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Neighborhood impacts on human capital accumulation of adolescents and young adults in Montevideo

Santiago Acerenza, Nestor Gandelman, and Daniel Misail[1]

Abstract

This paper explores the causal impacts of the neighborhood of residence on education outcomes for adolescents and young adults (15-24 years old) in Montevideo. We present stylized facts on educational outcomes between 1992 and 2019. We compute transition matrixes for the neighborhood effects (conditional on individual characteristics and unconditional) and find strong path dependency and geographical segmentation between the better off southeast of the city and the worse off outskirts. We model the neighborhood effects through the neighborhood average education level. We estimate their causal impact controlling for endogeneity of the choice of residence and find statistically significant results of a relatively large magnitude. We address heterogeneity of the effects and find that neighborhood effects are stronger for boys than girls, that family income buffers neighborhood effects, and that household education level and neighborhood education level are complements.

Keywords: neighborhoods, school enrollment, human capital, young people

JEL Codes: I24, I25, R23.

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1. Introduction

Educational and labor outcomes, health and risk attitudes of individuals tend to be highly correlated within neighborhoods. This is particularly relevant for adolescents and young adults. The place where they live nurtures their human capital accumulation, it shapes their aspirations and through them influences their decisions and future outcomes.[2] Educational choices do not only affect individual future wages (Mincer,1974) but they also have an impact on economic and social development of a country (Mankiw et al. 1992; Barro 1999). In this paper, we consider the neighborhood dimension of human capital accumulation in a South American city.

Traditionally, Uruguay has been considered a country with a strong and stable middle class formed mostly of European immigrants and descendants of these immigrants. The public education system was the melting pot where children of different family backgrounds met and conformed a society that had the lowest levels of inequality in Latin America. However, over the past decades social interaction deteriorated with increased levels of criminality[3] and a perception of worsening and segregation of the educational system (Ferrando et al 2020). In many dimensions Uruguay has become more like other Latin American countries with neighborhood segregation and social deterioration (Kaztman and Retamoso 2005 and Vargas and Garrido 2021). In Montevideo, the capital city with 1.3 million inhabitants, different realities coexist. Highly educated and rich neighborhoods are blocks away from highly violent neighborhoods infested with drug trafficking (Tenenbaum 2018).[4]

We consider the decision adolescents and young adults make to invest in their human capital through secondary or tertiary education. For several decades Uruguay has had an important problem in both dimensions. The rate of secondary completion is among the lowest in Latin America. Tertiary education is even more exclusive. Understanding the impact the place of residence has on educational choice is a prerequisite to consider policies aiming at reducing the negative consequences of segregation such as violence, labor force participation discouragement and illegal drug markets, to which, young individuals are attracted.

We measure the neighborhoods effects on the human capital accumulation decisions of Uruguayan youth. To do so, we propose two alternative strategies. In the first strategy, we consider neighborhood effects as a fixed effect changing the average level of human capital accumulation for individuals inside this neighborhood. In this strategy, we identify the effect by including regression dummies for each vicinity. Although not causal, it is useful to compute the differential effects that regions have on individuals controlling for their personal or household characteristics (conditional fixed effect of neighborhoods) and without controlling for them (an unconditional fixed effect of neighborhoods).

In a second approach, we model the effect of the neighborhood as the average education level of the household head which is a relevant contextual variable. In this manner, we consider a potential channel through which the neighborhood effect operates. We control for endogeneity

[2] See the seminal works of Wilson (1987), Miller (1977), Bjerk (2010) and a vast literature built over them.
[3] Homicides increased from 6 per 100,000 habitants in 2000 to 12 per 100,000 habitants in 2018.
[4] This has been reported in the popular press based on data from the Observatorio Nacional sobre Violencia y Criminalidad del Ministerio del Interior.
https://www.elobservador.com.uy/nota/barrio-a-barrio-mira-como-se-mueve-el-delito-en-montevideo-20232319260.

of neighborhood selection using a control function approach (Wooldridge, 2015); thus the result can be interpreted as a causal relation.

A neighborhood effect is the independent causal effect of the place of residence on any social or economic outcome. These effects have been categorized in several ways. One strand of literature (Oakes, 2004) divides between neighbors' social interactions and integral effects that emerge from toxic dumps, parks, sidewalks, etc. (Ozonoff et al. 1987; Geschwind et al. 1992; Susser & Susser 1996 and Diez-Roux 1998).

Another strand of literature in line with Manski (1993) classifies them in endogenous effects, correlated effects, and exogenous effects. An endogenous neighborhood effect is present if the behavior of an individual has a direct influence on the behavior of every other individual in the neighborhood. Endogenous effects are also known as bandwagon and peer effects. For example, suppose the consumption of drugs by a teen in a neighborhood leads to increased consumption by other teens in that neighborhood. A policy that reduces the demand for drugs of just one of them generates larger social effects due to the resulting decrease in demand by others. Correlated effects arise because the individuals in a neighborhood tend to have similar characteristics or institutional exposure. Contextual or exogenous effect (also known as place or compositional effects) arise if the actions of an individual depend on the exogenous characteristics of the individuals' neighbors. Examples include the racial or religious composition of a given neighborhood.

Consistently with the previous paragraph, the empirical identification of causal neighborhood effects faces two important challenges that we address in our empirical strategy. First, region influence is hard to disentangle from self-selection (Manski's correlation effects). In the neighborhood setting, the selection (or correlated effects) problem stems from the fact that household heads choose where to live based on their preferences for location, quality, costs, and other family or neighborhood features. Due to this sorting, it is natural to find that students share more characteristics within neighborhoods than between neighborhoods. A second problem with the identification of social spillovers is the difficulty in isolating the effect of peers' attitudes on the individual from the influence of the individual on his/her peers (Manski's reflection problem). In the context of neighborhoods, this is less of a problem because individuals are atomistic members that have minimum effects on the averages. Thus, we only must deal with self-selection, which we solve by correcting for neighborhoods choices of households (which affect the regional variables) using household average prices as the main ingredient of a control function approach. This sorts out the selection via inducing exogenous variation in prices of households that affect neighborhood choices and thus, relevant contextual neighborhood variables.

In applied research the question of external validity is always relevant. This paper contributes to the neighborhood effects literature and the human capital literature considering its interaction in a context that has been little explored. As such it provides interesting new data that make up a piece of the puzzle in understanding how under different national realities the place of residence has life-impacts beyond pure housing. We find strong path dependence and geographical segmentation of the neighborhood effects. The better off neighborhoods in the 1990s tend to also be the better off neighborhoods of the 2010s, mostly located in the southeast of the city. The opposite happens for the relatively deprived outskirts. We show casual estimates that the average neighborhood education level is a statistically significant channel through which neighborhoods effects impact in human capital accumulation decisions. The effects are economically meaningful and vary with individual and household characteristics. We find stronger effects for boys. Females are less affected than males by the general neighborhood educational level. We also find that household income helps to buffer outside neighborhoods impacts. On the other hand, we find complementarity between education of the household head and the average neighborhood education level.

The paper proceeds with the analytical framework and literature review in section 2. Section 3 presents the data and relevant summary statistics. Section 4 presents the relative impact of neighborhood and section 5 test for causal effects. Finally, section 6 concludes.

2. Analytical framework

Our paper interacts with the literature on human capital acquisition and the literature on neighborhood effects. In this section we summarize some of the most relevant previous work and place our contribution within this context.

The human capital literature recognizes that the acquisition of cognitive, socio-emotional and health related capabilities is the basis of successful economic and social trajectories over the lifetime (Heckman, 2007; Heckman and Kautz, 2012). Childhood, adolescence, and young adulthood are critical periods for the development of these skills. Family, school, and neighborhoods play key roles in the formation of these capabilities.

Educational as well as other socio-economic outcomes depend on peers' characteristics as well as family characteristics (Bisin and Verdier 2001, 2010). Differences in neighborhood and peer influences are related to inequality in schooling inputs. If parents choose to send their children to a private school or move to an expensive neighborhood because of the availability of better-quality public schools, this will also affect which peers and local role models' children are exposed to. Local inputs do matter, as prospects for upward mobility differ systematically across neighborhoods and regions.

During adolescence and young adulthood, peers acquire a critical role in the socialization process, competing with parental influences in the formation of skills and competencies (Windle, 2000; Wood et al., 2001). Peer influence attains special policy significance when the externality works through peers' current behaviors, as it implies that the individual-level effects of a particular policy will be multiplied by the influential processes that take place between peers. The study of peer effects has received profuse attention in the area of education (Hoxby, 2000; Sacerdote, 2001; Zimmerman, 2003; Angrist and Lang, 2004 among others).[5]

There is a specific economic literature on how to measure neighborhood or regional effects on a variety of socioeconomic outcomes and populations. There are studies focusing on neighborhood effects via determinants (such as neighborhood poverty rates and average neighborhoods education among others) on different outcomes. For example, labor market outcomes for adults (Bayer and Ross, 2005) and educational achievement of 10th graders (Ainsworth, 2002). There are studies focusing on the effect of the neighborhood itself, such as Agrawal et al. (2019) for education and wages of individuals who were 8th graders in 1988 and 10th graders in 2002, intergenerational effects of transmission of education (Patacchini and Zenou, 2011), forms of social capital measured among other forms as civic participation (Chetty et al, 2022 building over Chetty et al, 2014) and gendered neighborhood effects on the labor

[5] In Uruguay, peer effects have been addressed in Balsa et al (2018) for academic performance and alcohol consumption and in Balsa et al (2015) for risk preferences.

market (Mota et al., 2016). Another strand of papers focuses on the effect of neighborhood effects via living choices shifters such as the Moving to Opportunity program randomized housing mobility experiment sponsored by the U.S. Department of Housing and Urban Development or exogenous state scheduled demolitions. These include effects on labor market outcomes of adults (Aliprantis and Richter, 2020), mental health of adults and adolescents (Kling and Katz, 2007), criminal behavior of adolescents (Kling, Ludwig, and Katz, 2005) and labor market outcomes, criminal behavior, and educational outcomes of young adults (Chyn, 2018).

Besides economics, other disciplines such as sociology and epidemiology have focused on neighborhood effects.[6] Spatial variation in morbidity and mortality is associated with the clustering of genetic predispositions, cultural norms, opportunity structures, and/or environmental conditions. In that sense, epidemiologists have long recognized that people residing in different areas have differing health outcomes (Macintyre, Maciver, & Sooman, 1993, Oakes, 2004 among others) and that advantaged neighborhoods offer cleaner, safer, and less stressful environments as compared to, say, ghetto areas (Cassel, 1976; McMichael, 1999; Susser, 1999; among others). Social scientists and sociologists have also focused on neighborhood effects, which they view as a special case of context effects. Classical works in this tradition include Durkheim (1952) analysis of how social forces (e.g., norms and values) external to the individual influence suicide and Weber (1930) assessment of how religious ideology shape economic behavior.

Furthermore, sociologists defined the mechanisms by which a neighborhood effect may arise and operate. Jencks and Mayer (1990) classified these mechanisms into contagion theories, collective socialization, competition theories and relative deprivation theories. Contagion theories focuses on peer influences that are responsible for the spread of negative social behavior.[7] Collective socialization focuses on the spread of socially positive behavior due to the interaction of individuals with role models or community networks. Competition theory states that the presence of social or economic ‘‘winners’’ has a detrimental effect on the other members of the community. The underlying assumption is that resource allocation or the possibility of achievement is a zero-sum game. Relative deprivation theory posits that the presence of individuals with socially positive outcomes has a negative effect on neighbors. Exposure to economic or social success leads to resentment or insecurity on the part of neighbors not achieving a comparable level of success. The inequality in social outcomes leads to a downward spiral in which the disparity causes the deprived to perform even more poorly in the future.

Finally, within the regional literature referring to the Uruguayan experience the closest to our study is Katzman and Retamoso (2007). Based on census data for 1996, they present estimates on the proportion of total educational variance attributable to differences within child, school, and neighborhoods in the city of Montevideo. They find that 67% of the variance is explained by individual level variables (gender, family, etc.) while 18% is attributable to the neighborhood. However, incidence is greater for the neighborhood level, i.e. improvements within the neighborhood may have a larger impact that improvements in family background.[8]

[6] For a more in-depth discussion of empirical papers in different disciplines see Dietz (2002).

[7] Studies examining contagion theories include Case and Katz (1991), Evans et al. (1992), and Corcoran et al. (1992).

[8] They measure the socio-economic level of a family as a score that combines family characteristics (such as education of parents, comfort of basic necessities and books in the household) and socio-economic level of schools and vicinities as the averages across these dimensions. They find that an increase of one

Our paper differs from Katzman and Retamoso (2007) in several dimensions. First, we consider a longer-term period (1992-2019) and analyze changes within subperiods. Second, we present novel geographical evidence of relative neighborhood effects and its path dependence. Third, we address the endogeneity of the place of residence and present causal impacts.

3. Data and education institutional background

a. Education system institutional background[9]

The governance of the education system in Uruguay is characterized by a high degree of functional and geographical centralization. The main responsibility for formulating and implementing policies in school education does not lie within the scope of the Ministry of Education and Culture (Ministerio de Educación y Cultura, MEC), but rather within the autonomous National Public Education Administration (Administración Nacional de Educación Pública, ANEP).

Five agencies with distinct levels of responsibility govern the education system. ANEP regulates and administers part of the early childhood and pre-primary education; all of school education; teacher education at the tertiary level; and technical and professional education at the secondary and tertiary levels. MEC regulates and oversees part of private early childhood and pre-primary education, and private tertiary education. The Child and Adolescent Institute of Uruguay (Instituto del Niño y Adolescente del Uruguay, INAU) oversees regulating and administrating both the network of day schools in early childhood education and the Childcare and Family Centers (Centro de Atención a la Infancia y la Familia, CAIF). The Universidad de la República (UDELAR) and Universidad Tecnológica (UTEC) are public tertiary education institutions. The main governance agencies (ANEP, UDELAR, UTEC) have technical and administrative autonomy from the government.

During the period considered for this study, the school system in Uruguay was organized in four consecutive stages: early childhood education (below 3 years of age) and pre-primary education (ages 3 to 5); primary education (6 years); lower secondary education (3 years); and upper secondary education (3 years). School attendance is compulsory from the age of 4 until lower secondary education (inclusive), that could be attained at age 14.

Secondary education, both lower and upper, can be conducted in three educational tracks with varying weights to general, technical, and vocational education (Universidad del Trabajo del Uruguay, UTU). Tertiary education (typically ages above 18) can be divided into university education and technical education.

Public education is dominant in Uruguay. In 2013, considering all pre-tertiary levels, 86% of students attended public schools.[10] Private schools and universities are not publicly funded but they benefit of certain tax exemptions (value-added tax, employer's contribution to social security). Private institutions are concentrated in Montevideo and its neighboring departments

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standard deviation unit in the socio-economic level of the vicinity has a greater effect than the socio-economic level of the school or of the family.

[9] Most of this section is based on OECD Reviews of School Resources: Uruguay 2016.

[10] OECD Reviews of School Resources: Uruguay 2016.

such as Canelones and Maldonado. Most private schools follow the national curriculum and have autonomy in the provision of extracurricular activities.

b. Data source and definitions

The data come from household surveys (Encuesta Continua de Hogares, ECH) conducted annually by the National Institute of Statistics (Instituto Nacional de Estadística, INE). We use publicly available data from 1992 to 2019. We do not include data from 2020 onwards to avoid the influence of COVID-19 either in the observed variables or in the exceptional data gathering procedure implemented by the INE.

According to the ECH, Montevideo is divided in 62 neighborhoods. For sampling purposes, its geographic limits remained unchanged throughout the period of study.

The ECH gathers information on individuals and housing. It has detailed information on educational attainment and labor conditions. It also contains socio demographic information such as age, gender, marital status, and number of children in the household.

We define the household head to be the household main income provider. In this way, we avoid gender self-declaration bias that are subjective and affected by cultural traits that changed in the last decades.

At the housing level, the ECH includes information on rental values. For renters, we use the actual paid rent. For owners, we use the estimated rent they would have to pay if they were to rent the house where they live. This allows us to construct the average price of housing in any given location that we use to control for the endogenous choice of residence.

The dependent variables for this study refer to educational investment and educational outcomes. We focus on individuals between 15 to 24 years old. We divide them in two groups. For those between 15 and 18 years old, we focus on whether the adolescent has dropped out of secondary school or is still enrolled in the educational system. For those between 19 to 24 years old, we consider whether the young adult has completed secondary school or is enrolled in (or has finished) tertiary education. Thus, we consider four dependent variables: years of education for those 15-24 years old, high school enrollment for those 15-18 years old, and secondary completion and tertiary enrollment for those 19-24 years old.

c. Summary statistics

Figure 1 presents the overtime evolution of the four main indicators that we consider in this paper. Panel A presents secondary enrollment for those 15-18 years old. We consider regular secondary or vocational education including technical schools (UTU for the initials in Spanish). To compute this indicator, we include in the "enrolled" students those that already graduated, i.e. our definition considers those that are currently enrolled or have finished secondary. This indicator that has been stagnated (or decreasing) since the early 2000s shows a positive trend in the last part of our study. From less than 75% at the bottom it raises to close to 85%.

Panel B reports secondary completion for those aged 19-24. There is an improving tendency from close to 30% in the late nineties to above 50%. Although those considered in this panel are not in the same age bracket as those considered for secondary enrollment, while secondary enrollment is relatively high, secondary completion is low. Thus, secondary dropout is prevalent.

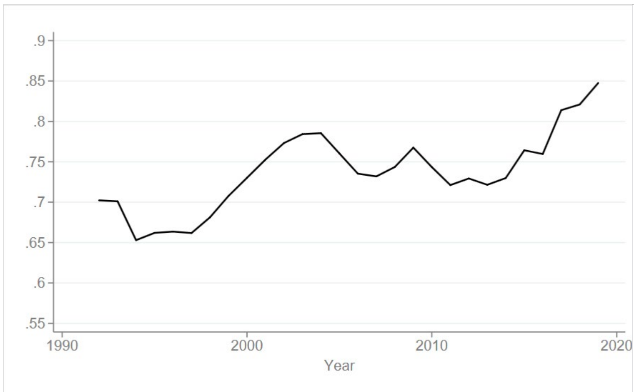
University enrollment is computed for those 19-24 years old. Like secondary enrollment we consider in this indicator those that are effectively enrolled in tertiary studies or those that have already graduated. Panel C shows a remarkable improvement from levels around 25% in the 1990s to levels close to 40% more recently.

Years of education are computed for every individual between 15 and 24 years. We considered only approved years of formal education but sum the different forms that this could take (secondary, technical, university or another tertiary). The last panel shows that there has been an increase over the period from an initial value below 9.5 years to more than 10.5.

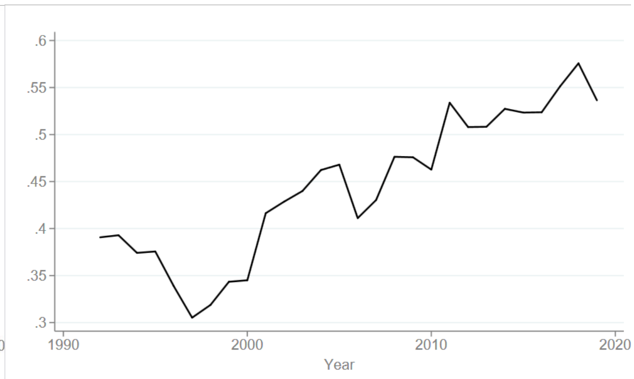
The summary view of the four indicators points to a positive trend. This is in contrast with the public perception of a worsening educational system. For instance, in a survey assessing public opinion towards education, 51% of the respondents claim that education has worsened in the past 10 years. (INNEd, 2017) There might be various explanations for this apparent contradiction. First, other indicators like the PISA evaluation show disappointing results with about half of the students not achieving satisfactory results. Second, most countries in Latin America also improved within the period, some of them substantially more than Uruguay. Third, improvements in education were uneven between social groups as we show next.

Figure 1. Over time evolution of educational indicators

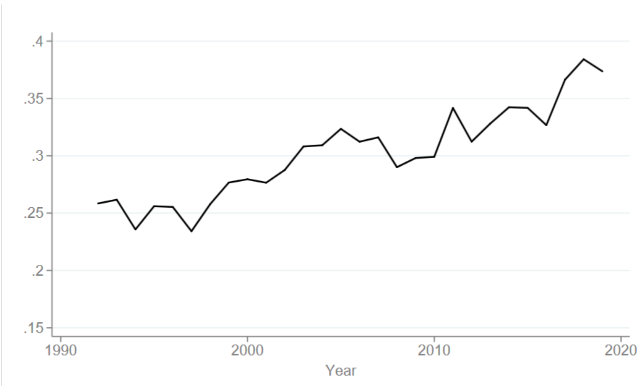
Panel A. Secondary enrollment (age 15-18)



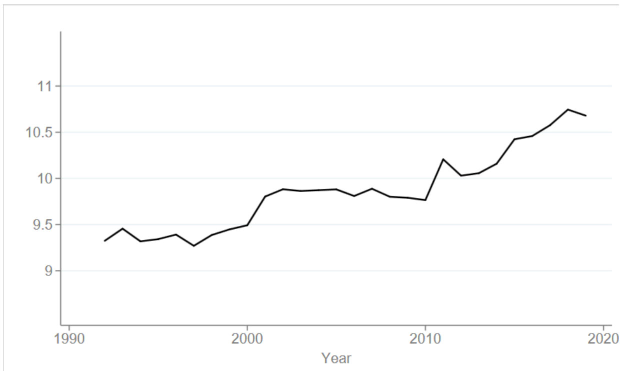
Panel B. Secondary completion (age 19-24)



Panel C. University enrollment (age 19-24)



Panel D. Years of education (age 15-24)



Source: Own elaboration based on the Encuesta Continua de Hogares from INE.

Table 1 shows that educational investment and outcomes are highly correlated with household income. Although during our sample period there have been improvements in all income quintiles, the improvements in years of education, secondary completion and university enrollment are concentrated among high-income families. While the average years of education improved by 0.8 years among the first two income quintiles, it has improved by 1.8-1.7 years for those in quintile 3 or above. Consequently, the gap in years of education between the top and bottom quintile increased from 3.2 years in 1992 to 4.1 in 2019.

Among those families in the first income quintile, university enrollment is a rare event. In the 1992 sample only 5% were enrolled and by 2019 this indicator only increased 2 percentage points to 7%. In contrast, university enrollment increased 17 percentage points from 22% to 39% for those in the third income quintile. For high-income households, university enrollment grew from 30% to 50% and from 45% to 69% for those in the fourth- and fifth-income quintile, respectively. As a result, the gap in university enrollment between the top and bottom income quintiles increased from 40 percentage points to 62 percentage points.

Secondary completion is also uncommon for the lowest-income adolescents. Between 1992 and 2019 it only increased from 15% to 16%. For those in the third and fifth quintile the improvement is much higher, from 35% to 57% and from 60% to 83% respectively. As a result, the gap in secondary completion between the fifth- and first-income quintiles increased from 45 percentage points to 67 percentage points.

Secondary enrollment shows a different pattern. While it is positively correlated with income, improvements in this indicator are mostly concentrated on low-income households. In 1992 only 49% of those in the bottom income quintile were enrolled, in contrast with 76% of those in the third quintile and 91% of those in the top quintile. Given the already large figures among high-income families, the largest improvement is among low-income ones. By 2019, the first, third and fifth quintile secondary enrollment rates were 73%, 89% and 97%, respectively. At the beginning of our sample period there was a gap between the top and bottom quintiles of 42 percentage points that decreased to 24 percentage points by 2019.

Table 1. Averages by income quintile

	Secondary Enrollment		**Secondary Completion**		**University Enrollment**		**Years of education**	
	1992	**2019**	**1992**	**2019**	**1992**	**2019**	**1992**	**2019**
q1	49%	73%	15%	16%	5%	7%	7,6	8,4
q2	65%	81%	29%	35%	18%	19%	8,9	9,8
q3	76%	89%	35%	57%	22%	39%	9,3	11,1
q4	83%	94%	47%	66%	30%	50%	10,0	11,7
q5	91%	97%	60%	83%	45%	69%	10,8	12,5

Note: Secondary enrollment is defined for age 15-18, secondary completion and university enrollment is defined for age for age 19-24 and year of education for age 15-24.

Table 2 reports the same statistics as Table 1 for selected neighborhoods. A similar pattern emerges. First, there are strong correlations between indicators and residence with high-income neighborhoods (Pocitos and Punta Carretas) showing better results than those medium-income neighborhoods (Aguada and Union) and even better than low-income ones (Cerrito and Casavalle). Second, improvements in university enrollment are larger for high-income neighborhoods than for low-income neighborhoods. Secondary enrollment does not have this pattern. Interesting, secondary completion improved the most in medium-income neighborhoods (Aguada and Union).

Figure 2 presents a complete graphical representation of the neighborhood averages for 2019. The better indicators are concentrated in the southeast while the worst correspond to the outskirts of the city. The range of variation is impressive. In 2019, the worst neighborhood results show secondary enrollment of 62%, secondary completion of 14%, university enrollment of 3% and average of 8.5 years of education. In contrast the better off neighborhood shows secondary enrollment of 100%, secondary completion of 95%, university enrollment of 89% and average of 13 years of education.

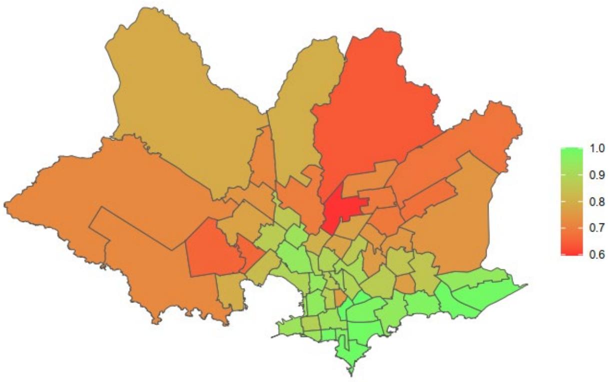
Table 2. Averages by neighborhood (selected)

	Secondary Enrollment		Secondary Completion		University Enrollment		Years of education	
	1992	**2019**	**1992**	**2019**	**1992**	**2019**	**1992**	**2019**
Pocitos	91%	100%	67%	90%	50%	77%	10,7	12,9
Punta Carretas	90%	100%	68%	89%	55%	72%	10,9	13,0
Aguada	78%	100%	31%	64%	29%	43%	10,0	11,6
Union	70%	90%	15%	67%	15%	44%	9,1	11,2
Cerrito	68%	72%	24%	45%	10%	31%	8,7	10,3
Casavalle	42%	65%	8%	20%	0%	9%	6,8	9,1

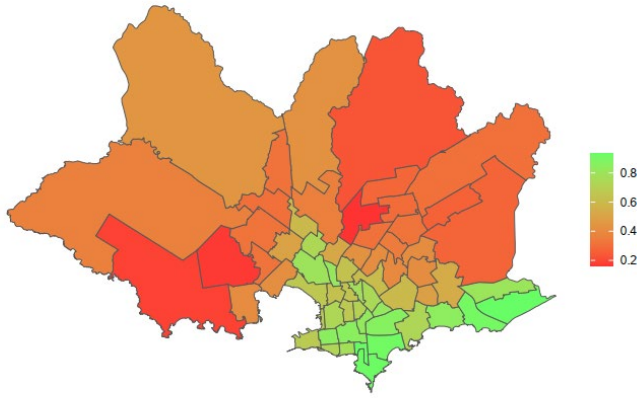
Note: Secondary enrollment is defined for age 15-18, secondary completion and university enrollment is defined for age for age 19-24 and year of education for age 15-24.

Figure 2. Averages by neighborhood - 2019

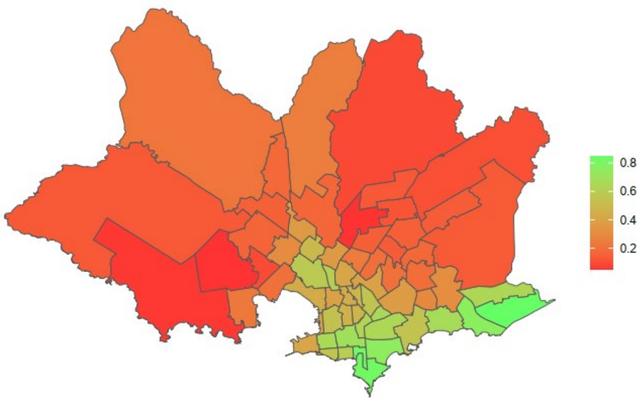
Panel A. Secondary enrollment (age 15-18)



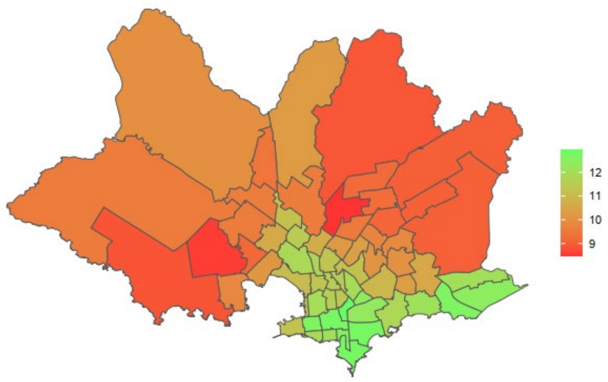
Panel B. Secondary completion (age 19-24)



Panel C. University enrollment (age 19-24)



Panel D. Years of education (age 15-24)



Source: Own elaboration based on the Encuesta Continua de Hogares from INE.

Table A1 in the appendix presents summary statistics for the four main variables that are considered in the paper and the explanatory independent variables to be used.

4. Neighborhood relative impact on human capital accumulation

In this section, we consider a relative effect of neighborhoods in two different time periods, the 1990s decade and the 2010s decade. Based on these effects, we compute transition tables showing the evolution the neighborhood effect had on individuals. To do so, we estimate for the two different time periods the following non-causal models:

$$y_{ig} = H(\beta X_i + \gamma_g) + e_{ig}$$

where H is either the identity link or the probit link, e_{ig} are unobserved factors, X_i are observed individual characteristics excluding a constant and γ_g are dummies that take the value 1 if the individual belongs to neighborhood g. By OLS (for years of education) or by MLE (for enrollment and completion) we can obtain estimates for γ_g (the effect the neighborhood has on the educational outcome y_{ig}) for the different time periods.

Based on the estimated coefficients we order neighborhoods from the lowest to the highest impact in the 1990s. We rank the neighborhoods in three groups: low neighborhood effects (bottom third), medium effect (between percentile 34 and 66) and top neighborhood effect (top third). We then repeat this procedure for the 2010s. Our estimates in this section are relative, by construction in each period there are better off and worse off neighborhoods.

Then we display the neighborhood classification in a 3x3 matrix form as in Table 3. The main diagonal shows the neighborhoods whose relative classification did not change. The center cell for example corresponds to the vicinities that are among the middle third both in the first 10 years of the sample as well as in the last 10. The off diagonal refer to those who transited to a better or worse position within the neighborhood ranking. The worse-off vicinities are below the main diagonal. The best-off regions are above the main diagonal. Since this is a relative classification the number of better off and worse off neighborhoods must be about the same.

Table 3 Transition matrix form

		2010s		
		1-33 percentile (1)	34-66 percentile (2)	67-100 percentile (3)
1990s	1-33 percentile (1)			
	34-66 percentile (2)			
	67-100 percentile (3)			

In the same fashion we also compute the unconditional transition tables. That is, we compute transition tables without including the vector of observed covariates (X_i) in these estimations. The analysis is non causal since unobserved components e_{ig} are correlated with the selection into the neighborhoods and thus to the neighborhood dummies γ_g.

In Table A2 in the appendix, we present the unconditional transition matrixes. We can see that most of the neighborhoods remained unchanged in the strength of their regional effects for years of education. Nevertheless, in the matrix for years of education we find 2 off-diagonal neighborhoods (1 improved and 1 deteriorated). Similarly for secondary enrollment most of the neighborhoods stayed the same, 16 changed their ranking (8 improved and 8 deteriorated). For university enrollment and secondary completion, we have 10 and 8 off diagonal effects, respectively. Overall, we see that there is a strong path dependence of the effects.

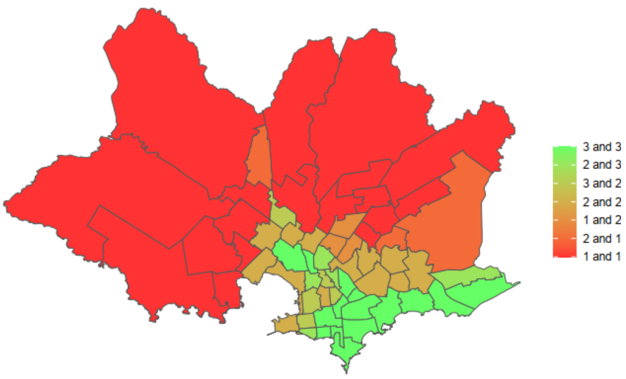
In the conditional transition matrix reported in Table A3 the rankings are constructed once the effects are cleaned from the effect of other potential individual determinants of educational outcomes (gender and age of the individuals, household income, age and years of education of the household head, an indicator for married household heads and the number of underage individuals in the household). We find that although most of neighborhood remained in the same classification, there is a higher percentage of neighborhoods changing their classification. For years of education, we have 12 neighborhoods changing their ranking bracket (6 improved and 6 worsened), for secondary enrollment there are 32 off-diagonal effects, for secondary completion we 24 and for university enrollment 22.

To the reader unfamiliar with the city of Montevideo the names of the neighborhoods listed in the Appendix are not of interest. Figures 3 and 4 present a graphical representation of the transition matrixes using a traffic light scale where in light green we have the extreme of the neighborhoods that remained associated to the better educational indicators and in dark red those that remained associated to the worse economic indicators.

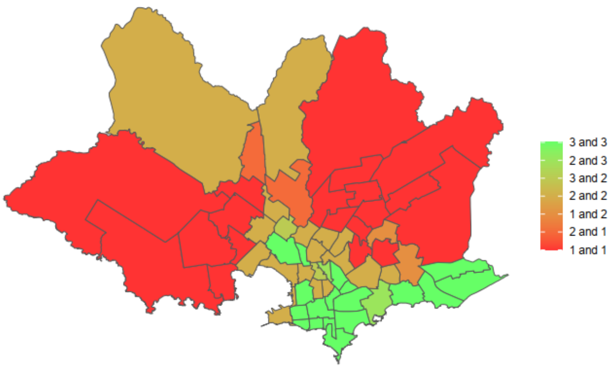
In summary, we have shown regions present strong path dependence, that this path dependence is weakened once we control for within neighborhood individual characteristics but is still substantive, and that there is a geographical segmentation between the better off southeast neighborhood and the worse of outskirts.

Figure 3. Unconditional neighborhood effects – transition 1990s to 2010s

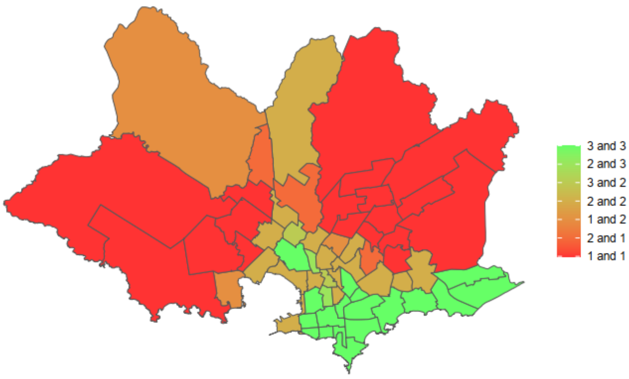
Panel A. Secondary enrollment (age 15-18)



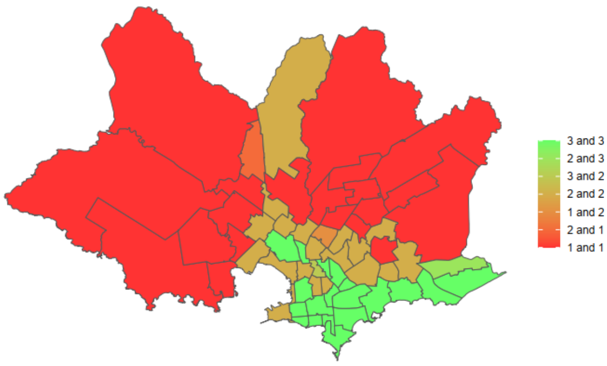
Panel B. Secondary completion (age 19-24)



Panel C. University enrollment (age 19-24)



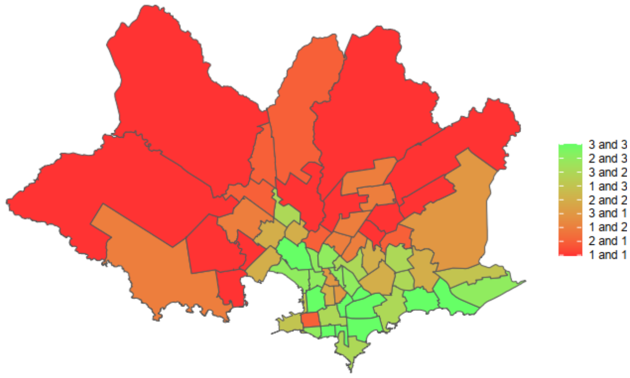
Panel D. Years of education (age 15-24)



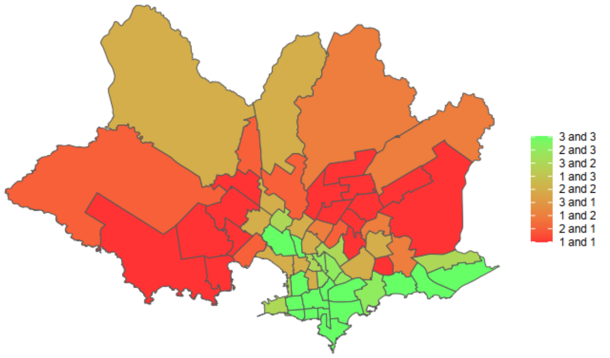
Source: Own elaboration based on the Encuesta Continua de Hogares from INE.

Figure 4. Conditional neighborhood effects – transition 1990s to 2010s

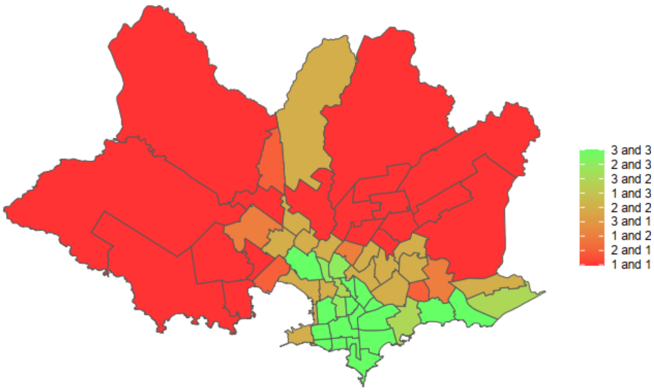
Panel A. Secondary enrollment (age 15-18)



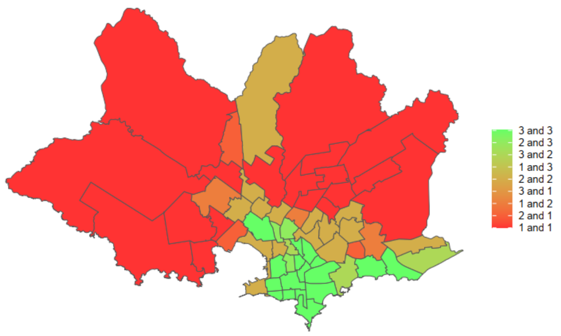
Panel B. Secondary completion (age 19-24)



Panel C. University enrollment (age 19-24)



Panel D. Years of education (age 15-24)



Source: Own elaboration based on the Encuesta Continua de Hogares from INE.

5. Neighborhood absolute impact on human capital accumulation

In this section we model how the neighborhood effects operate. To conceptualize the framework more clearly, we assume individuals make a choice y_{ig}. These choices depend on a combination of individual-specific and group-specific-determinants. Individual-specific factors can either be observable (X_i) or unobservable (e_{ig}). Group-specific factors are observable (X_g).

In our context, y_{ig} is one of the four main outcomes considered in this paper. It is observed for individual i in neighborhood g. Parental characteristics affect human capital, as more successful parents can provide more educational resources to their children and provide role models that enhance their children's aspirations. These types of effects are captured by X_i that contains the income of the household, the education level of the household head, the marital status of the household head, the number of underaged siblings and the age and gender of individual i. Neighborhood influences, such as how the sorts of occupations observed within the neighborhood affect student aspirations or how the distribution of incomes across families affects decisions on the level of expenditures on education, are proxied by the average neighborhood education level of household heads (X_g).

The relationship can be modeled as:

$$y_{ig} = \beta_0 + \beta_1 X_i + \beta_2 X_g + e_{ig}$$

where β_2, capture neighborhood effects.

This previous framework presents limitations. It is natural to believe that in many contexts, group membership is itself a choice variable. Families are not randomly allocated across neighborhoods; rather, families choose neighborhoods subject to constraints such as rent levels, house pricing and personal income. If one ignores self-selection in estimation, then one may produce spurious evidence of social interactions. For example, if richer neighborhoods contain relatively more productive individuals than deprived neighborhoods, and if some of this higher productivity individuals also have higher educational aspirations for their families, then the failure to account for self-selection could lead to the false conclusion that poor neighborhoods causally affect education. More generally, if neighborhoods are (partially) stratified according to unobservable individual-level characteristics that affect outcomes, then the danger of finding spurious evidence of social interactions is present.

Analyses of self-selection are sometimes based on explicitly modeling the self-selection and including it as part of the statistical analysis. The key to this modelling alternative is to find a suitable instrument for neighborhood selection. We follow Bayer and Ross (2006) and use housing rental values. They can solve the self-selection problem if they function as a shifter of neighborhood location decisions. If renters (owners) are price takers in the housing markets, then housing prices are exogenous and thus changes in them affect location choices independently of whatever other components such as unobservable ability affect both location choices and education. In this sense, we rewrite the model as follows:

$$y_{ig} = \beta_0 + \beta_1 X_i + \beta_2 X_g + E\left(e_{ig} \middle| X_i, X_g\right) + v_{ig}$$

where v_{ig} is independent of everything else. Identification can be achieved by means of modeling $E\left(e_{ig} \middle| X_i, X_g\right)$.

As individuals self-select into locations, we can use information on housing (rents) P_g to instrument the average educational level of the neighborhood, which suffers from endogeneity from the neighborhood self-selection. Then, $X_g = G(P_g) + V_g$ where V_g, can be estimated by the difference between their respective variables and the estimated conditional mean and then note that:

$$E(y_{ig}|X_i, X_g, V_g) = \beta_0 + \beta_1 X_i + \beta_2 X_g + E(e_{ig}|X_i, X_g, V_g)$$

$$= \beta_0 + \beta_1 X_i + \beta_2 X_g + E(e_{ig}|X_g, V_g)$$

$$= \beta_0 + \beta_1 X_i + \beta_2 X_g + E(e_{ig}|P_g, V_g)$$

$$= \beta_0 + \beta_1 X_i + \alpha\beta_2 X_g + E(e_{ig}|V_g)$$

where the first equality is due to linearity of the model, the second equality due to independence of the error from the individual covariates, the third equality is due to $X_g = G(P_g) + V_g$ and the fourth equality since $P_g\ is$ independent of e_{ig}. Then, once the errors V_g are estimated, assuming $E(e_{ig}|V_{1g}) = \pi V_g$ a linear model for $E(y_{ig}|X_i, X_g, V_g)$ as $\beta_0 + \beta_1 X_i + \beta_2 X_g + \pi V_g$ can be estimated by standard methods.

In the next section we report our results using bootstrapped standard errors clustered at vicinity level. We need bootstrapping because the control function used as a regressor in the models are not observed rather estimated. This induces estimation error on the asymptotic distributions of the parameters of interest that needs to be accounted for proper statistical inference. To clarify, on a first stage we estimate the error of the relationship between regional housing costs and regional average educational level as the residual of a regression between these two variables. We then use this residual as an additional regressor in a standard linear regression. This residual used as a regressor approximates the true first stage population error, as such, it has statistical uncertainty and needs to be considered for the second stage asymptotic variance.

a. Results

Table 4 reports the regressions results controlling for endogenous selection.[11] For secondary enrollment, secondary completion, and university enrollment we report the marginal effects after a probit model. For years of education, we estimate an OLS. The signs of all variables are as expected, and they are all statistically significant.

Our results suggest that indeed there is endogeneity. More precisely positive self-selection, in university enrollment and years of education since the control function coefficient which serves as a direct test for the endogeneity and a direct relationship between unobservable are positive and significant in three of the four educational outcomes considered.

Doubling income is associated with an increase in the probability of being enrolled in secondary education or completing secondary of 6 percentage points and an increase in the probability of being enrolled in university education of 5 percentage points. It is also associated with 0.35 more years of education. Given the unconditional values of the dependent variables reported in Table A1, the implied income elasticity is 0.11 for secondary enrollment, 0.13 for secondary

[11] Table A4 in the appendix reports the first stage regressions. Instruments are relevant at the 1% level. Table A5 reports the naïve version of Table 4 without the control for endogeneity. Results are similar in magnitude and sign.

completion, 0.18 for university enrollment and 0.05 for years for education.[12] These figures are close to the previous literature. Acemoglu and Pischke (2001) find that a 10% increase in family income is associated with a 1.4% increase in the probability of attending college, i.e. the income elasticity of college education is 0.14.

An extra year of education of the household head (implying and increase of 10% in years of education) is associated with an increase of 2.7 percentage points in the probability of being enrolled in secondary, of 3.3 percentage points in the probability of competing secondary, and of 3.0 percentage points in the probability of being university enrolled. It is also associated with 0.24 more years of education for the adolescent or young adult.

Family structure also has an effect. The adolescents that live with a married household head have 8 percentage points higher probability of being secondary enrolled, 6 points higher probability of completing secondary and 4 percentage points higher probability of begin university enrolled.

Parent's investment on children is also dependent on the number of minors they must take care of. The negative coefficients suggest that for every other underaged household member, the probability of being enrolled in secondary, completing secondary or being enrolled in university decreases by 2.2, 4.7 and 4.6 percentage points (respectively) and also decreases years of education by 0.27.

Female adolescents have a larger probability of being enrolled in secondary, completing secondary, or being enrolled in university than males (7, 10 and 10 percentage points, respectively). They also have 0.67 more years of education. This result is consistent with Acerenza and Gandelman (2019) that find household education spending in Latin America is larger for females than males.

Finally, the younger household heads have the worse educational indicators. An increase in one standard deviation in the household head age (14 years) is associated with 3.0 more percentage points for the probability of secondary enrollment, 2.4 higher percentage points in the probability of secondary completion, 2.6 more percentage points for the probability of university enrollment and 0.19 more years of education.

The neighborhood-average education level capturing contextual neighborhood environment also shows the expected sign and is statistically significant, thus it is a likely channel through which neighborhood effects operate. It has a positive and statistically significant impact on the four educational variables. The marginal effects are about the same size of the marginal effects of the variable capturing the education of the own adolescent household head. This means that average education of the neighborhood is as important as the education of the household head.

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[12] Slightly abusing notation in a model of the form:

$$y = \beta_1 \ln{(income)} + \gamma X + u$$

the y-income elasticity is given by:

$$\frac{\partial y}{\partial income}\frac{income}{y} = \frac{\beta_1}{y}$$

In a probit model instead of the coefficient we must consider the marginal effects. The unconditional means for our dependent variables are 0.74, 0.46, 0.29 and 9.90.

Table 4. Individual and neighborhood determinants of educational outcomes controlling for endogeneity

	Enr. Sec Probit Margins	Sec. compl. Probit Margins	Enr. Uni Probit Margins	Years of educ. OLS-Control function
Individual and family characteristics: $\boldsymbol{Xi}$				
Log-Income of the household	0.0796***	0.0658***	0.0508***	0.501***
	(0.00515)	(0.00501)	(0.00440)	(0.0345)
Years of Education of the household head	0.0271***	0.0329***	0.0295***	0.240***
	(0.00160)	(0.00107)	(0.00217)	(0.00575)
Dummy for married household head	0.0821***	0.0566***	0.0436***	0.368***
	(0.00578)	(0.00473)	(0.00374)	(0.0281)
Number of underage individuals in the household	-0.0223***	-0.0469***	-0.0457***	-0.265***
	(0.00201)	(0.00362)	(0.00404)	(0.0161)
Dummy if the individual is a woman	0.0704***	0.103***	0.101***	0.671***
	(0.00529)	(0.00599)	(0.00617)	(0.0304)
Age of the individual	-0.0754***	0.0158***	0.00322***	0.249***
	(0.00507)	(0.00113)	(0.000801)	(0.0209)
Age of the household head	0.00212***	0.00170***	0.00178***	0.0131***
	(0.000197)	(0.000320)	(0.000296)	(0.00189)
Neighborhood average: **Xg**				
Years of Education of the household head	0.0283***	0.0302***	0.0339***	0.154***
	(0.00444)	(0.00208)	(0.00240)	(0.0229)
Control Function (using housing prices as instrument for **Xg**)	0.000577	0.0381***	0.0450***	0.129***
	(0.0350)	(0.0107)	(0.0101)	(0.0255)
Years fixed effects	YES	YES	YES	YES
Observations	43,349	96,003	96,003	155,530

Note: Neighborhood clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The average effect that a neighborhood has on its youngster could differ according to the characteristics of the adolescent or young adult itself or by the characteristics of its household. In Table 5 we consider this heterogeneity by interacting the effects captured by the average educational level of neighborhoods with the log of household income, the educational level of the household head and a dummy for females.

We find that for three out of four outcome variables (school completion, university enrollment and years of education) higher household income can ameliorate the impact of the neighborhood. Own household income besides its direct impact on educational outcomes acts as a buffer of neighborhoods impacts. This is in line with Wodtke et al (2016) that finds that exposure to disadvantaged neighborhoods during adolescence negatively impacts high school graduation and that this impact is stronger for children of poor families.

On the other hand, the educational level of the household head reinforces the effects of the educational level of the neighborhood. More educated household heads can better channel an inspiring environment for their children while those living with worse educated households' heads suffer more strongly the negative impact of a relatively deprived neighborhood educational level. This result is consistent Patachini and Zenou (2011) that find that the better the quality of the neighborhood, the higher the parents' involvement in children's education and Balsa et al (2018) that finds that both peers and parental socialization efforts have a positive influence over adolescents' academic skills, and that these effects are complementary.

Finally, we find that male youth living in educationally deprived neighborhoods are more impacted by the general educational level than girls. This is different to the findings in Kling et al (2007) and Ludwig et al (2013) that found that moving to a better neighborhood had more beneficial impacts on teenage girls than on boys. In our paper a better neighborhood is one that has a higher educational level while Kling et al (2007) and Ludwig et al (2013) analyze the Moving to Opportunity program that considered neighborhoods in terms of their poverty rate.

Table 5. Heterogeneity analysis

	Enr. Sec	Sec. compl.	Enr. Uni	Years of educ.
	Probit Margins	Probit Margins	Probit Margins	OLS-Control function
Individual and family characteristics: ***Xi***				
Log-Income of the household	0.103***	0.0924***	0.140***	0.702***
	(0.0178)	(0.0174)	(0.0181)	(0.0659)
Years of Education of the household head	0.0337***	0.00983**	0.0112**	0.257***
	(0.00383)	(0.00473)	(0.00444)	(0.0323)
Dummy for married household head	0.0826***	0.0569***	0.0436***	0.366***
	(0.00578)	(0.00474)	(0.00374)	(0.0283)
Number of underage individuals in the household	-0.0221***	-0.0467***	-0.0446***	-0.260***
	(0.00200)	(0.00342)	(0.00381)	(0.0154)
Dummy if the individual is a woman	0.110***	0.118***	0.217***	0.950***
	(0.0233)	(0.0244)	(0.0286)	(0.145)
Age of the individual	-0.0760***	0.0159***	0.00327***	0.250***
	(0.00509)	(0.00114)	(0.000793)	(0.0211)
Age of the household head	0.00216***	0.00166***	0.00175***	0.0131***
	(0.000199)	(0.000316)	(0.000295)	(0.00194)
Neighborhood average (N. avg.): ***Xg***				
Years of Education of the household head	0.0586***	0.0411**	0.109***	0.499***
	(0.0165)	(0.0170)	(0.0140)	(0.0769)
Interacted terms: ***Xg * Xi***				
Years of Education of the household head (N.avg.) * Log-Income of the Household	-0.00255	-0.00308*	-0.00891***	-0.0245***
	(0.00191)	(0.00184)	(0.00191)	(0.00821)
Years of Education of the household head (N.avg.) * Years of Education of the household head	-0.000630	0.00204***	0.00156***	-0.00505
	(0.000495)	(0.000543)	(0.000526)	(0.00353)
Years of Education of the household head (N.avg.) * Woman	-0.00447*	-0.00191	-0.0115***	-0.0325**
	(0.00268)	(0.00262)	(0.00279)	(0.0161)
Control Function (using housing prices as instrument for **Xg** and ***Xg * Xi***)	-0.000295	0.00125***	0.00117***	0.00331***
	(0.00101)	(0.000282)"	(0.000280)	(0.000726)
Years fixed effects	YES	YES	YES	YES
Observations	43,349	96,003	96,003	155,530

Note: Neighborhood clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

6. Conclusions

In this paper, we present stylized facts and causal estimates on educational outcomes for young people in Montevideo. We find that educational investment and educational outcomes are highly correlated with household income. Although there have been improvements in all income quintiles, the improvements in secondary completion, university enrollment and years of education are concentrated among young people from the wealthiest families. Among families in the first income quintile, secondary completion or university enrollment is a rare event. Secondary enrollment shows different results. While it is positively correlated with income, improvements in this indicator are mostly concentrated on the bottom of the income distribution.

Second, based on transition tables, we find a strong path dependence of the vicinities, even after controlling for individual and household characteristics This implies that neighborhood effects have remained generally unchanged.

Third, geographically, the location of neighborhood effects shows spatial correlation. There is a clear pattern of better off neighborhoods in the southeast and worse off neighborhoods in the outskirts of the city suggesting a process of continuous segregation.

Fourth, we estimate the causal impact of neighborhood measured via the average years of education of household heads. Even after controlling for endogeneity of residence location, we find a positive and statistically significant neighborhood effect. The magnitude of the effect is large. The marginal effect of neighborhood education level is about the same as the marginal effect of the household head education level. Thus, average neighborhood education level is a powerful channel of neighborhood effects.

Finally, we address heterogeneity of the neighborhood effects. We find that neighborhood effects are stronger for boys than girls. We also find that family income can function as a buffer diminishing the impact of the environment. Relatively richer households living in educationally disadvantaged neighborhoods can better isolate their children than their poorer neighbors. And in our last interaction we find complementarity between the education of the household head and the average neighborhood education. In the least educated neighborhoods worse educational outcomes are associated with those living with less educated household heads.

Our results have immediate policy implications. First, the geographic disparity of outcomes reaffirms that uniform central policies are unlikely to solve problems that are nested in local inequality. Secondly, the persistence over time of these geographic disparities suggests that the process does not converge automatically and requires active regional policies to pursue it. Finally, the magnitude of the impact of the neighborhood educational level reinforces the convenience to locally disseminate positive role models that could compensate particularly deprived areas in terms of their general educational environment.

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Appendix

Table A1. Summary statistics

	Mean	S.D.	N
Secondary enrollment	0.74	0.44	59.558
Secondary completion	0.46	0.50	96.048
University enrollment	0.29	0.45	112.232
Years of education	9.90	2.87	155.606
Dummy if the youngster is a woman	0.50	0.50	161,823
Age of the youngster	19.59	2.83	161,823
Age of the household head	43.68	14.38	155,615
Dummy for married household head	0.51	0.50	161,823
Years of education of the household head	9.97	3.79	155,615
Number of underage individuals in the household	1.21	1.41	161,823
Per capita household income (constant 2010 Pesos)	10,803	10,051	155.606

Note: Household head is defined as the household main income provider.

Table A.2 Unconditional Transition Matrixes

SEC ENROLLMENT

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Casabó, Pajas blancas; Casavalle; Cerro; Colón Sureste; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson;Lezica, Melilla; Manga; Manga, Toledo Chico; Nuevo París; Paso de la Arena; Peñarol, Lavalleja; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural	Castro, Pérez Castellanos; Cerrito; Las Acacias	
	34-66 percentile	Bañados de Carrasco; Colón Centro y Noroeste; Flor de Maroñas	Aires Puros; Belvedere; Capurro, Bella Vista; Ciudad Vieja; La Teja; Las Canteras; Malvín Norte; Maroñas, Guaraní; Mercado Modelo y Bolívar; Paso de las Duranas; Unión; Villa Española; Villa Muñoz, Retiro;	Barrio Sur;Carrasco Norte; Reducto; Jacinto Vera; Brazo Oriental
	67-100 percentile		Aguada; Centro; La Comercial; La Figurita; Sayago	Atahualpa; Buceo; Carrasco; Cordón; La Blanqueada; Larrañaga; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

SECONDARY COMPLETION

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas blancas; Casavalle; Cerro; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Manga; Manga, Toledo Chico; Maroñas, Guaraní; Nuevo París; Paso de la Arena; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa Española; Villa García, Manga rural	Flor de Maroñas; Las Canteras	
	34-66 percentile	Peñarol, Lavalleja; Colón Centro y Noroeste	Aires Puros; Belvedere; Brazo Oriental; Capurro, Bella Vista; Castro, Pérez Castellanos; Cerrito; Ciudad Vieja; Colón Sureste; La Comercial; La Teja; Lezica, Melilla; Malvín Norte; Mercado Modelo y Bolívar; Reducto; Sayago; Unión; Villa Muñoz, Retiro	Buceo; Jacinto Vera
	67-100 percentile		La Figurita; Paso de las Duranas	Aguada; Atahualpa; Barrio Sur; Carrasco;Carrasco Norte; Centro; Cordón; La Blanqueada; Larrañaga; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

Table A.2 (continuation) Unconditional Transition Matrixes

UNIVERSITY ENROLLMENT

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas blancas; Casavalle; Conciliación; Flor de Maroñas; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Manga; Manga, Toledo Chico; Maroñas, Guaraní; Nuevo París; Paso de la Arena; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural	Cerrito; Cerro; Lezica, Melilla	
	34-66 percentile	Peñarol, Lavalleja; Colón Centro y Noroeste; Villa Española	Aires Puros; Belvedere; Brazo Oriental; Capurro, Bella Vista; Castro, Pérez Castellanos; Ciudad Vieja; Colón Sureste; Jacinto Vera; La Comercial; La Teja; Las Canteras; Malvín Norte; Mercado Modelo y Bolívar; Reducto; Sayago; Unión	Atahualpa; Villa Muñoz, Retiro
	67-100 percentile		La Figurita; Paso de las Duranas	Aguada; Barrio Sur; Buceo; Carrasco;Carrasco Norte; Centro; Cordón; La Blanqueada; Larrañaga; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

YEARS OF EDUCATION

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas blancas; Casavalle; Cerro; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Lezica, Melilla; Manga; Manga, Toledo Chico; Maroñas, Guaraní; Nuevo París; Paso de la Arena; Peñarol, Lavalleja; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural;	Cerrito	
	34-66 percentile	Colón Centro y Noroeste	Aires Puros; Belvedere; Brazo Oriental; Capurro, Bella Vista; Castro, Pérez Castellanos; Ciudad Vieja; Colón Sureste; Flor de Maroñas; La Comercial; La Teja; Las Canteras; Malvín Norte; Mercado Modelo y Bolívar; Paso de las Duranas; Reducto; Sayago; Unión; Villa Española; Villa Muñoz, Retiro	Carrasco Norte
	67-100 percentile		La Figurita	Aguada; Atahualpa; Barrio Sur; Buceo; Carrasco; Centro; Cordón; La Blanqueada; Jacinto Vera; La Blanqueada; Larrañaga; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

Table A.3 Conditional Transition Matrixes

SECONDARY ENROLLMENT

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Casavalle; Cerro; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Lezica, Melilla; Manga, Toledo Chico; Paso de la Arena; Peñarol, Lavalleja; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural	Casabó, Pajas Blancas; Castro, Pérez Castellanos; Cerrito; Las Acacias; Manga; Nuevo París; Piedras Blancas	Carrasco Norte; Ciudad Vieja
	34-66 percentile	Aires Puros; Centro ; Colón Centro y Noroste; Colón Sureste; Conciliación; Flor de Maroñas;	Belvedere; La Teja; Las Canteras; Paso de las Duranas; Unión; Villa Española; Villa Muñoz, Retiro	Atahualpa; Barrio Sur; Brazo Oriental; Capurro, Bella Vista; Carrasco; Jacinto Vera; Larrañaga; Reducto
	67-100 percentile	Bañados de Carrasco; La Figurita; La Comercial	Buceo; Cordón; Malvín Norte; Maroñas, Guaraní; Mercado Modelo y Bolívar; Sayago; Punta Carretas	Aguada; La Blanqueada; Malvín; Prado, Nueva Savona; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Tres Cruces; Pocitos; Punta Gorda;

SECONDARY COMPLETION

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas Blancas; Casavalle; Cerro; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Malvín Norte; Manga; Nuevo París; Piedras Blancas; Punta de Rieles; Tres Ombúes, Pueblo Victoria; Villa Española	Centro; Flor de Maroñas; Las Canteras; Manga, Toledo Chico; Villa García, Manga rural	
	34-66 percentile	Castro, Pérez Castellanos; Colón Centro y Noroeste; La Teja; Paso de la Arena; Peñarol, Lavalleja;	Aires Puros; Belvedere; Brazo Oriental; Capurro, Bella Vista; Colón Sureste; Lezica, Melilla ; Maroñas, Guaraní; Reducto; Sayago; Unión; Villa Muñoz, Retiro	Buceo; Jacinto Vera; La Blanqueada; La Comercial; Larrañaga
	67-100 percentile		Carrasco Norte; Ciudad Vieja; La Figurita; Mercado Modelo y Bolívar; Paso de las Duranas	Aguada; Atahualpa; Barrio Sur; Carrasco; Centro; Cordón; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

Table A.3 (continuation) Conditional Transition Matrixes

UNIVERSITY EROLLMENT

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas Blancas; Casavalle; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Manga; Manga, Toledo Chico; Nuevo París; Paso de la Arena; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural	Cerrito; Cerro; Las Canteras; Malvín Norte; Maroñas, Guaraní	
	34-66 percentile	Castro, Pérez Castellanos; Colón Centro y Noroeste; La Teja; Peñarol, Lavalleja; Villa Española	Aires Puros; Atahualpa; Belvedere; Brazo Oriental; Capurro, Bella Vista; ; Colón Sureste; Flor de Maroñas; Jacinto Vera; Lezica, Melilla; Reducto; Sayago; Unión	Buceo; Larrañaga; La Comercial; Villa Muñoz, Retiro
	67-100 percentile		Ciudad Vieja; La Figurita; Mercado Modelo y Bolívar; Paso de las Duranas	Aguada; Barrio Sur; Carrasco;Carrasco Norte; Centro; Cordón; La Blanqueada; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Gorda; Punta Carretas; Tres Cruces

YEARS OF EDUCATION

		10s		
		1-33 percentile	34-66 percentile	67-100 percentile
90s	1-33 percentile	Bañados de Carrasco; Casabó, Pajas Blancas; Casavalle; Cerro; Conciliación; Ituzaingó; Jardines del Hipódromo; La Paloma, Tomkinson; Las Acacias; Lezica, Melilla; Manga; Manga, Toledo Chico; Paso de la Arena; Peñarol, Lavalleja; Piedras Blancas; Punta de Rieles, Bella Italia; Tres Ombúes, Pueblo Victoria; Villa García, Manga rural	Cerrito; Las Canteras; Nuevo París	
	34-66 percentile	Colón Centro y Noroeste; La Teja; Malvín Norte	Aires Puros; Belvedere; Capurro, Bella Vista; Carrasco Norte; Castro, Pérez Castellanos; Ciudad Vieja; Colón Sureste; Flor de Maroñas; Maroñas, Guaraní; Mercado Modelo y Bolívar; Paso de las Duranas; Reducto; Sayago; Unión; Villa Española	Atahualpa; Brazo Oriental; Villa Muñoz, Retiro
	67-100 percentile		Buceo; Carrasco; La Figurita	Aguada; Barrio Sur; Centro; Cordón; Jacinto Vera; La Blanqueada; Larrañaga; La Comercial; Malvín; Palermo; Parque Batlle, Villa Dolores; Parque Rodó; Pocitos; Prado, Nueva Savona; Punta Carretas; Punta Gorda; Tres Cruces

Table A.4: First stage estimation

VARIABLES	Years of educ. HH	Years of educ. HH (family level) * Years of educ. HH (neighborhood level)	Years of educ. HH * Income	Years of educ. HH * Woman
Zg	0.000351***	0.00758***	0.00416***	0.000184***
	(6.63e-05)	(0.00135)	(0.000743)	(4.08e-05)
Constant	6.878***	42.23***	55.09***	3.427***
	(0.464)	(9.333)	(5.143)	(0.281)
Observations	161,823	155,615	161,738	161,823
R-squared	0.565	0.400	0.581	0.027

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5. Individual and neighborhood determinants of educational outcomes
(naïve version of Table 4 without the control for endogeneity)

	Enr. Sec Probit Margins	Sec. compl. Probit Margins	Enr. Uni Probit Margins	Years of educ. OLS-Control function
Individual and family characteristics: ***Xi***				
Log-Income of the household	0.0682***	0.0690***	0.0534***	0.486***
	(0.00333)	(0.00529)	(0.00516)	(0.0378)
Years of Education of the household head	0.0232***	0.0353***	0.0323***	0.241***
	(0.000711)	(0.000590)	(0.000792)	(0.00555)
Dummy for married household head	0.0703***	0.0591***	0.0455***	0.353***
	(0.00373)	(0.00485)	(0.00447)	(0.0313)
Number of underage individuals in the household	-0.0191***	-0.0514***	-0.0516***	-0.275***
	(0.00153)	(0.00342)	(0.00341)	(0.0179)
Dummy if the individual is a woman	0.0603***	0.111***	0.110***	0.673***
	(0.00382)	(0.00429)	(0.00660)	(0.0295)
Age of the individual	-0.0646***	0.0171***	0.00363***	0.249***
	(0.00238)	(0.00112)	(0.000767)	(0.0213)
Age of the household	0.00182***	0.00177***	0.00187***	0.0126***
	(0.000155)	(0.000345)	(0.000381)	(0.00209)
Neighborhood average: ***Xg***				
Years of Education of the household head	0.0243***	0.0364***	0.0407***	0.201***
	(0.00181)	(0.00185)	(0.00160)	(0.0150)
Constant				-4.409***
				(0.201)
Years fixed effects	YES		YES	YES
Observations	43,349	96,003	96,003	155,530
R-squared				0.483

Note: Neighborhood clustedred standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1