High-skilled workers' Segregation and Productivity in Latin American Cities

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Abstract

The aim of this work is to study the relationship between high-skilled workers' segregation and productivity in Latin American cities. This relationship is not clear at first sight. On the one hand high-skilled workers' spatial concentration would take advantage of agglomeration economies and cause positive spillovers amongst the most advantaged that could compensate productivity losses due the existence of low-skilled workers ghettos. On the other hand, it would be the case that those spillovers are not enough for compensating the worse-off groups' productivity losses, and hence the aggregated productivity would be negatively affected. We calculate this group segregation for a group of Latin American countries' most important cities. We found a negative and significant relationship amongst cities' productivity and high-skilled workers segregation. However, we found evidence of a quadratic relationship between segregation and productivity as well.

Resumen

El objetivo de este trabajo es estudiar la relación entre la segregación de trabajadores calificados y la productividad en la ciudades de Latino América. Esta relanción no es necesariamente evidente. Por un lado, la concentración espacial de los trabajadores calificados puede generar economías de aglomeración que sean ventajosas para este tipo de trabajadores y hacerlos aún más productivos, lo que eventualmente podría más que compensar las pérdidas de productividad resultado de la existencia de ghettos de trabajadores no calificados. Por otro lado, esta ganancia de productividad de los trabajadores calificados podría no ser suficientes para

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compensar la pérdida de productividad de los trabajadores no calificados, y en consecuencia, en este caso, la segregación de trabajadores calificados tendrá un efecto negativo en la productividad agregada. Calculamos la segregación de este grupo para un conjunto de las ciudades más importantes de Latino América. Encontramos una relación negativa y significativa entre la productividad de las ciudades y la segregación de trabajadores calificados. Sin embargo, también encontramos evidencia de una relación cuadrática entre la segregación y la prodcutividad.

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1 Introduction

The purpose of this research is to investigate on the effects that high-skilled workers' segregation would have upon Latin American cities productivity, understanding segregation as residential segregation. This relationship is not clear at first sight. On the one hand high-skilled's spatial concentration would take advantage of agglomeration economies and cause positive spillovers amongst the most advantaged that could compensate productivity losses due to the existence of worse-off ghettos, but, on the other hand, it would be the case that those spillovers are not enough for compensating the worse-off groups' productivity losses, and hence the city's aggregated productivity would be negatively affected.

In order to achieve this goal we calculate segregation indices of high-skilled groups, using census data for Latin American countries. Census information was obtained from the University of Minnesota Population Center's Integrated Public Use Microdata Series (IPUMS), for two dates: first around year 2000 and second around year 2010. We use individuals level of education as a skill proxy. As productivity measures we consider cities labour productivity and for comparability we deflect this measures using the Big-Mac index. We collect this information for countries most important cities, in several cases more than one per country. The empirical approach considers cities' productivity as the dependant variables and as explanatory variables well-off groups' segregation plus a group of controls. We run pooled regressions and a first differences model, the latter because results would be contaminated by omitted variables bias. Considering two segregation indices and more than one productivity measure for robustness, we found a significative and negative segregation's effects upon cities' productivity. We also found evidence of a quadratic relationship between segregation and productivity. According to this finding segregation of high-skilled has a negative impact but after a threshold has been reached this effect changes and become positive. Intuition tell us that below that threshold the segregation level is not capable of generating spillovers big enough to overcome the productivity loses due to the isolation of the low-skilled group.

2 Related Literature

There are a lot of academic efforts trying to understand the effects that segregation would have on individuals and cities performance like. For a long time the common opinion was that segregation has negative consequences only. More recently a bunch of articles point out the fact that this phenomenon would affect households in a positive way. Regarding either effects, positive or negative, the empiric investigation must deal with a severe problem of identification, which is particularly true for the case of segregation based on income. The questions that should be answered is: a household is poor because is segregated or is segregated because is poor? As a way to overcome this endogeniety problem the Department of Housing and Urban Development's Moving to Opportunity Program (MOP) was designed as an experiment, providing, in a randomized way, for low-income families living in some of the USA's most disadvantaged urban neighbourhoods the chance to move to private-market housing in much less distressed communities. After 11 year since it started empirical investigations using MOP's data have reached a striking conclusion: segregation has just negligible effects affecting only mental health. This finding has re opened the discussion about this topic and new investigations have been done looking for a different switch regarding the way that segregation would affect well-being. For instance Cuttler and Glaeser (1997), Anas (2002), Conejeros and Vargas (2012), Corvalan and Vargas (2015), look for macro effects of segregation, Bjerk (2010) investigates about segregation effects upon different types of crimes, finding evidence telling us that segregation increases violent crimes, but not the aggregated level of them. In this same line Kessler et al. (2014), Ludwig et al. (2013), Ludwig et al. (2012) investigates about the impact that segregation has upon self reported life satisfaction and mental health. A significant number of these new articles have found that segregation still has effects but not necessarily related to what the traditional literature has identified, particularly these investigations indicate that segregation has no consequences upon individuals ability to be economically independent. More recently Chetty et al. (2016) find an answer to this puzzle: segregation has irreversible effects, for this reason all previous studies that have used MOP data were not able to find significant consequences. Chetty et al. (2016) studies the consequences upon individuals that were very young when their families received the voucher finding that after a threshold of 13 years old the exposure to a better neighbourhood has no impact on individuals' outcome.

Despite its importance, however, little has been said about better-off's segregation and its consequences upon the society as a whole.[1] Probably the most important work that have addressed this issue are Benabou (1993), Benabou (1996) and Ananat (2011). According to these investigations the effect of high income groups segregation would be either positive or negative. For instance higher levels of income are correlated with greater levels of human capital, then these groups agglomeration would produce positive spillovers. If these spillover are capable of compensate the losses of productivity that worse-off households will face due to the existence of low skilled workers ghettos, the aggregated city productivity will be greater because of segregation. However, if these spillover are not enough for compensating worse-off productivity losses, then the aggregated effects will be negative. Given the relevance of these works for the present investigation, the following sub section will discuss with more detail Benabou (1993) and Ananat (2011).

2.1 High-skilled's segregation and city's outcome

Benabou (1993) develops a theoretical model for understanding the high-skilled segregation consequences upon city's outcomes. In this model agents should decide the skill level they want to achieve (high, low or none) and their residential location. If agents decide not to have any skill then they will be out of the labor market. An important assumption of this model is that the labor market embrace the full city, meanwhile education is a local public good. In every neighbourhood the higher agents' investment in education the easier to get skills either high or low, but the latter in a lower extent. This asymmetry makes high-skilled agents to bid for land in neighbourhood inhabited by high-skilled workers, which will affect city's surplus due to the mix of abilities and the labour force's education cost. As a consequence education costs will grow faster in those communities with a high concentration of low-skilled workers. Hence, in their attempt for living amongst peers, high-skilled workers will transform other communities

[1] Since Piketty and Saez (2003) the interest regarding top income analysis has grown very fast. Given the high level of inequality that could be observed in Latin America, this sort of analysis can be of great interest and have a lot of important policy implications for the region (see, for instance, Williamson (2010)).

in unproductive ghettos. A key element of this model is the relationship between local and global interactions, i.e. between education's spillovers, which are local at neighbourhood level, and neoclassic production complementarities, which work at city level. As a result of the high-skilled workers segregation, low-skilled workers' ghettos would be left out of the labor market, because in these ghettos education's costs will be so high that agents will choose to have no skills at all and therefore they will be out of the labor market. Then the easier high-skilled workers isolate themselves the higher the unemployment will be. When perfect segregation is reached the productive sector will colapse because the city production function needs both inputs: high and low skilled workers. Therefore, high-skilled workers segregation will harm city productivity, because albeit segregated high-skilled workers will get better qualification in an easier way, segregation will deprive them of working together low-skilled workers.

There are different ways through which local complementarities works. The most obvious is a fiscal externality: if school are financed by local resources and if they provide a complementary input to individual effort, the return to studying will be higher in communities with a high concentration of high-skilled workers because they earn higher salaries. This mechanism would work through pure human capital externalities as well. Amongst this human capital externalities we find peer effects in education and social networks which decreases the cost of getting a job or providing role models for young people, whom due to the presence of high-skilled workers in the neighbourhood will learn the relevance of education. Finally, an alternative explanation has to do with the negative externalities and disruptive influence that some unemployed and low-skilled workers would generate, such as crime or drugs abuse.

A different possibility offers Ananat (2011). The purpose of this investigation is to cast light on the casual effect that racial segregation may have on urban poverty and inequality. The work is empirical and test this causal effect exploiting the historic great migration of afro American and the railroad pattern within cities. To fix ideas she presents a very simple model and some of its main features are now discussed. First, there are two cities, one integrated (C_I) and one segregated (C_S) that exist for tow generations. The proportion of black in each city is β and therefore the proportion of whites is $1 - \beta$. The average human capital for blacks and whites are μ_{HB} and μ_{HW} respectively. From historic record 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 individual's offsprings human capital, λ_1 is the individual's human capital, α_{HI} is the individual's neighbourhood average human capital and $\alpha \geq 0$. In C_I blacks and whites are exposed to the same average human capital: $\beta\mu_{HB} + (1-\beta)\mu_{HW}$, meanwhile in C_S whites are exposed to a higher average human capital than black as $\mu_{HB}<\mu_{HW}$. If $\alpha < 1$ then own human capital and neighbourhood average human capital are substitutes in the production of the next generation human capital level, then integration will produce higher human capital than segregation. If $\alpha > 1$ then own human capital and neighbourhood average human capital are complements then 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 whites and blacks but reduces poverty of whites and inequality within whites.

Consequently, if either global complementarities are significant or local interactions are substitutes or both, then one could expect to observe a negative impact on city productivity due to high-skilled workers segregation, but if global complementarities are not important or local interactions are complements or both, then one could expect to observe a positive effects of segregation on city's productivity.

3 Methodology

For achieving our goal we calculate residential segregation based on education as a proxy of highly-skilled workers for Latin American cities. Specifically, we calculate segregation of households' head with a university degree. Then we obtain cities productivity and we regress productivity against traditional controls and segregation. We use an econometric specification capable to deal with potential endogeneity issues due to omitted variables bias. All these steps are discussed with more detail in the following subsections.

3.1 Segregation Measures

3.1.1 The Duncan index

This index can be obtained from the Lorenz curve. It represents the maximum vertical distance between the Lorenz curve and the diagonal line that represents full evenness. When the group under study is small in comparison to the number of geographical sub-areas (like the census tract) the Duncan index is highly affected by the deviation from evenness and it is not sensitive to redistribution between geographical sub-areas, where the proportion of the group under study is below the same group proportion of the city as a whole. According to this index, just by moving people belonging to the group under study from the geographical sub areas where they are over-represented to geographical sub areas where they are under-represented can affect the level of **RS** (Massey and Denton, 1988).

The functional form of the Duncan index is:

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

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.

3.2 Gini Index

As Massey and Denton (1988) explains, another measure of evenness is the Gini coefficient. Like the duncan index 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 shares weighted across all pairs of sub-areas, expressed as a proportion of the maximum weighted mean difference.

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

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.

3.3 City Productivity

In the Competitive Cities in the Global Economy report of the OECD Territorial Reviews Reviews (2006) it is shown that most metro-regions in the OECD have higher productivity and growth than their national average. 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 Territorial Reviews). Cities are centres of economic activity. As such, cities are the platform 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 gains in productivity. The first sources of positive effect of agglomeration where described by Marshall (1920). He argued that the localization of an industry in the same place, provides labor market pooling, input sharing and knowledge spillover generating the continued economic growth of the industry. Jane Jacobs (1969), in contrast to Marshalls specialization, stresses the importance of urban diversity to cross-fertilization of ideas. Rosenthal and Strange (2004) describes three sources of agglomeration economies that go beyond Marshall and Jacobs descriptions. Home Market Effect, Consumption and Rent-Seeking. Home market effect described by Krugman (1980) comes from the interaction between internal scale economies in production and transport costs. This interaction leads to an expansion of the home market size, in a self-reinforcing process of agglomeration. Consumption and Rent-Seeking are sources of agglomeration economies that work through mechanisms which are not related 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 that the elasticity of productivity to the city size is of about 0.05 for a sample of 13 large metropolitan areas from 1957 to 1977. This means that the Total Factor Productivity of the manufacturing sector increases in 10% when the size of the city is doubled. Tabuchi (1986) finds that the same elasticity is of about 0.02 for Japenese cities in 1980 using labor productivity. These works show the positive relationship between agglomeration economies and productivity on the cities.

Whether the agglomeration economies has sources on the city size or industry size is relevant for the metropolis in Latin American. Most of the economies in Latin America are dependents in primary commodities which are produced close to small cities. The abundance of nearby natural resources creates conditions that are favorable to the production of primary commodities. In these cities, the size of the industry is big, therefore the productivity of the city is high relative to bigger cities. The case of Antofagasta in Chile is a good example of an small city with a great mining industry. Although the copper is produced in rural areas, the sector that supply services to the mining industry works mainly in the city, and its productivity is high. Sveikauskas et al. (1988) shows that in these cases the productivity of the city is high, due to the high volume of the natural resources in the area, suggesting that industry concentration in not enough to obtain high productivity.

The productivity of an economy can be computed using different measures. Total Factor Productivity (TFP) is a heritage of the neoclassical literature (like (Solow, 1957)) and is one of the most used measures. An economy increases its productivity when its produces more with the same amount of labor and capital. Computing the TFP of the city requires to compute its stock of capital and number and qualities of its workers. Although number of employees is available, the capital stock of the cities is not available for most of Latin America ones. In the Competitive Cities in the Global Economy report of the OECD Territorial Reviews (2006), labor productivity, computed as the ratio between GDP in PPPs and employment, is used as the primary measure of productivity of the metro-region. Sveikauskas (1975) uses labor productivity of a set of manufacturing sectors as a proxy of city productivity. This measure is widely employed in the literature as presented in Eberts and McMillan (1999). Labor productivity has the advantage of being easy to be calculated due to few requirement of information.

Following this literature and due to the poor availability of information for the Latin America cities, the productivity of the cities will be approximated using labor productivity. The Labor Productivity for a city c is computed as,

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

where Y_c and L_c are the city valued added and the total number of workers in the city c. The 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 valued added by the sector i at the National Economy, $l_{i,c}$ is the number of employees working at the city r, in the sector i and $L_{i,N}$ is the total number of workers in the sector of the national economy. Using this specification to compute productivity assume that the technology employed to produce at 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 has effect on the proposed measure of productivity through the self-selection mechanism of economic sectors made by each city. Cities have more workers in sectors where agglomeration has greater effect.

4 Data

4.1 Segregation Data

As mentioned above we use census samples from IPUMS. The information has been gathered for Metropolitan Areas. To get consistent and comparable information is an important challenge. For doing so we have sacrificed accuracy and granularity in some Metropolitan Areas. For instance samples of Metropolitan Areas from Brazil have a very detailed information and is possible to get it at strata level, nevertheless samples from others countries have no the same level of detail. Consequently, for the calculation of segregation indices we have used municipalities as sub areal unit. We have proceed in this way in order to keep consistency between all the indices calculated for each city which give us the chance to do comparisons amongst the metropolitan areas and to have a reasonable number of observations for undertaking the empirical analysis. We calculate segregation indices for 49 metropolitan areas near year 2000 and 49 around year 2010. We calculate 23 indices for each Metropolitan Area, however given the high correlation that they exhibit we have used here for the analysis just the Duncan and Gini indices. We calculate segregation considering as highly-skilled individuals households' head with a university degree. The Metropolitan Areas considered are shown in Table 1. The specific metropolitan areas for each country and years are:

Argentina: In the case of Argentina cities are Gran Buenos Aires, Córdoba, Mendoza y Rosario. Gran Buenos Aires corresponds to the Ciudad Autónoma de Buenos Aires and the province of Buenos Aires. In the case of Córdoba the province of Córdoba was considered, the same was done with Mendoza and Rosario were provinces of Mendoza and Santa Fé were considered respectively.

Brazil: For Brazil we collect information for the 10 biggest Metropolitan Regions: Sao Paulo, Rio de Janeiro, Salvador, Fortaleza, Belo Horizonte, Curitiba, Porto Alegre, Goiana, Recife and Belen.

Bolivia: For Metropilitan Areas of La Paz, Cochabamba and Santa Cruz we use information for La Paz, Cochabamba and Santa Cruz departments.

Colombia: Colombian cities are: Medellín, Bogotá and Barranquilla. As Medellín metropolitan area proxy we use the Antioquía Department, for Bogotá we use Bogotá and Cundinamarca Departament and for Barranquilla the Atlántico Departament.

Costa Rica: San José Metropilitan Area is approximated using the San José province information.

Chile: Instead of using IPUMS data, in the case of Chile we use the Social Charecterization Survey (CASEN) for years 2000 and 2009. With this data we calculate segregation indices for Gran Santiago, Antofagasta, Valparaíso, Concepción and La Serena. Gran Santiago corresponds to 30 municipalities belonging to Santiago Metropolitan Area, Antofagasta to the province of Antofagasta, Valparaíso to the province of Valparaíso, Concepción to the province of Concepción and La Serena to the province of Elqui.

Ecuador: Cities considered for this country are Guayaquil, Quito, Cuenca and Santo Domingo and data was collected for the provinces of Guayas, Pichincha, Azuay and Santo Domingo respectively.

México: The Metropolitan Area of Mexico Valley is made out of 76 municipalities (delegaciones), 11 from Ciudad de México, 59 from México Estate and 1 from Hidalgo Estate. The others Metropolitan Areas are Guadalajara, Monterrey, Puebla, Toluca, Tijuana, Juarez, Laguna, San Luis de Potosí and León. All of them follow the metropolitan area definition given by the Instituto Nacional de Estadística y Goegrafía of México.

Panamá: Province of Panamá was used as a Ciudad de Panamá Metropolitan Area proxy.

Paraguay: Asunción Metropilitan Area is made out of 2 districts: Capital and Central.

Perú: Peruvian Metropolitan Areas considered here are : Lima/Callao, Chiclayo, Arequipa and Trujillo, using as proxy for them Lima and Callao, Lambeyeque, Arequipa and La Libertad provinces respectively.

República Dominicana: San José Metropolitan area is made up of the province of Santo Domingo.

Uruguay: In the case of Uruguay information is for Departamento de Montevideo.

Table 1: Cities' Sample

Country	Cities	Country	Cities
Argentina	Gran Buenos Aires	Ecuador	Guayaquil
	Córdoba		Quito
	Mendoza		Cuenca
	Rosario		Santo Domingo
Bolivia	La Paz	México	Ciudad de México
	Cochabamba		Guadalajara
	Sta Cruz		Monterrey
Brazil	Sao Paulo		Puebla
	Rio de Janeiro		Toluca
	Salvador		Tijuana
	Fortaleza		Juarez
	Belo Horizonte		Laguna
	Curitiba		Queretaro
	Porto Alegre		San Luis de Potosí
	Goiana		León
	Recife	Panamá	Ciudad de Panamá
	Belen	Paraguay	Gran Asunción
Colombia	Medellín	Perú	Lima
	Bogotá		Chiclayo
	Barranquilla		Arequipa
Costa Rica	San José		Trujillo
Chile	Gran Santiago	Rep Dominicana	Sto Domingo
	Antofagasta	Uruguay	Montevideo
	Valparaíso		Concepción
	La Serena		

Tables 12 and 13 present segregation rankings based on Duncan and Gini indices respectively. In both cases by far Santiago de Chile is the most segregated metropolitan area in 2000 and 2010. Considering the Duncan index ranking, Brazil has 4 cities amongst the most segregated in

2000 and 2010 (Porto Alegre, Bello Horizonte, Curitiba and Rio de Janeiro). Bolivian cities also are between the most segregated (Santa Cruz and La Paz). Montevideo is another city which exhibits high levels of segregation considering both the Duncan and Gini indices. Within the less segregated cities we can find Antofagasta and Valparaíso in Chile, Goiana in Brazil, Tijuana and León in México, Lima in Perú and Santo Domingo in Ecuador. We have calculated segregation of households' head without any kind of qualification as well. Table 2 shows descriptive statistics for these two types of segregation. As it can be appreciated segregation is higher in the case of high-skilled workers and in both cases is relatively constant.

Table 2: Segregation descriptive statistics by Skill groups

Variable	Mean	Std. Dev.	Min	Max
duncan High-Skilled Full Sample	0.2310194	0.1066767	0.0225	0.5237
duncan High-Skilled 2000	0.2314388	0.1083908	0.0355	0.4758
duncan High-Skilled 2010	0.2306	0.1060564	0.0225	0.5237
duncan Low-Skilled Full Sample	0.1791367	0.0849578	0.0151	0.3958
duncan Low-Skilled 2000	0.1799375	0.0827937	0.0359	0.3888
duncan Low-Skilled 2010	0.1779898	0.0886876	0.0151	0.3958

If we compare this results with cities from more developed countries we can see that these segregation values are not particularly different. For instance Table 3 presents the evolution of high income and low income segregation from 1970 upon till 2009. Segregation is very similar although is slightly higher in Latin American cities. It can be observed that better-off segregation is systematically higher as well. However mean values have increased in USA meanwhile in Latin American are more or less constant.

Table 3: USA Average Segregation by Income Group

	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: Bischoff and Reardon (2013)

4.2 Productivity Data

There are three main challenges related to data gathering for this project. First, the information has to be collected from countries having different models for constructing their statistical information, second there is no agreement on what a city is in each country, and third there are big differences related to data availability across Latin American countries. In order to reduce the sources of variability most of the data related to the computation of the indexes of segregation and employment were collected from IPUMS-International. This is an effort made 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 the OECD input-output tables.[2] Finally when there was lack of harmonized data, the information from the National Institute of Statistics and Central Banks of each country is used. Two criteria are applied to select the metropolis which are included in the regressions. On the one hand the importance of the city within a country and on the other hand the data availability for the city. The importance of a city is mainly measured as the population of the city related to the national population. Following these criteria 49 cities of 13 countries are reported. In many cases the lack of information of the countries, does not allow to compute the information for specific years. In Table 9 there is a list of data availability for each city, around the Initial and Final year. When the data information about the demography does not coincide with the information of Value Added, the demography is updated according to the population growth rate reported by each country during the period. In order to compare the productivity $y_c(t)$ of the city c at time t with other city in a different country or in the period $(t+1)$ all the productivities were transformed using the the Big Mac index. In addition to this, the productivity transformed into purchasing power parity and updated using the dollar inflation was used as an alternative to compare the productivity across countries. Table 4, shows a synthesis of the ranking of the cities according to their purchasing power parity per worker. In the first and second column there is the Ranking of cities according to their productivity in 2000 and 2010 respectively. Notice that there was an important change in the position of the most productive cities in the period of the ten years. However, the ranking is more static among the last five cities. Table 10 shows the full cities' ranking based on the Big Mac index.

[2]http://www.oecd.org/trade/input-outputtables.htm

Table 4: Cities Productivity Ranking

Ranking 2000	Ranking 2010	Country	City
18	1	Chile	Antofagasta
19	2	Chile	Santiago
23	3	Chile	Serena Coquimbo
20	4	Chile	Viña-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	Sto Domingo
47	47	Bolivia	La Paz
48	48	Bolivia	Santa Cruz
49	49	Bolivia	Cochabamba

Figure 1 is the scatter plot of the number of workers in the city against the productivity of the cities. The line represents the positive relationship suggesting the presence of economies of agglomeration. In the upper left corner there are two small cities, with high productivity. These are two cities from Chile, Antofagasta y Serena, which receive the influence of the mining sector.

Figure 1: Workers vs Productivity

5 Empirical Analysis and Results

The first empirical exercises that we perform is a pooled regression. The reason behind is that albeit to collect consistent and comparable information for 49 cities in Latina America is a challenging task, in terms of the empirical analysis this number corresponds to a small sample. Therefore using information for 2000 and 2010 in a pooled regression we can increase the sample to 98 observations, which is a more suitable number for the econometric analysis. For this regression we have used as additional controls the high-skilled workers share in the metropolitan area, the country GDP per capita in PPP, a year dummy and cities population. As dependent variables we have used productivity deflected by Big Mac index and productivity in PPP terms as was explained earlier on. Descriptive statistics for these variables are shown in Table 5. As it can be appreciated the mean of all these variable has increased during the 2000-2010 period. It is also possible to observe that the continent is rather heterogenous and unequal.

Table 5: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
2000					
Big Macs	49	6260.575	2894.455	1090.809	11166.74
Productivity	49	13592.87	6724.517	2465.228	26984.03
GDP per capita	49	8574.673	2445.306	3497	13188
hs_share	49	0.1024776	0.0324008	0.0318	0.1661
population	49	1,187,125	1,565,015	102,183	7,210,874
2010					
Big Macs	49	6627.128	3221.966	1208.268	11618.85
Productivity	49	22534.07	8384.848	4502.31	38739.53
GDP per capita	49	13292.18	3637.439	5289	18249
hs_share	49	0.1244531	0.0436779	0.0318	0.2298
Workers	49	1,441,099	1,820,342	112,930	8,545,510

Intuition says that these correlation should be all positive: most productive cities, on average, will have a greater income per worker and income per capita, most productive cities will attract more people to work in and will attract more educated labor force. Figure 2 presents histograms showing the unconditional relationship between these variables and productivity (Big Macs' log). As expected all these variables have a positive effect on productivity. The most clear impact is given by the GDP per capita and the income per worker. A similar impact can be observe in the high skill workers share. Albeit still positive the relationship between productivity and cities' workers is weaker than the previous ones. Of course these are just correlation and one should have in mind the fact that there is an important endogeneity issue between these variables.

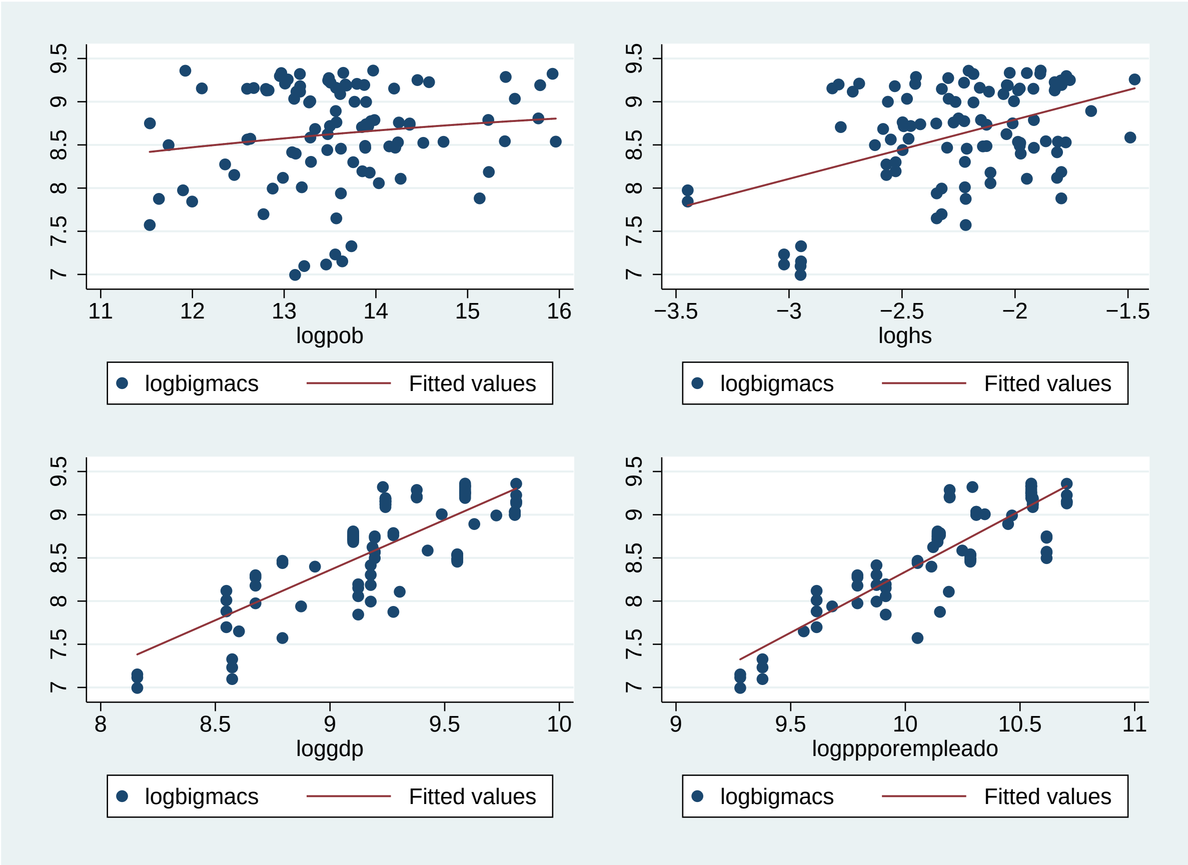

Figure 2: Variables Unconditional Effects on Productivity

For robustness we have conduct 4 regressions using as dependant variable productivity measured in PPP terms and deflected by the Big Mac index and segregation measured by the Duncan and Gini indices. Standard errors are clustered by country. Table 6 shows the results of these 4 pooled regressions. Segregation is not significant in any of these 4 regressions but the sign of the relevant parameters are always negative. However this regression most certainly suffer of a omitted variable bias problem. As Ananat (2011) explains " . . .some unmeasured economic, political or other attribute may lead to certain cities to have both more segregation and more negative characteristics than other cities. For example, cities as Detroit are highly segregated and their residents have poor economics outcomes, but other characteristics, such as political corruption or legacy of a manufacturing economy, may 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."

Table 6: Pooled Regressions

	(1)	(2)	(3)	(4)
	logproductivity	logproductivity	logbigmacs	logbigmacs
duncan	-0.100		-0.240	
	(0.186)		(0.254)	
hs_share	1.519*	1.548*	1.620**	1.677**
	(0.560)	(0.550)	(0.441)	(0.433)
loggdp	1.481***	1.486***	1.554***	1.564***
	(0.0616)	(0.0620)	(0.0551)	(0.0568)
logworkers	0.0190	0.0166	0.0231	0.0191
	(0.0443)	(0.0444)	(0.0590)	(0.0592)
year_d	-0.141	-0.143	-0.673***	-0.677***
	(0.0899)	(0.0890)	(0.0761)	(0.0748)
gini		-0.0296		-0.110
		(0.150)		(0.212)
_cons	-4.363***	-4.388***	-5.823***	-5.887***
	(0.751)	(0.785)	(0.832)	(0.905)
N	98	98	98	98
R^2	0.895	0.895	0.837	0.836

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 wides out time invariant omitted variable using the repeated observations over time. As Wooldridge (2001) explains if we have an omitted variable c_i in the following set of equations:

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

$$y_{it-1} = x_{it-1}\beta + c_i + u_{it-1}, t = 2, \cdots, T \tag{7}$$

Differencing both equations we get:

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

which removes the omitted variable c_i. As when $T = 2$ first differences and fixed effects estimators are numerically equivalent, we have implemented the first differences regressions using a panel data fixed effect model. As before standard errors are clustered by country. Results are exhibited in Table 7.

Table 7: First Differences

	(1)	(2)	(3)	(4)
	logproductivity	logproductivity	logbigmacs	logbigmacs
duncan	-0.422		1.594^{*}	
	(0.865)		(0.721)	
hs_share	1.310	1.335	-1.977	-2.194
	(1.865)	(1.997)	(2.109)	(2.092)
loggdp	1.716^{**}	1.711^{**}	1.061	1.074
	(0.553)	(0.543)	(0.700)	(0.716)
logworkers	0.277	0.291	0.0269	-0.0287
	(0.508)	(0.499)	(0.455)	(0.462)
year_d	-0.295	-0.295	-0.375	-0.368
	(0.340)	(0.333)	(0.374)	(0.384)
gini		-0.362		1.663^{*}
		(1.052)		(0.753)
_cons	-9.866	-10.01	-1.487	-0.911
	(11.65)	(11.52)	(12.15)	(12.38)
N	98	98	98	98
R^2	0.860	0.860	0.307	0.323

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Segregation remains being not significant but the case where productivity is measured using the Big Mac index and segregation using the Gini index. Something striking in this occasion is that segregation's sign is positive. This could be the result of the omitted variable bias correction due to 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 log of productivity (Big Mac) and the Gini index and a quadratic fitted curve.

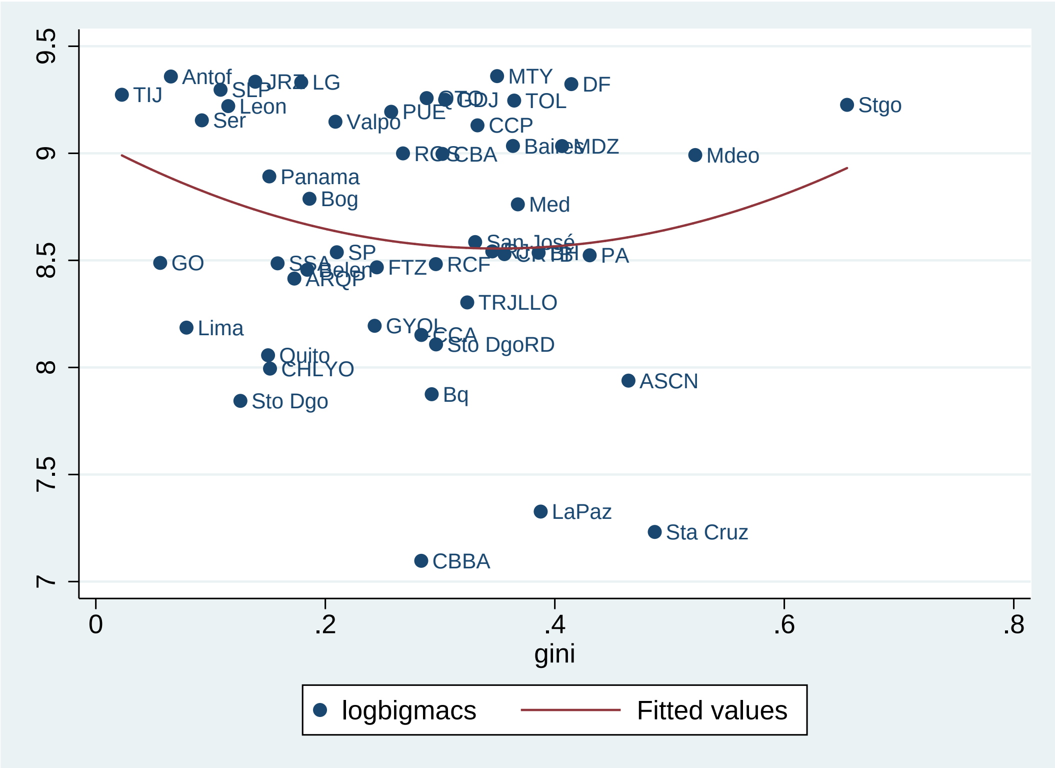

Figure 3: Big Mac vs Segregation Scatter Plot

As it can be observed, it seems to be a non linear relationship between productivity and segregation. Consequently we should include a segregation quadratic term into the regression. As the shape is concave upward we should expect a negative sign of the linear term and a positive one of the quadratic. Table 8 shows the results of this new group of first differences regressions including the segregation quadratic term.

Table 8: First Differences with Quadratic Segregation

	(1)	(2)	(3)	(4)
	logproductivity	logproductivity	logbigmacs	logbigmacs
duncan	1.142		-2.883*	
	(1.389)		(1.290)	
duncan2	-4.040		11.56**	
	(4.466)		(2.938)	
hs_share	1.280	1.345	-1.892	-2.054
	(1.719)	(1.998)	(1.994)	(2.079)
loggdp	1.743*	1.707**	0.985	1.018
	(0.582)	(0.550)	(0.585)	(0.618)
logworkers	0.283	0.286	0.0104	-0.106
	(0.513)	(0.499)	(0.434)	(0.422)
year_d	-0.309	-0.292	-0.334	-0.320
	(0.354)	(0.334)	(0.318)	(0.328)
gini		-0.746		-3.631***
		(2.319)		(0.480)
gini2		0.852		11.74***
		(6.604)		(1.567)
_cons	-10.28	-9.874	-0.305	0.984
	(11.99)	(11.61)	(10.97)	(11.10)
N	98	98	98	98
R^2	0.861	0.860	0.378	0.412

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As expected signs are negative in linear term and positive in the quadratic one in 3 of the 4 regressions, ratifying what can be seen in the Figure 3 scatter plot. An explanation of this finding would rest on the following argument. According to Benabou (1993) segregation consequences upon city's outcomes depend on the interplay between local and global complementarities. Local complementarities have to do with educational spillovers that individuals experience in their neighbourhoods meanwhile global complementarities are related to how high-skilled and low-skilled labor force complement each other in the production function. If segregation precludes the correct functioning of global complementarities because it leaves low-skilled workers out of the labor market, then segregation will have a negative effect on city's productivity and in the long run economy will colapse. Notwithstanding, if global complementarities are not significant enough, for instance because the city is specialised in productive sector were these complementarities are less important, like the financial sector, then city's productive will not suffer due to segregation but all the opposite: it will be improve.

If we look at Figure 3 scatter plot, we will see at the left side metropolitan areas such as Tijuana, León, Antofagasta and La Serena. These cities exhibit low levels of segregation and they are highly productive. The main productive sector of these cities are manufacturing and mining, which are clearly sectors that need both high-skilled and low-skilled workers, hence in this case a high level of segregation will have a negative impact on cities's outcomes, i.e. for the full economy global complementarities are more important than local ones. On the opposite extreme we can see Santiago and Montevideo with a high level of segregation and high level of productivity. These cities are specialised in the tertiary sector. For instance in the case of Santiago almost 80% of its economy corresponds to this sector and a 30% of it to financial services. Consequently in these cities global complementarities between high-skilled and low-skilled workers are less important and the local spillovers predominate.

The worst escenario is the one that Bolivian cities must face: they are specialised in economic sectors which take advantages of global complementarities, such as agriculture, but they exhibit high level of segregation (above the mean). Therefore in this case segregation has a negative effect on productivity as it could be inferred observing Figure 3.

6 Conclusions

The aim of this investigation has been to cast light upon the relationship between Latin American cities and high-skilled workers residential segregation. To undertake a research on this issue is important because as literature has pointed out, the better-off spatial isolation would produce momentous effects upon the economy as whole. In order to achieve this goal we collect information from censuses' samples available on the Minnesota Population Center webpage (IPUMS) for calculating cities' productivity measures and segregation indices. To gather this data has been a challenging task due to the differences that across countries can be observed regarding quality, detail and others data characteristics. Finally we have been able to get consistent and comparable information for 49 cities around 2000 and the same groups of cities around 2010.

As city definition we have used the closer to functional city as we can get. Consequently we work with metropolitan areas as they are defined in each country's statistic office. As high-skilled workers we consider those individuals that are households' head and have an university degree. We use Duncan and Gini index of segregation. We calculate the productivity per worker and then we deflect it by the Big Mac index as productivity measure. Then we conducted pooled and first differences regressions using productivity as dependant variable and segregation plus others controls as independent variables. We found evidence of a non linear relationship between productivity and segregation of high-skilled workers. Specifically this relationship exhibits u-shaped curve.

The potential explanation of this relationship goes as follow: segregation consequences upon city's outcomes depend on the interplay between local and global complementarities. Local complementarities have to do with educational spillovers that individuals experience in their neighbourhoods meanwhile global complementarities are related to how high-skilled and low-skilled labor force complement each other in the production function. If segregation precludes the correct functioning of global complementarities because it leaves low-skilled workers out of the labor market, then segregation will have a negative effect on city's productivity and in the long run economy will colapse. Notwithstanding, if global complementarities are not significant enough, for instance because the city is specialised in productive sector were these complementarities are less important, like the financial sector, then city's productive will not suffer due to 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. The latter can be explained using global and local complementarities. As these two cities are specialised in manufacturing sector and mining respectively, one could expect an strong global complementarity between high-skilled and low-skilled workers which are more important than local complementarities in education. Consequently as segregation leave low-skilled workers out of the labor market and they are relevant in the production function, segregation in this case will harm productivity.

In the case of Santiago we observe high productivity and high segregation. Then again this can be explained using the city specialization. As a significant part of the Santiago's economic activity is related to financial services where complementarities between high-skilled and low-skilled workers are less obvious, local complementarities in education turn to be more relevant and hence segregation has a positive impact on productivity.

Santa Cruz de la Sierra (Bolivia) presents the worst combination: it is a city which main productive sector is agriculture, where production complementarities between high-skilled and low-skilled workers are important but exhibits high levels of segregation, therefore segregation harms productivity.

Therefore the effect of segregation on cities productivity depends upon the interaction amongst production complementarities between high-skilled and low-skilled workers and educational complementarities at local level, as Benabou (1993) points out, which in turns is strongly connected to the city's kind of specialization. If the city's main productive sector requires global complementarities between these two type of workers, then, as segregation precludes them, the high-skilled residential isolation will harm productivity, as it would be the case of manufacturing, mining or agriculture. But if the city productive specialization does not need complementarities segregation will not harm productivity and it will improve local spillovers in education which will improve, at the end, city's outcomes.

References

Ananat, 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* **3**(2), 34–66.

Anas, A.: 2002, Prejudice, exclusion, and compensating transfers: the economics of ethnic segregation, *Journal of Urban Economics* **52**(3), 409–432.

Benabou, R.: 1993, Working of a city: Location, education and production, *The Quarterly Journal of Economics* **108**(3), 619–652.

Benabou, R.: 1996, Equity and efficiency in human capital investment: The local connection, *The Review of Economics Studies* **63**(2), 237–264.

Bischoff, K. and Reardon, S.: 2013, *Residential Segregation by Income, 1970-2009*, Vol. John R. Logan, The Lost Decade? Social Change in USA after 2000, Russell Sage Fundation.

Bjerk, D.: 2010, Thieves, thugs, and neighborhood poverty, *Journal of Urban Economics* **68**(3), 231–246.

Chetty, R., Hendren, N. and Katz, L.: 2016, The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experimen, *American Economic Review* **106**(4), 855–902.

Conejeros, R. and Vargas, M.: 2012, Segregation, exclusion and compensating transfers under a dynamic setting, *Applied Economics* **44**(17), 2203–2215.

Corvalan, A. and Vargas, M.: 2015, Segregation and conflict: An empirical analysis, *Journal of Development Economics* **116**, 212–222.

Cuttler, D. and Glaeser, E.: 1997, Are ghettos good or bad?, *The Quarterly Journal of Economics* **112**(3), 827–872.

Eberts, R. and McMillan, D. P.: 1999, *Handbook of Urban and Regional Economics*, North Holland, New York, chapter Agglomeration economies and urban public infrastructure.

Fogarty, M. and Garofalo, G.: 1978, Urban spatial structure and productivity growth in the manufacturing sector of cities, *Journal of Urban Economics* **23**, 60–70.

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

Kessler, R., Duncan, G., Gennetian, L., Katz, L., Kling, J., Sampson, N., Sanbonmatsu, L., Zaslavsky, A. and Ludwig, J.: 2014, Associations of housing mobility interventions for children in high poverty neighborhoods with subsequent mental disorders during adolescence, *The Journal of the American Medical Association* .

Krugman, P.: 1980, Scale economies, product differentiation, and the pattern of trade, *American Economic Review* **70**(1), 950–959.

Lucas, R.: 1988, On the mechanics of economic development, *Journal of Monetary Economics* **XXII**, 3–42.

Ludwig, J., Duncan, G., Gennetian, L., Katz, L., Kessler, R., Kling, J. and Sanbonmatsu, L.: 2012, Long-term neighborhood effects on low-income families: Evidence from moving to opportunity, *Science* **21**, 1505–10.

Ludwig, J., Duncan, G., Gennetian, L., Katz, L., Kessler, R., Kling, J. and Sanbonmatsu, L.: 2013, Long-term neighborhood effects on low-income families: Evidence from moving to opportunity, *American Economic Review Papers and Proceedings* **103**(3), 226–231.

Marshall, A. (ed.): 1920, *Principles of Economics*, MacMillan, London.

Massey, D. and Denton, N.: 1988, The dimensions of residential segregation, *Social Forces* **67**(2), 281–315.

Piketty, T. and Saez, E.: 2003, Income inequality in the united states: 1913-1998, *The Quarterly Journal of Economics* **68**(1), 1–39.

Reviews, O. T. (ed.): 2006, *Competitive Cities and the Global Economy*, OECD.

Rosenthal and Strange: 2004, *Handbook of Regional and Urban Economics*, Elsevier, chapter Evidence on the nature and sources of agglomeration economies.

Solow, R.: 1957, Technical change and the aggregate production function, *Review of Economic and Statistics* **39**(3), 312–320.

Sveikauskas, L.: 1975, The productivity of cities, *The Quarterly Journal of Economics* **89**(3), 393–413.

Sveikauskas, L., Gowdy, J. and Funk, M.: 1988, Urban productivity: City size or industry size, *Journal of Regional Science* **28**(2).

Tabuchi, T.: 1986, Urban agglomeration, capital augmenting technology, and labor market equilibrium, *Journal of Urban Economics* **20**, 211–228.

Williamson, J.: 2010, Five centuries of latin american inequality, *Journal of Iberian and Latin American Economic History* **28**(2), 227–252.

Wooldridge, J. M.: 2001, *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

A Tables

Table 9: Productivity's Sources of Information

City	Labor Data	Value Added Data	City	Labor Data	Value Added Data
Santiago	2000 Census	2000 OECD	San Luis de Potosi	2010 IPUM	2010 OECD
Santiago	2009 CASEN	2010 OECD	Leon	2000 IPUM	2000 OECD
Antofagasta	2000 Census	2000 OECD	Leon	2010 IPUM	2010 OECD
Antofagasta	2009 CASEN	2010 OECD	Buenos Aires	2001 IPUM	2000 OECD
Valparaiso	2000 Census	2000 OECD	Buenos Aires	2001 IPUM	2010 OECD
Valparaiso	2009 CASEN	2010 OECD	Cordoba	2001 IPUM	2000 OECD
Concepcin	2000 Census	2000 OECD	Cordoba	2001 IPUM	2010 OECD
Concepcin	2009 CASEN	2010 OECD	Rosario	2001 IPUM	2000 OECD
La Serena	2000 Census	2000 OECD	Rosario	2001 IPUM	2010 OECD
La Serena	2009 CASEN	2010 OECD	Mendoza	2001 IPUM	2000 OECD
Sao Paulo	2000 IPUM	2000 OECD	Mendoza	2001 IPUM	2010 OECD
Sao Paulo	2010 IPUM	2010 OECD	Medelln	2005 IPUM	2000 OECD
Rio de Janeiro	2000 IPUM	2000 OECD	Medelln	2005 IPUM	2010 OECD
Rio de Janeiro	2010 IPUM	2010 OECD	Bogot	2005 IPUM	2000 OECD
Salvador	2000 IPUM	2000 OECD	Bogot	2005 IPUM	2010 OECD
Salvador	2010 IPUM	2010 OECD	Barranquilla	2005 IPUM	2000 OECD
Fortaleza	2000 IPUM	2000 OECD	Barranquilla	2005 IPUM	2010 OECD
Fortaleza	2010 IPUM	2010 OECD	San Jos	2000 Census	2010 OECD
Belo Horizonte	2000 IPUM	2000 OECD	San Jos	2011 Census	2010 OECD
Belo Horizonte	2010 IPUM	2010 OECD	La Paz	2001 IPUM	2000 INE Bolivia
Curitiba	2000 IPUM	2000 OECD	La Paz	2001 IPUM	2010 INE Bolivia
Curitiba	2010 IPUM	2010 OECD	Cochabamba	2001 IPUM	2000 INE Bolivia
Porto Alegre	2000 IPUM	2000 OECD	Cochabamba	2001 IPUM	2010 INE Bolivia
Porto Alegre	2010 IPUM	2010 OECD	Santa Cruz	2001 IPUM	2000 INE Bolivia
Goiana	2000 IPUM	2000 OECD	Santa Cruz	2001 IPUM	2010 INE Bolivia
Goiana	2010 IPUM	2010 OECD	Lima	2007 Census	2000 INEI Peru
Recife	2000 IPUM	2000 OECD	Lima	2007 Census	2010 INEI Peru
Recife	2010 IPUM	2010 OECD	Chiclayo	2007 Census	2000 INEI Peru
Belen	2000 IPUM	2000 OECD	Chiclayo	2007 Census	2010 INEI Peru
Belen	2010 IPUM	2010 OECD	Arequipa	2007 Census	2000 INEI Peru
Distrito Federal	2000 IPUM	2000 OECD	Arequipa	2007 Census	2010 INEI Peru
Distrito Federal	2010 IPUM	2010 OECD	Trujillo	2007 Census	2000 INEI Peru
Guadalajara	2000 IPUM	2000 OECD	Trujillo	2007 Census	2010 INEI Peru
Guadalajara	2010 IPUM	2010 OECD	Asuncin	2002 Census	2005 Central Bank
Monterrey	2000 IPUM	2000 OECD	Asuncin	2002 Census	2010 Central Bank
Monterrey	2010 IPUM	2010 OECD	Ciudad de Panama	2000 IPUM	2007 INEC
Puebla	2000 IPUM	2000 OECD	Ciudad de Panam	2010 IPUM	2010 INEC
Puebla	2010 IPUM	2010 OECD	Montevideo	2006 Census	2000 INE
Toluca	2000 IPUM	2000 OECD	Montevideo	2006 Census	2010 INE
Toluca	2010 IPUM	2010 OECD	Guayaquil	2001 IPUM	2000 Central Bank
Tijuana	2000 IPUM	2000 OECD	Guayaquil	2001 IPUM	2010 Central Bank
Tijuana	2010 IPUM	2010 OECD	Quito	2001 IPUM	2000 Central Bank
Juarez	2000 IPUM	2000 OECD	Quito	2001 IPUM	2010 Central Bank
Juarez	2010 IPUM	2010 OECD	Cuenca	2001 IPUM	2000 Central Bank
Laguna	2000 IPUM	2000 OECD	Cuenca	2001 IPUM	2010 Central Bank
Laguna	2010 IPUM	2010 OECD	Santo Domingo	2001 IPUM	2000 Central Bank
Queretaro	2000 IPUM	2000 OECD	Santo Domingo	2001 IPUM	2010 Central Bank
Queretaro	2010 IPUM	2010 OECD	Santo Domingo	2000 IPUM	2007 Central Bank
San Luis de Potosi	2000 IPUM	2000 OECD	Santo Domingo	2010 IPUM	2010 Central Bank

Table 10: Cities's Big Mac Index Ranking

Ranking 2000			Ranking 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	Juarez	11318.6198
Argentina	Cordoba	9961.192768	Mexico	Laguna	11291.11744
Argentina	Rosario	9891.552209	Mexico	DF	11193.25867
Mexico	DF	9811.814948	Mexico	San Luis Potosi	10902.27451
Mexico	Monterrey	9770.052587	Mexico	Tijuana	10651.70953
Mexico	Tijuana	9697.043644	Mexico	Queretaro	10485.91086
Mexico	Juarez	9519.388056	Mexico	Guadalajara	10406.90449
Mexico	San Luis Potosi	9492.556654	Mexico	Toluca	10364.67466
Mexico	Guadalajara	9436.970204	Chile	Santiago	10161.11197
Mexico	Queretaro	9413.488672	Mexico	Leon	10101.04737
Mexico	Laguna	9248.405271	Mexico	Puebla	9836.425835
Mexico	Leon	9104.119414	Chile	Serena Coquimbo	9451.650954
Mexico	Toluca	9101.691903	Chile	VinaValparaiso	9391.068743
Mexico	Puebla	8851.451708	Chile	Concepcion	9232.065182
Panama	Panama	8145.913908	Argentina	Buenos Aires	8384.960162
Brazil	Sao Paoulo	6679.847307	Argentina	Mendoza	8381.844495
Brazil	Rio de Janiero	6558.941986	Argentina	Rosario	8099.204496
Brazil	Curitiba	6468.572587	Argentina	Cordoba	8080.177341
Brazil	Porto Alegre	6367.987802	Uruguay	Montevideo	8036.850976
Chile	Antofagasta	6308.845286	Panama	Panama	7273.621014
Brazil	Bello Horizonte	6296.322268	Colombia	Bogot	6552.569326
Brazil	Recife	6241.733271	Colombia	Medelln	6384.023835
Chile	Santiago	6206.434154	CostaRica	San Jos	5353.213481
Brazil	Goiana	6115.139454	Brazil	Rio de Janiero	5124.571709
Brazil	Salvador	6103.46939	Brazil	Sao Paoulo	5104.384167
Brazil	Fortaleza	6039.005177	Brazil	Bello Horizonte	5092.924787
Brazil	Belen	5909.315539	Brazil	Curitiba	5060.667619
RDominicana	Santo Domingo	5566.000039	Brazil	Porto Alegre	5032.341579
Chile	VinaValparaiso	5278.257951	Brazil	Goiana	4857.10337
Chile	Concepcion	5229.744615	Brazil	Salvador	4847.332604
Chile	Serena Coquimbo	4901.780204	Brazil	Recife	4829.722434
Colombia	Bogot	4752.925471	Brazil	Fortaleza	4757.989157
Colombia	Medelln	4629.978149	Brazil	Belen	4703.405616
CostaRica	San Jos	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	RDominicana	Santo Domingo	3319.768189
Ecuador	StoDomingo	2905.272975	Ecuador	Quito	3155.191171
Peru	Lima	2646.185677	Peru	Chiclayo	2964.603405
Peru	Chiclayo	2203.590951	Paraguay	Asuncin	2802.714553
Paraguay	Asuncin	2099.929668	Colombia	Barranquilla	2630.747011
Colombia	Barranquilla	1943.781739	Ecuador	StoDomingo	2550.215107
Bolivia	LaPaz	1276.043587	Bolivia	LaPaz	1520.774422
Bolivia	SantaCruz	1230.582007	Bolivia	SantaCruz	1382.599926
Bolivia	Cochabamba	1090.808814	Bolivia	Cochabamba	1208.268208

Table 11: Cities's Complete Productivity Ranking

Ranking 2000			Ranking 2010		
Country	City	PPP	Country	City	PPP
Argentina	Buenos Aires	26984.03336	Chile	Antofagasta	38739.52966
Argentina	Mendoza	24991.12449	Chile	Santiago	33938.11398
Argentina	Cordoba	24902.98192	Chile	Serena Coquimbo	31568.51419
Argentina	Rosario	24728.88052	Chile	VinaValparaiso	31366.1696
Mexico	DF	21782.22918	Chile	Concepcion	30835.09771
Mexico	Monterrey	21689.51674	Uruguay	Montevideo	30057.82265
Mexico	Tijuana	21527.43689	Argentina	Buenos Aires	29850.45817
Mexico	Juarez	21133.04148	Argentina	Mendoza	29839.3664
Mexico	San Luis Potosi	21073.47577	Mexico	Monterrey	29047.11407
Mexico	Guadalajara	20950.07385	Argentina	Rosario	28833.168
Mexico	Queretaro	20897.94485	Colombia	Bogot	28765.77934
Mexico	Laguna	20531.4597	Argentina	Cordoba	28765.43133
Uruguay	Montevideo	20323.46616	Mexico	Juarez	28296.54951
Mexico	Leon	20211.1451	Mexico	Laguna	28227.7936
Mexico	Toluca	20205.75603	Colombia	Medelln	28025.86464
Mexico	Puebla	19650.22279	Mexico	DF	27983.14667
Panama	Panama	18409.76543	Mexico	San Luis Potosi	27255.68628
Chile	Antofagasta	15456.67095	Panama	Panama	27103.3303
Chile	Santiago	15205.76368	Mexico	Tijuana	26629.27383
Chile	VinaValparaiso	12931.73198	Mexico	Queretaro	26214.77716
Chile	Concepcion	12812.87431	Mexico	Guadalajara	26017.26123
RDominicana	Santo Domingo	12579.16009	Mexico	Toluca	25911.68664
Chile	Serena Coquimbo	12009.3615	Mexico	Leon	25252.61842
CostaRica	San Jos	11593.66786	Brazil	Rio de Janiero	25161.64709
Colombia	Bogot	11169.37486	Brazil	Sao Paoulo	25062.52626
Brazil	Sao Paoulo	11021.74806	Brazil	Bello Horizonte	25006.2607
Colombia	Medelln	10880.44865	Brazil	Curitiba	24847.87801
Brazil	Rio de Janiero	10822.25428	Brazil	Porto Alegre	24708.79715
Brazil	Curitiba	10673.14477	Mexico	Puebla	24591.06459
Brazil	Porto Alegre	10507.17987	Brazil	Goiana	23848.37755
Brazil	Bello Horizonte	10388.93174	Brazil	Salvador	23800.40308
Brazil	Recife	10298.8599	Brazil	Recife	23713.93715
Brazil	Goiana	10089.9801	Brazil	Fortaleza	23361.72676
Brazil	Salvador	10070.72449	Brazil	Belen	23093.72157
Brazil	Fortaleza	9964.358542	CostaRica	San Jos	20502.80763
Brazil	Belen	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	RDominicana	Santo Domingo	12370.28622
Peru	Trujillo	7462.730208	Ecuador	Cuenca	12141.79094
Ecuador	StoDomingo	6565.916924	Colombia	Barranquilla	11548.97938
Peru	Lima	6562.540479	Ecuador	Quito	11043.1691
Peru	Chiclayo	5464.905558	Peru	Chiclayo	10494.69605
Paraguay	Asuncin	4745.841049	Paraguay	Asuncin	10443.6151
Colombia	Barranquilla	4567.887087	Ecuador	StoDomingo	8925.752875
Bolivia	LaPaz	2883.858507	Bolivia	LaPaz	5666.785691
Bolivia	SantaCruz	2781.115335	Bolivia	SantaCruz	5151.912973
Bolivia	Cochabamba	2465.227921	Bolivia	Cochabamba	4502.30941

Table 12: Duncan Index's Segregation Ranking

Ranking 2000			Ranking 2010		
Country	City	Duncan	Country	City	Duncan
Chile	Santiago	0.4758	Chile	Santiago	0.5237
Brazil	Porto Alegre	0.4264	Bolivia	SantaCruz	0.4092
Bolivia	SantaCruz	0.4092	Uruguay	Montevideo	0.3869
Uruguay	Montevideo	0.3869	Brazil	Porto Alegre	0.3864
Brazil	Bello Horizonte	0.3845	Bolivia	LaPaz	0.3834
Bolivia	LaPaz	0.3834	Paraguay	Asuncin	0.3825
Paraguay	Asuncin	0.3825	Brazil	Bello Horizonte	0.3444
Brazil	Curitiba	0.3496	Brazil	Curitiba	0.3404
Brazil	Rio de Janiero	0.3346	Brazil	Rio de Janiero	0.3143
Argentina	Buenos Aires	0.3317	Colombia	Medelln	0.3114
Argentina	Mendoza	0.3222	Argentina	Buenos Aires	0.3108
Colombia	Medelln	0.3114	Argentina	Mendoza	0.3071
Peru	Trujillo	0.2954	Mexico	Toluca	0.3024
Mexico	Toluca	0.2898	Peru	Trujillo	0.2954
Argentina	Cordoba	0.2852	Mexico	DF	0.2927
Ecuador	Cuenca	0.2818	Ecuador	Cuenca	0.2818
Colombia	Barranquilla	0.2787	Colombia	Barranquilla	0.2787
Bolivia	Cochabamba	0.2763	Bolivia	Cochabamba	0.2763
Mexico	DF	0.2715	Brazil	Recife	0.2594
Mexico	Monterrey	0.268	Chile	Concepcion	0.2565
CostaRica	San Jos	0.2579	Argentina	Cordoba	0.2514
Brazil	Fortaleza	0.2493	Brazil	Fortaleza	0.2408
RDominicana	Santo Domingo	0.2362	Mexico	Puebla	0.2383
Argentina	Rosario	0.2294	Mexico	Monterrey	0.2379
Mexico	Laguna	0.224	CostaRica	San Jos	0.2326
Chile	Concepcion	0.2202	Argentina	Rosario	0.2322
Mexico	Puebla	0.215	Mexico	Guadalajara	0.2261
Brazil	Recife	0.2148	RDominicana	Santo Domingo	0.2161
Ecuador	Guayaquil	0.213	Ecuador	Guayaquil	0.213
Brazil	Sao Paoulo	0.2055	Mexico	Queretaro	0.1837
Mexico	Guadalajara	0.186	Brazil	Sao Paoulo	0.1832
Brazil	Belen	0.1805	Colombia	Bogot	0.1788
Colombia	Bogot	0.1788	Brazil	Belen	0.1757
Chile	Serena Coquimbo	0.172	Peru	Arequipa	0.1705
Peru	Arequipa	0.1705	Chile	VinaValparaiso	0.1606
Peru	Chiclayo	0.1517	Mexico	Laguna	0.1596
Panama	Panama	0.1494	Brazil	Salvador	0.1543
Ecuador	Quito	0.1489	Peru	Chiclayo	0.1517
Brazil	Salvador	0.1364	Ecuador	Quito	0.1489
Mexico	Queretaro	0.1334	Panama	Panama	0.1404
Mexico	San Luis Potosi	0.1302	Mexico	Juarez	0.1389
Mexico	Leon	0.118	Mexico	Leon	0.1126
Ecuador	StoDomingo	0.111	Ecuador	StoDomingo	0.111
Mexico	Juarez	0.0892	Mexico	San Luis Potosi	0.1087
Chile	VinaValparaiso	0.0809	Peru	Lima	0.0754
Peru	Lima	0.0754	Chile	Serena Coquimbo	0.07
Mexico	Tijuana	0.0479	Chile	Antofagasta	0.0651
Chile	Antofagasta	0.0366	Brazil	Goiana	0.0557
Brazil	Goiana	0.0335	Mexico	Tijuana	0.0225

Table 13: Gini Index's Segregation Ranking

Ranking 2000			Ranking 2010		
Country	City	Gini	Country	City	Gini
Chile	Santiago	0.6323	Chile	Santiago	0.6547
Uruguay	Montevideo	0.5224	Uruguay	Montevideo	0.5224
Bolivia	SantaCruz	0.4871	Bolivia	SantaCruz	0.4871
Brazil	Porto Alegre	0.4675	Paraguay	Asuncin	0.4642
Paraguay	Asuncin	0.4642	Brazil	Porto Alegre	0.4304
Argentina	Mendoza	0.4375	Mexico	DF	0.4144
Argentina	Buenos Aires	0.4335	Argentina	Mendoza	0.4063
Brazil	Bello Horizonte	0.4049	Bolivia	LaPaz	0.3877
Bolivia	LaPaz	0.3877	Brazil	Bello Horizonte	0.3859
Mexico	DF	0.3807	Colombia	Medelln	0.3678
Colombia	Medelln	0.3678	Mexico	Toluca	0.3646
Mexico	Monterrey	0.3661	Argentina	Buenos Aires	0.3635
Brazil	Rio de Janiero	0.3659	Brazil	Curitiba	0.3561
Brazil	Curitiba	0.3582	Mexico	Monterrey	0.3497
CostaRica	San Jos	0.3576	Brazil	Rio de Janiero	0.3455
Mexico	Toluca	0.3504	Chile	Concepcion	0.3326
Argentina	Cordoba	0.3307	CostaRica	San Jos	0.3306
Peru	Trujillo	0.3237	Peru	Trujillo	0.3237
RDominicana	Santo Domingo	0.3016	Mexico	Guadalajara	0.3044
Chile	Concepcion	0.294	Argentina	Cordoba	0.3021
Colombia	Barranquilla	0.2927	RDominicana	Santo Domingo	0.2965
Ecuador	Cuenca	0.2837	Brazil	Recife	0.2963
Bolivia	Cochabamba	0.2836	Colombia	Barranquilla	0.2927
Mexico	Guadalajara	0.267	Mexico	Queretaro	0.2883
Argentina	Rosario	0.2587	Ecuador	Cuenca	0.2837
Brazil	Recife	0.2547	Bolivia	Cochabamba	0.2836
Brazil	Fortaleza	0.2516	Argentina	Rosario	0.2677
Ecuador	Guayaquil	0.243	Mexico	Puebla	0.2574
Brazil	Sao Paoulo	0.2374	Brazil	Fortaleza	0.2449
Mexico	Puebla	0.2374	Ecuador	Guayaquil	0.243
Mexico	Laguna	0.237	Brazil	Sao Paoulo	0.21
Chile	Serena Coquimbo	0.1948	Chile	VinaValparaiso	0.2088
Brazil	Belen	0.1862	Colombia	Bogot	0.1862
Colombia	Bogot	0.1862	Brazil	Belen	0.1843
Peru	Arequipa	0.173	Mexico	Laguna	0.179
Panama	Panama	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	0.1512
Mexico	Queretaro	0.1412	Ecuador	Quito	0.1501
Mexico	San Luis Potosi	0.1302	Mexico	Juarez	0.1389
Ecuador	StoDomingo	0.126	Ecuador	StoDomingo	0.126
Mexico	Leon	0.1207	Mexico	Leon	0.1154
Chile	VinaValparaiso	0.1148	Mexico	San Luis Potosi	0.1087
Mexico	Juarez	0.0892	Chile	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	Goiana	0.0561
Brazil	Goiana	0.0335	Mexico	Tijuana	0.0227