

School Access and City Structure*

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November 21, 2023

JOB MARKET PAPER

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Abstract

The location choices of households with children connect housing, labor, and school markets. These connections may shape the city structure, access to opportunities and the outcome of policies addressing each market separately. To study the consequences of these connections, I develop a quantitative spatial model that incorporates school choice. Parents with different skills select their residence by balancing access to schools and employment, choose a school considering its endogenous peer composition, and compete with childless households for houses and jobs. I use data from Madrid on school admissions and workers' commuting trips to estimate preferences for schools and workplaces. Combining households' location data with exogenous variation from the city's historical expansion, I estimate neighborhood preferences separately from endogenous school quality. I find that school access influences residential and job choices, decreasing segregation across parents by 15% and shifting workers towards productive areas. However, the opposite relocation of non-parents increases overall segregation. Work commuting costs concentrate skilled households in central locations, increasing school quality differences for students from high and low-skill families by 2.6% through peer effects. Finally, I show that interactions between schools and the labor market shape the effects of work-from-home and school transportation policies.

*I am particularly grateful to Milena Almagro, Paula Bustos and Diego Puga for their help and guidance in the development of this project. I am also indebted to Samuel Bentolila, Ignacio Berasategui, Caterina Calsamiglia and José Montalbán for help with the data. This paper benefited greatly from conversations with Pello Aspuru, Tomás Budí-Ors, Francesco Chiocchio, Jorge De la Roca, Cauê Dobbin, Nezih Guner, Claudio Luccioletti, Eduardo Morales, Josep Pijoan-Mas, Andrés Rodríguez-Clare, Clara Santamaría, Matteo Sartori, Nick Tsivanidis and Tom Zohar, and seminar discussants and participants at CEMFI and UC Berkeley, the European Meeting of the UEA, the UEA Summer School and the fRDB Fellows Workshop. All errors are mine only. E-mail: giorgio.pietrabissa@cemfi.edu.es.

1 Introduction

Differences in access to opportunities and amenities across space remain a relevant policy issue, as they contribute to inequality (Chetty and Hendren, 2018; Diamond, 2016). For this reason, policy-makers worldwide devote significant resources to transport investments, school choice expansions, and rent subsidies in an effort to guarantee better access to employment or education. However, households with children need to reach their workplaces and schools from a single location, facing a potential trade-off for their residential choices. As a result, housing, school, and labor markets may be spatially linked, with consequences for the outcome of policies addressing them separately. Yet, we lack a unified framework to evaluate the effects of these connections.

In this paper, I develop and estimate a quantitative spatial model that combines school, labor, and housing markets to evaluate the effects of their spatial interactions. The framework incorporates households with and without children, as well as differences in terms of skills, and allows for endogenous connections across these markets to arise through households' spatial choices. The paper relies on rich granular data from Madrid for estimation and exploits exogenous variation from the city's historical expansion to show how schools interact with other markets, shaping the spatial structure of the city and determining policy outcomes.

Specifically, three factors govern how schools affect other markets and shape the city's spatial structure. First, it is difficult to send children to faraway schools. Admission rules often prioritize students from nearby neighborhoods, and everyday trips to school can bear substantial costs for families. Consequently, these frictions constrain the residential choices of parents. Second, the quality of schools depends on the residential composition of nearby neighborhoods. This link derives from the value parents place on peer effects, which depend on the socioeconomic mix of students.¹ As parents tend to enroll children in schools close to their residence, schools become especially responsive to changes in the characteristics of nearby residents. Third, the location of schools directly affects the residential choices of a fraction of the population only, namely families with school-age children. Nonetheless, schools indirectly influence the choices of childless households as they interact with parents in housing and labor markets.

I incorporate these three features of schools in a general equilibrium spatial model. The framework expands on quantitative models of internal city structure (Ahlfeldt et al., 2015; Tsivanidis, 2019) to include school choice. It features a city populated by households with heterogeneous skills choosing where to reside, work, and send their children to school if they are parents. Both commuting to work and school trips are costly. Moreover, the probability of school admission depends on

¹In the US and similar contexts, local financing usually ties the value of housing to school funds through property taxes. In systems that privilege the private provision of education, schools opening in affluent neighborhoods tend to be more expensive and offer better services to their students. In both cases, school quality is a direct function of the school's parental mix. In Spain, regional governments administer and homogeneously fund the vast majority of schools, significantly muting local variation in the quality of educational infrastructure and programs. Thus, peer effects likely bear the responsibility for differences in school quality.

the allocation mechanism used to assign students.² In turn, school quality depends on the skill mix of students. Firms in every location hire workers and pay them skill-specific wages. Consequently, labor and school markets affect each other through their impacts on - and responses to - residential choices. Specifically, the strength of these cross-market effects depends on households' preferences for neighborhoods, workplaces, and schools, as well as on the endogenous responses of house prices, wages and school quality.

For estimation, I study the case of Madrid, a large urban area characterized by a strongly polarized residential distribution in terms of both skills and parenthood. To motivate the structure of the model, I start by showing that children condition residential choices, particularly for high-skill households. By creating a proxy measure for accessibility to labor and school opportunities across neighborhoods, I show that parents adjust their residential choices to locate nearby schools. This result is consistent with mobility data, which reveals that commuting to work takes twice the time than school trips on average.

Using administrative and survey data, I construct and analyze trips to school and work to bring the model to the data and evaluate how households make spatial choices. I first estimate school preferences of parents of different skills with a unique dataset on the universe of applications to public and charter schools, which enroll students through the same centralized system. The estimation exploits variation in travel times and probabilities of admission, and recovers school quality with a revealed preferences approach by matching the distribution of students across schools.³ I then quantify school access for each neighborhood, which measures the expected quality of the schools that children can potentially attend accounting for admission probabilities and travel costs.⁴ For the labor market, I obtain workplace preferences for high and low-skill workers by constructing commuting flows from survey data on mobility and estimating gravity regressions. Analogously to schools, I retrieve wages to match the distribution of workers and use them to quantify workplace access across neighborhoods. Results indicate trips to schools are three to four times more costly than those to work. Thus, schools end up being more relevant than jobs for the residential choices parents.

Next, I estimate households' preferences for neighborhoods. To this end, I leverage variation in school access as an attractive feature of residential locations. Moreover, the choices of non-parents allow me to control for unobserved amenities commonly valued by all households. However, peer effects on school quality establish a feedback loop between the residential choices of parents and school access. To separately identify neighborhood preferences from peer effects, I take advantage of differences in the year of construction and the elevation of schools, as these dimensions provide

²The Community of Madrid adopts the Boston Mechanism to allocate students to schools in cases where demand surpasses capacity limits.

³Priority points for admission are awarded based on several characteristics that vary in the time window of the data (2010-2015) and are described in Figure C.2.

⁴The measure of school access across residential neighborhoods is reminiscent of market access terms recently developed in the spatial and trade literature (Redding and Venables, 2004; Donaldson and Hornbeck, 2016; Ahlfeldt et al., 2015). The difference for schools is that there are two frictions: travel costs and admission probabilities.

exogenous variation related to the historical expansion of Madrid. The strategy delivers residential preference parameters in line with previous estimates in the urban literature, despite the substantially different procedure (Ahlfeldt et al., 2015; Diamond, 2016; Heblich et al., 2020; Tsivanidis, 2019). Moreover, I find that peer effects matter for school quality differences in the setting of Madrid. The background mix of students accounts for around 53% and 35% of the cross-school variation in quality for high and low-skill households, respectively. Finally, I use the residential choices of every household type to recover the appeal of each neighborhood in terms of non-modeled amenities.

With the estimated model, I explore the mechanisms linking schools and the labor market and investigate their implications for the city structure. To illustrate how parents' choices establish previously ignored cross-market effects, I remove frictions to access schools and workplaces, one at a time. I start by comparing the baseline data to a scenario without school frictions, to evaluate their impacts. The model reveals that frictions to school access attract both high and low-skill parents to residential locations near good schools, reducing their segregation by 15%. I find that school access also shifts workers towards highly productive areas, as these spatially overlap with the location of good schools. Notably, the model unveils an opposite endogenous response by non-parents, who are not directly affected by school access frictions but suffer the increase in house prices and leave the locations targeted by parents. As a consequence, segregation for non-parents increases, making it rise by 5% overall at the city level. The relocation of non-parents further reduces the average effect across locations of schools on house prices and workers by 40%. Thus, I find that the general equilibrium response of non-parents mutes the influence of school access on the other markets.

To isolate the effect of frictions to access workplaces, I next compare the baseline data with a city featuring no travel costs to work. Commuting costs in Madrid are low and thus have mild impacts on residential choices.⁵ Still, they induce small relocations that imply relevant changes for the school market. As high-skill households disproportionately concentrate near jobs, parents enroll their children in nearby schools, and peer effects boost their quality. Thus, because of commuting frictions, the average number of students is 3% higher in these schools. In addition, this larger concentration also increases differences in school quality across students from high and low-skill families by 2.6%. Therefore, I find that labor market frictions induce residential sorting, in turn increasing school segregation.

Additionally, to generalize results beyond the case of Madrid, I show that the strength of cross-market effects increases with the initial tightness of frictions. Stronger spatial frictions cause access to jobs and schools to be more skewed within the city and residential choices to be more consequential for the distribution of workers and students. Consequently, the city-wide effects of school access are more marked in settings with worse transportation infrastructure or in which admission policies strictly tie together the residential and school locations.

⁵This is the result of a well-functioning transport infrastructure that reduces travel times and costs. According to the EDM2018 mobility survey, the average commute time within the city of Madrid is 30 minutes, with 48% of commutes happening through the use of public transit services.

Finally, I use the model to illustrate how interactions between schools and the labor market further shape the outcomes of two policy experiments. First, I implement teleworking by reducing commuting costs for workers according to the estimates of [Delventhal et al. \(2022\)](#), who show that the occupations of high-skill workers are more likely to adopt remote working. Thus, this shock disproportionately affects high-skill households, who consequently move away from downtown locations to save on house prices. The model reveals that high-skill families also enroll children in peripheral schools inducing the quality of downtown schools to fall. As a result, low-skill parents face a trade off. Lower downtown prices make it more attractive for them to move towards central locations to improve their workplace access. At the same time, school quality is now lower in downtown areas due to peer effects. In equilibrium, the second effect dominates inducing low-skill parents to relocate outwards as well. Thus, I find that schools amplify the effect of remote work and strengthen the reduction in the appeal of central locations.

I also evaluate the effects of implementing busing, which offers school transportation services, for students from low-skill households. This policy is common in many cities worldwide and often aims at reducing the barriers to school access for disadvantaged groups. I implement the policy within the model by reducing school travel costs for students of low-skill families. Results show that busing is effective and reduces the difference in quality between schools attended by children of high and low-skill families by 31%. Even if not directly affected, high-skill families react to the influx of low-skill students enrolling their children in other schools without undoing the reduction in school quality differences. The model captures the residential changes of parents, who react to the transformations in school access. Importantly, I show that the relocation would have been stronger in the absence of the labor market. As parents move away, firms react to the changing supply of workers, adjust wages, and reshape workplace access to keep them attached to central areas.

Overall, this paper shows that schools significantly impact the structure of cities. This result is due to high travel times and admission policies restricting access to good schools and constraining the residential choices of parents. As a consequence, the effects of schools further expand to other markets and reach non-parents. I find that schools are a concentrating force as they pull parents together and raise the density of workers in productive locations. At the same time, the labor market attracts high-skill households with their children to the center and increases school segregation. Finally, quantitative results show that school, labor, and housing markets are spatially interconnected and that the general equilibrium effects of these links matter for policy outcomes.

This work relates to quantitative spatial models of internal city structure ([Ahlfeldt et al., 2015](#); [Heblich et al., 2020](#); [Miyauchi et al., 2020](#); [Tsivanidis, 2019](#)).⁶ In this paper, I extend this class of urban models to include school choice, accounting for residential decisions that depend on parenthood and skill differences. I illustrate how schools determine parental residential choices, indirectly affect non-parents, and uncover substantial spatial interactions with the labor and housing markets. Moreover, by including peer effects in school quality through the mix of students'

⁶See [Redding and Rossi-Hansberg \(2017\)](#) and [Proost and Thisse \(2019\)](#) for a comprehensive review of spatial quantitative models and their array of applications.

family backgrounds, I connect to the literature focusing on endogenous location characteristics and their effects for the sorting of heterogeneous households across space [Almagro and Domínguez-Iino \(2019\)](#); [Bayer et al. \(2007\)](#); [Couture et al. \(2023\)](#); [Diamond \(2016\)](#).

Secondly, I contribute to the extensive literature studying the residential effects of schools. Early contributions in public finance highlighted the relevance of this link, showing that local spillovers can generate segregation in communities, and evaluating the consequences of different school financing systems ([Benabou, 1993, 1996](#); [Epple and Sieg, 1999](#); [Epple and Romano, 2003](#); [Fernandez and Rogerson, 1996](#)). A related branch of the literature exploits spatial equilibrium properties to identify the willingness to pay to access schools of higher quality through boundary designs along catchment areas that remove variation in other neighborhood features ([Black, 1999](#); [Bayer et al., 2007](#)).⁷ However, these estimates are only local in their nature and cannot inform on the city-wide implications of school access. This paper, instead, embeds the school choice problem into a setting with housing and labor markets that vary across space and endogenously respond to the residential distribution of households. Moreover, this framework permit the quantification of school effects while accounting for the equilibrium responses of non-parents.

In contemporaneous work, [Agostinelli et al. \(2023\)](#) develop a spatial equilibrium model with school choice. However, different from this paper, they do not include a labor market. In the context of North Carolina, they explore the effect of different regulations and geography to determine inequality in access to schools. The study finds that spatial equilibrium effects are relevant in the context of admission, transportation, and zoning policies aimed at reducing the inequality in educational access. In a similar spirit, [Hahm and Park \(2022\)](#) and [Avery and Pathak \(2021\)](#) develop models to estimate school preferences jointly with residential choices, finding that the latter dampens the effects of school choice policies aimed at reducing educational inequalities. However, different from this paper, these contributions disregard the possibility that these spatial effects may depend on the interplay with the labor market and on the presence of childless households. [Eckert and Kleineberg \(2021\)](#) and [Fogli and Guerrieri \(2019\)](#) develop dynamic models linking education and location choices to study school financing policies and spatial inequalities. While the first highlights the importance of future expected earnings from the birth location and the second that of peer effects, they take a regional perspective and do not model the within-city school and workplace choices of families. Moreover, they disregard the role played by non-parents, which I show counteract the effects of schools on the city structure.

This research integrates elements of the school choice literature, in a setting where differences in funding and school characteristics are limited. [Abdulkadiroğlu and Sönmez \(2003\)](#) firstly highlighted that immediate acceptance mechanisms for school admissions distort parents' choices away from their preferences. In particular, the Boston Mechanism employed in Madrid induces parents to prioritize schools where admission is more likely ([Calsamiglia and Güell, 2018](#); [Calsamiglia et al., 2020](#)). I take this distortion directly into account to estimate school preferences. In the same set-

⁷See [Black and Machin \(2011\)](#) for a review of the first studies on the housing market consequences of school access.

ting of this work, Gortázar et al. (2023) shows how parents start enrolling their children in schools further away from their residences once points for within-district schools are reduced. I further show that friction to school access matters for the residential choices of parents. Moreover, I also discuss the implications of providing busing to students from low-skill households, contributing to an unexplored but important channel of school choice (Agostinelli et al., 2023; Angrist et al., 2022; Trajkovski et al., 2021). In particular, as the model features equilibrium interactions across markets, I illustrate how the residential consequences of busing also depend on the endogenous response in the labor market.

Finally, I contribute to the literature on the spatial consequences of remote work. The literature has focused on the consequences for cities, and there is a strong consensus that remote work effectively reduces the density of downtown locations (Althoff et al., 2022; Delventhal et al., 2022; Monte et al., 2023); the so-called "donut effect" (Ramani and Bloom, 2021). Contrary to work-from-home, the experience with online education during the pandemic did not exert a lasting impact. The substantial losses in students' skill development alongside the widening inequalities between children of high and low-skill parents confirm the superiority of in-person schooling (Agostinelli et al., 2022; Werner and Woessmann, 2023). Consequently, schools may alter the effect of working from home on the spatial relocation of parents. However, no previous study has investigated the consequences of this channel. The framework developed in this paper allows me to quantify these effects and uncover the novel outcome that schools significantly boost the "donut effect" by endogenously responding to the residential movements of parents.

The remainder of the paper is organized as follows. In section 2, I first describe in detail the context of Madrid and its educational system, and present evidence for sorting based on skill and parenthood. Section 3 describes in detail the structure of the model. The description of the data and estimation strategy follows in section 4. Then, in section 5, I describe the mechanisms of the model and quantify cross-market interactions and their importance for city structure. Section 6 follows showing how these cross-market effect matter for policy outcomes. Finally, section 7 concludes.

2 Schools and Residential Choices

In this section, I first outline the details of the school system in Madrid, and then provide compelling evidence that the spatial sorting behavior of households based on parenthood and skills is linked to the need to access schools and jobs.

2.1 The School System in Madrid

Madrid is ideal for studying school choice because publicly funded schools dominate its system covering 85% of students. This structure of the educational system implies two relevant consequences for the estimation of school choices. First, differences in the quality of schools do not arise from

variations in financing or study programs across schools, as it is the regional government that administers both. Therefore, parents' school valuation depends on peer effects, which establish a link between schools and the socioeconomic composition of surrounding neighborhoods. Second, students are allocated to schools with the so-called Boston Mechanism, with parents applying through a centralized system. Under this system, admission rules are common to the quasi-universe of students.

Schools in Spain are divided into three types: public, concerted, and private schools. The first two types are publicly funded and are obliged to offer the same type of curriculum and to accept students according to the centralized mechanism. The only difference is that concerted schools are privately managed.⁸ I rely on administrative data from the Community of Madrid to observe school choices and admissions, so that I focus on public and concerted schools only. The Community of Madrid uses the Boston Mechanism for allocation, and the centralized system works as follows. After parents submit their rank-ordered choices, the central system starts filling schools in rounds according to them. The system assigns priority points to applications to select students when schools are over-demanded. The final score is based on some family characteristics, on whether the family resides within the catchment area of the school, and on other family-school pair-specific features.⁹ Importantly, the probability of being admitted to a second choice is lower, given that the school may have been already filled in the first round, more so if the school is of good quality and thus potentially in high demand. Consequently, parents have a strong incentive to target first a school with high admission chances, rather than their preferred one, which makes the procedure non-strategy-proof, as shown by the mechanism design literature ([Abdulkadiroğlu and Sönmez, 2003](#)). Moreover, in the case of Madrid, once a student is admitted to a school, a spot for the next academic year is always guaranteed by default, so the chances of changing schools in later years are also very slim. Accordingly, the majority of applications are for the first year of preschool, when students are three years old (see [Figure 4](#)). This difficulty magnifies the importance of getting the first school right. Thus, it should not come as a surprise that 92% of students applying for a spot in the first year of preschool get admitted into their first choice.

School segregation is a significant issue in Madrid's education system. According to a recent report by EsadeEcPol and Save the Children, the Community of Madrid has the most segregated schools among all OECD countries ([Ferrer and Gortazar, 2021](#)). This is often the outcome of admission systems that prioritize students living within school districts or other types of catchment areas. However, it may also mirror residential segregation under very high transportation costs. Additionally, peer effects may matter for the valuation of schools, inducing parents to prefer residential locations next to schools with other students from high socioeconomic backgrounds, and thus determine skill sorting in equilibrium. For all these reasons, carefully estimating the contribution of each channel to school choice is essential to understanding what drives such high levels

⁸The majority of these centers are distinguished by being administered by institutions linked to the catholic church.

⁹See [Figure C.2](#) for the precise description of what determines priority points in the years for which data is available, as described in [Gortázar et al. \(2023\)](#).

of segregation.

2.2 Motivating Evidence: Parenthood and Skill Sorting

I start the analysis by comparing the residential choices of households that differ in terms of skills and parenthood. Residential data show that households choose neighborhoods based on both characteristics and that having children induces more sorting for high-skilled households. I use the administrative residential registry of Madrid (Padrón municipal), which records the universe of households with residences within the city limits. This data source reports both the age and the educational attainment of each member of the household, which allows me to distinguish them based on education levels and the presence of children. Households with at least one member who has obtained a college degree or higher are defined as high-skilled. Such a division implies that in low-skilled households no member has a university or equivalent degree. I identify parents as those households with at least one member below 20 years old; the rest are non-parents.¹⁰ This procedure leads to a city-wide share of high-skilled households without children of around 26%, while high-skilled parents amount to 14%, low-skilled households without children to 45% with low-skilled parents covering the final 15% of the total. The average number of households registered in the municipality of Madrid between 2010 and 2015 was slightly higher than 1.235 million.

The maps in Figure 1 show the distribution of households across the 128 official neighborhoods composing Madrid.¹¹ Starting with panels (a) and (b) for high-skilled households, the picture reveals a significant change in sorting patterns across parenthood. As the young and skilled workers choose to reside in central areas, they become more likely to select the city outskirts, particularly the northern half, once they have children. The correlation between the two distributions is positive and significant at 0.37. The same does not apply to low-skilled households, as shown further in panels (c) and (d) in orange. This group concentrates in the southern half of the city, where housing prices are notoriously lower. Most interestingly, the degree of sorting across parenthood is substantially lower. The correlation between the two distributions reaches 0.92. These visual patterns stress the importance of skills for residential segregation, and also reveal that having children matters for sorting beyond differences in skills, and in particular for high-skill households.

Because parents need to reach both their workplaces and the schools of their children, they are potentially exposed to a spatial trade-off for their residential choices: if they decide to live closer to one of the two, they may have to travel more to reach the other. To start unpacking the relationship between residential, workplace, and school choices, in Figure 2 I plot the distribution of travel times from the mobility survey conducted in Madrid, the *Encuestas Domiciliarias de Movilidad 2018*.¹²

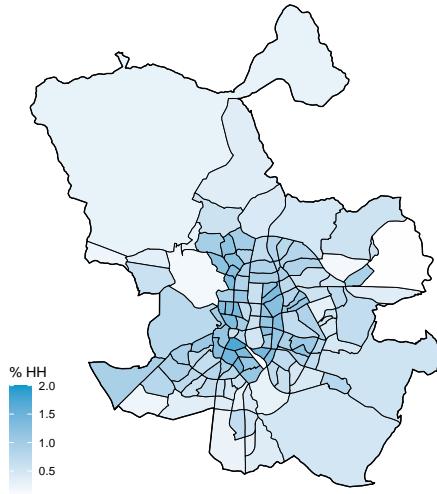
¹⁰This choice is due to the age bins in the data. The empirical analysis in this section remains similar when I use 11 or 14 years as thresholds. The residential patterns are also qualitatively similar if one excludes households with the youngest members being 65 or above, i.e. households made of retirees.

¹¹The number of neighborhoods increased to 131 in 2017, along with some changes in their boundaries. The whole analysis in the paper is based on the administrative definition pre-2017, and I apply the methodology detailed in Eckert et al. (2020) for consistency across geographical units whenever a data source follows post-2017 limits.

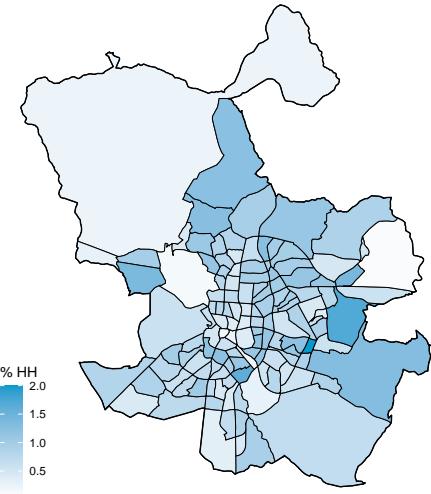
¹²The anonymized dataset with the results of the survey contains the self-reported daily trips of 75208 individuals,

Figure 1: Household residential distribution across types in the municipality of Madrid.

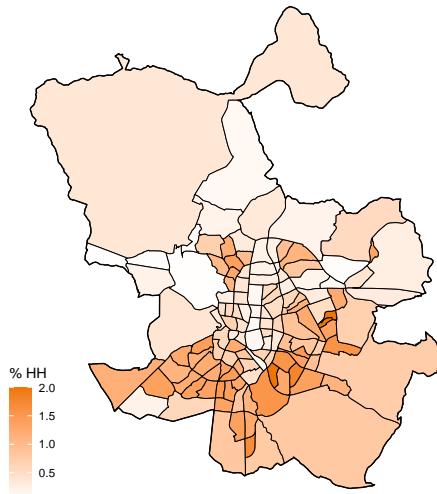
(a) High-skill households without kids



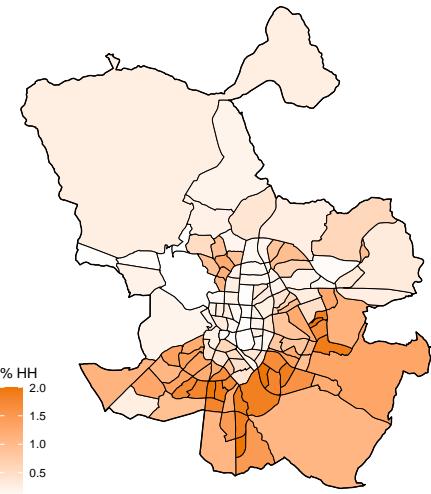
(b) High-skill households with kids



(c) Low-skill households without kids



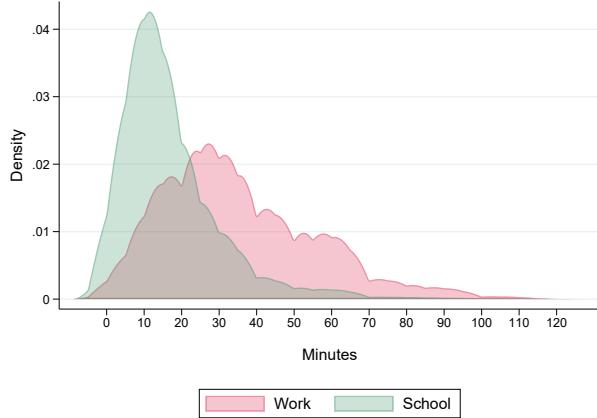
(d) Low-skill households with kids



Note: Maps plot the within-type distribution of households differentiated by skills and parenthood across neighborhoods in the municipality of Madrid. Households counts are normalized by the buildup surface of each area, to account for the difference in size of the geographical units. For each group, darker colors indicate a higher density of households. Residential data comes from the Padrón Municipal for the year 2015. Households with at least one member who has obtained a college degree or higher are defined as high-skilled. Households with at least one member below 20 years old are counted as having children, and the rest as non-parents.

Comparing the self-reported travel times to commute to work in red, with those for going to any school in green, shows how the latter concentrates significantly more on shorter trips. In particular, the average commute to work is 30 minutes, twice the average time students spend going to school. This difference may be related to the rules prioritizing students that live near a school, but could also depend on travel costs being substantially higher to reach schools than workplaces.

Figure 2: Kernel density of travel times by trip motive.



To illustrate the importance of accessibility more directly, I next study the relationship between households' residential distributions and that of workers and students. In particular, I regress the same data mapped in Figure 1 against the ratio of the number of jobs to the number of school seats in a ring of 1 km around the center of each *Barrio*.¹³ In the regression, I control for house prices to account for different levels of constraints faced by high and low-skill households. This exercise connects residential choices to employment and school opportunities accounting for the mobility of households. The resulting coefficients do not have any causal interpretation but highlight correlations in the raw data. Moreover, this analysis does not account for differences in school quality and wages across space, as they are not readily available. I later turn to the structure of the model to recover information on the level of wages across neighborhoods and on the quality differences across schools.

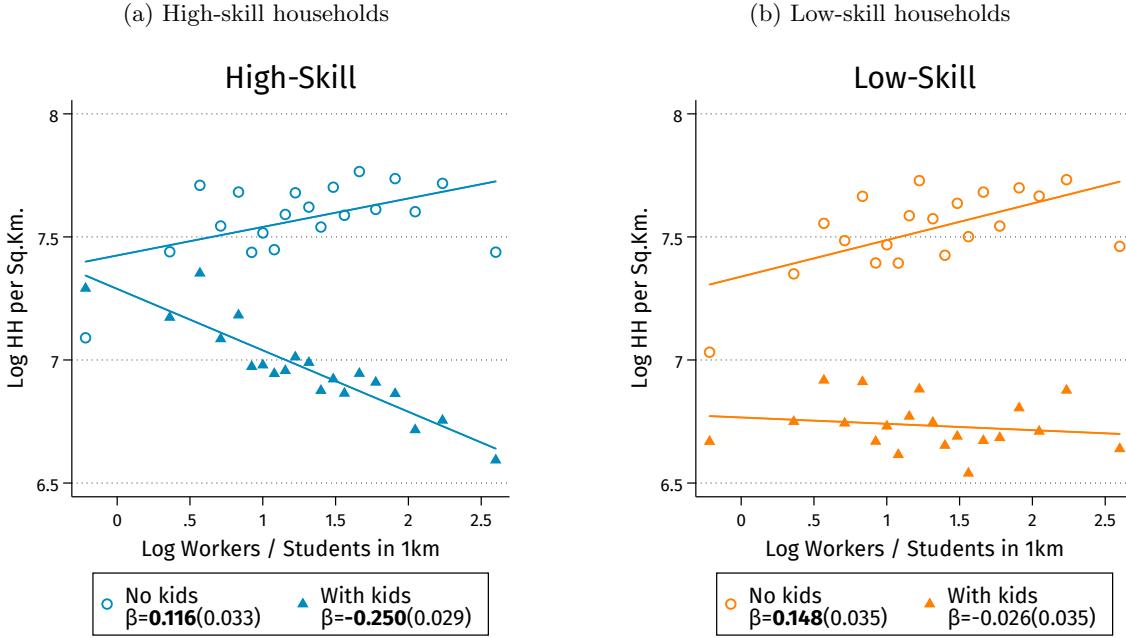
Panel (a) in Figure 3 plots the binned result of the regression for high-skill households, separating between those with and without children. Non-parents display a significant and positive coefficient, indicating that they tend to be located in areas that have more jobs than school seats in the vicinity. Notably, the sign of this relationship flips for high-skilled parents, signaling that residential choices now follow more the location of schools. This difference mirrors the previous maps, i.e. the suburbanization of parents. Low-skilled households in panel (b) behave very simi-

grouped by their households, with information on their demographic characteristics, including educational attainment.

¹³I construct the ratio within 1km from the center of Barrios from two sources of data. First, the counts of employed workers in their workplace by *Barrio* as distributed by the municipality of Madrid, which originates from social security accounts. The number of students is, instead, provided by the Consejería de Educación of the Community of Madrid, aggregating the number of students in preschool and primary to the *Barrio* level.

larly if they do not have children. Instead, the correlation for parents virtually disappears. This signals that, even when controlling for house prices, low-skilled households may be responding to different incentives for their residential choices with respect to their high-skilled counterparts. The results hold when changing the definition of family, i.e. adjusting for the cut-off age of the youngest member, as well as when I increase the radius considered for the ratio up to 8 kilometers, as shown in Figure C.1.

Figure 3: Residential choice for every HH type against work-school relative accessibility.



Note: Graphs report the regression coefficient of the residential distribution of households on the relative accessibility of employment versus schools as measured by the ratio of the number of workers to the number of students in a 1km radius around each *Barrio*. House prices are partialled-out to plot the binned two-way scatter. Bold coefficients represent significance at the 10% level, and heteroskedastic robust standard errors are reported in parentheses.

Overall, the patterns in the data show how households make residential choices differently according to both their skills and the presence of children. In particular, the evidence presented above suggests that high-skilled households move towards the city's outskirts with parenthood, while the same is less evident for the low-skilled. As travel times to reach schools are substantially lower with respect to commutes to the workplace, it could be that households with children choose different residential areas to locate nearby schools. Indeed, the correlation between residential choices and the location of jobs and schools shows that parenthood shifts households away from areas that concentrate more employment opportunities to those that have relatively more schools nearby. I bring this evidence to the model, motivating the choice of allowing for different preferences across skills, differences in house price elasticities, and the fact that only parents care about accessing schools.

3 A Quantitative Urban Model with School Choice

In this section, I develop a general equilibrium quantitative spatial model to study the residential choices of households that differ in terms of skills and parenthood. The model features three modules: a housing market within which households make residential choices; a labor market differentiating between high- and low-skill workers who choose workplaces; and a school choice problem with parents deciding where to enroll their children. Given its primitives, the model characterizes the distribution of housing prices, wages, and school quality, in equilibrium. Moreover, these values influence each other, as every element affects - and responds to - the residential distribution of households.

3.1 Set Up

The economy is a closed city, with a fixed number of neighborhoods $n = 1, \dots, N$, each characterized by a fixed amount of floorspace available for either housing or production. A fixed measure of households \bar{R} populates the city, and they are ex-ante heterogeneous along two dimensions: the education level that can be either high or low ($g \in \{L; H\}$), and the family status ($k \in \{0; 1\}$), indicating the presence of children. Each household has to decide where to live, where to go to work and, in the presence of children, where to go to school. Mobility across neighborhoods is determined by the access to transportation technologies, which is reflected in travel times.

3.2 Households

A household ω living in location n , maximizes her utility by choosing how much to consume (C_n) of a freely traded numeraire and of residential floor-space (H_n), with a Cobb-Douglas structure flexibly allowing for different preferences across types g, k . Consuming floor-space has a price in each neighborhood (r_n), and these rents are collected for the whole city and equally redistributed to households through an endogenous transfer π . All agents value local amenities in the residential neighborhood B_{ngk} . Households work in some location $i = 1, \dots, N$ of the city, bearing commuting costs for travel between the residence and workplace τ_{nig}^W . Supplying work determines income depending on their skill group g , with $w_{iH} > w_{iL} \forall i$. If the household is composed by parents with children ($k = 1$), her utility depends as well on the quality of the specific school S_{jg} where the children go (which may include the price of attending the school and is allowed to vary across skills), discounted by the travel cost from the residence (τ_{njg}^S). If the worker does not have children ($k = 0$), I assume it does not care for schooling and this last part is absent from the utility maximization problem.

Every household is subject to a specific shock for every location choice that she has to make: $b_{ng}(\omega)$ for the residence, $z_{ig}(\omega)$ for the workplace and $s_{jg}(\omega)$ for the school. Each shock is drawn from a different Fréchet distribution, which is allowed to also differ across skill types. Thus, the

utility structure of a household ω with the budget constraint looks as follows:

$$\begin{aligned} \max_{C,H} & \left[C_n^{\alpha_{gk}}(\omega) H_n^{1-\alpha_{gk}}(\omega) B_{ngk} b_{ng}(\omega) \left(\frac{S_{jg} s_{jg}(\omega)}{\tau_{njg}^S} \right)^k \right] \\ \text{s.t. } & C_n(\omega) + r_n H_n(\omega) = \frac{w_{ig} z_{ig}(\omega)}{\tau_{njg}^W} + \pi. \end{aligned} \quad (1)$$

Both travel costs are expressed as exponential function of travel times ($\tau_{njg}^W = \exp(\kappa_g^W d_{njg}^W)$, $\tau_{njg}^S = \exp(\kappa_g^S d_{njg}^S)$), where the parameter κ is the semi-elasticity of travel costs o travel times, and is allowed to change according to the type of trip (W, S) and the skill level g . Then, solving for optimal demand, determines the indirect utility for a household ω of type $\{g, k\}$ living in area n , working in i and sending children (if any) to school j is given by:

$$V_{nijgk}(\omega) = \frac{B_{ngk} b_{ng}(\omega)}{r_n^{1-\alpha_{gk}}} \left(\frac{w_{ig} z_{ig}(\omega)}{\tau_{njg}^W} + \pi \right) \left(\frac{S_{jg} s_{jg}(\omega)}{\tau_{njg}^S} \right)^k, \quad k \in \{0; 1\}, \quad g \in \{H; L\}. \quad (2)$$

This utility structure requires some simplifying *assumptions*, which need to be discussed with respect to the expected results of the model. Firstly, the model abstracts from any dynamics in the location choices of households, assuming costs of changing locations to be negligible, as well as from changes in family status. Secondly, there is full abstraction from the household internal structure, so that, in line with the unitary household model, this is represented by a unique agent tacking all the decisions while maximizing welfare for all members. Third, workplace and school choices are independent, i.e. there is no scope for chain trips around the city. Finally, the timing of the location choices depends on the order in which the shocks are revealed to the households, whom I assume, in line with the literature, first chooses where to live, and after where to go to work and where to send children to school. This structure allows me to solve the location choice problem backwards, so that when deciding the residential neighborhood, households take into account the access in terms of workplaces and their wages, as well as the in terms of schools and their quality (Miyauchi et al., 2020; Tsivanidis, 2019).

3.3 Workplace Choice

As the household has already decided where to live, it now chooses where to go to work, independently from the other locations. The Fréchet distribution assumption for the idiosyncratic shocks delivers the well-known logit structure for bilateral commuting probabilities, as follows:

$$\lambda_{njg|n}^W \equiv \Pr \left[\frac{w_{ig} z_{ig}(\omega)}{\tau_{njg}^W} > \max_{i' \neq i} \frac{w_{i'g} z_{i'g}(\omega)}{\tau_{ni'g}^W} \right] = \frac{(w_{ig}/\tau_{njg}^W)^{\theta_g^W}}{\sum_l (w_{lg}/\tau_{nlg}^W)^{\theta_g^W}}, \text{ with } z_{ig}(\omega) \sim \exp(-z^{-\theta_g^W}). \quad (3)$$

Taking the expectation over the idiosyncratic shock, delivers a measure of the utility contribution that a resident in n can get in terms of work, i.e. the workplace access, which corresponds to

expected income in a residential neighborhood n for a household of skill type g before it draws the preference shock:

$$\mathbb{W}_{ng} \equiv \mathbb{E}_i \left[\frac{w_{ig} z_{ig}(\omega)}{\tau_{nig}^W} \right] = \Gamma \left(1 - \frac{1}{\theta_g^W} \right) \left[\sum_i (w_{ig}/\tau_{nig}^W)^{\theta_g^W} \right]^{\frac{1}{\theta_g^W}} = \gamma_g^W (\Phi_{ng}^{RW})^{\frac{1}{\theta_g^W}}. \quad (4)$$

Notice that both these results are not dependent on the family status k , which only directly affects the school choice and consequently the residential choices of parents directly. Both equations (3) and (4) are, instead, dependent on the skill group g of individuals, as wage levels are different across groups, in each work location i . One can also compute the labor supply for each workplace for each skill group g which is upward sloping as wages are the attractors for commuting:

$$L_{ig} = \sum_n \frac{(w_{ig}/\tau_{nig}^W)^{\theta_g^W}}{\Phi_{ng}^{RW}} R_{ng} = w_{ig}^{\theta_g^W} \cdot \Phi_{ig}^{WR} \quad (5)$$

Here, R_{ng} is the endogenous measure of households of type g that live in area n . The relationship between the two perspectives of workplace market access becomes evident from (5), where the one for firms (Φ_{ig}^{WR}) is a function of the one for workers (Φ_{ng}^{RW}), as extensively discussed in [Tsivanidis \(2019\)](#).

3.4 School Choice

Parents ($k = 1$) need to choose where to send their children to school by trading off the quality of each school in the city and the travel costs associated with bringing them there every morning. However, this location choice does not happen in a context of a free market, but rather in a heavily controlled market, where a central planner sets rules on how to allocate students across schools. This determines the need to add a further element into the picture: the probability of admission.

Given all this characteristics of the admission system of Madrid described previously, the model follows closely that of [Calsamiglia et al. \(2020\)](#), where I assume that every family supplies one school choice instead of a list. If the application scored enough points, the student is admitted, otherwise it will be sent to the preferred school from a pool of schools that have no capacity constraints and that are identified as *leftover* schools. The school choice problem then looks as follows:

$$\max_j \left\{ p_{\omega j} \frac{S_{jg} s_{jg}(\omega)}{\tau_{njg}^S} + (1 - p_{\omega j}) \max_{\ell \in \text{leftovers}} \left[\frac{S_{\ell g} s_{\ell g}(\omega)}{\tau_{n\ell g}^S} \right] \right\}, \quad (6)$$

where the probability of admission is denoted as $p_{\omega j}$. Call the points obtained by a household ω to school j as $g_{\omega j}$, and \bar{g}_j the minimum number of points to get admitted to school j . Then, the probability of admission is an equilibrium object determined by the demand for a school, its fixed supply of seats and the consequent cut-off level \bar{g}_j : $p_{\omega j} = \Pr\{g_{\omega j} \geq \bar{g}_j\}$. Assuming the household as perfect information and is fully sophisticated, this probability becomes an indicator, as the

household can perfectly retrieve the equilibrium cut-off level for every school in the city, as well as know her own points for any school. Given this structure, the problem boils down to choosing the preferred school among the ones where the household knows it can be admitted to (defined by the set $\mathcal{J}_\omega \equiv \{j | \mathbb{1}(g_{\omega j} \geq \bar{g}_j) = 1\}$). Then, it is easy to see that it is possible to obtain a closed-form solution to the school choice, and one can proceed as done for the workplace choice and obtain the the logit probabilities through the Fréchet shocks:

$$\lambda_{\omega jg}^S \equiv \Pr \left[\frac{p_{\omega j} S_{jg} s_{jg}(\omega)}{\tau_{njg}^S} > \max_{j' \neq j} \frac{p_{\omega j'} S_{j'g} s_{j'g}(\omega)}{\tau_{nj'g}^S} \right] = \frac{p_{\omega j} (S_{jg}/\tau_{njg}^S)^{\theta_g^S}}{\sum_\ell p_{\omega \ell} (S_{\ell g}/\tau_{n\ell g}^S)^{\theta_g^S}}, \text{ with } s_{jg}(\omega) \sim \exp(-s^{-\theta_g^S}). \quad (7)$$

The probability of admission ($p_{\omega j}$) in (7) is the main difference with respect to a normal gravity setting, as it introduces a wedge due to priority points. Moreover, notice that the logit probabilities exhibit zeros for some household-school pairs.

School access, i.e. the measure for the likelihood of attending schools of high quality from a residential neighborhood, is then easily derived. I take the assumption that before having chosen where to live the household cannot yet observe its own points precisely, so that the probability of admission is measured as the share of admitted households from neighborhood n to school j . Thus, school access takes the following structure:

$$\mathbb{S}_{ng} \equiv \frac{1}{N_{ng1}} \sum_{\omega \in n} \mathbb{E}_j \left[\frac{p_{\omega j} S_{jg} s_{jg}(\omega)}{\tau_{njg}^S} \right] = \frac{1}{N_{ng1}} \sum_{\omega \in n} \left[\gamma_g^S \sum_j (p_{\omega j} S_{jg}/\tau_{njg}^S)^{\theta_g^S} \right]^{\frac{1}{\theta_g^S}}. \quad (8)$$

Finally, the model then characterizes the allocation of students as a direct function of school quality:

$$K_{jg} = \sum_{\omega \in g} \lambda_{\omega jg}^S = \sum_{\omega \in g} \frac{p_{\omega j} (S_{jg}/\tau_{njg}^S)^{\theta_g^S}}{\sum_\ell p_{\omega \ell} (S_{\ell g}/\tau_{n\ell g}^S)^{\theta_g^S}} = S_{jg}^{\theta_g^S} \sum_{\omega \in g} \frac{p_{\omega j}/(\tau_{njg}^S)^{\theta_g^S}}{\Phi_{\omega g}^S}. \quad (9)$$

3.5 Neighborhood Choice

The first stage of the location decision problem finally consists of maximizing the expected indirect utility that a household can enjoy across locations in the city:

$$V_{ngk}(\omega) = \frac{B_{gnk} b_{ng}(\omega)}{r_n^{1-\alpha_{gk}}} (\mathbb{W}_{ng} + \pi) \mathbb{S}_{ng}^k. \quad (10)$$

The probability of a household of type g, k to choose residential neighborhood n is given by the logit structure from the Fréchet idiosyncratic shock:

$$\lambda_{ngk} \equiv \Pr \left[V_{ngk}(\omega) > \max_{n' \neq n} V_{n'gk}(\omega) \right] = \frac{1}{\Phi_{gk}} \left(\frac{B_{gnk}}{r_n^{1-\alpha_{gk}}} (\mathbb{W}_{ng} + \pi) \mathbb{S}_{ng}^k \right)^{\theta_g^B}, \text{ with } b_{jg}(\omega) \sim \exp(-b^{-\theta_g^B}). \quad (11)$$

Intuitively, neighborhoods with better amenities, lower rents, and better school and workplace access are more demanded and will exhibit a higher share of residents. Indeed, it is easy to get the distribution of residents by type, from their total measure by group: $R_{ngk} = \lambda_{ngk} * \bar{R}_{gk}$.

At this point, one can also characterize the demand for housing in every neighborhood by aggregating the residential probabilities and the stock of every type of household:

$$H_n = \sum_{g,k} (1 - \alpha_{gk}) \left[\frac{\mathbb{W}_{ng} + \pi}{r_n} \lambda_{ngk} \bar{R}_{gk} \right]. \quad (12)$$

Then, taking the expectation on the residential idiosyncratic shock, one gets to the expected utility of living in the city for each skill group:

$$\bar{V}_{gk} \equiv \mathbb{E}_n [V_{ngk}(\omega)] = \Gamma \left(\frac{\theta_g^B - 1}{\theta_g^B} \right) \left[\sum_l \left(\frac{B_{lgk} (\mathbb{W}_{lg}^k + \pi)}{r_l^{(1-\alpha_{gk})}} \mathbb{S}_{lg}^k \right)^{\theta_g^B} \right]^{\frac{1}{\theta_g^B}} = \gamma_g^B (\Phi_{gk})^{\frac{1}{\theta_g^B}}. \quad (13)$$

The residential probabilities in (11), as well as the indirect expected utility in (13), are both skill group g and family status k specific. This key result stems from three assumptions. First, the fact that the workplace channel generates a wedge between high and low skilled agents through different wage levels. Second, the school access part, being of interest only for parents ($k = 1$), will generate a different overall attractiveness of neighborhoods, and hence an heterogeneous probability of residence. Lastly, as house price elasticities are flexibly heterogeneous across households types, sorting will happen as a response to variation in house prices across neighborhoods. Hence, in equilibrium the model displays a spatial distribution of residents for each category, delivering segregation in both dimensions.

3.6 Production

There is a representative firm in each area of the city, producing the tradable numeraire by employing both high and low-skilled workers, and renting commercial floorspace. Assuming a CRS technology under a perfectly competitive environment, the firm combines labor types imperfectly with a constant rate of substitution ρ . Each location has a productivity fundamental A_i and a shifter affecting demand for the skilled labor factor ϕ_i :

$$Y_i = A_i L_i^\beta H_i^{(1-\beta)}, \quad \text{with} \quad L_i = \left[\phi_i L_{iH}^\rho + (1 - \phi_i) L_{iL}^\rho \right]^{\frac{\rho}{\rho-1}}. \quad (14)$$

Profit maximization combined with the zero profit condition leads to the following factor demands:

$$L_i = \frac{\beta Y_i}{\mathcal{W}_i} \quad \text{and} \quad H_i = \frac{(1 - \beta) Y_i}{r_i^C}. \quad (15)$$

where $\mathcal{W}_i = [\phi_i^\rho (w_{iH})^{1-\rho} + (1 - \phi_i)^\rho (w_{iL})^{1-\rho}]^{\frac{1}{1-\rho}}$ is the aggregate labor cost for firms in workplace i . The relative demand for labor inputs is then given by:

$$\frac{L_{iH}}{L_{iL}} = \left(\frac{w_{iH}}{w_{iL}} \frac{1 - \phi_i}{\phi_i} \right)^{-\rho}. \quad (16)$$

Productivity is subject to agglomeration economies, reflecting the usual forces that make dense locations on average more productive (Duranton and Puga, 2001):

$$A_i = \left(\frac{L_i}{H_i} \right)^{\delta^A} \nu_i^A. \quad (17)$$

3.7 Floorspace

I assume there is an exogenous fixed amount of floorspace in every neighborhood of the city. An exogenous share is allocated to housing, while the remaining is used by the firm for production (\bar{H}_n and \bar{H}_i^C). The absence of developers implies that the model deals with a short-term horizon, where changes to the built environment in response to the other features of the city are not happening. One could easily expand the model to include a developing sector that uses land and capital to produce floorspace for every type of use as a response to changes in prices, or as well model landlords choosing endogenously the use of the available fixed floorspace in every neighborhood.

It is important to stress out that the current assumption determines the existence of two separate floorspace markets, for residential and commercial purposes, which are independent from one another. Thus, there will be two prices r_n for residential and r_i^C for commercial floorspace.

3.8 School Quality

The supply of public schools is kept as exogenous as possible in this framework. The idea, is that schools are exogenously present in some areas of the city, and have different quality levels. However, there is ample evidence that school quality also responds to the students that are attending it (Agostinelli et al., 2023; Allende, 2019; Epple and Romano, 2003). This could happen for various reasons, the most obvious being represented by peer effects. Hence, I propose to parametrize school quality levels as a function of the relative presence of students from high and low skill families:

$$S_{jg} = \left(\frac{K_{jH}}{K_{jL}} \right)^{\delta_g^S} \nu_{jg}^S, \quad (18)$$

where the mix of students attending school in neighborhood j is an equilibrium outcome of the residential distribution of groups around the city, and δ_g^S is the elasticity of the attendee mix to school quality. This structure poses a strong weight on composition to explain the differences in perceived school quality, as all schools in the data are publicly funded and follow the same

educational program as defined by the legislator in the Community of Madrid. This formulation renders school quality an endogenous object within the model. The quality of a given school changes according to the enrollment choices of parents, and so it is connected to the residential composition of households' with children that live in areas granting access to the school.

3.9 Equilibrium

Having defined the full static location choice model, I can now define the equilibrium. Given exogenous neighborhood and geographic features $\{\bar{H}_n, \bar{H}_i^C, \nu_i^A, \phi_i, \nu_j^S, B_{ngk}, d_{nlg}^W, d_{nlg}^S, p_{\omega j}\}$, parameters from model equations $\{\alpha_{gk}, \beta, \rho, \theta_g^B, \theta_g^W, \theta_g^S, \kappa_g^W, \kappa_g^S, \delta_g^A, \delta_g^S\}$ and city residential stock for each group \bar{R}_{gk} , the city equilibrium is given by prices $\{w_{ig}, r_n^R, r_i^C\}$ and school quality S_{jg} such that:

1. *Goods market clears,*
2. *Labor markets clear*, i.e. the supply of both types of workers (5) is consistent with the demand by firms (16) in every neighborhood i ,
3. *Floorspace markets clear*, i.e. the demand for residential floorspace (12) clears with the fixed supply \bar{H}_n , and the demand by firms for commercial floorspace (15) clears with the fixed supply \bar{H}_i^C ,
4. *School market clears*, i.e. the demand for schools (9) is consistent with their quality (18),
5. *City is closed*, so that $\sum_n \lambda_{ngk}^B = 1 \quad \forall g, k$.

4 Estimation

This section presents the estimation procedures to recover the main parameters of the model first, their results and, finally, the inversion of the model equations to recover amenities (B_n), school quality (ν_j^S) and productivity fundamentals (ν_i^A) that rationalize the data as an equilibrium of the model.

4.1 Data

Residential choices. Household counts by type come from the Padrón Municipal of the city of Madrid. This is the registry of municipal residents that is maintained by every municipality of Spain, and where every resident must be registered to access basic public services. Each individual reports her nationality, place and date of birth, sex, educational attainment and address. Moreover, cohabitants are linked together, whether they are blood related or not. The Padrón data available covers the period between 2010 and 2018.

Workplace choices. Information on commuting trips is taken from the 2018 Encuesta Domiciliaria de Movilidad (EDM2018), produced by the Transport Consortium of the Community of Madrid.

This is a survey asking to a representative pool of respondents to declare all their movements in a day, recording the reasons for the trip, the travel time and the origin and destination locations of the travel. Critically, the survey also records some demographic information, such as the level of educational attainment. Thus, I am able to construct skill-specific commuting matrices across neighborhoods, also including municipalities of the Urban Area. Travel times are available in the EDM surveys but they do not cover all possible combinations of origin-destination pairs. For this reason, I measure them by querying Google Maps across centroids of geographic units. As these can be quite large and include areas that are not inhabited, I obtain the centroids as a weighted average of the population counts of all census tracts within them. Importantly, I measure travel times as the average three modes: walking, car and transit. From the EDM2018 I then observe the share that each mode represents for various distance bins, differentiating by educational level, and use these as weights, as shown in Figure C.4. This simple procedure returns different travel times, taking into account the modes used by differently skilled workers.

School choices. Administrative data from the Community of Madrid reporting school applications and admissions provides the information on families' choices. For every student, the dataset contains an observation for the first chosen school and one for the school where the student has been admitted. The two correspond in 92% of the cases. Every record includes the residential location of the family, the school code, the score of the application, some characteristics relevant for the admission. Information on skills or education of the household is absent. To separate the choices of differently skilled households, I attach to them the share of population with a college degree or higher of their *Sección* of residence¹⁴. I construct a student-by-school level dataset with an indicator for the chosen school, and I predict how many points would a student have scored for every other school in the city. In order to do this, I exploit the geography of districts, as the admission policy grants higher points for applications within them. As there is no available information on the shape of districts for municipalities other than Madrid, I limit this dataset to the capital only. The data covers years 2011 to 2015, and private institutes are obviously not included. Madrid's public and concerted schools, however, cover approximately 85% of all students, and 90% of those in preschool. In order to construct travel times for each student-school combination, I first reduce combinations by approximating residential and school locations with the centroid of their *Sección*. I use the Open Source Routine Machine (OSRM) to compute walking and car travel times through from Open Street Map. This allows to compute the many combinations much faster than with Google Maps. However, I still rely on GM to complete the measure with transit, even if at the coarser neighborhoods. Finally, I exploit the shares in the EDM2018 for school-related trips, differentiated by type of skill and distance bins, to compute a weighted average across means of transport, as shown in Figure C.4.

Other data. School quality is unfortunately unobserved at the school level. However, I leverage on information available at the *Barrio* level for year 2011-2015 and aggregate it with a the first

¹⁴Figure C.7 in the Appendix shows the level of geographical disaggregation of this unit for the centre of Madrid, where it is easy to see that they correspond to few blocks only.

component of a PCA. Variables available include the results of standardized tests administered to 3rd and 6th graders in primary schools, the number of students in each type of school (public, concertated and private) at each schooling stage, and services offered by schools (such as the availability of transport, if it has a canteen providing lunch for students and if it includes prolonged schooling hours for children to stay longer after the end of class time). Finally, a number of neighborhood features complete the data collected. Available floorspace and its value both for residential and commercial uses form the Spanish cadastre, and second-hand prices from the online sale platform Idealista. Aggregate numbers of workers by neighborhood and municipality of workplace (excluding public employees) are elaborated by the municipality of Madrid and the Community of Madrid with data from the Social Security accounts. Lastly, information on income by *Sección* is elaborated and distributed by the INE starting from tax returns of 2015. This includes many sources, among which labor income is separately identified. Other geographical data is elaborated from various sources.

4.2 Parameter Estimation

As there is a timing to the location choices of households, so there is an order that the estimation must follow. I start with the parameters for the labor supply curves, which are estimated using a standard gravity regression on bilateral commute flows across geographic units. Then, I proceed to estimate the school choice parameters with a Maximum Likelihood Estimator strategy. Finally, I employ IV strategies to estimate the residential preference parameters, as well as the school quality endogeneity with respect to the skill mix of students.

4.2.1 Commuting and Labor Supply

I estimate the elasticity of labor supply with a gravity regression that follows directly from (3). Origin and destination fixed effects capture quantities not varying at the origin-by-destination level. I follow the urban and trade literature by using the Pseudo Poisson Maximum Likelihood (PPML) estimator that returns unbiased estimates in constant elasticity models, while also accounting for the many zeros problem in sparse data ([Santos Silva and Tenreyro, 2006](#)). The following equation is estimated separately for the two skill groups in order to recover the corresponding composed parameter values of $\phi_g^W = \theta_g^W * \kappa_g^W$:

$$\ln \lambda_{nig|n}^W = \xi_{ig}^W - \zeta_{ng}^W - \phi_g^W d_{ni} + u_{nig}^W.$$

Results are presented below in Table 1.

The estimates of the composite semi-elasticity ϕ_g^W in columns (1) and (2) indicate that for each additional minute of travel time between two areas, the likelihood of the commute decreases by 8.9% and 9.4% for the high and low skilled workers respectively. The data rejects the hypothesis that the two values are statistically different. This is likely due to the fact that travel times are

Table 1: Commuting Gravity Equation

| | High Skill (1) | Low Skill (2) |
|----------------|----------------------|----------------------|
| Travel Time | -0.089*** (0.002) | -0.094*** (0.002) |
| Orig & Dest FE | Yes | Yes |
| Obs. | 32041 | 32041 |
| Pseudo R2 | 0.161 | 0.191 |

Note: Travel times from Google Maps vary by skill through different mode shares. Standard errors are clustered two-way at origin and destination.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

higher for low skilled workers for every commute, as this group tends to use slower modes to reach their workplace. Consistently, [Tsivanidis \(2019\)](#) and [Kwok-Hao and Tan \(2021\)](#) find that low-skilled individuals respond more strongly when regressing commute matrices on the same measure of travel times.

Through the gravity regression of Table 1, one only recovers the combined semi-elasticities of travel times to commute probabilities ($\phi_g^W = \theta_g^W \kappa^W$), and cannot separate the elasticities of travel time to travel costs (κ^W) from the variance terms of the idiosyncratic shocks (θ_g^W). To obtain values for the two, one would have to observe wages, which unfortunately are not available at this level of geographical detail. Thus, I assume $\kappa_g^W = 0.015$ for both skills, to obtain supply parameters in line with what found by the previous literature ([Ahlfeldt et al., 2015](#)), and recover $\theta_H^W = 5.93$ and $\theta_L^W = 6.27$.

The labor supply condition in (5) allows to recover a scale-free vector of wages for every location and skill, given observe travel times and worker allocations. I fix the two vectors to have a mean difference of 30%, from the high-skill premium observed in social security data for Madrid. I then target aggregate income levels across *Barrios* and municipalities of the Urban Area of Madrid derived from tax records in Spain, by aggregating wages at the residential level through commuting flows and then across skills weighting by residential shares. Figure C.5 shows the fit between the two, with the reported correlation of 0.9.

Given the parameter values retrieved with the gravity regression and the distribution of wages for each *Barrio* in the city, I can then proceed to measure workplace access as in 4. The resulting geographical distribution, represented in Figure C.6, shows that for both groups of workers central locations offer the best accessibility to high-paying jobs in the city.

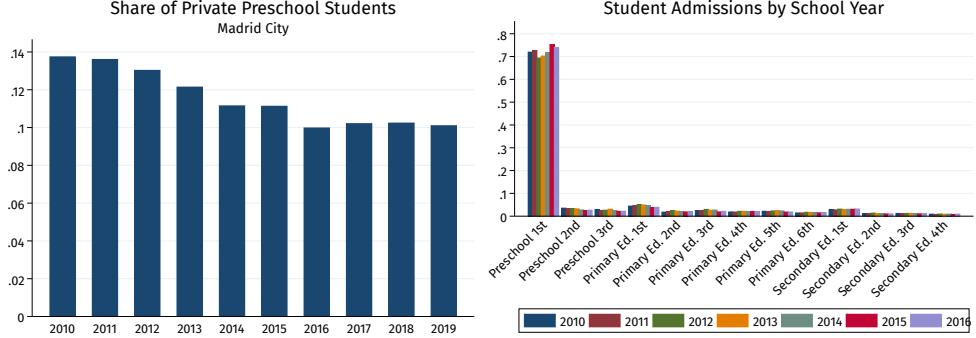
4.2.2 School Choice

The school choice problem faced by parents trades off school quality with travel costs. Moreover, students are admitted only in schools for which the points of their application surpasses the cut-off. This is measured in the data and used in the estimation under the assumption that a single student does not change the equilibrium cut-off, and that this is observed by the household. The data

seems to support this claim, as over 90% of applications obtain the admission to their first choice.

Figure 4: School admission.

(a) Share of private school students by year. (b) Share of admission across grades by year.



For the empirical estimation, I select only students applying to the first year of preschool, i.e. when children are 3 years old. This is for two reasons. First, because the admission system prioritizes students who are already enrolled in a school by reserving a spot in the next year by default, throughout the whole school years. Thus, this makes it a salient feature of the data that the vast majority of families select a school at the first available stage and then never changes, as all good schools are generally already full. Panel (b) of Figure 4 shows the share of applications by year of schooling across the years available in the data, confirming the previous point. Secondly, the selection is due to the fact that students applying for other years than the first of preschool may come from families changing residential location for idiosyncratic reasons outside of the scope of the model.

Another selection excludes from the analysis those applicants that likely have older siblings in the chosen school. This because the systems assigns more points to these applicants, inducing different incentives for the school choice, as this is influenced by the previous choices made for the other siblings, which could have been taken under different priority rules. Moreover, the whole structure of the model is aimed at understanding location choices of households with children, which likely happen once with arrival the firstborn. The selection leaves for the analysis approximately 500 school per year in the city of Madrid, 12000 students per year, over a period of 5 years, generating a dataset of 30 million observations.

In order to estimate the key parameters of the demand for schooling, I follow a methodology that is very similar to the housing choice in Bayer et al. (2007). I set up a MLE to target the parameters that allow the model to match the actual school choices of parents. Since families' skill levels are not directly observed, I use the share of high-skill residents in their *Sección* to measure the probability of being high-skilled ($p_{\omega H}$), and set up the following log-likelihood:

$$\mathcal{L} = \sum_{\omega} \sum_{j \in \mathcal{J}_{\omega}} [\mathcal{I}_{\omega j} \ln(p_{\omega H} \lambda_{\omega j H}^S + (1 - p_{\omega H}) \lambda_{\omega j L}^S)] . \quad (19)$$

The skill-specific choice probabilities come from (7), which can be rewritten to better understand which parameters the estimation is after, i.e. the mixed parameter controlling the sensitivity to travel times ($\phi_g^S \equiv \theta_g^S * \kappa_g^S$) and a residual indicating the overall quality of the school as perceived by every type of family ($\tilde{S}_{jg} \equiv S_{jg}^{\theta_g^S}$):

$$\lambda_{\omega j g}^S = \frac{p_{\omega j}(S_{jg}/\exp\{\kappa_g^S d_{\omega j}\})^{\theta_g^S}}{\sum_\ell p_{\omega \ell}(S_{\ell g}/\exp\{\kappa_g^S d_{\omega \ell}\})^{\theta_g^S}} = \frac{p_{\omega j}(\tilde{S}_{jg}/\exp\{\phi_g^S d_{\omega j}\})}{\sum_\ell p_{\omega \ell}(\tilde{S}_{\ell g}/\exp\{\phi_g^S d_{\omega \ell}\})}. \quad (20)$$

The first order condition of the log-likelihood for ϕ_g^S identifies the parameter under the assumption that travel times are not correlated with the preference shocks for schools. This may happen if households already target specific schools at the time of the residential choice. In order to dismiss such concerns, I use the 2013 data to estimate the MLE, as in that year priority points for applications within district were substantially reduced, partially decoupling residential and school locations¹⁵. Within the estimation procedure, I use the following fixed point algorithm to recover the unique vectors of residual school quality that match the observed student share by skill:

$$\frac{\sum_\omega p_{\omega g} \lambda_{\omega j g}^S}{\sum_{\omega j} p_{\omega g} \lambda_{\omega j g}^S} = \frac{K_{jg}}{\sum_j K_{jg}}, \quad \forall j, g. \quad (21)$$

In order to separate ϕ_g^S into θ_g^S and κ_g^S , I exploit of the limited information available on school quality at the *Barrio* level and target its variance at the city level. This allows to recover θ_g^S separately for every skill by minimizing the difference with the variance of the average residual previously obtained (\tilde{S}_{jg}) aggregated to the *Barrio* level. Such procedure is in the spirit of (Ahlfeldt et al., 2015) which does a similar exercise to separate labor supply parameters:

$$\min_{\theta_g^S} \left\{ \text{Var} \left[S_n^{\text{data}} \right] - \text{Var} \left[\frac{1}{N_{S_n}} \sum_{j \in n} \tilde{S}_{jg}^{\frac{1}{\theta_g^S}} \right] \right\}. \quad (22)$$

Results for ϕ_g^S from the MLE strategy are obtained on a random sample of 200 schools and their 4330 admitted students in 2013. With these two parameters, I can estimate \tilde{S}_{jg} for every school in every year. Then, with the school quality data I recover θ_g^S and finally obtain κ_g^S and the implied school quality S_{jg} . Results for the parameters are shown in the following table:

The estimation reveals substantial differences across skills. The semi-elasticity of school choice to travel times is higher for low-skilled parents, as they tend to choose closer schools. This is partly due to the fact that travel times for low-skilled households are on average higher by one and a half minutes, as measured by the different transport mode shares. Estimates of school preferences

¹⁵Under the assumption that the two choices are not perfectly overlapped in time, households applying in 2013 were exogenously exposed to a different school set given the change in policy environment. Gortázar et al. (2023) show that this specific reform induced applications and admissions to schools further away from the residential locations. The change in priority points, from 4 to 0.5, was thus effective in increasing the pool of schools available to students and in inducing admissions to better-performing schools.

Table 2: School Choice Parameters

| | ϕ_g^S | θ_g^S | κ_g^S |
|------------|---------------------|--------------|--------------|
| High-skill | 0.245*** (0.005) | 6.202 | 0.039 |
| Low-skill | 0.315*** (0.000) | 9.897 | 0.032 |

Note: Results of the school choice estimation. The first two columns are estimated with MLE and variance minimization as explained in text. The third column reports the ratio of the previous two. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

across skill also reveal a big difference, showing that choices for high-skill households are more idiosyncratic. Finally, the resulting semi-elasticities of travel costs are substantially higher than for commuting ($\kappa^w = 0.015$). This implies that traveling around the city to reach a school is very costly, slightly more for high-skill households, as potentially due to higher opportunity costs. Thus, the trade-off faced by parents seems to tilt residential choices towards locations with good access to schools, rather than those with close access to jobs.

Given the parameter values retrieved with the MLE and the distribution of school quality values for each preschool in the city, I can then proceed to measure school access as in 8. The resulting geographical distribution, represented in Figure C.8, shows that for both groups of workers northern locations offer the best accessibility to the best schools in the city.

4.2.3 Peer Effects in School Quality

Within the model, school quality depends on the skill composition of students. This is generally referred to as peer effects, and they become particularly relevant in settings with little differences in school financing, such as the case of Madrid. Identifying the elasticity of school quality to peer effects from (18), requires exogenous variation in school composition. This follows from school quality determining the choices of parents in the first place, thus feeding into the skill mix of students. For this reason, the required exogenous variation needs to be independent with respect to the quality fundamentals that are invariant to which students are attending a school, but still matter for families' choices.

The elevation of each school, as measured in meters over the sea level, provides the sought after variation. The reason behind this choice stems from the historical development of the city of Madrid. In its expansion started and planned in the second half of the 19th century, northern areas have typically attracted more affluent residents because of their altitude. These areas had better views, healthier and less dry lands, and allowed for waste waters to flow downwards to other neighborhoods before sewage systems were fully introduced (Pallol Trigueros, 2015; Otero Carvajal and Pallol Trigueros, 2011). As a consequence wealthy elites of the city initially abandoned the old and crowded central neighborhoods towards the north, constructing there high quality and single-

family housing. Southern areas, instead, were inhabited by the nascent working-class population that would find occupation in the factories concentrated there, and by the waves of immigrants arriving from the southern and poorer parts of Spain. This development resembled that of nowadays' slums. Moreover, this initial social distribution was exacerbated by the public provision of infrastructure, the funding of which was linked to the price of housing in each area, further increasing the dispersion in quality of life across the newly formed neighborhoods. These social and spacial divisions still persist today, having survived and replicated throughout the subsequent boom that the city experienced in the 20th century.

Panel A of figure C.9 maps the average altitude for each Sección of the city, where darker areas indicate higher altitudes. It is easy to see that northern neighborhoods are more elevated than the rest of the city, and that the lighter ones follow the valley created by the Manzanares river. I argue that the elevation of each school is independent from the structural components of school quality that do not depend on peer effects. Critically, at the same time, given the gravity structure for school choices, it likely predicts the composition of residents around them, and thus the skill ratio of students. Indeed, Panel B of figure C.9 shows that altitude is a strong predictor of the high-to-low ratio of households with children across Secciones of the city in the data. This is true even when controlling for other exogenous features of Secciones that may matter for the relative choices of households of different skills, as can be seen in C.1.

To estimate peer effects, I use the revealed-preference measure of school quality recovered in the previous estimation step for each skill group. I further select schools with at least 20 students to consistently measure the ratio across skills. In all regressions I include a vast array of other school characteristics as controls. The results are reported in Table 3.

Table 3: Estimates of peer effects in school quality valuations.

| | High S.Q. (1) | Low S.Q. (2) | High S.Q. (3) | Low S.Q. (4) |
|----------------|---------------------|---------------------|---------------------|---------------------|
| Ln Skill Ratio | 0.191*** (0.019) | 0.154*** (0.011) | 0.238*** (0.026) | 0.320*** (0.033) |
| Controls | Yes | Yes | Yes | Yes |
| School Size | 20 or more | 20 or more | 20 or more | 20 or more |
| IV | | | Ln Elevation | Ln Elevation |
| F-Stat | | | 72.736 | 72.736 |
| Obs. | 415 | 415 | 415 | 415 |

Note: Columns (1) and (2) present OLS coefficients, while (3) and (4) report the ones from two stage least squares. The sample is selected for schools with at least 20 students to precisely measure the ratio of high-to-low students. Every regression include indicators for whether the schools is public or concertated, which grades it covers, whether it is religious, its price group, whether it offers alternative pedagogical methods, classes of english and other languages. The year of construction of the school and its size in square meters are also included as controls. Heteroskedastic robust standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Columns (1) and (2) report the OLS results which show a difference in the spillovers for perceived school quality, i.e. high-skill parents appear more sensible to school composition. A one percent increase in the skill ratio will determine a 0.191 and 0.154 percent increase in the school

quality by high and low-skill households respectively. However, columns (3) and (4), exploiting the exogenous variation from elevation, increase both coefficients and reverse the results. This is consistent with residential sorting being at play, with the OLS coefficients suffering from substantial downward bias, more so for the low-skilled families that tend to live in neighborhoods with lower quality schools. The reported F-statistic for the first stage is sufficiently high, indicating strong predictive power of the average school elevation on the skill ratio of families sending their children there and laying further credibility to the validity of the exogenous variation.

4.2.4 Neighborhood Choice

In order to identify the elasticity of residential choices to neighborhood characteristics (θ_g^B), I leverage the information available at the Sección level for both the distribution of households and that of neighborhood characteristics. The heart of the estimation strategy rests on exploiting the heterogeneity across households with and without children in the cross-section of the data. Comparing the relative choices of the two groups, within each skill level, allows to drop all characteristics of a location for which preferences are the same. Within the model, taking the ratio across households by their parenthood from equation (11), reveals that differences in residential choices depend on three elements: school access, house prices and unobserved amenities.

$$\ln \frac{\lambda_{ng1}^B}{\lambda_{ng0}^B} = \ln \frac{\Phi_{g0}}{\Phi_{g1}} + \theta_g^B \ln S_{ng} + \theta_g^B (\alpha_{g1} - \alpha_{g0}) \ln(r_n) + \theta_g^B \ln \left(\frac{B_{ng1}}{B_{ng0}} \right). \quad (23)$$

Including house prices in the estimation is necessary only if the expenditure shares of the two groups are different. However, this is not the case in the data. Indeed, I estimate the Cobb-Douglas preference parameters for each household type (α_{gk}) with microdata from the Encuesta de Presupuestos Familiares (EPF), the consumption survey conducted regularly by the Spanish national statistical institute (INE). Using data between 2010 and 2015 for the Community of Madrid, I predict the average share of income devoted to housing depending on skills and parenthood. Regression results are reported below in the Table 4.

While column (1) reports a significant and negative effect of the household being a family, this is likely due to the fact that households with children are older and have multiple earners. This inflates income and consequently reduces the share of housing. Indeed, adding controls such as the age of the primary household earner, the number of earners within the household brings the coefficient of the family indicator to zero. The regression then predicts expenditure shares that only depend on skill levels, hinting to non-homotheticities in consumption, and cannot reject a test for differences across parenthood.

To get to θ_g^B , I then exploit variation in school access. However, as school quality is a function of the surrounding neighborhood skill composition due to peer effects, unobserved amenities that disproportionately attract specific types of households are correlated with school access. Reverse causality thus threatens the identification of θ_g^B in equation 23. This is the same issue faced

Table 4: Cobb-Douglas preference parameters estimation.

| | Housing Share of Income | |
|---------------------|-------------------------|----------------------|
| | (1) | (2) |
| Family | -0.095*** (0.000) | -0.005 (0.004) |
| High-Skill | -0.105*** (0.000) | -0.066*** (0.003) |
| Family x High-Skill | 0.010*** (0.000) | -0.006 (0.003) |
| Obs. | 8,716 | 8,715 |
| R2 | 0.057 | 0.234 |
| Controls | No | Yes |

Note: The dependent variable is the ratio between the expenditure in housing and the total income of the household. Controls in column (2) include the age of the household head, the number of earners in the household, the size and density of the municipality. Standard errors clustered by family and skill level are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

in the identification of the peer effect elasticity, simply going in the opposite direction. Once again, I exploit the historical expansion of Madrid to find exogenous variation that isolates the effect of school access on location choices. Specifically, I leverage the year of construction of each school institute as an instrument. This choice is due to the fact that the construction year depends solely on the gradual expansion of the city into newly formed neighborhoods. Moreover, I show that newly built schools are preferred by parents. Table 5 reports the coefficients of the regression of quality on the year of construction, and shows that even when including the student skill mix and other school features. This may be due to many different reasons, for example to concerns of the safety of the building or to newer buildings being better structured to support modern educational methods. There are two key reasons why the instrument allows me to identify the residential elasticity. First because, as the city grew, schools had to be built everywhere irrespective of the local skill composition. Secondly, because replacing the educational infrastructure is costly and complex, so that the investment has a particularly slow depreciation and long life. Consequently, the construction year predicts school quality independently from the composition of students and of residents in the nearby areas.

I further transform the instrument by measuring the average year of school construction within a 1km radius from each *Sección* of the city, using the total number of admitted students as weight. This is because I need to instrument school access, which is an aggregator of all schools quality from equation 8. Remaining concerns about the instrument may come from observing that the construction year is merely a function of the distance to the historical neighborhoods. This is clearly visible in the map of the average construction year in Figure C.10. The worry is that the instrument ends up correlating with other relevant location features such as the size of housing, the age of the stock of housing, the presence of green areas and so on. This is why they are included in the estimation, as seen below in table 6.

Table 5: School quality and construction year.

| | High Skill (1) | Low Skill (2) | High Skill (3) | Low Skill (4) |
|-------------------------|---------------------|---------------------|-------------------|---------------------|
| Ln Year of Construction | 4.838*** (1.434) | 4.774*** (1.051) | 1.941* (1.086) | 2.904*** (0.889) |
| Obs. | 518 | 524 | 506 | 509 |
| R2 | 0.026 | 0.041 | 0.492 | 0.473 |
| Controls | | | Yes | Yes |

Note: The independent variable is the residual school quality obtained in the school choice estimation for high and low-skilled households. Controls in columns (2) and (3) include the ratio of high-to-low skill students, the school building size and indicators of the school characteristics (religious institute, foreign languages taught, pedagogical methods, price bins, public or concerted). Heteroskedastic robust standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Residential choice estimation.

| | High with kids (1) | High no kids (2) | Low with kids (3) | Low no kids (4) | High ratio (5) | Low ratio (6) |
|------------------|-----------------------|----------------------|----------------------|----------------------|---------------------|----------------------|
| ln $\$_{nH}$ | 2.386 (1.785) | -1.903 (1.919) | | | 4.289*** (1.533) | |
| ln $\$_{nL}$ | | | 3.272*** (1.069) | -1.773*** (0.435) | | 5.045*** (1.098) |
| ln Distance Sol | -0.314*** (0.042) | -0.693*** (0.048) | 0.026 (0.065) | 0.109*** (0.028) | 0.379*** (0.037) | -0.083 (0.068) |
| Share Green 1km | -0.209 (0.642) | -2.277*** (0.702) | 1.824*** (0.469) | -0.530*** (0.193) | 2.069*** (0.556) | 2.354*** (0.511) |
| Avg constr. year | 0.028*** (0.003) | 0.007** (0.003) | 0.025*** (0.002) | 0.001 (0.001) | 0.020*** (0.002) | 0.025*** (0.002) |
| ln House Size | 0.850** (0.334) | 1.471*** (0.361) | -3.091*** (0.240) | -0.873*** (0.101) | -0.621** (0.289) | -2.218*** (0.246) |
| Obs. | 2208 | 2208 | 2208 | 2208 | 2208 | 2208 |
| R2 | 0.472 | 0.150 | 0.098 | 0.451 | - | - |
| First-stage F | 13.251 | 13.251 | 32.390 | 32.390 | 13.251 | 32.390 |

Note: The independent variables are the share of each type of household across *Secciones* in columns (1) to (4), and the ratio across parenthood for the high and low skilled in columns (5) and (6). School access vary by skill because of different valuations, preference parameters and travel times across households with different skill levels. Both school access values are instrumented with the average construction year in a radius of 1km around each *Sección*, and the table reports the Fstat of the first stage. Heteroskedastic robust standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The main results of the estimation are presented in columns (5) and (6), with reported values of 4.289 and 5.045 for low and high-skills respectively. Two comments are worth stating. First, that, even though the estimation procedure is novel with respect to the literature, the obtained values are in line with what found in other urban economics papers ([Ahlfeldt et al., 2015](#); [Diamond, 2016](#); [Hebllich et al., 2020](#)). This is true both in terms of the magnitudes, and in terms of the relative strength, with the high-skill having more idiosyncratic preferences (i.e. a lower value of the parameter). Secondly, the importance of using the ratio across households with and without children is revealed in the negative coefficients reported in columns (2) and (4). Indeed, as higher school access values attract households with children, this likely generates a disamenity for those without. However, these are likely experienced as negative spillovers by other families, so that the true value of schools is only obtained by netting out the negative spillover. All the estimation, however, depends on the assumption that households without children do not take school access into account for their residential choices. For this reason, it is paramount to highlight that the repeated cross-section nature of the data may introduce a downward bias in the estimation. Specifically, this happens whenever a household that is observed without children makes its choice under the prospect that it will have them later, and thus cares about schools. Similarly, a household that had children in the past, and that after they left did not change its residence may have taken its choice with schools as a priority. For this reason, if anything, the true value of the preference parameters is likely higher than the one obtained.

4.3 Other Parameters

The remaining parameters are taken from the literature. The elasticity governing agglomeration forces is taken as $\delta^A = 0.08$ from [Ahlfeldt et al. \(2015\)](#), which estimates the strength of agglomeration economies in a similar within city setting exploiting the natural experiment offered by the fall of the Berlin Wall. The elasticity of substitution between high and low skilled labor inputs in the CES aggregator for production $\rho = 1.6$ is taken from [Acemoglu and Autor \(2011\)](#). Finally, the share of labor in production $\beta = 0.6$ is taken as a reference parameter in the literature.

4.4 Model Inversion

Given parameters, this class of models allows to recover exogenous fundamentals in order to match the observed data. Thus, I firstly recover the school quality levels that rationalize the school choice patterns by matching it to the student shares of each school, as explained above. Then, I recover the productivity fundamental from the zero profit condition as a direct function of both the aggregate wage and rent of commercial floorspace. Intuitively, if firms in a location can afford to pay higher wages and rents, then it means that they must be more productive in order to produce:

$$\nu_i^A \propto \mathcal{W}_i^\beta (r_i^C)^{(1-\beta)} \left(\frac{L_i}{\bar{H}_i^C} \right)^{-\delta^A}, \quad \forall i. \quad (24)$$

Table 7: Model parameters.

| Parameter | High Skill | Low Skill | Source |
|--------------------------------------|------------|-----------|---|
| <i>Expenditure share in housing:</i> | | | |
| No Kids | 0.36 | 0.42 | Prediction from OLS expenditure regression |
| With Kids | 0.36 | 0.43 | |
| <i>Location preferences:</i> | | | |
| θ_g^W | 5.93 | 6.27 | Commuting gravity regression |
| κ_g^W | 0.015 | 0.015 | Commuting gravity regression |
| θ_g^S | 6.20 | 9.90 | School choice MLE |
| κ_g^S | 0.039 | 0.032 | School choice MLE |
| θ_g^B | 4.29 | 5.05 | Residential choice IV regression |
| <i>Other parameters:</i> | | | |
| β | 0.6 | | Labor share in production |
| ρ | 1.6 | | Elasticity of substitution across workers |
| δ^A | 0.08 | | Agglomeration elasticity |
| δ_g^S | 0.24 | 0.32 | Peer effects IV regression |

Note: Bold description indicates own estimate, see text for sources of other parameters.

Through the labor market equilibrium conditions for every type of skilled labor input, I recover the labor market intensities by which firms combine workers (ϕ_i). Finally, I also recover the level of amenities in every neighborhood from equation (11) in order to rationalize the observed residential choices for every group of households. Essentially, amenities are the residual that the model is not able to explain. The intuition is simple, higher level of amenities characterize neighborhoods that, even with high rents and low expected income and school utility for parents, are disproportionately inhabited by a higher share of households, for every group.

5 Understanding How School and Labor Markets Interact

Access to both school and labor markets determine the residential choices of households. At the same time, wages and school quality also respond to the distribution of households. As a result, the residential decisions of households establish an interconnection between these two markets. In this section, I demonstrate how these previously ignored cross-market effects arise, by removing frictions to access each market in turn. It is worth noting that these mechanisms can be applied to any market that is relevant enough to impact residential choices.

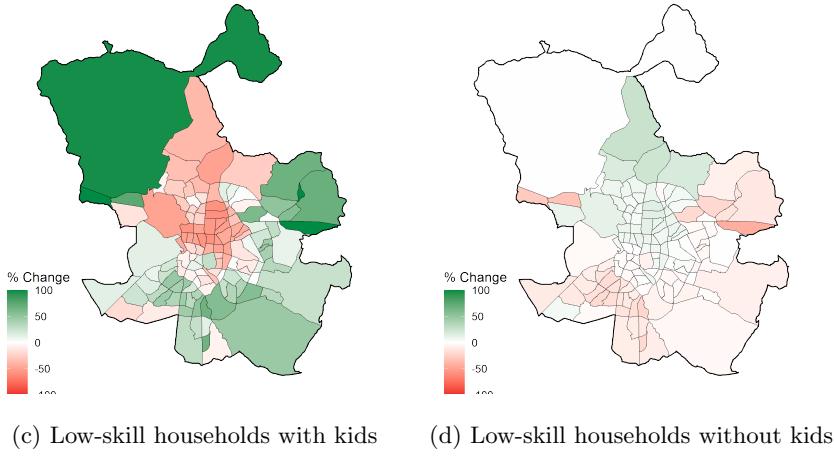
I find that frictions to school access attract high numbers of households with children towards locations near top-rated schools. As a consequence, these choices draw workers and drive up house prices in the same locations. Similarly, commuting frictions mildly concentrate households in productive areas, as they are less binding. Nonetheless, the labor market exerts stronger impacts on schools than vice versa. This result follows from non-parents offsetting the consequences of school frictions on the distribution of employment, while peer effects boost the labor market impacts on school quality.

5.1 Quantifying the Impact of Frictions to School Access

In order to quantify the effect that schools exert on the economic structure of the city, I set up a counterfactual in which frictions to school access are fully removed. Specifically, I set school-related travel times to zero and admission probabilities to one; this makes school access equal in every location, removing its relevance for the residential choices of parents. All results can be either interpreted as the consequences of removing these frictions, or, on the flip side, as the impact of school access on the city.

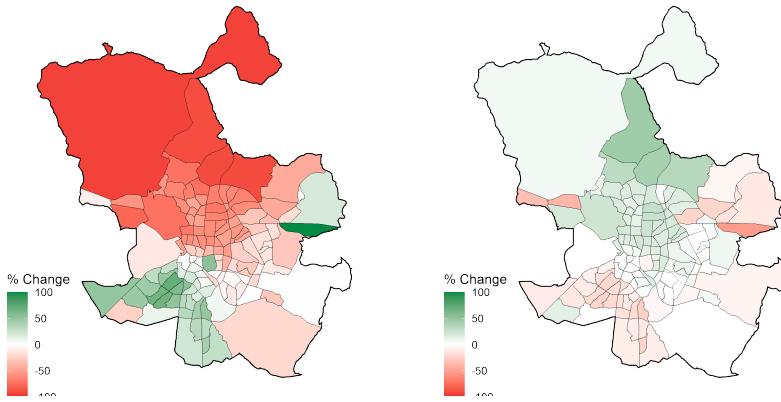
Figure 5: Change in residential choices after removing school frictions.

(a) High-skill households with kids (b) High-skill households without kids



(c) Low-skill households with kids

(d) Low-skill households without kids

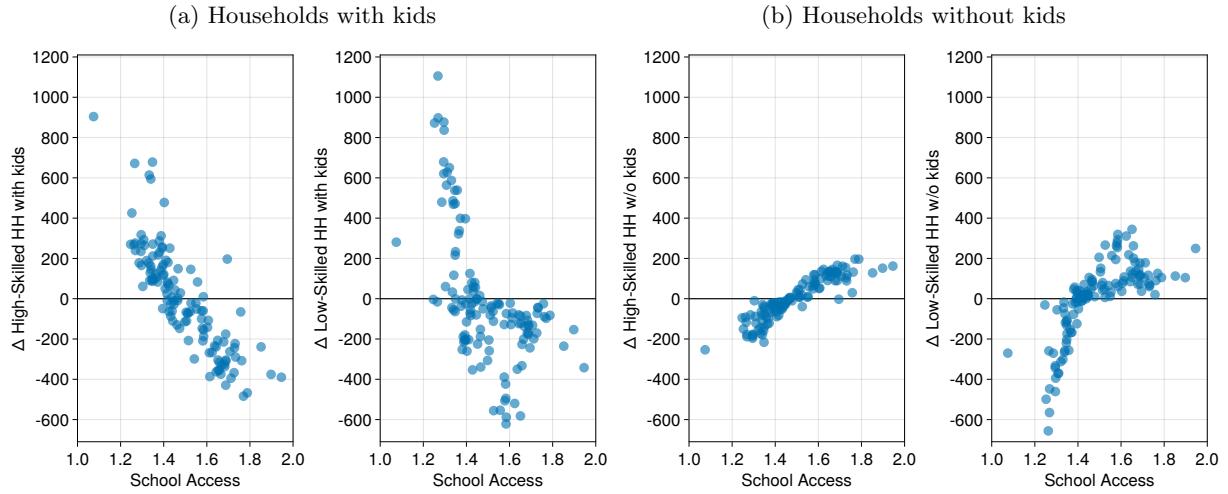


Note: Percentage change in the number oh households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario where frictions to school access are removed versus the baseline data.

Figure 5 maps the changes in the residential choices of every type of household across neighborhoods induced by the absence of school frictions. Panels (a) and (c) show that households with children would avoided the central and northern locations if it was not to access schools. Households with children flee these initially attractive neighborhoods, denoted by the red areas on the maps,

when frictions are removed. In absolute terms, these locations lose an average of 385 high and 318 low-skill households with children, respectively, as high-skill parents were disproportionately more likely to reside there. More peripheral areas, depicted in green, consequently experience similar gains in terms of households with children. Next, Panels (b) and (c) reveal that non-parents, even though not directly affected by the removal of school frictions, respond with an opposite relocation. This reaction is less pronounced than the direct effect on parents, with average changes of around 7% and 11% for high and low-skill households without children, respectively. Consequently, school frictions attract parents to areas near good schools, inducing an increase in density even if childless households are driven off. To generalize results beyond the case of Madrid, in section A.1 I further discuss how these effects vary depending on the initial tightness of frictions, implying that the effects of school are stronger in settings endowed with a worse transportation infrastructure or in which admission policies strictly tie together the residential and school locations. Moreover, I also show that the attractive effect of schools on parents would have been milder absent the endogenous response of non-parents, as these groups switch locations due to their misaligned preferences for neighborhood features.

Figure 6: Change in residential distributions against the initial level of school access.



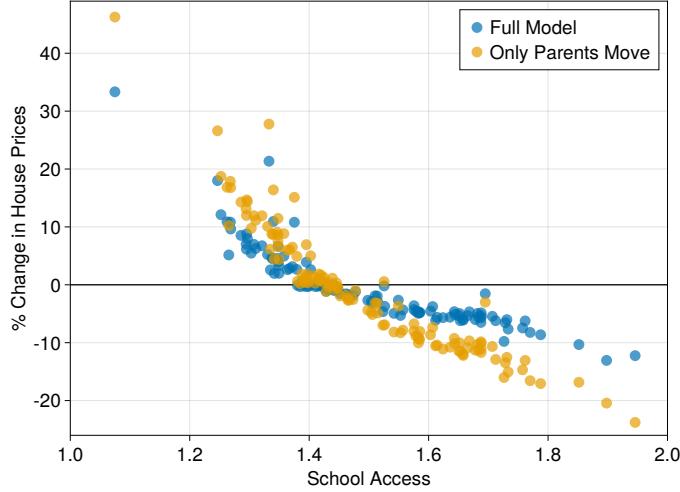
Note: Percentage change in the number of households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario one the y-axis. The average of high and low school access is plotted on the x-axis.

The effect of school frictions on location choices bear consequences for segregation. Interestingly enough, residential segregation for parents increases by around 15% when frictions are removed.¹⁶ This implies that schools were concentrating both high and low-skill parents towards the same areas. Indeed, the correlation of school access across households of different skills was around 70% to begin with. To further illustrate this point, Panel (a) in Figure 6 plots the changes in the number of households that follows the removal of frictions against the initial level of school

¹⁶I measure here segregation through the difference in the average share of high-skilled households experienced in the neighborhood by each household type (Diamond and Gaubert, 2022).

access. Both high and low-skill parents flee the areas that granted the best school access, moving towards the periphery in partially different directions as shown in the maps of Figure 5. Part of the reason why low-skill parents do not take advantage of the lower housing pressure in these areas is driven by the inflow of non-parents, plotted in Panel (b). Their response prevents the reallocation of low-skill parents and the reduction in segregation. On the contrary, the comovement of non-parents actually reduces segregation for this category by 6.5%, inducing a fall by 5% of aggregate segregation given that they cover a higher share of the city residents.

Figure 7: School access and changes in house prices.



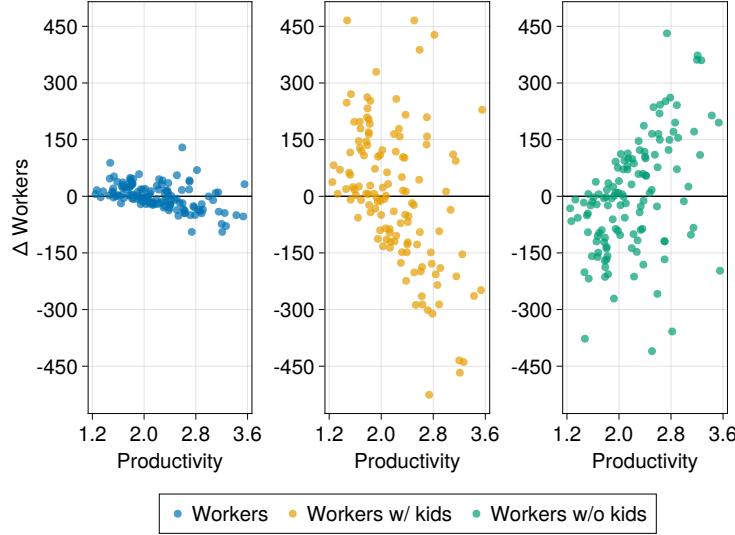
Note: Relationship between log changes in house prices and school access in the baseline data. School access on the X axis is the neighborhood level average of the access for high and low-skill households. The Y axis reports the log change in house prices in every *Barrio* between counterfactual scenarios without frictions to school access and the baseline data. Blue dots represent the full equilibrium, while yellow dots are from a model not allowing households without children to reallocate.

The general equilibrium response of non-parents is generated by changes in house price, following the concentration of parents near good schools. Notably, however, the endogenous response of childless households counterbalances that of parents, and thus ends up reducing the impact of school frictions on house prices. Figure 7 illustrates this point, by plotting changes in house prices against the initial level of school access. In fact, the elasticity of house price changes to the initial level of school access is almost halved once accounting for the endogenous response of non-parents, from -0.95 to -0.53. Under the full model, peripheral locations that gain population experience an average increase in house prices of 5.6%, while the others see an average fall of 4.1%, which correspond to a difference of 132€/sq.m and -123€/sq.m in these areas, respectively. Overall, school frictions increase demand for locations nearby good schools. The model unveils that excluding childless households from the analysis, would have substantially biased the consequences for the residential structure of the city and house prices.

Next, I show how the implications of school frictions go beyond the housing market and alter the distribution of economic activity in the city. In particular, the need to locate near good schools

to get access reshapes the geography of parents because of the gravity structure of commuting. However, even if removing school frictions has significant impacts on the residential choices of households first, the consequent impact on the labor market remains somewhat limited due to the response non-parents.

Figure 8: Changes in the distribution of workers from removing school frictions.



Note: Absolute change in the number of total workers (left), workers with children (center), and without children (right). The difference compares counterfactual scenarios without school frictions with the original equilibrium, showing that overall workers leave productive locations, as parents move more than the relocation of non-parents.

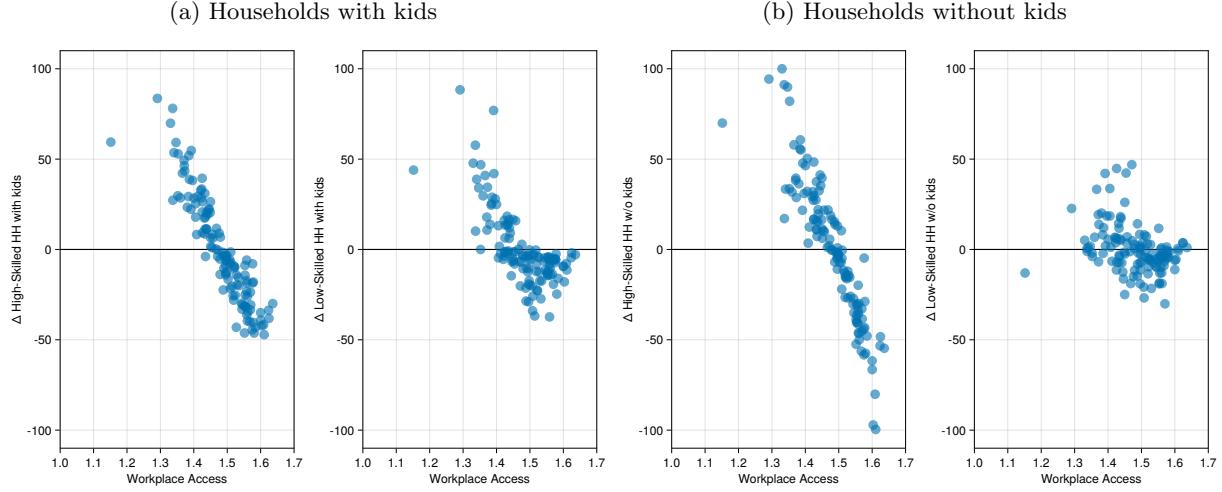
To this end, Figure 8 depicts the changes in the allocation of workers against the initial level of productivity across neighborhoods, as school frictions are removed. It reveals that workers with kids, plotted in the center, flee the locations that had the highest productivity when leaving the areas near good schools, as the two overlap geographically. At the same time, the opposite response by workers without kids who are perfect substitutes to parents, on the right, cannot compensate for the change in the geography of labor supply of parents. Thus, the overall distribution of workers is move away from productive locations, with well-known negative consequences for agglomeration and productivity (Duranton and Puga, 2001). Maps of the geographical distribution of the same changes in Figure A.4 further confirm that workers flee the central and northern areas of the city in favor of firms located in the periphery. Moreover, in Figure A.3, I show how school frictions affect equally high and low-skill workers, and that the effects are muted by two forces: low initial commuting costs and the response of non-parents.

5.2 Quantifying the Impact of Commuting Costs

Next, I simulate the city under a different scenario in which workplace access frictions are removed and uncover the other direction in cross-market effects. In particular, I set travel costs related

to commuting to zero. This results in a flattened workplace access across *Barrios*, so it becomes neutral for residential choices.

Figure 9: Change in residential distributions against the initial level of workplace access.



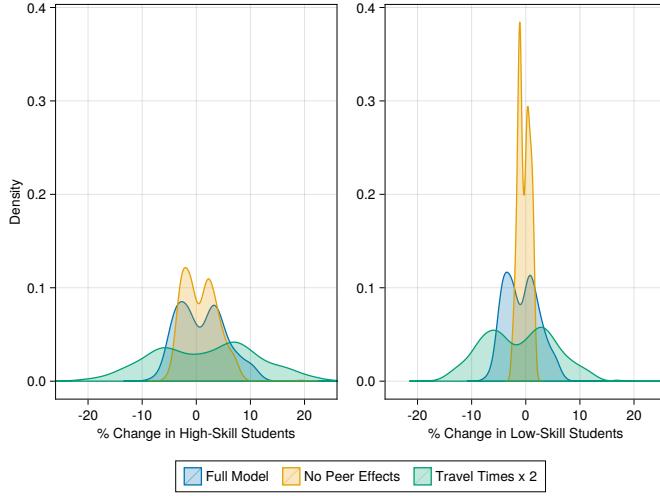
Note: Percentage change in the number oh households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario one the y-axis. The average of high and low workplace access is plotted on the x-axis.

First, Figure 9 depicts the changes in residential choices for each type of household as a consequence of the removal of commuting costs. There are two key differences with respect to the changes observed when removing school frictions. The magnitude of responses are substantially smaller, and all households move away from previously high access areas. This results is due to commuting costs being significantly lower than frictions to get to schools, as revealed by the empirical analysis of commuting and school choices in previous sections. Moreover, all household types participate in the labor market, eliminating the scope for indirect effects by some part of the population. Figure A.5 maps changes and shows how reallocation of all households goes towards peripheral locations, away form the previously attractive central productive areas.

Nonetheless, Figure 10 shows that the consequences of this simulation for the distribution of students to schools are significantly stronger. The blue distribution illustrates changes in the allocation of students across schools comparing the new fully solved equilibrium with the baseline data. The range of these changes is substantially larger than the effect of school friction on the allocation of workers. The gains and losses experienced by schools in terms of students range between +10% and -10% for both skills. Moreover, I find that the difference across school quality enjoyed by children of high and low-skill families decreases by 2.5%. This result follows from commuting frictions concentrating all types of households in the center, more so high-skill ones. In turn, this attraction also increases school quality in schools nearby because of peer effects and decreases it to the periphery where low-skill students are more likely to be enrolled.

Three elements determine the difference in the effects' magnitude. First, even though commut-

Figure 10: Changes in the distribution of students from removing commuting costs.



Note: Percentage change in the distribution of high (left) and low-skilled (right) students. The difference compares counterfactual scenarios without workplace access frictions solving the full model with the original equilibrium. First, in the baseline data (blue), and then in a world with doubled travel costs to start with (green).

ing frictions are not particularly strong, they nonetheless imply effects on the residential choices of households. However, even small relocations imply important changes for the school market as school access frictions are strong and tie together residential and school locations. Secondly, under this scenario, there is no counterbalancing response playing a similar role to the one of childless households in the previous counterfactual. Finally, and most importantly, peer effects magnify changes by inducing a shift in school quality, following the reallocation of high-skill parents. This last point is clearly illustrated by the yellow curves of Figure 10 through the smaller changes in the distribution of students in the absence of peer effects. Again, like in the case of school frictions, the impact of commuting costs is stronger in contexts with worse transport infrastructure, as shown in the green line.

Overall, the case of labor and school markets illustrate how, through their role for residential choices, different markets can generate connections and influence each other within cities. In particular, the model shows how the school effects on the distribution of employment are partially muted by the presence of non-parents, through competition in the housing market. At the same time, the consequences of the labor market on schools is propelled by their endogenous response to the composition of nearby neighborhoods through peer effects. Thus, I conclude that the strength of cross-market effects is asymmetric in nature. This result, in turn, affects the outcomes of policies targeting each market, as I discuss in the next section.

6 Policy Counterfactuals

In this section, I use the model to evaluate the consequences of the asymmetric cross-market interactions between school and labor markets for policy outcomes. First, I use the model to quantify the consequences of the adoption of a partial work-from-home schedule. Importantly, evidence suggests that high-skill jobs are more amenable to teleworking so this matters most for these households. As a result, the city experiences a decrease in density in the central areas initially offering most employment opportunities, which is more pronounced for high-skilled households. Due to the influence of peer effects on school quality, the model uncovers further reallocation towards the periphery, amplifying the overall effect of remote work through the endogenous response of schools. Secondly, I simulate a policy offering busing to schools for the children of low-skill families. I find that the policy reduces by 30% the school quality differences across families' skills. At the same time, it implies substantial changes for residential choices, but only limited ones for the labor market.

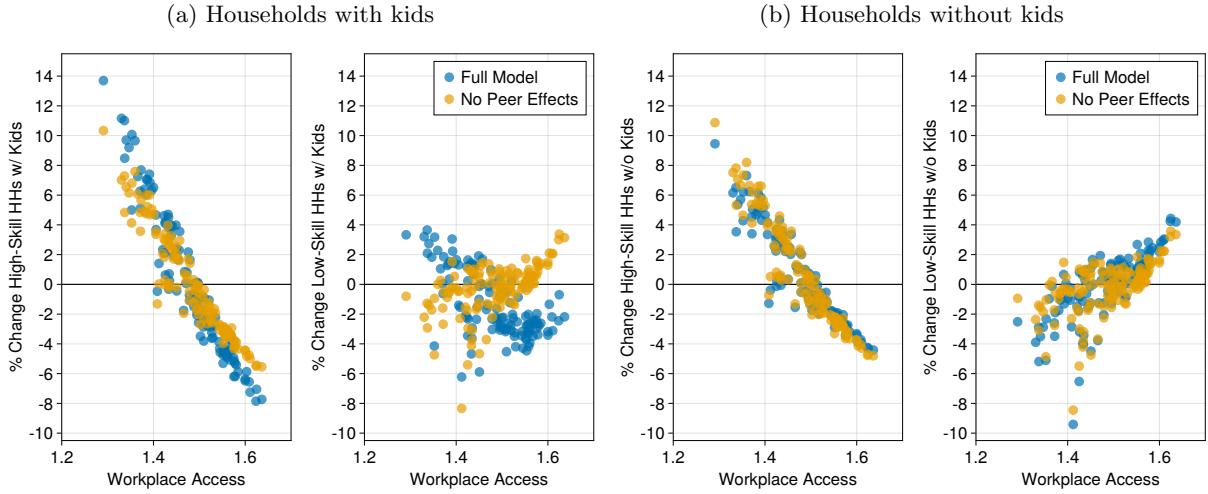
6.1 Work-From-Home and Schools

The spatial structure of the model allows me to evaluate the city-wide consequences of a work-from-home policy following recent trends in the labor market. These changes, caused by forced lockdowns during the Covid-19 pandemic, now allow a substantial share of the workforce to fully work remotely, or to do so at least for some days of the week.¹⁷ I proceed by using figures from [Delventhal and Parkhomenko \(2021\)](#), who document that 60% of jobs done by college graduates in the US can be done remotely. The same figure drops to around 25% for workers without a college degree. Consequently, I set a corresponding reduction in commuting costs of households, depending on their skill levels.

Figure 11 plots the resulting residential changes for each family type against the initial level of workplace access. Given the equilibrium interactions that the model is designed to capture, the effects of work-from-home depend on the peer effects in school quality and their consequences for the residential choices of parents. This can be seen by comparing the full model changes in blue to the model solved without accounting for peer effects in yellow. The endogenous response of schools reverses the sign of the residential choices of low-skilled parents. This group would have behaved like their low-skill non-parents, who move towards central areas even if their commuting costs go down 25%, as they face the competition of high-skill households suburbanizing to the periphery to enjoy lower house prices. As high-skilled parents move with their children, schools in peripheral neighborhoods are improved and this attracts other parents too. Additionally, the magnitude of effects changes significantly: on average the number of high-skill households with children increased by 4.9% in the outskirts, but would have only grown by 3.7% without the

¹⁷Recent evidence shows that bigger cities are more likely to have transitioned to a state of high use of remote working ([Monte et al., 2023](#)), that cities undergo profound changes as a consequence of the decoupling of work and residential locations ([Althoff et al., 2022; Ramani and Bloom, 2021; Delventhal et al., 2022](#)).

Figure 11: Change in residential distributions with work-from-home.



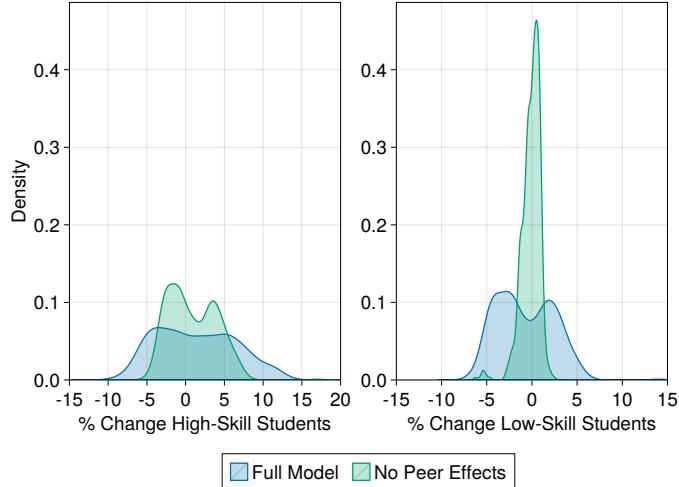
Note: Percentage change in the number of households by type, comparing the new equilibrium choices under work-from-home against the initial level of workplace access, as averaged between high and low-skill households. Blue dots represent results solving the full model, while yellow ones results without peer effects in school quality.

endogenous reaction of schools. Similarly, the number of low-skill parents rises by 1.8%, and by only 0.9% without peer effects. Because of competition for space, the opposite is true for childless households, who move slightly less to the periphery when accounting for schools (3.2% instead of 3.7% for the high-skilled, and 1.2% instead of 0.95% for the low-skilled). Maps in Figure B.1 show that the movements follow the so-called "donut effect" Ramani and Bloom (2021), as households all move away from the productive center. Only low-skill households without children take advantage of the lower prices there to move in, even if their commuting costs go down as well.

Next, Figure 12 shows how remote working also influences the allocation of students across schools in the city. In particular, it shows how, absent peer effects, changes would have been substantially lower. If the children of high-skill parents increase their presence in peripheral schools by 3.3%, initially, they then spur a further attraction and end up growing by 5.2%. The same works for students from low-skill households, who quadruple their rise from 0.6% up to 2.4%. Finally, Figure B.2 shows that the "donut effect" also holds for students, as they move to schools outside the center.

In terms of welfare, all households gain from the introduction of teleworking, thanks to the reduction in commuting costs. Importantly, the response of school quality through peer effects improves the welfare changes for low-skill parents from 3% to 3.7%, and for high-skilled ones from 9.4% to 9.7%, as can be seen in Figure B.3.

Figure 12: Changes in student allocations with work-from-home.



Note: The graphs depicts the density of changes in the allocation fo students comparing the work-from-home counterfactual scenario against the data for both children of high and low-skill students. The blue curves represent the full model solution, while the green one the model solved without accounting for peer effects.

6.2 Transportation for Students of Low-Skill Households

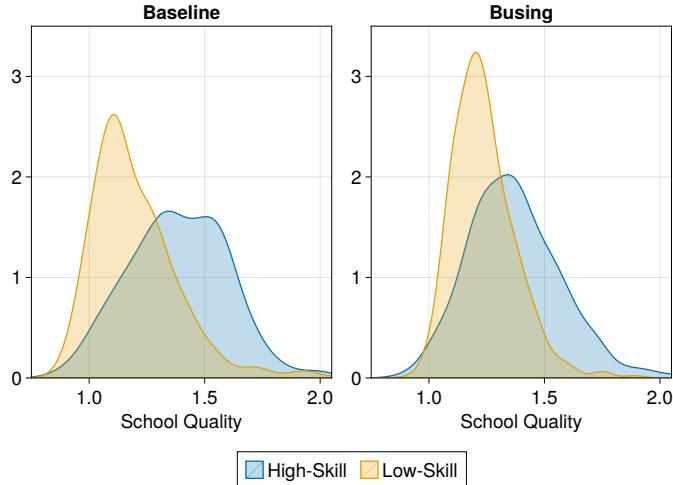
Many local governments worldwide spend significant resources on the provision of transportation to school in an effort to improve school choice. The effectiveness of busing services has received less attention with respect to school choice, but recent evidence suggests they increase demand for far away schools effectively improving choice (Trajkovski et al., 2021). However, little is known in terms of their effectiveness at fostering integration of students from heterogeneous backgrounds, as well as at improving the educational achievement of students (Angrist et al., 2022). Moreover, the result of busing may go beyond schooling, as parents react by adjusting their location choices (Agostinelli et al., 2023); the residential effects will depend on the interactions with other markets in the city and on the response of households without children.

In the case of Madrid, publicly funded preschools only offer busing service to a slim share of students that barely reaches a coverage of 5% (see Figure C.3). Thus, providing such service to low-skill families may be particularly important since the geography of school access is more affected by transport costs than it is by admission policies.¹⁸ Next, I show the results of such a policy, which I implement in the model by reducing transport costs for school to the level of commuting for work, only for low-skill families.

First, I find that the busing policy reduces by 31% the differences in school quality that high and low-skill households children are exposed to. Figure 13 shows the changing distribution of school quality enjoyed by each type of student. Importantly, the average school quality does not

¹⁸Madrid's allocation mechanism to schools does not imply a particularly restrictive menu of choices. For details refer to section 4.2.2.

Figure 13: School quality by skills.



Note: The graphs depicts the density of school quality across schools weighted by the distribution of students from high and low-skill families. The graph on the left shows the distributions from the data, while the one on the right the counterfactual with busing for students from low-skill households.

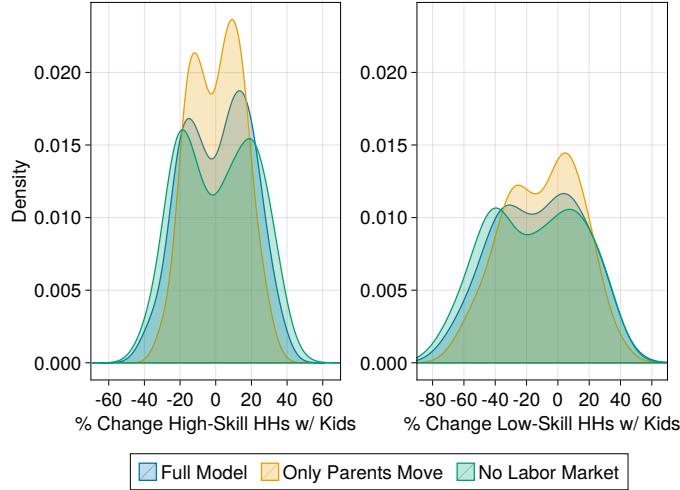
diminish for students from high-skilled families, and it is rather the one for low-skill family children that increases. Hence, the result does not come at the expenses of the high-skilled group. At the same time, segregation across students from backgrounds with different skills is reduced by 26%.

I find that the response of schools through peer effects matters for results. In fact, high-skill families do not suffer virtually any consequence from the busing service: the average school quality for their children goes down by 1% only. This is because as low-skill students start enrolling in better schools thanks to the busing service, the quality of receiving schools gets reduced. Consequently, the city-wide gradient of school quality is tilted and differences are muted, as shown in Figure B.4. This is further reinforced by the consequent relocation of high-skill parents, who do not need to pay high house prices to live near top-rated schools anymore. Maps in Figure B.5 show that parents flee the locations that previously granted access to best schools, including high-skill households who are not targeted by the policy. Consequently, these same areas receive a higher number of childless households.

Next, Figure 14 plots the density of changes in residential choices of parents, showing how their strength varies with the endogenous responses of non-parents and when accounting for the labor market. In particular, it reveals that residential changes for high-skill parents are reduced by -2.7%, as the labor market reacts by offering better wages in locations that lose population. The presence of non-parents instead increases changes by 3.6%, as they respond by leaving receiving neighborhoods and allow the relocation of households with children. The same figures are 0.5% and 3.5% for the low-skill.

Finally, in terms of welfare measured in consumption equivalent, low-skill households experience an increase of 20.8%, as their schooling options are significantly increased. High-skill house-

Figure 14: Changes in residential choices of parents with busing.



Note: The graph plots the density of residential changes as a consequence of the introduction of busing for students from low-skill families.

holds also benefit, thanks to their endogenous responses, with an increase in welfare of 0.4%, as can be seen in Figure B.6. These figures do not account for the cost of the policy, which could be funded through local taxes, potentially changing the overall welfare effects.

7 Conclusion

This paper has investigated how schools impact the structures of cities. To do so, I first use residential data from Madrid to unveil that households spatially sort based on their skills and parenthood. Then, I built a general equilibrium spatial model that accounts for the school choice problem faced by parents. As the labor market and schools endogenously react to the residential distribution of households within the city, they affect each other through equilibrium forces. Equipped with unique data on the application of the quasi-universe of students, the commuting flows of differently skilled workers, and the residential choices of every household in the city, I then estimate preferences for schools, workplaces, and neighborhoods. To understand the underlying mechanisms behind the connections between schools and the labor market, I simulate counterfactuals where accessibility frictions to each market are removed in turn. The exercise reveals that school frictions shift the distribution of economic activity by attracting parents to locations granting access to good schools. Moreover, central productive locations attract students to schools in the center through their appeal to parents. I further show how the presence of non-parents mutes the effects exerted by schools, while peer effects amplify those from the labor market. The model also reveals how the cross-market effects are reduced by the efficiency of the infrastructure making travel costs lower. Finally, I simulate the diffusion of teleworking and the introduction of busing for students of low-skill families and show that cross-market interactions affect their outcomes. The endogenous

response of schools boosts the abandonment of downtown locations due to remote work, while the labor market mutes the reallocation of parents following the increase in educational access from the bus service.

Results overall show that the geography of schools is exceptionally consequential for the structure of cities. This result is due to high travel times and admission policies that restrict access to good schools, constraining the residential choices of parents. Consequently, the choices of other households are indirectly affected by schools, and their impact further expands to other markets. These results show how increasing school choice in admission policies is not enough to keep parents from sorting and concentrating next to good schools. This paper demonstrates that having an efficient transportation infrastructure or implementing busing services, is particularly beneficial, as these reduce frictions to mobility around the city and mute cross-market interactions. In the presence of travel costs and other access frictions, this paper has highlighted how ignoring the general equilibrium interactions across markets substantially biases the expected outcome of policies. Further research using this framework could provide new insights on the effect of rent subsidies and moving to opportunity policies by integrating the general equilibrium effects of local markets. Finally, the analysis presented in this work can be generalized to any market appealing enough to significantly change the residential choices of households.

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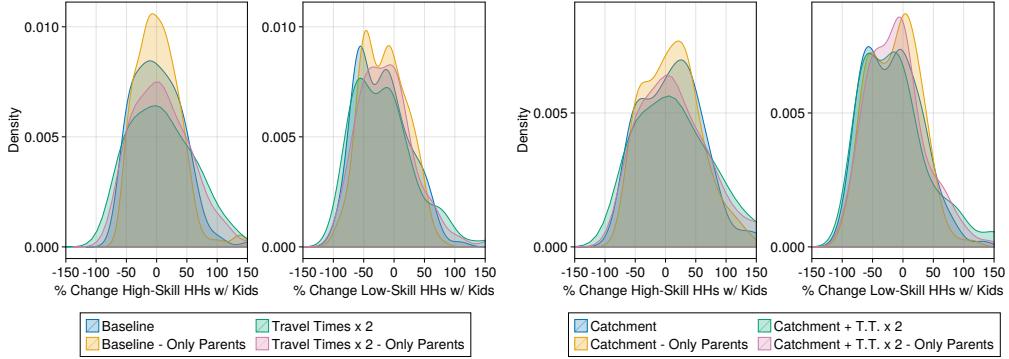
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Appendix A: Additional Counterfactual Results

A.1 Quantifying the Impact of Frictions to School Access

Figure A.1: Removing school frictions - changes in the distribution of HHs with kids

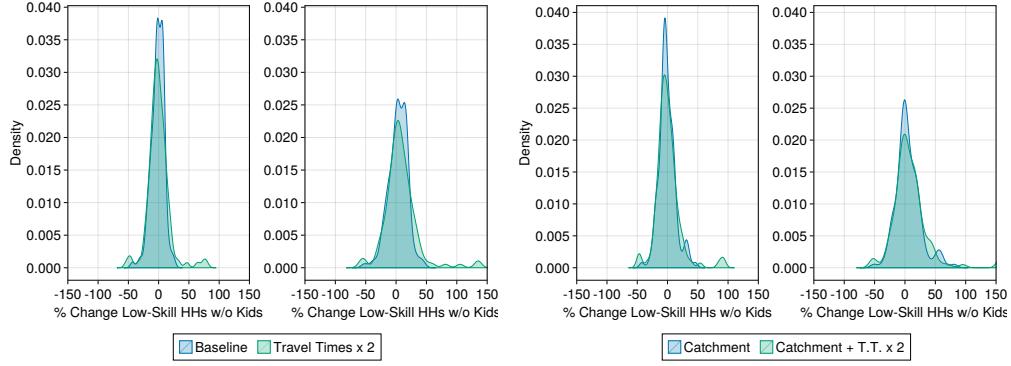


Note: Changes in the distribution of HHs with children when school frictions are removed. Results are reported for counterfactuals under different initial conditions: baseline values, double travel times, catchment areas along Madrid's *Districtos* to define school admissions, and the two together. Each is then run by solving first the full model, and then one in which only parents can adjust their residential choices.

The graphs in figures A.1 and A.2 represent the changes in the distribution of households for every type, under the simulation in which school frictions are removed, and school access is equalized across the city. They show that the geography of school access across neighborhoods generates substantial changes in residential choices. These are more pronounced the tighter frictions are in the first place, as exemplified by the changes obtained under doubled travel times, when using Madrid's *Districtos* as hard catchment areas determining which schools students can be admitted to, and both implemented at the same time. Moreover, they also show that the response of non-parents, which is opposed to the reallocation of parents, allows them to move even more. Finally, Figure A.2 shows that the response of childless households is more moderate and that it does not vary particularly with the initial frictions.

The maps in Figure A.4 depict the percentage changes across *Barrios* of the city in terms of high and low-skill workers. They show how the new distribution of workers follows the changes happening in terms of residential choices for households, as shown in Figure 5. This is a clear consequence from the gravity structure that labor supply takes across space, which reshapes where workers can go to work given their residential choices. Overall, as school frictions are removed and parents do not need to live along the center-north axis of the city, the same locations loose employment, at the expenses of more peripheral neighborhoods. So in the case of Madrid, as school and workplace access display high levels of covariance, schools act as a concentrating force in the labor market. Next, Figure A.3 shows the changes in the labor market across workers of different skills when school frictions are removed in blue, while also illustrating that low commuting costs and non-parents mute the changes. In fact, the model does not differentiate between those with and

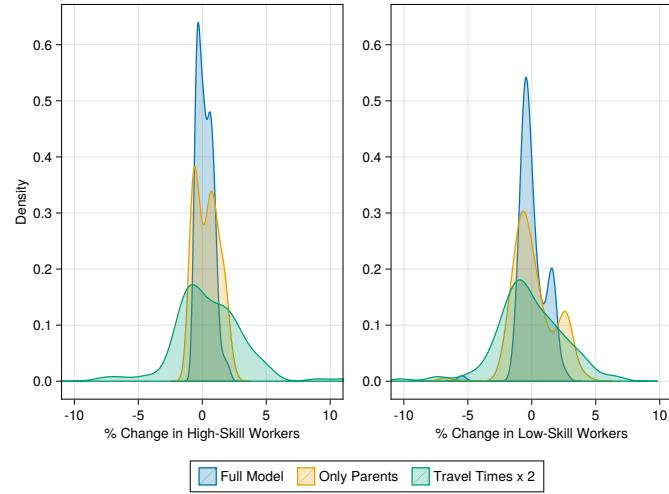
Figure A.2: Removing school frictions - changes in the distribution of HHs without children



Note: Changes in the distribution of HHs without children when school frictions are removed. Results are reported for counterfactuals under different initial conditions: baseline values, double travel times, catchment areas along Madrid's *Distritos* to define school admissions, and the two together.

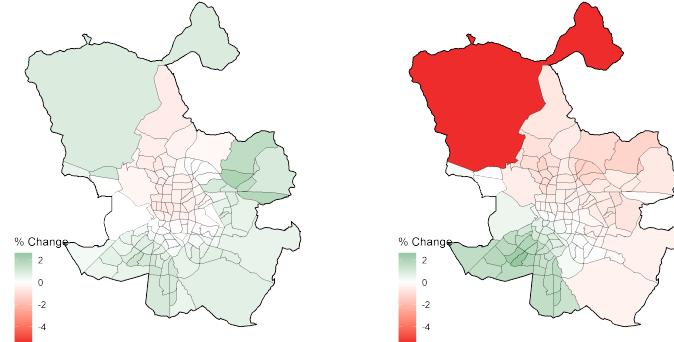
without children, and the data suggests that their labor supply responds equivalently to commuting distances. The relevance of both forces is represented in the other curves of Figure A.3. The yellow lines show that changes would have been stronger without the reallocation of non-parents. Similarly to what found for residential choices, the resulting effects would be stronger in contexts with higher transport costs, as shown by the green lines.

Figure A.3: Changes in the distribution of workers from removing school frictions.



Note: Percentage change in the distribution of high (left) and low-skilled (right) workers. The difference compares counterfactual scenarios without school frictions with the original equilibrium. First, in the baseline data solving the full model (blue) and without allowing households without children to adjust (yellow). Secondly, in a world with doubled travel costs solving the full model again (green).

Figure A.4: Changes in the distribution of workers when removing school frictions.

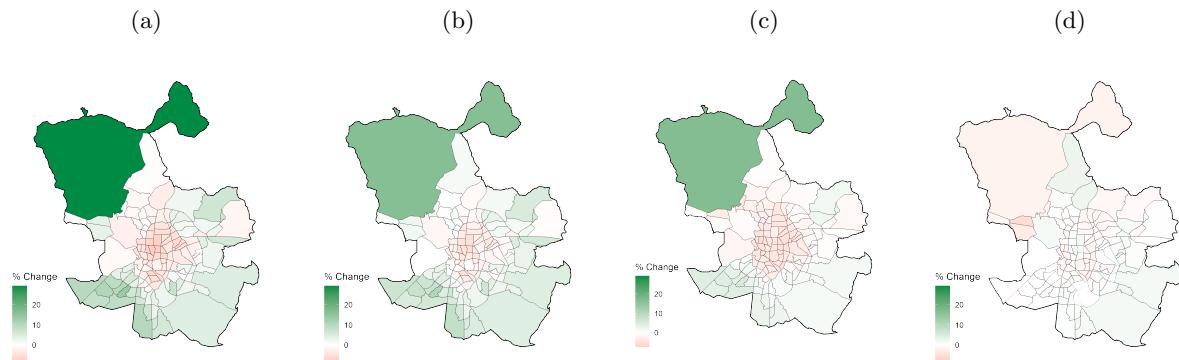


Note: Changes in the distribution of high and low-skill workers as a result of the removal of school frictions across the *Barrios* of Madrid.

A.2 Quantifying the Impact of Commuting Costs

Maps in Figure A.5 represent the residential changes for every household type as workplace access frictions are fully removed, or under the universal implementation of WFH. They show how central locations of the city attracted residents because of they close proximity to employment opportunities. Under the implementation fo WFH, then their value is reduced and households flee these areas in favor of more peripheral locations where house prices are lower. Differently to what observed in Figure 5, under the removal of school frictions, in this case all households comove away from the central location, as everyone is affected directly by the change. Also, it is important to note that residential changes are substantially lower under this scenario, as the level of frictions to access workplaces is substantially lower than that measured for schools.

Figure A.5: Change in residential distributions when removing labor market frictions.

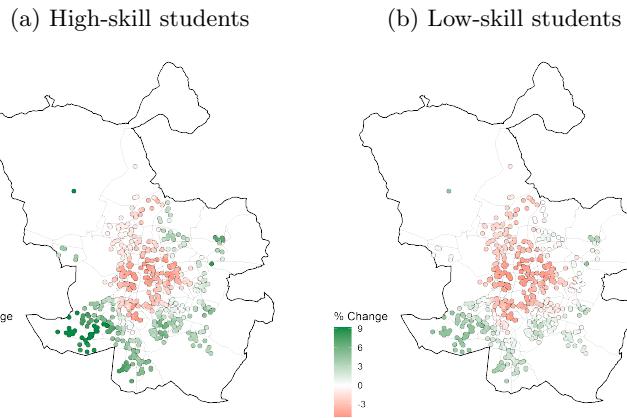


Note: Percentage change in the number oh households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario where commuting frictions to workplace access are removed versus the baseline data.

Finally, Figure A.6 illustrates a consequence of the so-called "donut effect" of WFH (Ramani and Bloom, 2021), which has been observed for the reallocation of households outside of the cen-

tral location of cities and impacting the housing markets in the outskirts. Thanks to the model developed in this paper, being able to quantify cross-market effects, it is possible to uncover the consequences of WFH on the school market. This is, that the doughnut effect is revealed to be relevant as well for the school market. As parents leave central areas of the city and relocate in more peripheral neighborhoods, they bring their children along and send them in nearby schools, as travel costs for school trips remain high. It is important to notice here, that, absent peer effects, the extent of these changes would have been muted by school quality remaining highest in the center and not reacting to the reallocation of households.

Figure A.6: Change in student distributions.



Note: Percentage change in the number of students by school and household skill, comparing the new equilibrium choices in the counterfactual scenario where frictions to workplace access are removed versus the baseline data.

Appendix B: Additional Results on Policy Counterfactuals

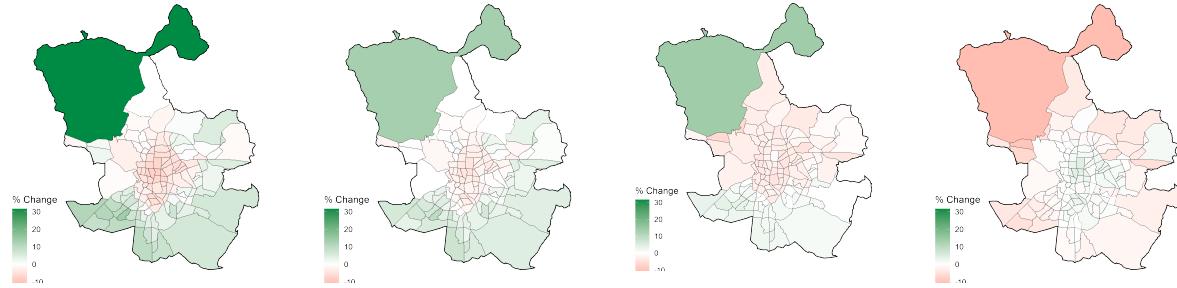
B.1 Work-From-Home and Schools

B.2 Transportation for Students of Low-Skill Households

Appendix C: Additional Figures and Tables

Figure B.1: Change in residential distributions with work-from-home.

(a) High-Skill HHs w Kids (b) High-Skill HHs w/o Kids (c) Low-Skill HHs w/o Kids (d) Low-Skill HHs w/o Kids

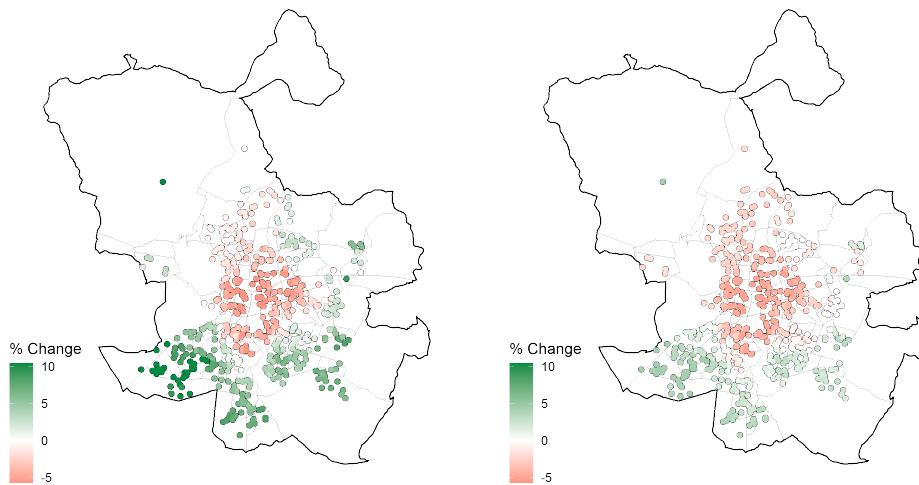


Note: Percentage change in the number of households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario with work-from-home versus the baseline data.

Figure B.2: Change in student distributions.

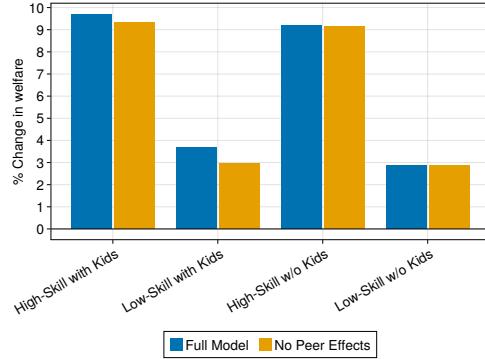
(a) High-Skill

(b) Low-skill



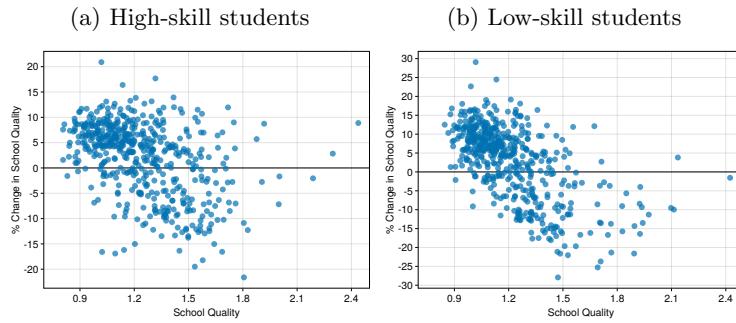
Note: Percentage change in the number of students by school and household skill, comparing the new equilibrium choices in the counterfactual scenario with work-from-home versus the baseline data.

Figure B.3: Change in welfare from work-from-home.



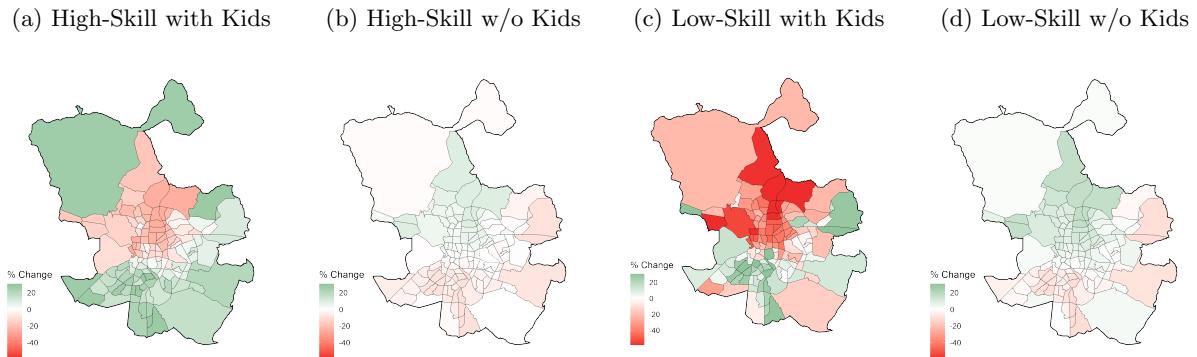
Note: Percentage change in welfare, comparing the new equilibrium choices in the counterfactual scenario with work-from-home versus the baseline data.

Figure B.4: Change in school quality with busing for students of low-skill households.



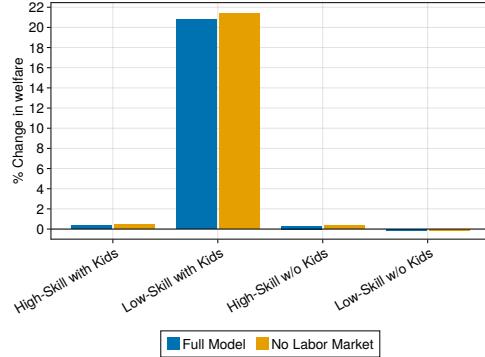
Note: Percentage change in school quality against its initial level, comparing the new equilibrium choices in the counterfactual scenario with busing versus the baseline data.

Figure B.5: Change in residential distributions with busing for students of low-skill households.



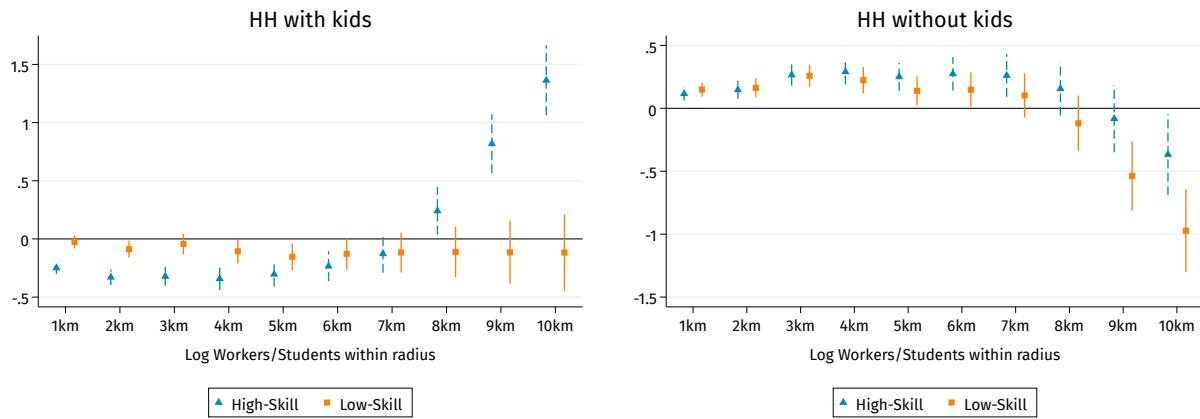
Note: Percentage change in the number of households by neighborhood and type, comparing the new equilibrium choices in the counterfactual scenario with busing versus the baseline data.

Figure B.6: Change in welfare from busing.



Note: Percentage change in welfare, comparing the new equilibrium choices in the counterfactual scenario with busing versus the baseline data.

Figure C.1: Coefficients for the relative accessibility measure, by radius length.



Note: The coefplots report the correlation between the residential choices of each type of household and the relative accessibility measure to jobs and schools. The distances on the x-axis is the length of the radius used to compute the circle around each *Barrio*. The circle is the used to count the number of workers and students in their workplace and students respectively from administrative sources of data.

Figure C.2: Point system in the Boston Mechanism of Madrid. Taken from Gortázar et al. (2023).

| BONUS | CRITERIA | NUMBER OF POINTS | | |
|---------------------------------|--|------------------|-----------|-----------|
| | | Before 2012/2013 | 2012/2013 | 2013/2014 |
| Proximity -Madrid city- | Family house or parents' work in: | | | |
| | School district | 4 | 4 | |
| | Boundary school district | 2 | 2 | |
| | Family house or parents' work in: | | | |
| | Same municipality | | 4 | |
| | School district | | 0.5 | |
| | Region of Madrid | | 2 | |
| | Income<=IPREM | 2 | | |
| | IPREM <Income <=2IPREM | 1 | | |
| | Minimum Insertion Subsidy | | 2 | 2 |
| Low-income | | | | |
| Siblings | First one 4pts, and additional 3pts One or more | 4 | 8 | 10 |
| Disability | Parents, students or siblings | 1.5 | 1.5 | 1.5 |
| Large Family | General | 1.5 | 1.5 | 1.5 |
| | Special | 2.5 | 2.5 | 2.5 |
| Alumni family member | Family member is alumni student | | 1.5 | 1.5 |
| School discretionary | | 1 | 1 | 1 |

Notes: The changes beyond the proximity criteria were applied together across all medium and large municipalities. IPREM is the acronym in Spanish for the Multiple Effects Income Public Index, which was €7,455.14 in the period of study. The Minimum Insertion Subsidy (*Renta Mínima de Inserción*) is a special provision granted for people with lower income than IPREM. School discretionary is a point that the schools have freedom to assign based on “public and objective” criteria.

Figure C.3: Share of students with specific services in preschool in Madrid.

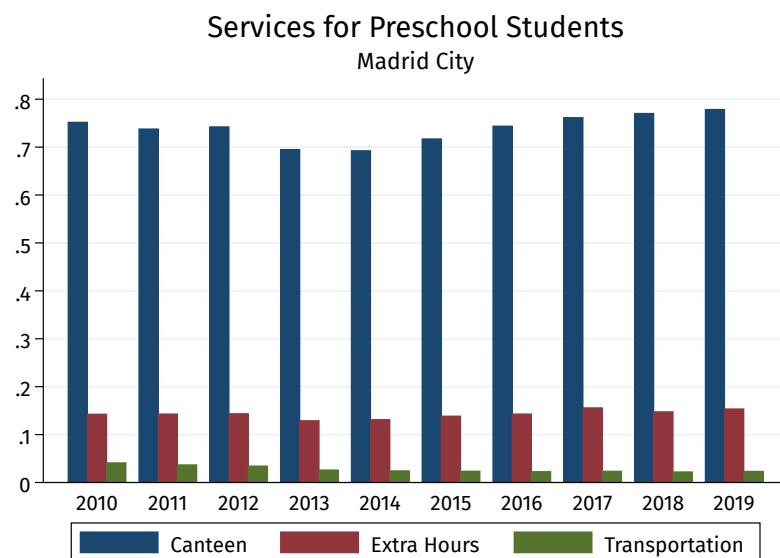


Figure C.4: Weights to average travel times across transport modes and skill levels.

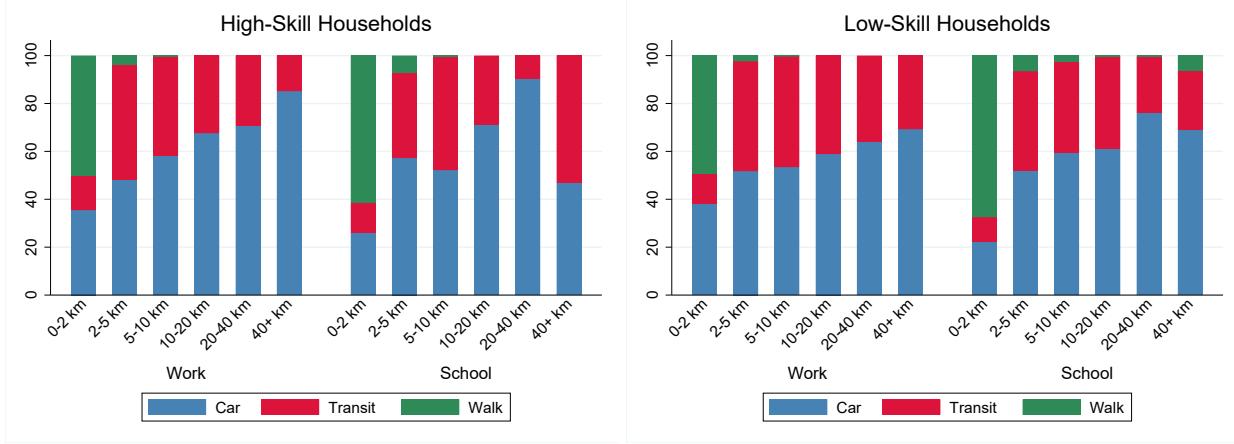


Figure C.5: Estimated aggregate income against data across geographical units of the Urban Area.

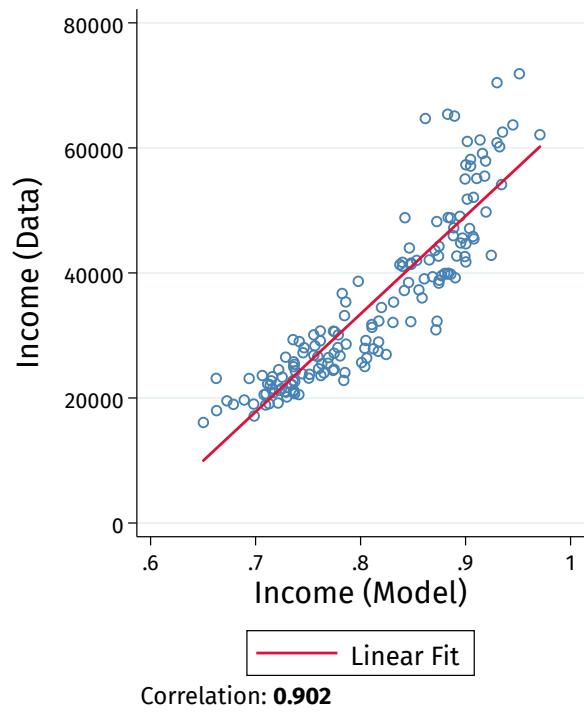


Figure C.6: Distribution of workplace access across *Barrios*.

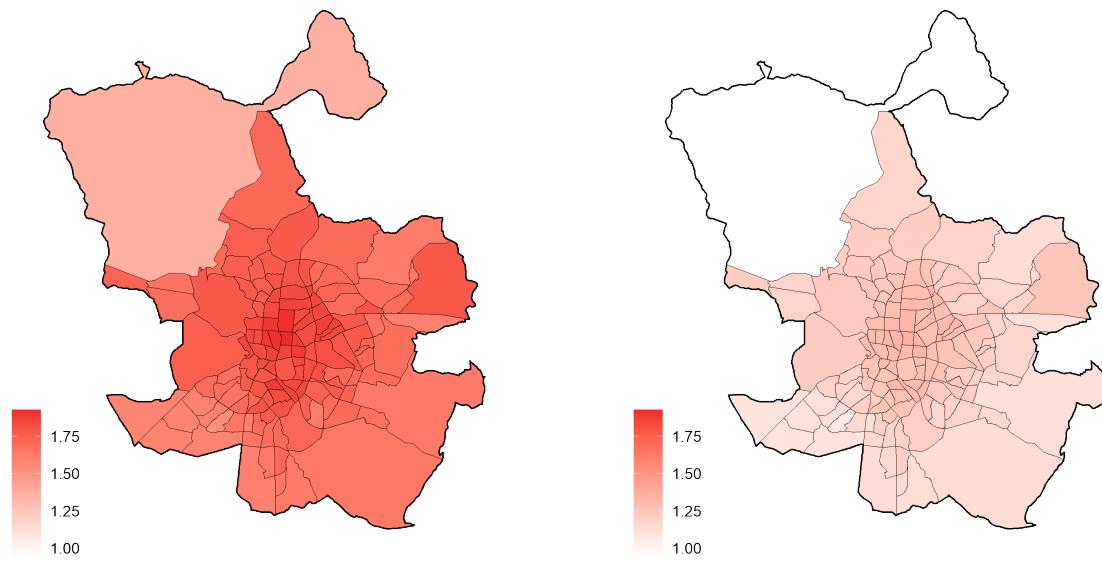


Figure C.7: *Secciones* of the center of Madrid in black. Dots indicate the geolocation of families that have applied to a publicly funded school.



Figure C.8: Distribution of school access across *Barrios*.

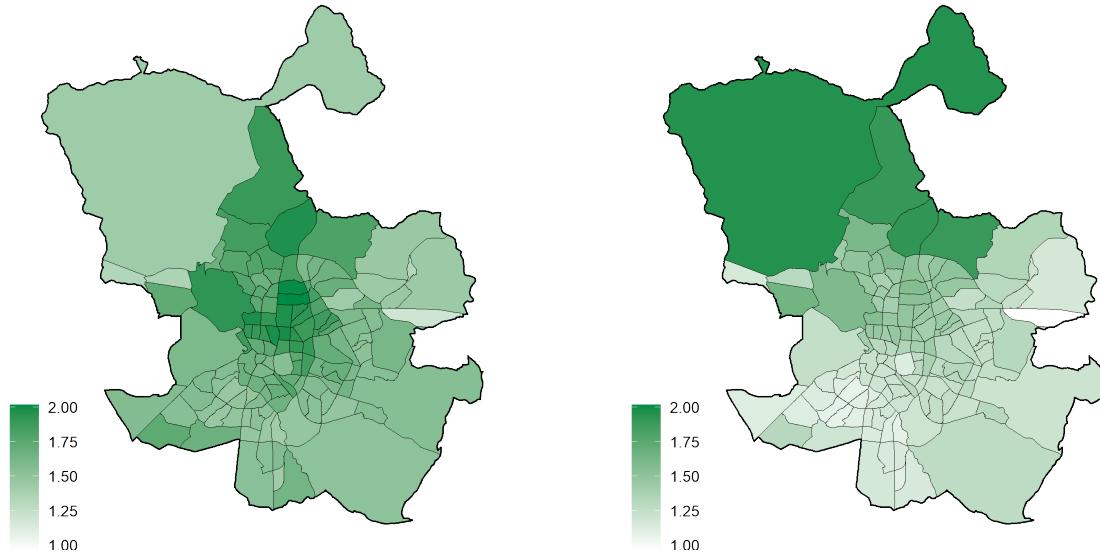


Figure C.9: Variation in elevation within Madrid.

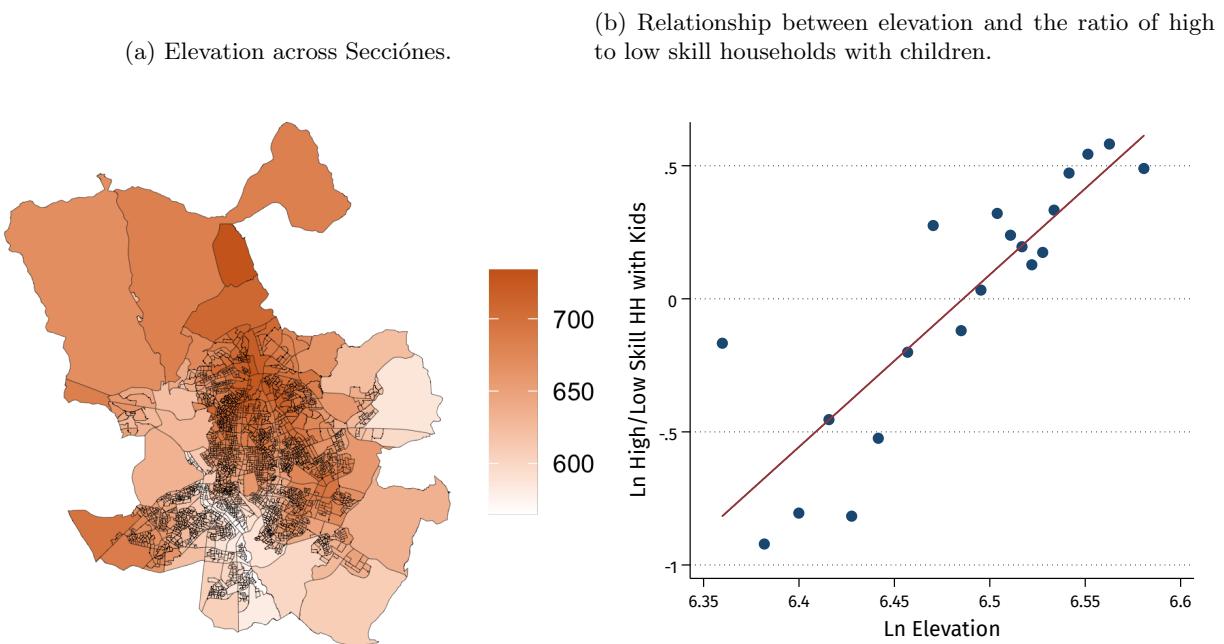


Table C.1: Regression of residential choices by households with kids and elevation of Secciones.

| | High with Kids (1) | Low with Kids (2) | Ratio (3) |
|------------------------|-----------------------|----------------------|----------------------|
| Ln Elevation | 2.722*** (0.256) | -3.443*** (0.212) | 6.165*** (0.343) |
| Green Areas within 1km | -0.460*** (0.131) | -0.062 (0.134) | -0.399** (0.186) |
| Ln Dist. from Sol | -0.487*** (0.031) | 0.359*** (0.030) | -0.846*** (0.048) |
| Avg. Constr Year | 0.028*** (0.001) | 0.017*** (0.001) | 0.011*** (0.002) |
| Ln Avg. House Size | 1.038*** (0.055) | -2.109*** (0.061) | 3.148*** (0.087) |
| Obs. | 2418 | 2418 | 2418 |
| R2 | 0.399 | 0.613 | 0.610 |

Note: Cross-sectional regressions of the distribution of high (1) and low (2) households with kids and their ratio (3) across Secciones. Heteroskedastic robust standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure C.10: Average school construction year within 1km of each *Sección*, weighted by number of admitted students.

