Estimating Preferences for Neighborhood Amenities Under Imperfect Information *

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Abstract

This paper presents a new framework to estimate preferences for neighborhoods in the presence of individual imperfect information about every amenity in each neighborhood. We estimate the model with data from a new neighborhood choice program that provided information about market rents and same-school network, and collected neighborhood rankings for the same individual before and after receiving information. We find that switchers - who change rankings after the information intervention - increase network shares by 1.46 percentage points and decrease rents by $430. This variation from the panel data of individual rankings is critical to produce a latent quality index that addresses biases arising from imperfect information. Estimates from the neighborhood sorting model reveal a strong negative marginal utility of rents, and a positive marginal willingness to pay of $123 per month to live in a neighborhood with a larger network. Finally, information also influenced residential choices after graduation.

Keywords: Neighborhood Choice, Residential Sorting, Imperfect Information, Housing Demand, Amenities, Unobserved Heterogeneity

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1 Introduction

Choosing a neighborhood is an important and complex decision. Several neighborhood amenities are critical for the well-being of adults and children, such as exposure to the social and professional network, and access to public and private goods, among others.[1] But choosing a neighborhood in which to live can be a challenging process given the many neighborhoods available in a labor market area, with each neighborhood having an exceedingly large number of characteristics. In practice individuals have varying knowledge about neighborhoods and their multitude of amenities, and face difficulties processing the terabytes of information available in public websites, such as Zillow. These problems may be even more salient for young adults, since they do not have much experience with residential choices, and may rely on social norms and a limited network of friends to gather information.[2]

In this paper we provide a new framework for estimating the value of neighborhood amenities, accounting for heterogeneity in how much individuals know about a neighborhood. A standard assumption in choice models is that individuals have perfect information about their choice set characteristics – all neighborhoods and their amenities in our case.[3] We present a more general model that allows for heterogeneity in individual knowledge about neighborhood amenities, i.e., some individuals may have imperfect information about the cost of living in a neighborhood, while others may have imperfect information about neighborhood demographic composition or the presence of trees and sidewalks in other neighborhoods, while a third set of individuals could have different expectations about future amenities. In this context, standard methods to account for unobserved neigh-

[1]A few examples from this literature include how neighborhoods impact long-term outcomes for children (Chetty, Friedman, Hendren, Jones, and Porter, 2018; Chetty and Hendren, 2018a,b; Chetty, Hendren, and Katz, 2016), the value heterogeneous households place on endogenous neighborhood amenities, such as school quality and sociodemographic composition (Bayer, Ferreira, and McMillan, 2007; Wong, 2013), how informal hiring networks arise from place of residence (Bayer, Ross, and Topa, 2008), the importance of private consumption goods (Allcott, Diamond, Dubé, Handbury, Rahkovsky, and Schnell, 2019), negative consequences of local disamenities such as pollution (Chay and Greenstone, 2003, 2005; Isen, Rossin-Slater, and Walker, 2017), and crime (Linden and Rockoff, 2008).

[2]There were almost 20 million individuals enrolled in college in 2019 in the United States (National Center for Education Statistics, 2020), who will soon have to choose where to live. Recent research has highlighted the role of housing costs, amenities, social and professional networks in shaping the location choices of young adults (Moretti, 2013; Diamond, 2016) and the importance of friends and social norms in their decision-making (Bailey, Cao, Kuchler, Stroebel, and Wong, 2018; Bursztyn and Jensen, 2017).

[3]Discrete choice models applied to neighborhood choice have roots in the work of McFadden (1978); Berry (1994); Berry, Levinsohn, and Pakes (1995, 2004); Nevo (2001); Petrin (2002); Train (Train); Pakes, Porter, Ho, and Ishii (2015). Perfect information is a standard assumption in all these models.

borhood quality using neighborhood fixed effects or market share inversions (Berry, 1994; Berry, Levinsohn, and Pakes, 1995) can still lead to biased estimates because of unobserved heterogeneity across individuals about what they know. Moreover, given the high dimensionality of this type of imperfect information, it is generally difficult to sign the potential resulting bias.[4]

To deal with this issue we integrate our generalized model with panel data from a new neighborhood choice program that allows us to observe individual rankings before and after an information intervention. We partnered with a large professional school in the East Coast to develop a neighborhood choice program to help graduating students choose where to live. The school was worried about students having imperfect information about neighborhood quality, and students had concerns about cost of living and access to professional and social networks. Given those issues, the program focused on providing information to all students about two neighborhood characteristics: average rent and the same-school network shares.

The neighborhood choice program was offered in April 2019 to students who by and large had already completed their job search, and were in the early stages of their housing search in a given metropolitan area (MSA). The first part of the program was a six-minute survey with four main components: 1) Elicitation of neighborhood rankings in chosen MSA; 2) Elicitation of knowledge about rents and network shares in those neighborhoods; 3) Information provision of market rents (from Zillow) and network shares for all neighborhoods (from administrative data); 4) Elicitation of updated neighborhood rankings. The second part of the program, received upon completion of the survey, was an interactive map with granular information about rents and the same-school network. Students had permanent access to the map, and could use that information during their summer housing search and final neighborhood choice.

A total of 341 students completed the survey (40% response rate), with 309 respondents choosing one of our 20 available MSAs.[5] For each MSA students had a menu with an average of 19 neighborhoods, and they could rank up to 10 of their preferred neighbor-

[4]For example, individuals may think expensive neighborhoods such as Tribeca tend to have better unobserved school quality and more trees and sidewalks relative to the average neighborhood quality, giving rise to a positive correlation between prices and unobserved heterogeneity about neighborhood quality. But other individuals may under-estimate the cost of living in expensive neighborhoods given their experiences of living in low or middle cost areas, giving rise to a negative correlation between price and unobserved knowledge about cost of living.

[5]Students moving to a different MSA or country are not part of the final sample, even though they could still complete the survey by choosing a secondary MSA. See survey section for details on choice of MSAs and neighborhood construction.

hoods – an average of five neighborhoods were actually ranked. Survey responses showed significant heterogeneity in their initial knowledge of neighborhood amenities. On average, respondents under-estimated monthly rent by \$620 relative to data from Zillow, and over-estimated network shares significantly (by six percentage points, relative to an average of five percent). There is also asymmetric heterogeneity with respondents over-estimating rents by \$140 for neighborhoods below \$2,500 and under-estimating rents by more than \$1,000 for neighborhoods above \$4,000. Respondents also tended to over-estimate network shares by more in expensive neighborhoods, consistent with the administrators' concerns that students had imperfect information.

Comparing rankings pre and post information reveal that individuals systematically prefer expensive neighborhoods with better amenities. In particular, neighborhoods that are always ranked in the top three for a given student tend to have higher rents and network shares relative to neighborhoods that are never ranked in the top three. Importantly, we also observe switchers who change their rankings after the information intervention in a way that increases the network shares by 1.46 percentage points and decreases rents by \$430 for their top neighborhoods. These patterns suggest a negative marginal utility for rent, and a positive marginal willingness to pay to live close to a larger network. The variation from switchers is critical since students who exhibit persistent tastes have perfect collinearity between pre and post information rankings and therefore cannot help with the identification of preferences for amenities. There is tremendous variation in individual rankings: a large number of students (76%) had at least one change in their neighborhood rankings after receiving the information, including 64% who had at least one change in their top neighborhoods.

Estimation of our neighborhood choice model under imperfect information follows two stages. In the first stage we recover heterogeneity in preferences by estimating a rank ordered logit model where post information neighborhood rankings are a function of market rents, actual same-school network shares, and neighborhood-by-individual unobservables that include all types of individual level imperfect information. The first stage also produces estimated neighborhood fixed effects that are decomposed into mean preferences in a second stage. Individuals have their own unique consideration sets, based on their selected neighborhoods. We allow for ample heterogeneity in preferences by age, gender, first-generation and minority groups, marital status, school major, industry, and location of prior residence.

To account for endogeneity due to heterogeneity in individual knowledge, we use pre information rankings to construct latent quality indices that capture what individuals know about neighborhoods. The validity of the indices relies on two key assumptions: a) Individuals report pre information rankings given their best knowledge so that pre information rankings are relevant proxies for the desirability of neighborhoods; b) Changes in rankings after the information intervention reflect the new information about the networks and rents. These two assumptions are akin to index sufficiency assumptions (Dahl, 2002) and basically require that our quality indices constructed using the pre information rankings exhaust all the information about how unobserved heterogeneity influences post information rankings. We demonstrate that our latent quality indices have rich identifying variation, above and beyond the standard model with neighborhood fixed effects.

Our results show that a model without the latent quality indices produces a marginal willingness to pay of $400 per month for a 1 percentage point increase in network shares. Our generalized model with latent quality indices estimates a 70% lower willingness to pay of $123, given an average monthly rent of $2,470. This reduction in marginal willingness to pay is mainly driven by a more negative and precise estimate of the marginal utility for rents, while preferences for the network remain somewhat constant. This suggests the omitted variable bias due to imperfect information is consistent with the notion that individuals perceive that higher rent neighborhoods having higher quality, even after conditioning on neighborhood fixed effects. The nature of this imperfect information gives rise to a positive correlation between rent and latent preferences for neighborhood quality that biases the marginal utility of rent towards zero, leading to inconsistent estimates of MWTP for amenities. Such biases are addressed by our latent quality index which utilizes information about individual rankings for neighborhoods.

A number of robustness tests confirm the internal validity of our main estimates. For example, we test different ways of estimating latent indices for unobserved neighborhood quality. We find that just adding neighborhood-level averages of pre information rankings can reduce the MWTP by 61% to $157, while just including the individual-level rankings reduces the MWTP by 54% to $184. Including both is needed to reduce the MWTP to $123. Thereafter, the MWTP remains stable even if we augmented the model with additional proxies using initial knowledge about rents and network shares. We also use our survey data to better understand why individuals prefer to live in a neighborhood with a larger same-school network. Social and professional interactions account for the largest fraction of the responses. Moreover, we include richer measures of individual heterogeneity using administrative data, including industry, major, stage of search, but none of them lead to significant changes in the main MWTP estimate.

Finally, we demonstrate that the patterns in the online survey persist up to a year after the program by collecting data on how individuals searched for neighborhoods and their neighborhood choices after graduation. Our measure of search is based on neighborhood clicks from the interactive maps made available to students upon the survey completion. We also obtained administrative data on actual neighborhood choices after graduation. Reassuringly, both datasets reveal similar patterns consistent with stated preferences in the online survey. Students have persistent tastes, generally choosing neighborhoods with higher rents and network shares. We find the same behavior for switchers, i.e., students tend to switch into neighborhoods with lower rents and larger network, while switching out of neighborhoods with higher rent and smaller network. This confirms that our marginal utility estimates from the neighborhood choice model with imperfect information, based on stated preferences, also translated into changes in revealed neighborhood preferences. Moreover, it indicates that the new neighborhood choice program successfully provided consistent and systematic information that allowed students to improve their location decisions by choosing places with lower cost of living and higher network amenities.

This work is in the intersection of many literatures. We contribute to a long line of neighborhood choice papers by showing how to flexibly account for imperfect information. Other recent work have made progress in modeling neighborhood choice using observational data and structural assumptions in different ways, such as Bayer, Keohane, and Timmins (2009) who account for moving costs, Bayer, McMillan, Murphy, and Timmins (2016) who consider neighborhood choice in a dynamic framework, Calder-Wang (2019) who allows for changes in the supply of houses in a neighborhood, Caetano and Maheshri (2019) who allow for choices to be observed out of equilibrium, Büchel, Ehrlich, Puga, and Viladecans-Marsal (2020) who utilize high frequency mobile phone data to understand spatial mobility patterns, and Almagro and Domínguez-Iino (2020) who allows for changes in the supply of amenities in neighborhoods. We also complement recent methodological advances in discrete choice models that address selection bias using hedonic indices (Epple, Quintero, and Sieg, 2020) and fixed effects (Pakes and Porter, 2016; Honoré and Hu, 2020).

Our research is also part of a growing body of work that combines surveys, experiments, and structural estimation, such as Benjamin, Heffetz, Kimball, and Rees-Jones (2014) who study life satisfaction of students who submit choice rankings to medical schools, and Galiani, Murphy, and Pantano (2015) who use the moving to opportunity experiment to simulate the effect of changes in the subsidies, Bottan and Perez-Truglia (2017) who apply information surveys to medical students in order to understand the importance of relative income in city-level choices, and Bergman, Chan, and Kapor (2020) who study the role of imperfect information about school quality.

There is a theoretical literature on different dimensions of imperfect information, such as Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) and Gao, Sockin, and Xiong (2020), and applications to household mobility, such as Fujiwara, Morales, and Porcher (Fujiwara et al.) and Kosar, Ransom, and Van der Klaauw (2019). Finally, our work is related to programs that provide information and assistance for low income families to move to better neighborhoods, such as Kling, Liebman, and Katz (2007) and Bergman, Chetty, DeLuca, Hendren, Katz, and Palmer (2020), but in our context students are unlikely to have the same constraints faced by very low income and at risk families. While we focus on imperfect information of neighborhood choices for young college-educated adults, our framework can be generalized to other settings, such as choice of college, college majors, and type and location (city) of first job.

The paper proceeds as follows: In section 2 we describe our general neighborhood choice model, and we present the survey design in section 3 and descriptive analysis in section 4. In section 5 we explain our estimation approach, and results are shown in section 6. Section 7 concludes the paper.

2 Neighborhood Choice Model

We model the neighborhood location decision of each individual as a discrete choice, following the utility function specification of the random utility models originally developed by McFadden (1973, 1978) and Berry, Levinsohn, and Pakes (1995). The individual i's indirect utility from choosing neighborhood j in labor market area m is:

$$u_{ijm} = \omega_{jm}\beta_i^c + \varepsilon_{ijm} \tag{1}$$

where ω_{jm} is a C-dimensional vector that includes all neighborhood amenities, β_i^c is a vector of individual preferences for each neighborhood amenity, and ε_{ijm} is an error term that is i.i.d. with a Type-I extreme value distribution. For simplicity, we will suppress the subscript m for now. Preferences for each amenity c are a function of the individual's own observed demographic attributes z_{id}:

$$\beta_i^c = \beta_o^c + \sum_{d=1}^{D} \beta_d^c z_{id} = \beta_o^c + \beta_{id}^c \tag{2}$$

The vector ω_j literally includes all characteristics that define a neighborhood, such as price, quality of the housing stock, demographic composition, number and type of trees, air quality, crime rates, number and type of restaurants and bars, access to sidewalks, etc. Under the assumption of perfect information individuals have common and complete knowledge about all characteristics from all neighborhoods.

However, given the high dimensionality of neighborhoods and amenities, imperfect information is likely pervasive and individuals may observe a large set of amenities with error. We re-write equation 1 to account for imperfect knowledge of amenities using the notation $\Delta\omega$. This captures a generalized notion of imperfect information, allowing flexibly for some individuals to have imperfect information about the cost of living in a neighborhood, while others may have imperfect information about the presence of trees and sidewalks in other neighborhoods. It can also allow different knowledge about expectations over future amenities.[6] We decompose $\Delta\omega$ into two components:

$$u_{ij} = \omega_j \beta_i^c + \Delta\omega_j \beta_i^c + \Delta\omega_{ij} \beta_i^c + \varepsilon_{ij} \tag{3}$$

where $\Delta\omega_j$ captures the neighborhood average of the error, and $\Delta\omega_{ij}$ allows for heterogeneity in how much individual i's error deviates from the neighborhood mean. For example, Δp_j represents the average error of the cost of living for neighborhood j and Δp_{ij} allows for heterogeneity in individual i's mis-perception above and beyond the average error. Our generalized model nests perfect information as a special case if individual i observes each neighborhood characteristic ω^c perfectly, so $\Delta\omega_j$ and $\Delta\omega_{ij}$ are just null vectors.

In practice econometricians do not observe all characteristics ω^c, and in general it is not feasible to estimate choice models with thousands of characteristics. Assuming the econometrician observes a limited number of characteristics x^k:

$$u_{ij} = x_j^k \beta_i^k + x_j^{k^-} \beta_i^{k^-} + \Delta\omega_j \beta_i^c + \Delta\omega_{ij} \beta_i^c + \varepsilon_{ij} \tag{4}$$

The new term $x_j^{k^-}$ for neighborhood j represents the $c-k$ neighborhood characteristics

[6] See Bayer, McMillan, Murphy, and Timmins (2016) for a more structural approach to model evolving local amenities.

that are unobserved by the econometrician. In models with perfect information the key source of bias in the estimation of β_i^k is that observed neighborhood characteristics (x^k) are generally correlated with the unobserved neighborhood quality in $x_j^{k^-}$. To address this identification problem, one can control for unobserved neighborhood quality using a combination of neighborhood fixed effects - which can be estimated using panel data or market share inversions (Berry, 1994) - and neighborhood shifters.[7] However, once we allow for imperfect information, the identification problem cannot be solved using standard methods alone, since they generally account only for the omitted factor $x_j^{k^-}$ but not for the other two terms associated with imperfect information.

To simplify our notation we can collect the terms in equation 4 that are unobserved by the econometrician and express them using a neighborhood-specific term, ξ_j, as well as a term for individual heterogeneity around the neighborhood mean, ξ_i. The former captures the average neighborhood quality that is not observed by the econometrician, $x_j^{k^-}$, and also the average errors for neighborhood j arising from imperfect information, $\Delta\omega_j$. Next, ξ_i represents deviation from the neighborhood means arising from heterogeneity in mis-perceptions, $\Delta\omega_{ij}$.

$$u_{ij} = x_j\beta_i^k + \xi_j + \xi_i + \varepsilon_{ij} \tag{5}$$

It will generally be difficult to sign the bias due to the endogeneity of ξ_j and ξ_i as it depends on the nature of the imperfect information for each individual. For example, individuals may use price as a signal of quality. They may think expensive neighborhoods such as Tribeca tend to have better unobserved school quality and more trees and sidewalks, giving rise, to a positive correlation between p_j and ξ_j. In addition, some individuals may under-estimate the cost of living in expensive neighborhoods, giving rise to a negative correlation between p_j and ξ_i. Still, others may over-estimate the cost of living in Tribeca if they think that all the houses there have similar costs to the most expensive brownstones in Tribeca. These different sources of endogeneity can potentially bias the estimate of preferences for cost of living in opposite directions, therefore biasing MWTP estimates.

In our empirical strategy below we propose a new method for estimating preferences in equation 5 using repeated data on neighborhood choices by the same individual with and

[7] This strategy involves estimating the relationship between estimated fixed effects and average neighborhood characteristics in a second stage, where instrumental variables are needed in order to deal with the correlation between observed characteristics and unobserved quality. See for example Bayer, Ferreira, and McMillan (2007).

without information about certain amenities. Repeated choice data by the same individual will be useful to construct latent quality indices to control for ξ_j and ξ_i. Given that neighborhood preferences tend to be stable over time, it is rare to have within-individual, across-time variation in choices. To address this, we use data from a new neighborhood choice program that generates exogenous variation by observing individuals switch their choices before and after receiving information about some amenities. Given the importance of those data requirements, before delineating our estimation method in section 5 we first introduce the neighborhood choice program and describe the data sets used in the structural estimation.

3 Information Survey and Data

3.1 Neighborhood Choice Program

We partnered with a large professional school in the East Coast to design a neighborhood choice program to help students choose where to live after graduation. In our discussions with students and administrators to understand how students chose neighborhoods, many acknowledged that this was a complex decision given the large number of neighborhood characteristics and the large number of neighborhoods to choose from. The school detected four main issues in qualitative interviews. First, students mentioned anxiety about cost of living due to high housing costs in many cities. Second, students highly value access to the professional and social network of fellow students and alums, and wanted to preserve that network after graduation. Third, students had unequal access to information and relied on limited networks to obtain neighborhood information.[8] Finally, students believed in a social norm where the same-school network tended to live in neighborhoods with high cost of living, inadvertently leading students to choose expensive neighborhoods upon graduation. To address these concerns, we designed a program to provide all students access to information to help them choose neighborhoods.

In April 2019, the Vice Dean of the school emailed all students from the graduating cohort to introduce the new neighborhood choice program. April is the ideal timing because it is about a month before graduation and a majority of the students already have a job and know which city they want to move to - and at the same time most students had just

[8]In our survey, 88% of respondents report speaking to fewer than four contacts about their search process, 95% connected with fewer than four contacts online or through social media.

started the process of searching for housing in their new destination. The program provided neighborhood information in two ways. Students would first access an online survey which provided information about the neighborhoods in their preferred metropolitan area in the United States and also asked basic questions about their neighborhood choices. Students were given a $25 Amazon gift card to encourage them to complete the survey. After completing the survey, students can access a mapping tool which provides the same information at a more granular spatial resolution for all metropolitan areas available in our data.

3.2 Neighborhood Information

Below, we describe how we defined neighborhoods. Then, we explain the type of information we provided to the students.

Neighborhood names. We begin by selecting the top 20 most popular labor markets (MSAs) in the United States, based on the current residence of all school cohorts who graduated from 2010 to 2018. Other MSAs with a small number of graduates were not used in order to preserve data confidentiality. We then split each MSA into a set of comprehensive yet parsimonious neighborhoods. As a baseline, we used shapefiles from Zillow which classifies the urban core into neighborhoods. In places without Zillow neighborhoods - usually suburban areas - each county would be a neighborhood. In some instances where we had to combine neighborhoods to reduce the total number of choices in each MSA, we joined adjacent neighborhoods with similar levels of college graduates, based on the census, and reported both names in the survey. To generate a list of neighborhood names that students would be familiar with, we relied on Google Trends data. In particular, when there were multiple ways to identify a location, we chose the most popular name according to Google Trends. Ultimately, we ended up with an average of 18.5 neighborhoods across all MSA's. Columns 1 and 2 of Table 1 lists the MSA's and the number of neighborhoods in each MSA.

Cost of Living. Cost of living was a major concern since many students have student loans and live in cities with high housing costs. We focus on rental housing costs as the main metric for cost of living. Monthly rents were preferred over housing prices because the vast majority of students occupy rented residences in their first few years after graduation. We obtained monthly rents from Zillow, which publicly provides a monthly rent index for an average home in each neighborhood. We chose to present information about the average

Table 1: Number of Neighborhoods and Percent of Respondents by MSA

MSA	Number of Neighborhoods	Percent of Respondents
Atlanta	19	2.3
Austin	14	0.6
Baltimore	19	0.3
Boston	21	5.5
Chicago	22	4.2
Washington, DC	20	4.9
Dallas	18	1.6
Denver	19	1.0
Houston	15	0.6
Los Angeles	22	2.9
Miami	20	0.6
Minneapolis	17	0.3
New York	25	43.7
Philadelphia	20	6.1
San Diego	20	0.3
San Francisco	22	20.4
San Jose	18	1.0
Seattle	22	3.6
Total	353	100.0

Notes: Top 18 MSA's in the neighborhood choice program with the number of neighborhoods and percent of respondents for each MSA. We offered 20 MSA's but Bridgeport (10 neighborhoods) and Trenton (7 neighborhoods) were not chosen by any student.

2018 rent using all months in order to mitigate outliers coming from solely using one or two months of data.

Same-School Network. Given the professional school setting, students highly value access to a close knit professional network of fellow students and alums. At the same time, administrators were concerned about unequal access to information and social norms that the same-school network tended to live in expensive neighborhoods, which can potentially lead some students to only consider those neighborhoods. To describe the same-school network comprehensively, we first obtained proprietary administrative data with the current street addresses of all recent graduates of the school. The school utilizes various sources to ensure that the addresses are current and accurate. We focused on the cohorts who graduated between 2010 and 2018 - this aggregation was required in order to preserve student privacy. Additionally, survey respondents do not have access to the total number of individuals living in individual neighborhoods. Instead, we present respondents with same-school network shares in neighborhood j in MSA m (N_{jm}), by dividing the total number of graduates currently living in neighborhood j by the total number of graduates living in the MSA.

3.3 Survey Design

We designed the neighborhood choice survey to collect unique information about how individuals make choices before and after receiving information about neighborhoods. Each student would first choose a metropolitan area in which they were planning to live upon graduation. They had to choose among 20 MSAs or select the option "None of the above". In this latter case students self-reported the name of another city in the US or abroad - 32 students picked that option and we exclude them from the remaining analysis. Another 309 students chose one of the top 20 MSAs and completed the survey. Column 2 of Table 1 shows that forty four percent of these respondents selected New York, followed by San Francisco (20%), Philadelphia (6%), Boston (6%) and DC (5%).

Around 40% of the graduating cohort of students participated in the neighborhood choice program. Panel A of Table A1 in the Appendix reports the summary statistics of our respondents. The average age is 29, half of them are female, 15% are first-generation or part of an under-represented minority, 12% are married or have children, and 23% are international students (by citizenship). We also show that average characteristics of survey takers are not that different from non-respondents, except respondents are less likely to be international students since they are less likely to want to live in the United States.[9]

Then we asked students to rank up to ten neighborhoods in that metropolitan area, allowing them to create their own neighborhood consideration sets. Only for these neighborhoods we then ask students to provide their best estimates of the same-school network shares and the monthly rent for the average home. Right after that we displayed the program information about the rent and network shares in *all* neighborhoods in that MSA.[10] Here, each respondent would also see in a figure how this new information compared with her own unique estimates.

After presenting the information, we asked students to re-rank up to ten neighborhoods.

[9]Indeed, the coefficient on the international student dummy falls from 0.17 to 0.09 when comparing the 309 respondents who chose the top-20 MSA's in our neighborhood choice program (Panel A of Table A1) versus the full set of respondents, including the 32 who chose other cities (Panel B). These demographics are based on administrative data from the school.

[10]We randomly assigned the order students would receive the information about rents and network shares. This order did not have any impact on our results described below.

Table 2: Summary Statistics for All and Considered Neighborhoods

	All			**Considered (pre)**			**Considered (post)**		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Same-School Network Share	353	5.10	5.01	213	6.17	5.08	193	7.08	5.25
Rent (thousands)	353	2.47	1.01	213	2.72	1.14	193	2.80	1.14
Income (thousands)	353	80.26	25.45	213	83.52	28.05	193	86.81	27.15
Bachelor′s Degree+	353	0.46	0.19	213	0.52	0.19	193	0.55	0.18
Non-White Share	353	0.38	0.19	213	0.40	0.19	193	0.40	0.18

Notes: Summary statistics for amenities in all (353) neighborhoods in the neighborhood choice program, as well as the 213 (193) neighborhoods considered pre (post) information. The five amenities include the same-school network share, average monthly rent from Zillow, average income, share of population with a college degree or more, non-White share. The latter three are from the 2010 Census.

This page looks identical to the pre information stage, except with the new information just so students would not need to scroll back in order to check the data. Students could choose from a menu of all the neighborhoods along with information about the rent and network shares. We did not pre populate this page with their prior rankings so as not to prime their post information choices. Finally, at the end of the survey we also asked some questions about whether and why they thought the information influenced their neighborhood choices, and other factors related to their neighborhood search processes. The Survey Appendix provides more details about the survey questions.

The survey was designed to be short. The median student completed the survey in six minutes, spending one minute on the pre information ranking of neighborhoods, seventy seconds to estimate the rent and network shares in their chosen neighborhoods, forty seconds to read about the rent and network shares for the full set of neighborhoods, and another one minute to re-rank neighborhoods.

The neighborhood choice program did not include a control group since the objective of the program was to promote equal access to information. Having a control group which did not receive the same information intervention would raise equity concerns. Given the nature of the information intervention, it would also be difficult to prevent treated students from sharing information with those assigned to the control group. Nonetheless, this is not as relevant to our estimation because the key identifying variation in our model comes from comparing neighborhood rankings by the same individual before and after the information intervention.

Table 2 presents the neighborhood characteristics of all the 353 neighborhoods, as well as the 213 the neighborhoods considered in the pre information rankings and the 193 neighborhoods considered post information. Interestingly, individuals only rank an average of 5 neighborhoods, even though they can rank up to 10 neighborhoods in each MSA. The chosen neighborhoods have higher monthly rent ($2,720 pre information and $2,800 post information) relative to $2,470 for all neighborhoods. The ranked neighborhoods also have higher network shares (6 percent pre information and 7 percent post information) compared to all the neighborhoods (5 percent). Moreover, the average income and the college share in the chosen neighborhoods are also higher.

Upon completion of the survey, students were directed to a restricted-access mapping service with the information about rents and network shares at an even more granular geographic resolution for all metropolitan areas available in our data. These interactive maps require students to click in neighborhood geographies in order to access the relevant information. The maps became permanently available in order to help students during their housing and neighborhood search, and we collected data on map clicks. Almost 55% of the students had at least one recorded interaction with the maps from the time of survey completion until graduation. We count the number of clicks students make in each neighborhood as a proxy of how intense they are searching in a neighborhood.

Even though the survey does not formally request information about students' actual neighborhood choices, we obtained post graduation residential locations from the school alumni office. That office utilizes various sources to keep updated location information of alums, and was able to provide accurate addresses for 137 graduates from our sample as of July 2020.[11] We georeferenced them in order to compare where students chose to live after graduation relative to stated preferences in the online survey. Table A2 in the Appendix shows that both samples of students where we have map clicks data and actual post graduation locations are largely representative.

We also obtained rich administrative data to supplement our online survey, which had to be short. Our baseline demographic variables include age, gender, married and/or with children, first-generation or minority status, and citizenship status. We also observe other pre-determined characteristics, such as, their industry, intended major, where they worked before attending school.

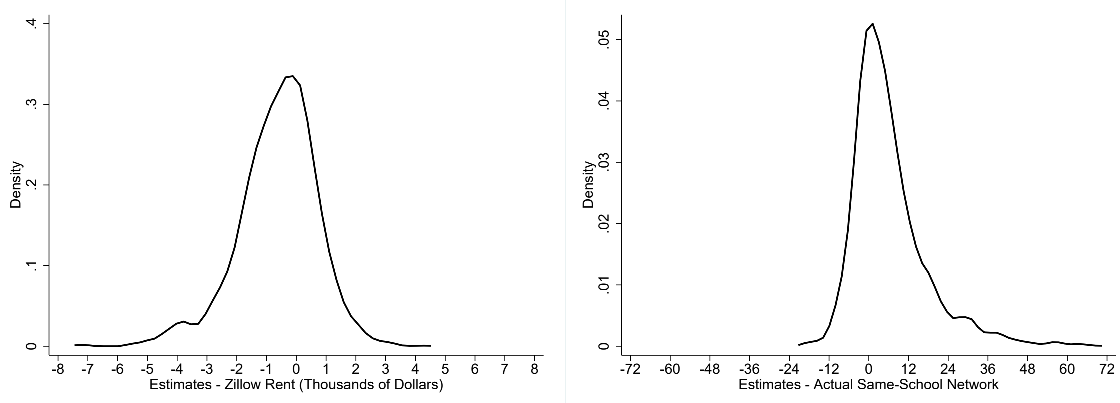
[11]The process to update the location information of alums has been disrupted due to the Covid pandemic. Most of the address information reflect post graduation choices made long before the Covid pandemic. As a conservative robustness exercise, our conclusions remain the same using a subset (110 out of 137) of location information identified in January 2020, before the pandemic.

4 Descriptive Analysis

4.1 Heterogeneity in Neighborhood Knowledge

Figure 1: Differences Between Reported and Actual Neighborhood Attributes

Panel A: Rent **Panel B:** Same-School Network Shares



Notes: Panel A presents kernel density estimates of the difference of individuals' best guesses of neighborhood rent and Zillow rent for each neighborhood ranked in the pre information period. Panel B repeats the same for same-school network shares.

Panel A of Figure 1 presents a kernel density of respondents' estimates of rents minus the neighborhood rents from Zillow. This figure includes 1,910 neighborhood-by-individual choices where we have rent estimates for neighborhoods considered in the pre period by 309 respondents. On average, respondents under-estimate monthly rent by $620 relative to the average monthly rent of $2,700 for neighborhoods considered in the pre period. But there is a fair amount of heterogeneity: about two-thirds of the choices are underestimates and about one-third of the choices are over-estimates.

Interestingly, the differences are correlated with rent levels in that respondents under-estimate rents in expensive neighborhoods and over-estimate rents in cheap ones. Panel A of Figure 2 shows that respondents over-estimated rents by $140 for neighborhoods below $2,500, and under-estimated rents by more than $1,000 for neighborhoods above $4,000.

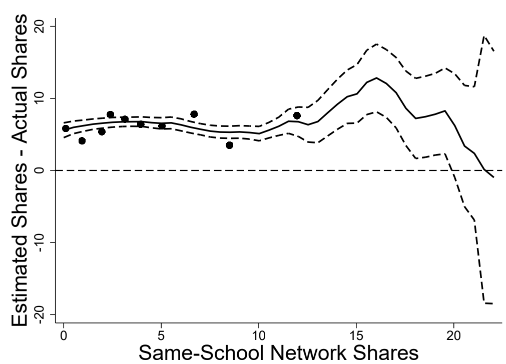
Turning to knowledge about same-school network shares, Panel B of Figure 1 compares estimates and actual network shares for neighborhoods ranked in the pre period. Of the 1,910 estimates of network shares, sixty-nine percent are over-estimates. On average, respondents over-estimate the network shares by 6 percentage points - a fair amount relative

Figure 2: Binscatter for Differences in Reported and Actual Amenity

Panel A: Rent Differences vs. Zillow Rent

Panel B: Network Share Differences vs. Zillow Rent

Panel C: Network Share Differences vs. Actual Network Shares



Notes: The solid line in Panel A represents the estimate from a local polynomial regression of the differences in the vertical axis (e.g. individuals' estimate minus Zillow rent) on Zillow rent. The dashed lines correspond to 95% confidence intervals. We trimmed the figure by dropping estimates at the boundaries. The dots correspond to the average within each decile for Zillow rent. Panel B presents the same but using differences in network shares versus Zillow rent. Panel C presents differences in network shares versus network shares.

to a mean of 5 percent for all neighborhoods.

Respondents also appear to over-estimate network shares by more in expensive neighborhoods. In particular, Panel B of Figure 2 shows a positive correlation between the degree of over-estimation and rent levels for neighborhoods with rents above $4,000. This echoes the concern of school administrators that a social norm whereby same-school alums tended to live in expensive neighborhoods could influence students to only consider a small set of expensive neighborhoods. Panel C in the same figure shows no relationship between the difference in network share estimates and the actual shares.

Overall, the figures above show remarkable heterogeneity around the nature of imperfect information. The differences between respondents' estimates and the data provided also correlate with rent levels. Such imperfect information could lead to omitted variable biases in the estimation of neighborhood preferences, especially the taste coefficient for rent.

4.2 Rankings Before and After Information

Table 3 presents a simple cross-tabulation to compare network shares and rents for neighborhoods ranked in the top 3 before and after information. We investigate compositional changes in top neighborhood choices by using actual network shares and rents, not the individuals' estimates.

The sample includes 7,012 potential individual-by-neighborhood choices. The diagonal entries in Panel A show that individuals systematically prefer high rent neighborhoods, consistent with the common omitted variable problem that neighborhoods that have high rent tend to have high unobserved quality relative to neighborhoods that are never chosen. Specifically, the top left cell reports the average Zillow rent ($3,627) for neighborhoods that are always ranked in the top 3 before and after information (9% of 7,012 choices were always ranked in the top 3). The bottom right cell reports the average Zillow rent ($3,007) for neighborhoods that are never ranked in the top 3 (83%).

The key sources of variation we use to identify preferences for amenities rely on changes in rankings after the information intervention. The off-diagonal cells show that respondents tended to switch in neighborhoods that have lower average rent ($3,380) and switch out neighborhoods that have higher average rent ($3,844). This is consistent with individuals responding to new information and updating their neighborhood rankings to choose neighborhoods with lower rent. Both types of top 3 switches correspond each to

Table 3: Comparing Top Three Neighborhoods Pre and Post Information

Panel A: Rent

		Pre	
		Yes	No
Post	Yes	Always Top 3 $3,627	Switch In $3,380
	No	Switch Out $3,844	Never Top 3 $3,007

Panel B: Same-School Network

		Pre	
		Yes	No
Post	Yes	Always Top 3 7.73%	Switch In 7.18%
	No	Switch Out 5.72%	Never Top 3 3.87%

Notes: Panel A reports the average rent of neighborhoods. The diagonal cells include neighborhoods that are always and never ranked top three by a given individual before and after the information intervention. The off-diagonal cells report average rent for neighborhoods that are switched in or out of the top three for a given individual, after information relative to before. Panel B repeats the same for same-school network shares.

4% of all individual-by-neighborhood choices with 64% of individuals switching their top-three choices.[12]

Panel B reports an analogous pattern of switching behavior for network shares. Respondents tended to switch in neighborhoods with high network shares (7.18 percent) and switch out neighborhoods with low network shares (5.72 percent). Always top 3 neighborhoods have the highest average network shares (7.73 percent) and never top 3 neighborhoods have the lowest average network shares (3.87 percent).

Together, comparing the rents and network shares for the switchers before and after the information shows that respondents updated their rankings to favor neighborhoods with higher network shares and lower rents, consistent with a positive marginal willingness-to-pay for same-school network. Table 4 shows that this pattern is robust to a regression analysis controlling for MSA fixed effects and demographic controls (odd columns) and even

[12]Table A3 in the Appendix show minimal compositional differences along demographics when comparing switchers to non-switchers.

Table 4: Rent and Same-School Network for Switched Neighborhoods

Dependent variable:	**Rent**		**Same-School Network**	
	(1)	(2)	(3)	(4)
Always in top 3	0.68***	0.68***	3.79***	3.78***
	(0.03)	(0.03)	(0.17)	(0.17)
Switch in	0.39***	0.41***	3.30***	3.36***
	(0.05)	(0.05)	(0.25)	(0.26)
Switch out	0.82***	0.84***	1.86***	1.91***
	(0.06)	(0.06)	(0.21)	(0.22)
N	7012	7012	7012	7012
R-squared	0.40	0.41	0.13	0.13
Switch in - Switch out	**-$434**	**-$432**	**1.44**	**1.46**
p-value	**0.00**	**0.00**	**0.00**	**0.00**
MSA FE	Y	N	Y	N
Demographics	Y	N	Y	N
Individual FE	N	Y	N	Y

* 0.10 ** 0.05 *** 0.01

Notes: OLS regressions including the full set of 7,012 neighborhood-by-individual level choices. The dependent variables are monthly Zillow rent in thousands of dollars (columns 1 and 2) and same-school network shares (columns 3 and 4). The key regressors include a dummy that is one for neighborhoods that are always ranked in the top three by a given individual before and after information, as well as neighborhoods that were switched in and switched out of the top three choice set after information, relative to neighborhoods that were never top three (the omitted group). Columns 1 and 3 have MSA fixed effects and demographic controls, including age, and a dummy for female, married or with children, under-represented minority and first-generation, international. Columns 2 and 4 include 309 individual fixed effects. Standard errors are clustered by individuals.

individual fixed effects (even columns). In the most saturated specification with individual fixed effects, neighborhoods that are switched in have network shares that are greater by 1.46 percentage points on average and $430 lower monthly rent, relative to neighborhoods that were switched out of the top 3. Our findings are similar if we used top one, top five, or top ten.

Below, we describe how the identification of our neighborhood sorting model relies on variation in choice rankings by the same individual, before and after receiving information about amenities. Our model will make use of all rankings, not just in and out of top 3. A large number of students (76%) had at least one change in their neighborhood rankings after receiving the information, including 64% who had at least one change in their top 3 neighborhoods. About 50% of the individual neighborhood choices involve a change of at least 2 ranks. Our model also captures remarkable heterogeneity across the individual-level rankings, with close to half of the neighborhoods ranked as an always top neighborhood by someone.

4.3 Neighborhood Preferences Persist After Neighborhood Survey

The stated preference behaviors uncovered in our analysis of the neighborhood choice program are also present in revealed preference behavior during the search and actual neighborhood choices after graduation. Starting with search, Panels A and B of Table A4 present cross-tabulations to compare rents and network shares for neighborhoods ranked in the top 3 pre information, and top 3 in the post-survey search. Our measure of search is based on neighborhood clicks from the interactive maps made available to students upon the survey completion, i.e., for each individual we count and rank neighborhoods based on the number of clicks.[13] As with Table 3, we compare actual rents and neighborhood shares for the four groups of neighborhoods.

The diagonal entries show that always top 3 and never top 3 neighborhoods have patterns consistent with stated preferences, i.e., students tend to search more in neighborhoods that are more expensive and with a larger network. More interestingly, we also find consistent behavior for switchers, i.e., students tend to switch into neighborhoods with lower rents and larger networks, while switching out of neighborhoods with higher rents and smaller networks.

Turning to post graduation choices, Panels A and B of Table 5 present cross tabulations for the actual post survey neighborhood choice and the pre intervention top 1 neighborhood. We restrict to top 1 rank because individuals only chose one actual neighborhood to live. Again, the patterns echo those in Table 3, with students having persistent tastes, generally choosing neighborhoods with higher rents and network shares. Neighborhoods that are always top 1 in the survey and post graduation have higher rent on average ($3,385) and larger network shares (8.17%) relative to never-top-1 neighborhoods which tend to have lower average rent ($3,058) and lower average network shares (4.18%). Once again, switchers influenced by the intervention tend to switch in neighborhoods with lower rents ($3,364) and larger network shares (7.27%) and switch out neighborhoods with higher rent ($3,884) and lower network shares (6.44%).

These results indicate that the new neighborhood choice program successfully provided consistent and systematic information that allowed students to improve their location deci-

[13]This analysis uses a more limited number of observations since only 44% of individuals used the interactive maps.

Table 5: Comparing Neighborhood Choices Post Graduation with Survey Data

Panel A: Rent

		Pre	
		Yes	No
Post	Yes	Always Selected $3,385	Switch In $3,364
	No	Switch Out $3,884	Never Selected $3,058

Panel B: Same-School Network

		Pre	
		Yes	No
Post	Yes	Always Selected 8.17%	Switch In 7.27%
	No	Switch Out 6.44%	Never Selected 4.18%

Notes: Repeats Table 3 but the pre rankings use top neighborhoods instead of top three and the post rankings use data from actual home addresses after graduation.

sions by choosing places with lower cost of living while preserving similar or higher levels of network amenities. Indeed, students are living in neighborhoods where the monthly Zillow rent is $627 lower relative to the Zillow rent in the pre information top-ranked neighborhood stated in their survey.

5 Estimation

In section 2 we described a general neighborhood choice model that allows for individuals to have imperfect information about every amenity in each neighborhood in a given labor market. This introduces new omitted variable biases (ξ_i and ξ_j in equation 5). Now we provide details on how to estimate the model using data and neighborhood rankings before and after information as explained in section 3.3. While the post information rankings are the backbone of our choice model, the pre information rankings are used to construct latent quality indices ($f(\widetilde{\xi}_i)$ and $g(\widetilde{\xi}_j)$). Finally, estimated preferences are converted into measures of willingness-to-pay to live in a neighborhood with higher (or lower) network shares. Below we cover each of these steps.

5.1 Neighborhood choice model and rank-ordered logit

We estimate a version of equation 5 in two stages. We first estimate heterogeneous parameters β_{id} and a set of neighborhood fixed effects δ_{jm} in equation 6. In the second stage we decompose the neighborhood fixed effects into their average components to infer the average MWTP for amenities by estimating equation 7.

The neighborhood amenities we observe include post information network share amenity N and rents p, a set of 2010 Census neighborhood characteristics X, including average income, the share of college graduates, and the non-White share. The preference heterogeneity terms β_{id} for each of these five neighborhood amenities follow equation 2 and are a function of five observed demographic variables: age, gender, married and/or with children, first-generation or minority status, and citizenship status. The unobserved heterogeneity terms in equation 6 include ξ_{im} as described in equation 5 and also ε_{ijm} which is i.i.d. with a Type-I extreme value distribution:

$$u_{ijm} = \delta_{jm} + N_{jm}\beta_{id}^{N} + p_{jm}\beta_{id}^{p} + X_{jm}\beta_{id}^{X} + \xi_{im} + \varepsilon_{ijm} \tag{6}$$

In the second stage we decompose the neighborhood fixed effects δ_{jm} to recover mean preferences β_o, and also the metropolitan area effects, μ_m. The unobserved errors in equation 7 include the unobserved neighborhood quality ξ_{jm} as described in equation 5 and η_{jm} is an idiosyncratic error term:

$$\delta_{jm} = \mu_m + N_{jm}\beta_{o}^{N} + p_{jm}\beta_{o}^{p} + X_{jm}\beta_{o}^{X} + \xi_{jm} + \eta_{jm} \tag{7}$$

We estimate equation 6 using a rank-ordered logit model (Beggs, Cardell, and Hausman, 1981) based on the post information neighborhood rankings in each individual's consideration set. For each individual i choosing metropolitan area m, our data reveals:

$$U_{ir_{i1}} > U_{ir_{i2}} > \ldots > U_{ir_{iL_i}} \tag{8}$$

where r_{il} denotes the neighborhood that received post information ranking l by individual i. Each individual could rank between two and ten neighborhoods, and we denote the last ranked neighborhood for each individual as L_i. The probability of individual i choosing a ranking r_i is:

$$
\begin{aligned}
P_{ir_i} &= P[U_{ir_{i1}} > U_{ir_{i2}} > \ldots > U_{ir_{iL_i}}] && (9)\\
&= \prod_{l=1}^{L_i-1} \frac{\exp(u_{ir_{il}})}{\sum_{h=l}^{L_i} \exp(u_{ir_{ih}})} && (10)
\end{aligned}
$$

We rely on maximum likelihood to estimate the model. The log likelihood function is just the sum of the log of the individual probabilities across all individuals:

$$
\mathscr{L} = \sum_{i=1}^{I} \log P_{ir_i} \tag{11}
$$

This first step returns the heterogeneity in preference parameters and the neighborhood fixed effects that maximize the log likelihood function above, i.e., maximize the probability that each individual makes the correct rank ordering of neighborhoods. We estimate the second step using OLS. In order to credibly estimate these parameters we still need to construct proxies for ξ_j and ξ_i, otherwise estimated preferences will suffer from omitted variable bias.

5.2 Latent Quality Indices

We integrate the survey design with the choice model to develop latent quality indices to address endogeneity due to ξ_i and ξ_j. For simplicity, we will suppress the subscript m in this subsection. So far the neighborhood choice model above has solely used the post information data on individual rankings, network shares, and rents. Now, we introduce the pre information rankings to construct latent quality indices $f(\widetilde{\xi_i})$ and $g(\widetilde{\xi_j})$ to respectively control for selection bias due to ξ_i and ξ_j. According to the same logic of the general model described in equation 3, the pre information rankings should capture all neighborhood-by-individual factors (observed by the econometrician or not) that influence individual i's utility.

To construct $f(\widetilde{\xi_i})$, we include pre information rank dummies using six categorical variables based on whether each individual pre ranked a neighborhood in her consideration set as top 1, 2, 3, 4, 5, or from 6 to 10. We omit from the estimation a dummy for neighborhoods never ranked in the pre information data. Additionally, we include the average of these pre rank dummies and interact these averages with demographics. We include these heterogeneity terms in equation 6. Next, to construct $g(\widetilde{\xi}_j)$, we include six averages of the rank dummies in equation 7. In the results section we report robustness tests that investigate the use of different variables to construct latent quality indices.

Estimated mean preferences for rents and network shares (β_o^p and β_o^N) will be unbiased η_j is uncorrelated with p_j and N_j, conditional on observables. This will be true if (i) individuals report pre information rankings given their best knowledge about neighborhoods consistent with equation 3 and that (ii) changes in rankings after the information intervention only reflect the new information about networks and rents. We require the former so that pre information rankings are valid proxies for an individual's latent knowledge about neighborhood quality. The latter condition ensures that pre information rankings remain relevant proxies for individual's knowledge about neighborhood quality in the post information rankings. Our identifying strategy echoes the index sufficiency assumption (Dahl, 2002) which requires that our quality indices $f(\widetilde{\xi}_i)$ and $g(\widetilde{\xi}_j)$ constructed using the pre rankings exhaust all the information about how ξ_i and ξ_j influence post information rankings.

The empirical validity of our latent quality indices is shown in two parts. First MWTP estimates change significantly with and without $f(\widetilde{\xi}_i)$ and $g(\widetilde{\xi}_j)$. Importantly, the coefficient on rent becomes more negative once we control for latent quality. We would not see this pattern if individuals completely updated their neighborhood rankings after the information intervention in a way that renders the pre information rankings uninformative. This shift in the coefficient on rent also shows that $Cov(\eta_j, p_j) > 0$ even in a model with neighborhood fixed effects. Our latent quality indices mitigate this bias using additional moments that capture the share of individuals that give neighborhood j a rank of 1, rank of 2, etc. instead of just the share of individuals who chose j as their the most preferred neighborhood. These pre information rankings are useful since individuals have persistent preferences that systematically favor expensive neighborhoods with better amenities, as shown in Table 3.

Second, changes in the rankings after the information intervention are associated with rents and network shares. The descriptive analysis in section 4 showed that individuals switched in neighborhoods with higher network shares and lower rents, and switched out neighborhoods with lower network shares and higher rents. Absent this identifying variation from the switchers, pre information rankings would be highly correlated with post information rankings, and preferences for rents and network would not be identified.

One concern of the identification strategy is that the new information about network shares and rents may indirectly cause updates on individual's knowledge about other amenities. For example, if they saw that Tribeca was more expensive than they thought, they may also indirectly update that other amenities in Tribeca tend to be above average, using price as a signal of quality. While it is impossible to measure this indirect effect, we can rule out that the indirect updates are significant enough to overturn the direct effects of the new information since price and quality affect utility in *opposite* manners. In particular, the direct effect of the new rent information suggests someone who under-estimated the price of Tribeca would rank it less favorably after learning that Tribeca is more expensive than the other neighborhoods, consistent with the evidence of individuals switching out of expensive neighborhoods. By contrast, if she also indirectly updated that Tribeca has better amenities upon learning that Tribeca is more expensive than she thought, she would rank Tribeca more favorably, which would offset her choice above to switch out Tribeca.

Turning to the estimation of the heterogeneity preference terms in equation 6, the identifying assumption is that the six pre information rank dummies and the average rankings interacted with demographics sufficiently address endogeneity arising from ξ_i. We also assume that heterogeneity in preferences is solely a function of our observed demographic variables, following Bayer, Ferreira, and McMillan (2007)

5.3 Average and heterogeneity in willingness-to-pay

We define the average marginal willingness to pay for the same-school network neighborhood characteristic as:

$$MWTP = -\frac{\beta_o^N}{\beta_o^p} \tag{12}$$

whose components are estimated in the second stage decomposition of the estimated neighborhood fixed effects δ_j. Moreover, we combine first and second stage estimations to calculate heterogeneity in marginal willingness to pay for N according to the following formula:

$$MWTP_i = -\frac{\beta_o^N + \sum z_{id}\beta_d^N}{\beta_o^p + \sum z_{id}\beta_d^p} \tag{13}$$

Subsequently we compare this MWTP for a baseline individual, representing the majority groups in all dimensions of heterogeneity, against another individual who shares similar demographics with the exception of just one feature d. Standard errors for both average and heterogeneity in willingness to pay are calculated used the delta method.

6 Results

6.1 Estimated Preferences

The first column of Table 6 reports estimates of mean preferences (β_o) for the same-school network and for rents, using a version of equation 6 that does not include the latent quality indices. Students have negative preference for higher rents, but the estimate is not statistically different from zero. This a common problem in sorting models, i.e., estimated marginal utility of rents is generally biased towards zero because expensive places tend to have higher unobserved neighborhood quality. On the other hand, the network amenity estimate is positive and statistically significant. Those two estimates are then converted into a mean MWTP for the network amenity, according to equation 12, and presented in the third row. Students, on average, are willing to pay $400 per month in rent (given an average rent of $2,470) to live in a neighborhood with a one percentage point higher network share (the average network share is 5.1%). Such mean MWTP is likely upward biased because the rent estimate is downward biased.

The second column of Table 6 reports similar estimates, but now for a model that includes the latent quality indices. Interestingly, the rent estimate becomes more negative (-0.55) and statistically different from zero - this is exactly the expected effect of properly controlling for the correlation between rents and unobserved neighborhood quality. Moreover, conditional on rent, the network estimate is quite similar to the model in column 1, perhaps because that information was truly new for most survey respondents. The combination of those two estimates lead to a new mean MWTP for the network amenity of $123 per month and is now statistically significant at the 5% level.[14] This estimate is 70% smaller than the comparable mean MWTP without the latent index.

Next, Table 7 provides a few robustness tests for the latent quality indices. Column 1 is our baseline estimate and columns 2 to 4 repeat the same model but including different latent quality indices. Column 2 shows that the MWTP estimate changes by 61% from $400 to $157 by just including $g(\widetilde{\xi}_j)$ using the average rankings in the delta regression.

[14]As a robustness check, we also find that this MWTP estimate remains significant at the 5% level if we clustered standard errors by MSA's (the standard error for the MWTP is 45 instead of 40). Given that we only have 18 MSA's, which is less than the rule-of-thumb of 40 clusters (Angrist and Pischke, 2008), we opted to not cluster standard errors in our primary estimation.

Table 6: MWTP Estimates With and Without Latent Quality Indices

	(1)	(2)
Same-School Network	0.330***	0.310**
	(0.075)	(0.092)
Rent	-0.180	-0.550***
	(0.118)	(0.126)
Implied MWTP	**$400**	**$123****
	(257)	(40)
MSA FE	Y	Y
Census Characteristics	Y	Y
Latent Quality Indices	N	Y

Notes: Mean preference estimates of the neighborhood choice model using neighborhood-by-individual choices post information intervention. The first stage involves a rank-ordered Logit model using post information neighborhood rankings, neighborhood fixed effects, neighborhood amenities (rent, same-school network shares, as well as Census characteristics - average income, share college graduates, average non-White share). The second stage represents a decomposition of the neighborhood fixed effects from the first stage, including MSA fixed effects. Column 2 adds the latent quality indices, $g(\widetilde{\xi}_j)$ and $f(\widetilde{\xi}_i)$. Table A5 presents the coefficients on the different latent quality indices. Standard errors calculated using the Delta method.

Table 7: Robustness Results for Latent Quality Indices

	(1)	(2)	(3)	(4)
Same-School Network	0.310**	0.293***	0.328***	0.311**
	(0.092)	(0.071)	(0.093)	(0.094)
Rent	-0.550***	-0.408***	-0.389**	-0.552***
	(0.126)	(0.120)	(0.121)	(0.127)
Implied MWTP	**$123****	**$157****	**$184****	**$123****
	(40)	(54)	(65)	(41)
$g(\widetilde{\xi}_j)$	Y	Y	N	Y
$f(\widetilde{\xi}_i)$	Y	N	Y	Y
Pre rent, Pre network	N	N	N	Y

Notes: Column 1 reports our baseline model (column 2 in Table 6). Column two only includes $g(\widetilde{\xi}_j)$ using the averages of the six pre information rankings. Column three only includes $f(\widetilde{\xi}_i)$ using six pre information rank dummies and the average of the rankings interacted with demographics in the first stage. Column 4 adds pre information estimates of same-school network shares and rent to the baseline model. Standard errors calculated using the Delta method.

In column 3, the MWTP changes by 54% to $184 if we only include $f(\widetilde{\xi_i})$ in the first stage (equation 6), using the six rank dummies as well as the average rankings interacted with demographics. In column 4, we augment our baseline model in column 1 with pre information estimates of rents and network shares. In principle, these continuous measures of individual perceptions could also proxy for latent quality to the extent that individuals perceive that higher quality neighborhoods have a larger network and higher rent. Interestingly, the MWTP estimate remains stable at $123 suggesting these additional proxies are not adding more information above and beyond our baseline model. Table A5 presents the key coefficients for our latent quality indices.

Table 8 reports the implied heterogeneity in MWTP for the network amenity. Panel A presents the overall MWTP across the different specifications and Panel B presents the heterogeneous WTP estimates. There is some heterogeneity in MWTP estimates, but the results are understandably less precise given that only 309 students completed our survey. Four measures of heterogeneity generally have negative values relative to the baseline: Age, married and/or with children, international, first-generation and under-represented minorities. Estimates for female are positive and small.

Our administrative data from the school provides a number of other features about the survey respondents. Columns 2, 3, and 4 of Table 8 report results that additionally include, respectively, measures of student heterogeneity by type of industry, school major, and whether the student previously worked in that same MSA. The mean MWTP remains practically unchanged in all models, and none of the extra heterogeneity measures are statistically different from zero. Next we include a variable from the survey related to the stage of the housing search process, i.e., whether the student had already visited rental properties or signed a lease. Accounting for the stage of the search process does not seem to change our main MWTP estimate. Finally, Column 6 includes all measures of heterogeneity in one model. The mean MWTP from this model is $104.

How do students interpret the new information about the share of same-school network living in a neighborhood? At the very end of the survey we asked students to consider a neighborhood with a large network, and asked them to check at most three reasons for why that neighborhood would be desirable. The most common response was related to professional networking opportunities and social activities with the same-school network. Next came good restaurants and shops, which is not only an indicator of local availability of services, but also an indicator of venues that promote social interactions within the network. Convenient commute was next, followed by high income and well-educated neighbors, and

Table 8: Robustness Results for Demographic Attributes

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Overall MWTP						
Implied MWTP	**$123*** **	**$110*** **	**$130*** **	**$103*** **	**$114*** **	**$104*** **
	(40)	(37)	(38)	(37)	(38)	(29)
Panel B: Heterogeneity in MWTP						
Age	-12	-20	-14	4	-20	-25
	(45)	(49)	(31)	(36)	(45)	(31)
Married/Kids	-1,031	-992	-3,300	808	-1,466	309
	(4,400)	(5,284)	(55,334)	(6,354)	(9,055)	(1,299)
International	-83	-68	-14	-55	-93	12
	(108)	(102)	(89)	(94)	(107)	(79)
First-gen/URM	-428	-433	-249*	-317	-427	-194*
	(413)	(445)	(147)	(243)	(435)	(116)
Female	49	52	55	73	40	56
	(82)	(78)	(60)	(71)	(84)	(55)
Industry - Consulting		-50				-57
		(94)				(62)
Industry - Finance		61				47
		(130)				(76)
Previous worked			128			112
			(192)			(154)
Visited/Signed				54		62
				(92)		(68)
Major - Finance/Real estate					-20	-42
					(98)	(63)
Demographics	Y	Y	Y	Y	Y	Y
Industry	N	Y	N	N	N	Y
Previous worked	N	N	Y	N	N	Y
Visited/Signed	N	N	N	Y	N	Y
Major	N	N	N	N	Y	Y

Notes: This table presents robustness estimates with additional observed heterogeneity. Panel A reports the overall MWTP while Panel B reports the heterogeneous WTP estimates. Column 1 repeats the baseline (column 2 in Table 6). Column 2 adds industry dummies, column 3 adds a dummy for individuals who previously worked in the MSA, column 4 adds a dummy for individuals who have visited or signed a lease, column 5 controls for intended majors. Column 6 includes all controls.

safe area with good schools and parks.

7 Conclusion

We introduce a generalized neighborhood choice model to estimate preferences for amenities under imperfect information. This is a complex and pervasive problem given the many amenities and the large number of neighborhoods in a labor market. Moreover, we show that the endogeneity problem cannot be solved with standard methods since the nature of the imperfect information is heterogeneous across individuals and has a high dimension. To address this, we introduce latent quality indices which we estimate by observing the same individual choosing neighborhoods before and after receiving information about amenities.

Our empirical strategy integrates structural estimation with a survey design associated with a neighborhood choice program for graduating students of a large professional school. The program provided information about cost of living and same-school professional and social network. We observe switchers changing their neighborhood rankings after the information intervention to increase network shares by 1.46 percentage points and decrease rents by $430 for their top-three neighborhoods, implying a positive willingness-to-pay for the same-school network.

The structural preference estimates show that controlling for the latent quality index significantly reduces bias in the marginal utility for rents, implying a mean MWTP for network shares of $123 (with the latent quality index) relative to $440 (without the quality index). We probe the robustness by examining additional demographic variables and different ways to estimate the latent quality index. We also find that social and professional networking opportunities are the main reason for the students' desire to live close to the network.

Finally, the empirical framework developed in this paper can be fruitfully applied to estimate preferences for any other neighborhood amenity. It can also be applied in many other settings where imperfect information is pervasive or in which individuals have difficulties processing information about choice sets and product characteristics. Examples faced by young adults include choice of college, college major, and type and location (city) of first job.

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Online Appendix Tables (Ferreira and Wong, 2020)

Table A1: Characteristics of Respondents and Full Sampling Frame

	All	Respondents	Non-respondents	Difference	p-value
Panel A: Survey respondents in top 20 MSA's					
Female	0.44	0.50	0.41	0.09***	0.01
Age	29.68	29.36	29.87	-0.51***	0.00
Married/Kids	0.13	0.12	0.14	-0.02	0.33
First-gen/URM	0.19	0.15	0.20	-0.05*	0.06
International	0.34	0.23	0.40	-0.17***	0.00
N	852	309	543	852	852
Panel B: Survey respondents choosing all cities					
Female	0.44	0.49	0.41	0.07**	0.03
Age	29.68	29.46	29.83	-0.37**	0.01
Married/Kids	0.13	0.14	0.13	0.01	0.69
First-gen/URM	0.19	0.16	0.20	-0.05*	0.10
International	0.34	0.28	0.38	-0.09***	0.00
N	852	341	511	852	852

* 0.10 ** 0.05 *** 0.01

Notes: Panels A and B show how the demographics for survey respondents compare to the full student population of 852 students. Panel A includes the 309 students in our primary estimation sample, i.e. those who chose the top MSA's in our program. Panel B includes 341 students who responded to the survey, including 32 who chose other cities not in the Neighborhood Choice Program. The five demographic characteristics include an indicator for females, age, an indicator for married individuals or those who have children, an indicator for first-generation or under-represented minorities, an indicator for international students who are not U.S. citizens.

Table A2: Students in the Map and Post Graduation Samples Relative to Survey Respondents

	Survey	Post Survey	Missing	Difference	p-value
Panel A: Map clicks					
Female	0.50	0.43	0.54	-0.10*	0.09
Age	29.36	29.51	29.28	0.23	0.28
Married/Kids	0.12	0.16	0.10	0.06	0.11
First-gen/URM	0.15	0.17	0.14	0.03	0.53
International	0.23	0.22	0.24	-0.02	0.63
N	309	106	203	309	309
Panel B: Post graduation choices					
Female	0.50	0.54	0.47	0.07	0.23
Age	29.36	29.34	29.37	-0.02	0.91
Married/Kids	0.12	0.09	0.15	-0.06	0.12
First-gen/URM	0.15	0.16	0.15	0.02	0.71
International	0.23	0.17	0.28	-0.12**	0.02
N	309	137	172	309	309

* 0.10 ** 0.05 *** 0.01

Notes: Similar to Table A1 but Panel A compares demographics for 106 students in the map clicks data relative to the survey respondents that are missing map clicks. Panel B compares demographics for 137 students we have post graduation location data relative to those with missing addresses.

Table A3: Demographics for Switchers and Non-Switchers

	Always in top 3	Switch in	Switch out	Switch in - Switch out
Female	0.00	0.01	0.01	0.00
	[0.64]	[0.71]	[0.64]	[0.87]
Age	-0.01	0.02	0.02	-0.01
	[0.83]	[0.87]	[0.81]	[0.82]
Married/Kids	0.01	0.00	0.00	-0.01
	[0.37]	[0.98]	[0.74]	[0.36]
First-gen/URM	0.00	0.01	0.01	0.01
	[0.84]	[0.54]	[0.71]	[0.36]
International	-0.03***	0.08***	0.07***	0.01
	[0.00]	[0.00]	[0.00]	[0.45]
N	7012	7012	7012	7012

* 0.10 ** 0.05 *** 0.01

Notes: Each row repeats the OLS regression in column 1 of Table 4 but the dependent variables are now student demographics instead of Zillow rent or network shares. We include MSA fixed effects but no demographic controls. Standard errors clustered by individuals.

Table A4: Rent and Same-School Network for Top Three Neighborhoods Pre and Post Information (Map Clicks)

Panel A: Rent

		Pre	
		Yes	No
Post	Yes	Always Top 3 $3,437	Switch In $3,179
	No	Switch Out $3,672	Never Top 3 $2,931

Panel B: Same-School Network

		Pre	
		Yes	No
Post	Yes	Always Top 3 9.06%	Switch In 7.73%
	No	Switch Out 6.48%	Never Top 3 3.88%

Notes: Repeats Table 3 but using the number of map clicks in each neighborhood to define top three neighborhoods post information.

Table A5: Estimates for Latent Quality Indices

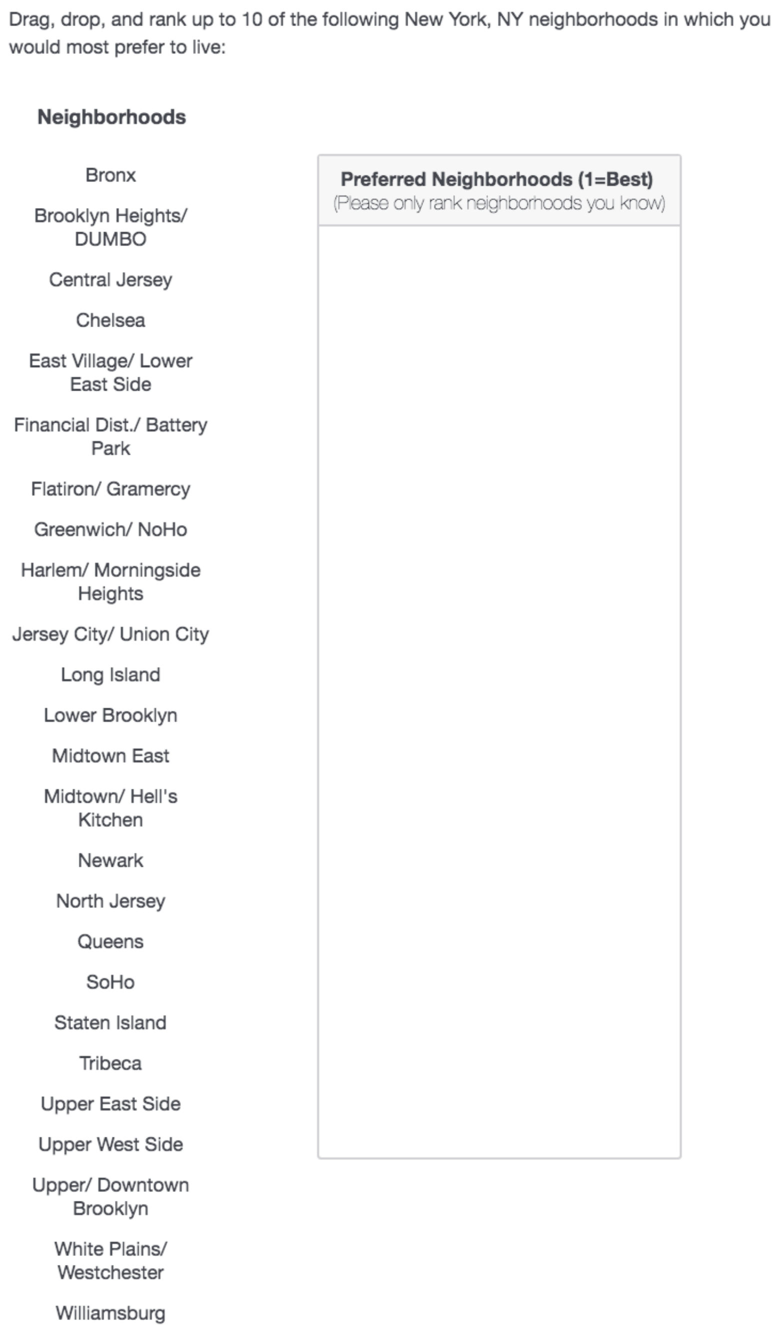
	(1)	(2)	(3)	(4)
Same-School Network	0.310**	0.293***	0.328***	0.311**
	(0.092)	(0.071)	(0.093)	(0.094)
Rent	-0.550***	-0.408***	-0.389**	-0.552***
	(0.126)	(0.120)	(0.121)	(0.127)
Implied MWTP	**123****	**157****	**184****	**123****
	(40)	(54)	(65)	(41)
Average Rank 1	0.296***	0.377***		0.298***
	(0.076)	(0.070)		(0.077)
Average Rank 2	0.165*	0.233***		0.165*
	(0.064)	(0.062)		(0.065)
Average Rank 3	0.086	0.149**		0.089
	(0.066)	(0.057)		(0.067)
Average Rank 4	0.092	0.200***		0.086
	(0.065)	(0.045)		(0.068)
Average Rank 5	0.087	0.118*		0.088
	(0.074)	(0.056)		(0.076)
Average Rank 6-plus	0.138	0.086		0.141
	(0.096)	(0.073)		(0.097)
Rank 1	0.711***		0.711***	0.712***
	(0.065)		(0.065)	(0.076)
Rank 2	0.436***		0.436***	0.438***
	(0.063)		(0.063)	(0.074)
Rank 3	0.205***		0.205***	0.208**
	(0.057)		(0.057)	(0.067)
Rank 4	0.033		0.033	0.037
	(0.055)		(0.055)	(0.064)
Rank 5	-0.061		-0.061	-0.056
	(0.052)		(0.052)	(0.059)
Rank 6-plus	-0.209**		-0.209**	-0.202**
	(0.065)		(0.065)	(0.076)
Pre information rent				0.006
				(0.065)
Pre information network shares				0.067
				(0.096)
$g(\widetilde{\xi}_j)$	Y	Y	N	Y
$f(\widetilde{\xi}_i)$	Y	N	Y	Y
Pre rent, Pre network	N	N	N	Y

* 0.10 ** 0.05 *** 0.01

Notes: Coefficients on the latent quality indices for each of the four specifications reported in Table 7. In column 1, we present estimates for our baseline model by reporting coefficients for the six average rank dummies in the second stage ($g(\widetilde{\xi}_j)$) as well as coefficients for the six individual rank dummies in the first stage $f(\widetilde{\xi}_i)$. We suppress interactions of the average rankings with demographics due to space constraints. Column 2 only includes $g(\widetilde{\xi}_j)$ and column 3 only includes $f(\widetilde{\xi}_i)$. Column 4 includes both and adds the pre information estimate of rent and network shares.

Survey Appendix

Figure A1: Pre Information Choice Set

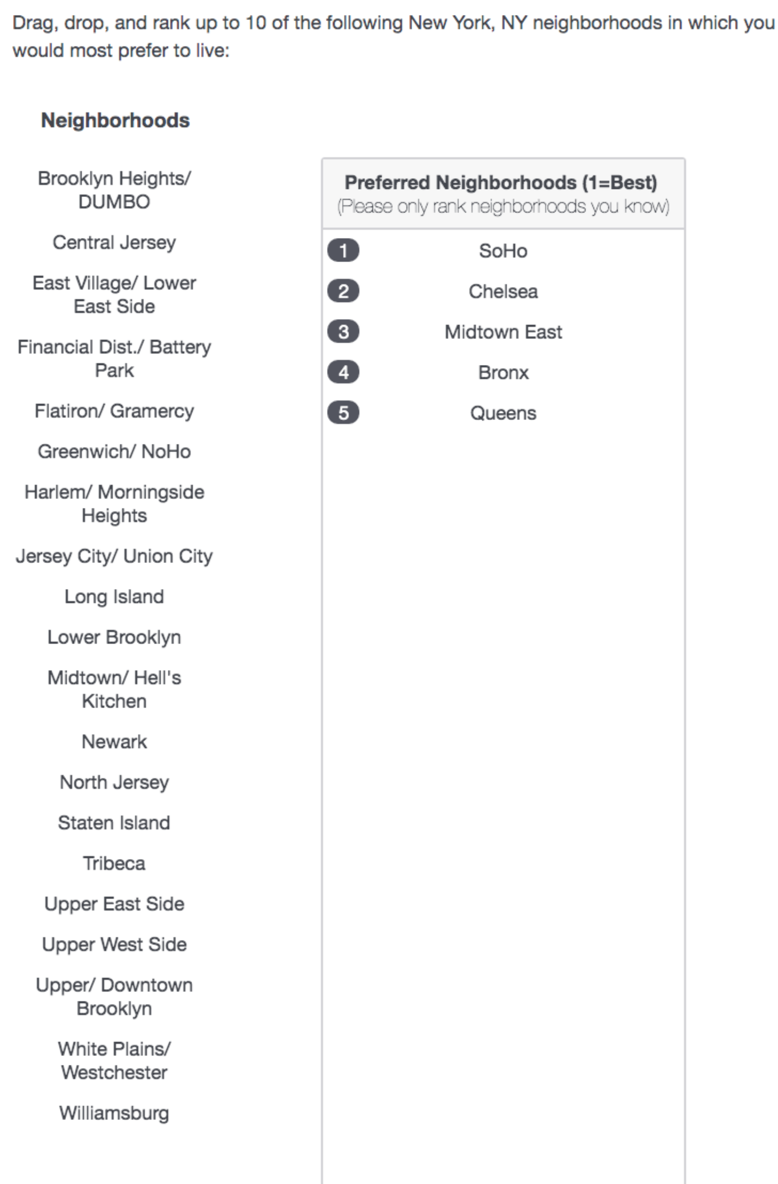

Drag, drop, and rank up to 10 of the following New York, NY neighborhoods in which you would most prefer to live:

Neighborhoods

Bronx
Brooklyn Heights/ DUMBO
Central Jersey
Chelsea
East Village/ Lower East Side
Financial Dist./ Battery Park
Flatiron/ Gramercy
Greenwich/ NoHo
Harlem/ Morningside Heights
Jersey City/ Union City
Long Island
Lower Brooklyn
Midtown East
Midtown/ Hell's Kitchen
Newark
North Jersey
Queens
SoHo
Staten Island
Tribeca
Upper East Side
Upper West Side
Upper/ Downtown Brooklyn
White Plains/ Westchester
Williamsburg

Preferred Neighborhoods (1=Best)
(Please only rank neighborhoods you know)

Figure A2: Pre Information Ranking of Neighborhoods



Drag, drop, and rank up to 10 of the following New York, NY neighborhoods in which you would most prefer to live:

Neighborhoods

Brooklyn Heights/ DUMBO
Central Jersey
East Village/ Lower East Side
Financial Dist./ Battery Park
Flatiron/ Gramercy
Greenwich/ NoHo
Harlem/ Morningside Heights
Jersey City/ Union City
Long Island
Lower Brooklyn
Midtown/ Hell's Kitchen
Newark
North Jersey
Staten Island
Tribeca
Upper East Side
Upper West Side
Upper/ Downtown Brooklyn
White Plains/ Westchester
Williamsburg

Preferred Neighborhoods (1=Best)
(Please only rank neighborhoods you know)

1. SoHo
2. Chelsea
3. Midtown East
4. Bronx
5. Queens

Figure A3: Estimates of Monthly Rent in Considered Neighborhoods

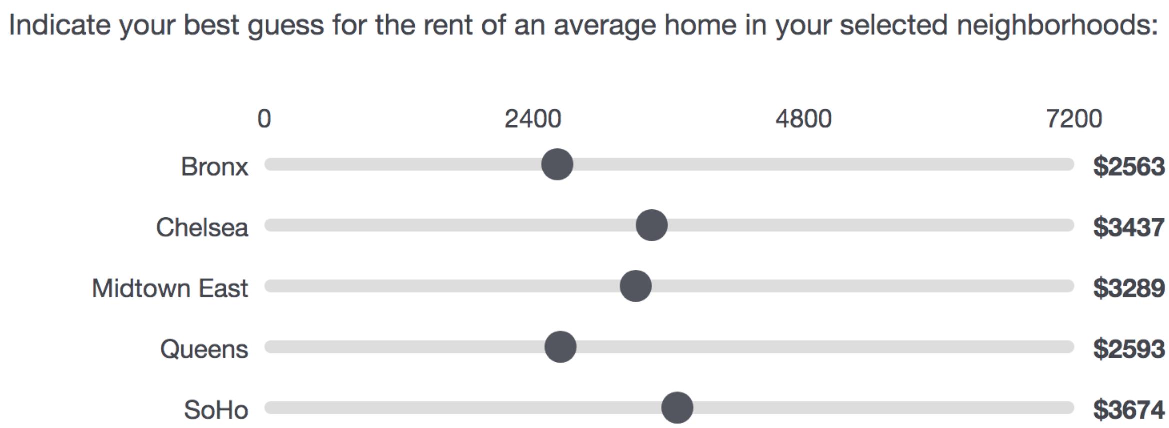


Figure A4: Estimates of Same-School Network Shares in Considered Neighborhoods

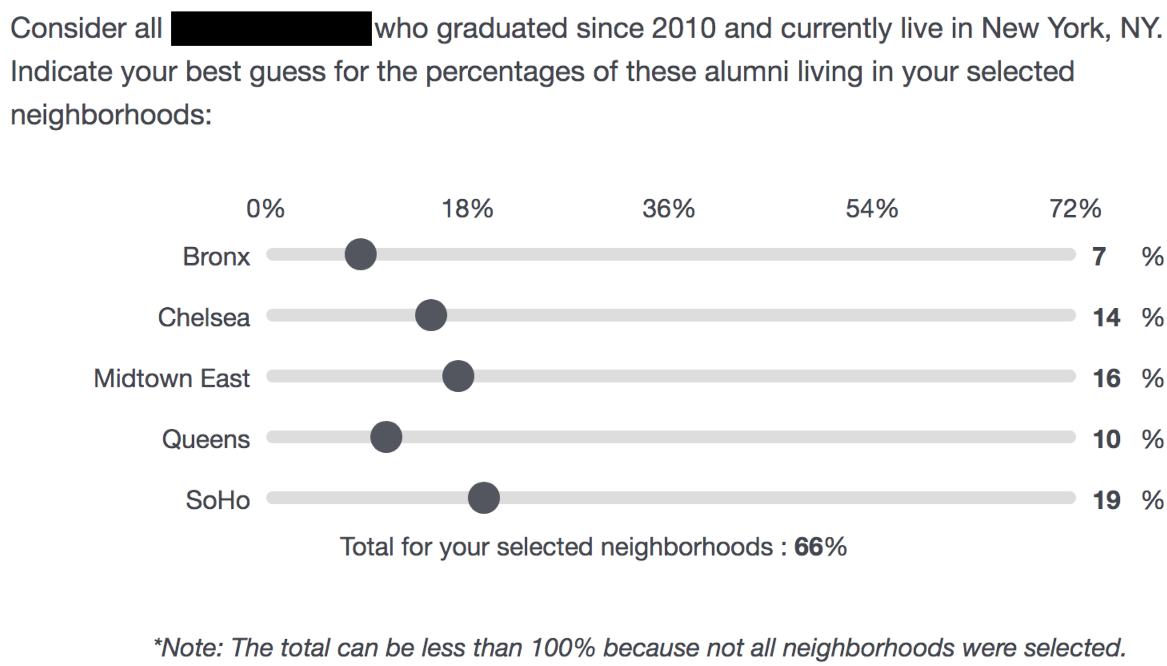
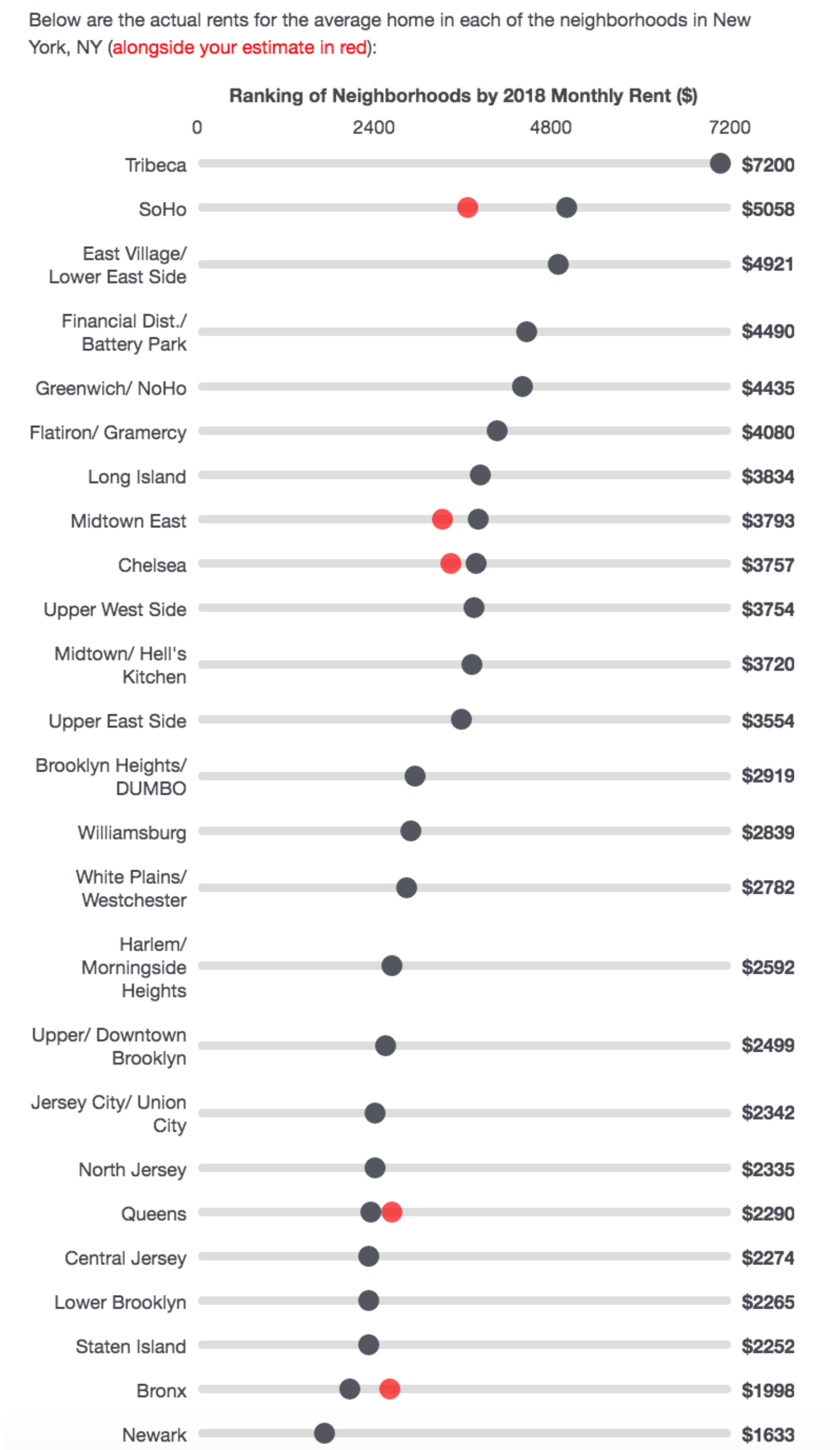
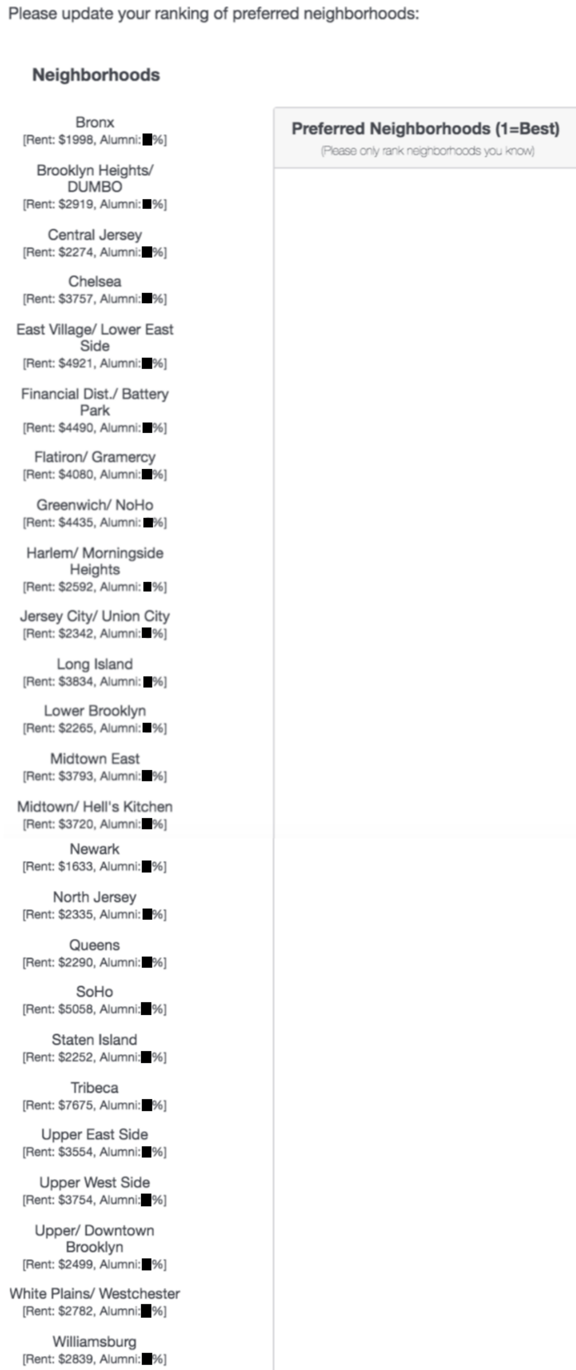


Figure A5: Monthly Zillow Rent (Alongside Pre Information Estimates) in All Neighborhoods



Notes: We also presented an analogous figure for same-school network shares but suppressed it here due to the proprietary nature of the data.

Figure A6: Post Information Ranking of Neighborhoods



Notes: Survey repondents saw a full schedule of all neighborhoods, as well as the Zillow rent and network shares (suppressed here due to the proprietary nature of the data).