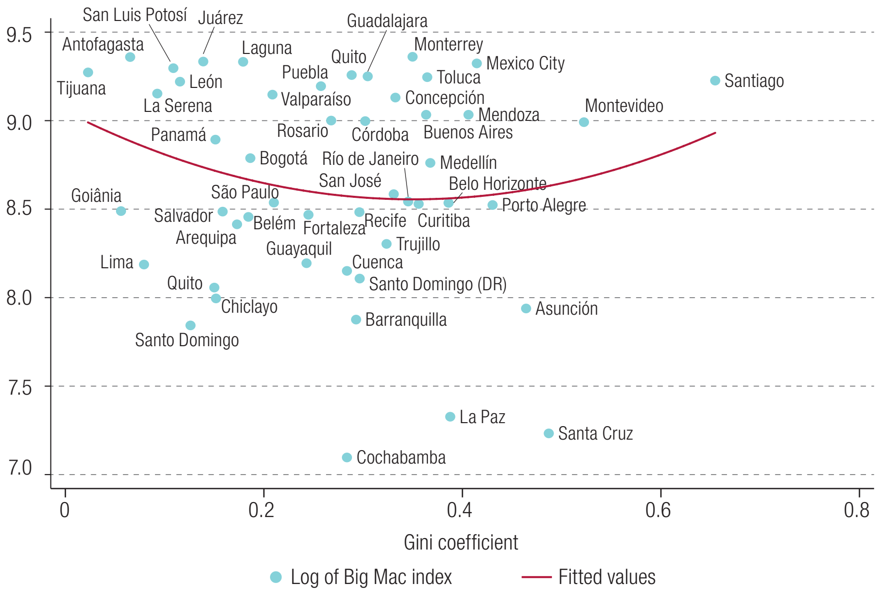
	(1)	(2)	(3)	(4)
	Log of productivity	Log of productivity	Log of Big Mac index	Log of Big Mac index
Duncan Segregation Index	-0.422		1.594*	
	(0.865)		(0.721)	
Proportion of high-skilled workers	1.310	1.335	-1.977	-2.194
	(1.865)	(1.997)	(2.109)	(2.092)
Log of GDP	1.716**	1.711**	1.061	1.074
	(0.553)	(0.543)	(0.700)	(0.716)
Log of number of workers	0.277	0.291	0.0269	-0.0287
	(0.508)	(0.499)	(0.455)	(0.462)
Year dummy	-0.295	-0.295	-0.375	-0.368
	(0.340)	(0.333)	(0.374)	(0.384)
Gini coefficient		-0.362		1.663*
		(1.052)		(0.753)
Constant	-9.866	-10.01	-1.487	-0.911
	(11.65)	(11.52)	(12.15)	(12.38)
N	98	98	98	98
R-squared	0.860	0.860	0.307	0.323

Source: Prepared by the authors.
Note: Standard errors are in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Segregation is still not significant, except in the case where productivity is measured using the Big Mac index and segregation using the Gini index. Something striking on this occasion is that the sign for segregation is positive. This could be the result of the omitted variable bias being corrected by the first difference regression. Nevertheless, we explore the hypothesis of a potential non-linear relationship between productivity and segregation. Figure 3 presents the scatter plot between the log of productivity (Big Mac index) and the Gini index and a quadratic fitted curve.

As can be observed, there seems to be a non-linear relationship between productivity and segregation. Consequently, we should include a segregation quadratic term in the regression. Since the line is U-shaped, we should expect a negative sign for the linear term and a positive one for the quadratic. Table 10 shows the results of this new group of first difference regressions, including the quadratic segregation term.

Figure 3
Latin America (13 countries):[a] Non-linear relationship between productivity and segregation, 2000 and 2010



Source: Prepared by the authors.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Table 10
Latin America (13 countries):[a] first differences with quadratic segregation of variables in empirical analysis of segregation in selected cities, 2000 and 2010

	(1)	(2)	(3)	(4)
	Log of productivity	Log of productivity	Log of Big Mac index	Log of Big Mac index
Duncan Segregation Index	1.142		-2.883*	
	(1.389)		(1.290)	
Duncan Segregation Index 2	-4.040		11.56**	
	(4.466)		(2.938)	
Proportion of high-skilled workers	1.280	1.345	-1.892	-2.054
	(1.719)	(1.998)	(1.994)	(2.079)
Log of GDP	1.743*	1.707**	0.985	1.018
	(0.582)	(0.550)	(0.585)	(0.618)
Log of number of workers	0.283	0.286	0.0104	-0.106
	(0.513)	(0.499)	(0.434)	(0.422)
Year dummy	-0.309	-0.292	-0.334	-0.320
	(0.354)	(0.334)	(0.318)	(0.328)
Gini coefficient		-0.746		-3.631***
		(2.319)		(0.480)
Gini coefficient 2		0.852		11.74***
		(6.604)		(1.567)
Constant	-10.28	-9.874	-0.305	0.984
	(11.99)	(11.61)	(10.97)	(11.10)
N	98	98	98	98
R-squared	0.861	0.860	0.378	0.412

Source: Prepared by the authors.
Note: Standard errors are in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

As expected, the signs are negative in the linear term and positive in the quadratic one in three of the four regressions, ratifying what can be seen in the figure 3 scatter plot. Of the regressions, regression 4 in table 10 is the one that exhibits the best fit. This regression uses the Gini and quadratic Gini as the segregation variable and the logarithm of the Big Mac index as the productivity measure. To learn whether this procedure has been successful in removing the omitted variables problem, we used the Shapiro-Wilk test to ascertain whether the errors of this regression exhibited a normal distribution. In the case of regression 4 in table 10, the hypothesis that the errors have a normal distribution cannot be rejected.

This finding can be explained by the following argument. According to Benabou (1993), the consequences of segregation for cities' outcomes depend on the interplay between local and global complementarities. Local complementarities concern educational spillovers that individuals experience in their neighbourhoods, while global complementarities concern the way the high-skilled and low-skilled labour forces complement each other in the production function. If segregation precludes the correct functioning of global complementarities because it shuts low-skilled workers out of the labour market, then segregation will have a negative effect on a city's productivity and in the long run the economy will collapse. However, if global complementarities are not very significant, e.g. because the city specializes in a production sector such as the financial sector where these complementarities are less important, then the city's output will not suffer from segregation but, on the contrary, will be improved by it.

The left side of the scatter plot in figure 3 shows metropolitan areas such as Tijuana, León, Antofagasta and La Serena. These cities exhibit low levels of segregation and are highly productive. The main production sectors in these cities are manufacturing and mining, which are clearly sectors that need both high-skilled and low-skilled workers, so that in this case a high level of segregation would have a negative impact on cities' outcomes, i.e. for the overall economy, global complementarities are more important than local ones. At the other extreme, Santiago and Montevideo are highly segregated and highly productive. These cities specialize in the tertiary sector. In the case of Santiago, for instance, almost 80% of the economy is accounted for by this sector and 30% by financial services. Consequently, global complementarities between high-skilled and low-skilled workers are less important in these cities, and local spillovers predominate.

The worst situation is that found in Bolivian cities: they specialize in economic sectors which take advantage of global complementarities, such as agriculture, but exhibit high levels of segregation (above the mean). In this case, therefore, segregation has a negative effect on productivity, as can be inferred from figure 3.

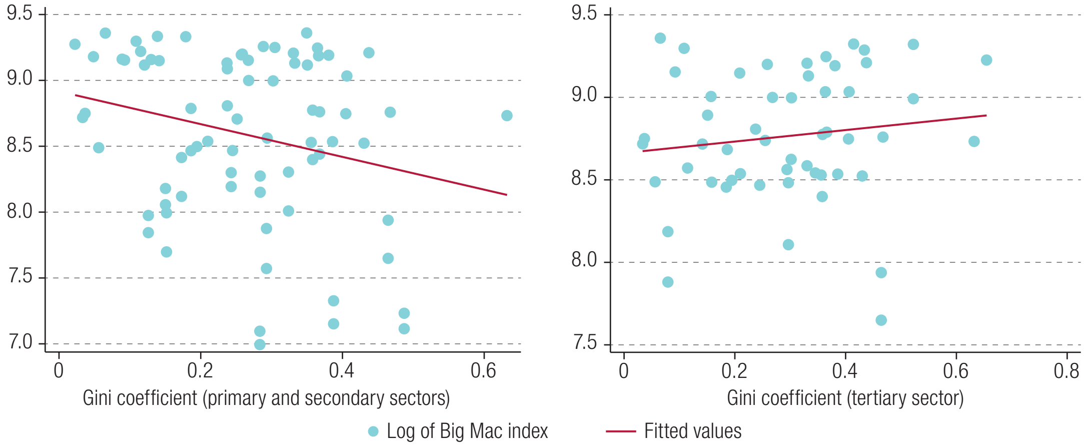
To provide a clearer picture, figure 4 presents the correlation between productivity and the Gini coefficient. The left panel shows this correlation when cities specialize in primary and secondary sectors.[4] As can be appreciated, the correlation in this case is negative. The right panel shows the correlation when cities specialize in tertiary sectors.[5] By contrast with the previous case, the correlation between productivity and high-skilled workers' segregation is positive.

Additionally, we run two regressions incorporating both the scenarios explained in the previous paragraph. Table 11 shows the results of these regressions. In the first case, the correlation is negative and significant at 10%, while in the second case, the correlation is positive but not statistically significant, perhaps because of the small size of the sample (just 53 observations).

[4] The share of a city's primary sector is computed as the proportion of workers employed in agriculture, fishing, forestry, mining and energy supply in the city. The share of the secondary sector is computed as the proportion of workers in manufacturing and construction.

[5] The share of the tertiary sector is computed as the proportion of all the city's workers employed in transportation, communications, financial services, insurance, education, business services, public administration, health services and social work. Note that wholesale and retail trade, hotels and restaurants were left out of this definition.

Figure 4
Latin America (13 countries):[a] correlation of productivity and segregation in selected cities, by sectors of specialization, 2000 and 2010



Source: Prepared by the authors.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Table 11
Latin America (13 countries):[a] sectoral productivity and segregation, 2000 and 2010

Variable	Primary and secondary sectors	Tertiary sector
	Log of Big Mac index	Log of Big Mac index
Gini coefficient	-0.408*	0.22
	(0.239)	(0.21)
Proportion of high-skilled workers	2.109**	1.21
	(0.806)	(0.98)
Log of GDP	1.551***	1.62***
	(0.0894)	(0.15)
Log of population	0.0479	0.0075
	(0.0348)	(0.03)
Year dummy	-0.646***	-0.748***
	(0.0655)	(0.101)
Constant	-6.102***	-6.3***
	(0.866)	(1.52)
Observations	75	53
R-squared	0.87	0.7

Source: Prepared by the authors.
Note: Standard errors are in parentheses. *p < 0.01, **p < 0.05, ***p < 0.1.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

This analysis seems to validate the argument that the segregation of high-skilled workers has a negative effect on productivity when cities specialize in the primary and secondary sectors but a positive effect when cities specialize in the tertiary sector.

VI. Conclusions

The aim of this study has been to cast light on the relationship between Latin American cities and the residential segregation of high-skilled workers. It is important to research this issue because, as the literature has pointed out, spatial isolation of the better-off can be expected to produce momentous effects for the economy as whole. To achieve our goal, we collected census sample information from the Minnesota Population Center website (IPUMS) in order to calculate measures of productivity and segregation indices for cities. Gathering this data was a challenging task owing to differences between countries in the quality, detail and other characteristics of data. We were finally able to obtain consistent and comparable information for 49 cities around 2000 and the same groups of cities around 2010.

Our definition of a city is as close to a functional city as possible. Consequently, we work with metropolitan areas as defined by each country's office of statistics. High-skilled workers are defined as household heads with a university degree. We use the Duncan and Gini segregation indices. We calculated productivity per worker and deflated it by the Big Mac index as a productivity measure, then conducted pooled and first difference regressions using productivity as the dependent variable and segregation plus other controls as independent variables. We found evidence of a non-linear relationship between productivity and segregation of high-skilled workers. Specifically, this relationship presents as a U-shaped curve.

The potential explanation of this relationship is that the consequences of segregation for cities' outcomes depend on the interplay between local and global complementarities. Local complementarities concern educational spillovers that individuals experience in their neighbourhoods, while global complementarities are related to the way high-skilled and low-skilled workers complement each other in the production function. If segregation precludes the correct functioning of global complementarities because it leaves low-skilled workers outside the labour market, then segregation will have a negative effect on a city's productivity and in the long run the economy will collapse. Notwithstanding, if global complementarities are not very significant, for instance because the city specializes in a production sector such as the financial sector where these complementarities are less important, then the city's output will not suffer from segregation.

As an example of this relationship, we can observe what happens in cities such as Tijuana, Antofagasta, Santiago and Santa Cruz de la Sierra. The first two cities have high levels of productivity but low levels of segregation. This can be explained in the light of global and local complementarities. As the two cities specialize in manufacturing and mining, respectively, global complementarity between high-skilled and low-skilled workers can be expected to be strong and more important than local complementarities in education. Since segregation leaves low-skilled workers outside the labour market, and these are important in the production function, segregation in this case will harm productivity.

In the case of Santiago, we observe high productivity and high segregation. This too can be explained by the city's specialization. Because a substantial part of Santiago's economic activity is in the area of financial services, where complementarities between high-skilled and low-skilled workers are less obvious, local complementarities in education turn to be more important, and hence segregation has a positive impact on productivity.

Santa Cruz de la Sierra in the Plurinational State of Bolivia presents the worst combination: it is a city whose main specialization is in agriculture, a sector where production complementarities between high-skilled and low-skilled workers are important, yet it exhibits a high level of segregation, which harms productivity in this case.

The effect of segregation on cities' productivity thus depends on the interaction of production complementarities between high-skilled and low-skilled workers and educational complementarities at the local level, as Benabou (1993) points out, which in turn is strongly connected to the city's specialization. If the city's main production sector requires global complementarities between these two types of workers, as in manufacturing, mining and agriculture, then residential isolation of the high-skilled, which precludes them, will harm productivity. If the city's productive specialization does not require complementarities, however, segregation will not harm productivity but will improve local spillovers in education, which will ultimately enhance the city's outcomes.

Bibliography

Anas, A. (2002), "Prejudice, exclusion, and compensating transfers: the economics of ethnic segregation", *Journal of Urban Economics*, vol. 52, No. 3, Amsterdam, Elsevier.

Benabou, R. (1996), "Equity and efficiency in human capital investment: the local connection", *The Review of Economic Studies*, vol. 63, No. 2, Oxford, Oxford University Press.

___(1993), "Workings of a city: location, education and production", *The Quarterly Journal of Economics*, vol. 108, No. 3, Oxford, Oxford University Press.

Bjerk, D. (2010), "Thieves, thugs, and neighborhood poverty", *Journal of Urban Economics*, vol. 68, No. 3, Amsterdam, Elsevier.

Chetty, R., N. Hendren and L. Katz (2016), "The effects of exposure to better neighborhoods on children: new evidence from the moving to opportunity experiment", *American Economic Review*, vol. 106, No. 4, Nashville, American Economic Association (AEA).

Conejeros, R. and M. Vargas (2012), "Segregation, exclusion and compensating transfers under a dynamic setting", *Applied Economics*, vol. 44, Milton Park, Taylor and Francis.

Corvalan, A. and M. Vargas (2015), "Segregation and conflict: an empirical analysis", *Journal of Development Economics*, vol. 116, Amsterdam, Elsevier.

Cuttler, D. and E. Glaeser (1997), "Are ghettos good or bad?", *The Quarterly Journal of Economics*, vol. 112, No. 3, Oxford, Oxford University Press.

Eberts, R. and D. McMillan (1999), "Agglomeration economies and urban public infrastructure", *Handbook of Urban and Regional Economics*, vol. 3, P. Cheshire and E. Mills (eds.), Amsterdam, Elsevier.

Fogarty, M. and G. Garofalo (1988), "Urban spatial structure and productivity growth in the manufacturing sector of cities", *Journal of Urban Economics*, vol. 23, No. 1, Amsterdam, Elsevier.

Jacobs, J. (ed.) (1969), *The Economy of Cities*, New York, Vintage.

Kessler, R. and others (2014), "Associations of housing mobility interventions for children in high-poverty neighborhoods with subsequent mental disorders during adolescence", *Journal of the American Medical Association*, vol. 311, No. 9, Chicago, American Medical Association (AMA).

Krugman, P. (1980), "Scale economies, product differentiation, and the pattern of trade", *American Economic Review*, vol. 70, No. 5, Nashville, American Economic Association (AEA).

Ludwig, J. and others (2013), "Long-term neighborhood effects on low-income families: evidence from moving to opportunity", *American Economic Review*, vol. 103, No. 3, Nashville, American Economic Association (AEA).

___(2012), "Neighborhood effects on the long-term well-being of low-income adults", *Science*, vol. 337, No. 6101, Washington, D.C., American Association for the Advancement of Science (AAAS).

Marshall, A. (ed.) (1920), *Principles of Economics*, London, Macmillan Publishers.

Massey, D. and N. Denton (1988), "The dimensions of residential segregation", *Social Forces*, vol. 67, No. 2, Oxford, Oxford University Press.

OECD (Organisation for Economic Co-operation and Development) (2021), "Input-Output Tables (IOTs)" [online] https://www.oecd.org/sti/ind/input-outputtables.htm.

___(2006), *Competitive Cities in the Global Economy*, OECD Territorial Reviews, Paris.

Oltmans, E. (2011), "The wrong side(s) of the tracks: the causal effects of racial segregation on urban poverty and inequality", *American Economic Journal: Applied Economics*, vol. 3, No. 2, Nashville, American Economic Association (AEA).

Piketty, T. and E. Saez (2003), "Income Inequality in the United States, 1913-1998", *The Quarterly Journal of Economics*, vol. 118, No. 1, Oxford, Oxford University Press.

Solow, R. (1957), "Technical change and the aggregate production function", *Review of Economics and Statistics*, vol. 39, No. 3, Cambridge, The MIT Press.

Strange, W. and S. Rosenthal (2004), "Evidence on the nature and sources of agglomeration economies", *Handbook of Regional and Urban Economics*, vol. 4, J. Henderson and J. F. Thisse, Amsterdam, Elsevier.

Sveikauskas, L. (1975), "The productivity of cities", *The Quarterly Journal of Economics*, vol. 89, No. 3, Oxford, Oxford University Press.

Sveikauskas, L., J. Gowdy and M. Funk (1988), "Urban productivity: city size or industry size", *Journal of Regional Science*, vol. 28, No. 2, Hoboken, Wiley.

Tabuchi, T. (1986), "Urban agglomeration, capital augmenting technology, and labor market equilibrium", *Journal of Urban Economics*, vol. 20, No. 2, Amsterdam, Elsevier.

Williamson, J. (2010), "Five centuries of Latin American income inequality", *Journal of Iberian and Latin American Economic History*, vol. 28, No. 2, Cambridge, Cambridge University Press.

Wooldridge, J. (2001), *Econometric Analysis of Cross Section and Panel Data*, Cambridge, The MIT Press.

Annex A1

The tables in this annex supplement those presented in the main body of the text.

Table A1.1
Latin America (13 countries):[a] sources of productivity data used in the study of segregation in selected cities

City	Employment data	Value added data	City	Employment data	Value added data
Santiago	2000 CASEN	2000 OECD	San Luis de Potosí	2010 IPUMS	2010 OECD
Santiago	2009 CASEN	2010 OECD	León	2000 IPUMS	2000 OECD
Antofagasta	2000 CASEN	2000 OECD	León	2010 IPUMS	2010 OECD
Antofagasta	2009 CASEN	2010 OECD	Buenos Aires	2001 IPUMS	2000 OECD
Viña del Mar-Valparaíso	2000 CASEN	2000 OECD	Buenos Aires	2010 IPUMS	2010 OECD
Viña del Mar-Valparaíso	2009 CASEN	2010 OECD	Córdoba	2001 IPUMS	2000 OECD
Concepción	2000 CASEN	2000 OECD	Córdoba	2010 IPUMS	2010 OECD
Concepción	2009 CASEN	2010 OECD	Rosario	2001 IPUMS	2000 OECD
La Serena	2000 CASEN	2000 OECD	Rosario	2010 IPUMS	2010 OECD
La Serena	2009 CASEN	2010 OECD	Mendoza	2001 IPUMS	2000 OECD
São Paulo	2000 IPUMS	2000 OECD	Mendoza	2010 IPUMS	2010 OECD
São Paulo	2010 IPUMS	2010 OECD	Medellín	2005 IPUMS	2000 OECD
Rio de Janeiro	2000 IPUMS	2000 OECD	Medellín	2005 IPUMS	2010 OECD
Rio de Janeiro	2010 IPUMS	2010 OECD	Bogotá	2005 IPUMS	2000 OECD
Salvador	2000 IPUMS	2000 OECD	Bogotá	2005 IPUMS	2010 OECD
Salvador	2010 IPUMS	2010 OECD	Barranquilla	2005 IPUMS	2000 OECD
Fortaleza	2000 IPUMS	2000 OECD	Barranquilla	2005 IPUMS	2010 OECD
Fortaleza	2010 IPUMS	2010 OECD	San José	2000 census	2010 OECD
Belo Horizonte	2000 IPUMS	2000 OECD	San José	2011 census	2010 OECD
Belo Horizonte	2010 IPUMS	2010 OECD	La Paz	2001 IPUMS	2000 INE
Curitiba	2000 IPUMS	2000 OECD	La Paz	2012 IPUMS	2010 INE
Curitiba	2010 IPUMS	2010 OECD	Cochabamba	2001 IPUMS	2000 INE
Porto Alegre	2000 IPUMS	2000 OECD	Cochabamba	2012 IPUMS	2010 INE
Porto Alegre	2010 IPUMS	2010 OECD	Santa Cruz	2001 IPUMS	2000 INE
Goiânia	2000 IPUMS	2000 OECD	Santa Cruz	2012 IPUMS	2010 INE
Goiânia	2010 IPUMS	2010 OECD	Lima	2007 census	2000 INEI
Recife	2000 IPUMS	2000 OECD	Lima	2007 census	2010 INEI
Recife	2010 IPUMS	2010 OECD	Chiclayo	2007 census	2000 INEI
Belém	2000 IPUMS	2000 OECD	Chiclayo	2007 census	2010 INEI
Belém	2010 IPUMS	2010 OECD	Arequipa	2007 census	2000 INEI
Mexico City	2000 IPUMS	2000 OECD	Arequipa	2007 census	2010 INEI
Mexico City	2010 IPUMS	2010 OECD	Trujillo	2007 census	2000 INEI
Guadalajara	2000 IPUMS	2000 OECD	Trujillo	2007 census	2010 INEI
Guadalajara	2010 IPUMS	2010 OECD	Asunción	2002 census	2005 Central Bank
Monterrey	2000 IPUMS	2000 OECD	Asunción	2002 census	2010 Central Bank
Monterrey	2010 IPUMS	2010 OECD	Panama City	2000 IPUMS	2007 INEC
Puebla	2000 IPUMS	2000 OECD	Panama City	2010 IPUMS	2010 INEC
Puebla	2010 IPUMS	2010 OECD	Montevideo	2006 census	2000 INE
Toluca	2000 IPUMS	2000 OECD	Montevideo	2011 census	2010 INE
Toluca	2010 IPUMS	2010 OECD	Guayaquil	2001 IPUMS	2000 Central Bank
Tijuana	2000 IPUMS	2000 OECD	Guayaquil	2001 IPUMS	2010 Central Bank
Tijuana	2010 IPUMS	2010 OECD	Quito	2001 IPUMS	2000 Central Bank

Table A1.1 (concluded)

City	Employment data	Value added data	City	Employment data	Value added data
Juárez	2000 IPUMS	2000 OECD	Quito	2001 IPUMS	2010 Central Bank
Juárez	2010 IPUMS	2010 OECD	Cuenca	2001 IPUMS	2000 Central Bank
Laguna	2000 IPUMS	2000 OECD	Cuenca	2001 IPUMS	2010 Central Bank
Laguna	2010 IPUMS	2010 OECD	Santo Domingo, Dominican Republic	2002 IPUMS	2000 Central Bank
Querétaro	2000 IPUMS	2000 OECD	Santo Domingo, Dominican Republic	2010 IPUMS	2010 Central Bank
Querétaro	2010 IPUMS	2010 OECD	Santo Domingo, Ecuador	2001 IPUMS	2007 Central Bank
San Luis de Potosí	2000 IPUMS	2000 OECD	Santo Domingo, Ecuador	2010 IPUMS	2010 Central Bank

Source: Prepared by the authors.
Note: CASEN: National Socioeconomic Survey; IPUMS: Integrated Public Use Microdata Series; OECD: Organisation for Economic Co-operation and Development; INE: National Institute of Statistics; INEI: National Institute of Statistics and Informatics; INEC: National Institute of Statistics and Census.
[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.

Table A1.2
Latin America (13 countries): rankings of cities on the Big Mac index, 2000 and 2010

Ranking in 2000			Ranking in 2010		
Country	City	Big Macs	Country	City	Big Macs
Uruguay	Montevideo	11166.73965	Mexico	Monterrey	11618.84563
Argentina	Buenos Aires	10793.61334	Chile	Antofagasta	11598.66157
Argentina	Mendoza	9996.449794	Mexico	Juárez	11318.6198
Argentina	Córdoba	9961.192768	Mexico	Laguna	11291.11744
Argentina	Rosario	9891.552209	Mexico	Mexico City	11193.25867
Mexico	Mexico City	9811.814948	Mexico	San Luis Potosí	10902.27451
Mexico	Monterrey	9770.052587	Mexico	Tijuana	10651.70953
Mexico	Tijuana	9697.043644	Mexico	Querétaro	10485.91086
Mexico	Juárez	9519.388056	Mexico	Guadalajara	10406.90449
Mexico	San Luis Potosí	9492.556654	Mexico	Toluca	10364.67466
Mexico	Guadalajara	9436.970204	Chile	Santiago	10161.11197
Mexico	Querétaro	9413.488672	Mexico	León	10101.04737
Mexico	Laguna	9248.405271	Mexico	Puebla	9836.425835
Mexico	León	9104.119414	Chile	La Serena-Coquimbo	9451.650954
Mexico	Toluca	9101.691903	Chile	Viña del Mar-Valparaíso	9391.068743
Mexico	Puebla	8851.451708	Chile	Concepción	9232.065182
Panama	Panama City	8145.913908	Argentina	Buenos Aires	8384.960162
Brazil	São Paulo	6679.847307	Argentina	Mendoza	8381.844495
Brazil	Rio de Janeiro	6558.941986	Argentina	Rosario	8099.204496
Brazil	Curitiba	6468.572587	Argentina	Córdoba	8080.177341
Brazil	Porto Alegre	6367.987802	Uruguay	Montevideo	8036.850976
Chile	Antofagasta	6308.845286	Panama	Panama City	7273.621014
Brazil	Belo Horizonte	6296.322268	Colombia	Bogotá	6552.569326
Brazil	Recife	6241.733271	Colombia	Medellín	6384.023835
Chile	Santiago	6206.434154	Costa Rica	San José	5353.213481
Brazil	Goiânia	6115.139454	Brazil	Rio de Janeiro	5124.571709
Brazil	Salvador	6103.46939	Brazil	São Paulo	5104.384167
Brazil	Fortaleza	6039.005177	Brazil	Belo Horizonte	5092.924787
Brazil	Belém	5909.315539	Brazil	Curitiba	5060.667619
Dominican Republic	Santo Domingo	5566.000039	Brazil	Porto Alegre	5032.341579
Chile	Viña del Mar-Valparaíso	5278.257951	Brazil	Goiânia	4857.10337
Chile	Concepción	5229.744615	Brazil	Salvador	4847.332604
Chile	La Serena-Coquimbo	4901.780204	Brazil	Recife	4829.722434
Colombia	Bogotá	4752.925471	Brazil	Fortaleza	4757.989157

Table A1.2 (concluded)

Ranking in 2000			Ranking in 2010		
Country	City	Big Macs	Country	City	Big Macs
Colombia	Medellín	4629.978149	Brazil	Belém	4703.405616
Costa Rica	San José	4442.018337	Peru	Arequipa	4513.754623
Ecuador	Guayaquil	4022.255526	Peru	Trujillo	4038.392012
Ecuador	Cuenca	3921.051866	Ecuador	Guayaquil	3620.84656
Ecuador	Quito	3563.973573	Peru	Lima	3590.05369
Peru	Arequipa	3356.775861	Ecuador	Cuenca	3469.083125
Peru	Trujillo	3009.165406	Dominican Republic	Santo Domingo	3319.768189
Ecuador	Santo Domingo	2905.272975	Ecuador	Quito	3155.191171
Peru	Lima	2646.185677	Peru	Chiclayo	2964.603405
Peru	Chiclayo	2203.590951	Paraguay	Asunción	2802.714553
Paraguay	Asunción	2099.929668	Colombia	Barranquilla	2630.747011
Colombia	Barranquilla	1943.781739	Ecuador	Santo Domingo	2550.215107
Bolivia (Plurinational State of)	La Paz	1276.043587	Bolivia (Plurinational State of)	La Paz	1520.774422
Bolivia (Plurinational State of)	Santa Cruz	1230.582007	Bolivia (Plurinational State of)	Santa Cruz	1382.599926
Bolivia (Plurinational State of)	Cochabamba	1090.808814	Bolivia (Plurinational State of)	Cochabamba	1208.268208

Source: Prepared by the authors.

Table A1.3
Latin America (13 countries): full productivity rankings of selected cities, 2000 and 2010

Ranking in 2000			Ranking in 2010		
Country	City	Output per employee *(purchasing power parity dollars)*	Country	City	Output per employee *(purchasing power parity dollars)*
Argentina	Buenos Aires	26984.03336	Chile	Antofagasta	38739.52966
Argentina	Mendoza	24991.12449	Chile	Santiago	33938.11398
Argentina	Córdoba	24902.98192	Chile	La Serena-Coquimbo	31568.51419
Argentina	Rosario	24728.88052	Chile	Viña del Mar-Valparaíso	31366.1696
Mexico	Mexico City	21782.22918	Chile	Concepción	30835.09771
Mexico	Monterrey	21689.51674	Uruguay	Montevideo	30057.82265
Mexico	Tijuana	21527.43689	Argentina	Buenos Aires	29850.45817
Mexico	Juárez	21133.04148	Argentina	Mendoza	29839.3664
Mexico	San Luis Potosí	21073.47577	Mexico	Monterrey	29047.11407
Mexico	Guadalajara	20950.07385	Argentina	Rosario	28833.168
Mexico	Querétaro	20897.94485	Colombia	Bogotá	28765.77934
Mexico	Laguna	20531.4597	Argentina	Córdoba	28765.43133
Uruguay	Montevideo	20323.46616	Mexico	Juárez	28296.54951
Mexico	León	20211.1451	Mexico	Laguna	28227.7936
Mexico	Toluca	20205.75603	Colombia	Medellín	28025.86464
Mexico	Puebla	19650.22279	Mexico	Mexico City	27983.14667
Panama	Panama City	18409.76543	Mexico	San Luis Potosí	27255.68628
Chile	Antofagasta	15456.67095	Panama	Panama City	27103.3303
Chile	Santiago	15205.76368	Mexico	Tijuana	26629.27383
Chile	Viña del Mar-Valparaíso	12931.73198	Mexico	Querétaro	26214.77716
Chile	Concepción	12812.87431	Mexico	Guadalajara	26017.26123
Dominican Republic	Santo Domingo	12579.16009	Mexico	Toluca	25911.68664
Chile	La Serena-Coquimbo	12009.3615	Mexico	León	25252.61842
Costa Rica	San José	11593.66786	Brazil	Rio de Janeiro	25161.64709
Colombia	Bogotá	11169.37486	Brazil	São Paulo	25062.52626
Brazil	São Paulo	11021.74806	Brazil	Belo Horizonte	25006.2607
Colombia	Medellín	10880.44865	Brazil	Curitiba	24847.87801
Brazil	Rio de Janeiro	10822.25428	Brazil	Porto Alegre	24708.79715

Table A1.3 (concluded)

Ranking in 2000			Ranking in 2010		
Country	City	Output per employee *(purchasing power parity dollars)*	Country	City	Output per employee *(purchasing power parity dollars)*
Brazil	Curitiba	10673.14477	Mexico	Puebla	24591.06459
Brazil	Porto Alegre	10507.17987	Brazil	Goiânia	23848.37755
Brazil	Belo Horizonte	10388.93174	Brazil	Salvador	23800.40308
Brazil	Recife	10298.8599	Brazil	Recife	23713.93715
Brazil	Goiânia	10089.9801	Brazil	Fortaleza	23361.72676
Brazil	Salvador	10070.72449	Brazil	Belém	23093.72157
Brazil	Fortaleza	9964.358542	Costa Rica	San José	20502.80763
Brazil	Belém	9750.37064	Peru	Arequipa	15978.69137
Ecuador	Guayaquil	9090.29749	Peru	Trujillo	14295.90772
Ecuador	Cuenca	8861.577217	Peru	Lima	12708.79006
Peru	Arequipa	8324.804135	Ecuador	Guayaquil	12672.96296
Ecuador	Quito	8054.580276	Dominican Republic	Santo Domingo	12370.28622
Peru	Trujillo	7462.730208	Ecuador	Cuenca	12141.79094
Ecuador	Santo Domingo	6565.916924	Colombia	Barranquilla	11548.97938
Peru	Lima	6562.540479	Ecuador	Quito	11043.1691
Peru	Chiclayo	5464.905558	Peru	Chiclayo	10494.69605
Paraguay	Asunción	4745.841049	Paraguay	Asunción	10443.6151
Colombia	Barranquilla	4567.887087	Ecuador	Santo Domingo	8925.752875
Bolivia (Plurinational State of)	La Paz	2883.858507	Bolivia (Plurinational State of)	La Paz	5666.785691
Bolivia (Plurinational State of)	Santa Cruz	2781.115335	Bolivia (Plurinational State of)	Santa Cruz	5151.912973
Bolivia (Plurinational State of)	Cochabamba	2465.227921	Bolivia (Plurinational State of)	Cochabamba	4502.30941

Source: Prepared by the authors.

Table A1.4

Latin America (13 countries):[a] collinearity diagnostics in the study of segregation in selected cities, 2000 and 2010

Variable	Variance inflation factor	Variance inflation factor	Square root tolerance	R-squared
Duncan Segregation Index	1.17	1.08	0.8582	0.1418
Proportion of high-skilled workers	1.3	1.14	0.7707	0.2293
Log of gross domestic product	1.67	1.29	0.6005	0.3995
Log of population	1.21	1.1	0.8248	0.1752
Year dummy	1.48	1.21	0.6777	0.3223
Gini coefficient	1.12	1.06	0.8914	0.1086
Proportion of high-skilled workers	1.28	1.13	0.779	0.221
Log of gross domestic product	1.63	1.28	0.6141	0.3859
Log of population	1.2	1.1	0.8316	0.1684
Year dummy	1.46	1.21	0.6832	0.3168

Source: Prepared by the authors.

[a] Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru, Plurinational State of Bolivia, Uruguay.