From Urban Form to Friending Bias: Testing Jane Jacobs' Hypotheses

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Abstract

Recent work has shown that social integration can influence a variety of outcomes ranging from educational attainment to overall health to income inequality. This paper examines the extent to which urban design can foster cross-class interactions and promote social integration in American cities. Measuring cross-class interactions using individual-level GPS cellphone mobility data and cross-class social ties using large-scale Facebook friendship data, I show that three features of the urban built environment — small city blocks, entertainment place density, and mixed primary-use buildings — promote interactions between individuals of different socioeconomic groups, leading to greater cross-class social ties. The findings remain significant with instrumental variable estimates. Consistent with the ideas of Jane Jacobs and Gordon Allport, these results suggest that the urban built environment can reduce cross-class social segregation by promoting greater cross-class interactions.

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Finally, I am extremely grateful for my parents, Jennifer and Chris Crowne, whose love and support has made this journey and everything else possible. This thesis is dedicated to them.

Contents

1 Introduction

Group segregation continues to be a major concern in American society, prompting questions about the role that cross-group interactions play in facilitating cross-group integration. Insufficient interactions between groups can create inter-group prejudice, suspicion, and anxiety (Allport 1954; Enos 2017; Enos and Gidron 2016). Increased cross-group integration has been shown to improve cross-group generosity and acceptance (Rao 2019; Carrell et al. 2015), and to influence outcomes ranging from educational attainment (Sacerdote 2011) to overall health (Carrell et al. 2011) to income inequality (Robert Putnam 2016). The nature of inter-group contact impacts whether the interaction promotes integration or segregation. Seminal work by Gordon Allport argues that physical interactions under certain conditions facilitate integration by reducing the salience of group differences and increasing the frequency and quality of interactions, which can lead to more positive inter-group attitudes and perceptions (Allport 1954).

Influential work over half a century ago by Jane Jacobs emphasized the impacts of the urban built environment on mobility patterns and social behaviour (Jacobs 1961). But can the built environment affect the people with whom we interact? Do interactions caused by effective urban design meet the conditions for Allport's contact hypothesis? With approximately 80% of the US population (approximately 260 million people) living in cities[1], and with these urban areas exhibiting vast socioeconomic and racial diversity, the potential to foster cross-group relationships is high. Furthermore, increased residential density and more walkable neighborhoods may increase the likelihood of random, unplanned, cross-group interactions when compared with rural or suburban America. In addition to the natural forces of cities, Jacobs theorized a handful of urban planning techniques that can further increase the number of unplanned interactions.

In this paper I empirically examine the hypothesis that the urban built environment can promote interactions between individuals in different socioeconomic groups, and that these

[1] https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/ua-facts.html

interactions can reduce class-based friending bias. To this end, I study three features of the urban built environment that Jacobs' framework implies might increase random interactions: small city blocks, entertainment place density, and mixed primary-use buildings. I begin by showing that these three features strongly predict experienced cross-class interactions, as measured by individual-level GPS cellphone mobility data. I then turn to the second step in the causal chain: do these random cross-class interactions also increase cross-class social cohesion? I show that experienced cross-class interactions are strongly correlated with greater cross-class relationships, as measured by large-scale Facebook friendship data. Last, I find a similar relationship when I instrument cross-class interactions with the three features of the urban environment. Together, the results imply that features of the urban environment can reduce cross-class social segregation by promoting greater cross-class interactions.

The three features of urban built environment which I hypothesize promote interactions between people of different socioeconomic statuses are: small city blocks, mixed primary-use buildings, and the density of entertainment places. Jacobs emphasizes small city blocks and mixed primary-use buildings in her influential book: *The Death and Life of Great American Cities*. She theorized that small city blocks could mechanically increase unplanned interactions on sidewalks through their cascading effects on pedestrian choices. A long block with no intersecting roads minimizes both the number of places a pedestrian is exposed to, as well as the path options en-route to their destination. Jacobs also thought that mixed primary-use buildings could increase unplanned interactions by attracting a variety of people at a variety of times to a single place. She cites lower Manhattan, where restaurants at lunch time are filled with white collar customers on lunch breaks but are empty at all other times. More primary uses for these buildings would enable a more diverse set of visitors throughout the day, and thus increase random cross-class interactions both on the street and within places (Jacobs 1961). In addition to Jacobs' theories, I posit that greater entertainment place density will increase random interactions due to their social nature. These places, such as bars, cafes, restaurants, and nightclubs, are places that people visit with friends, or visit hoping to meet new people, and are therefore more conducive to unplanned interactions.

To measure the effects of these three forms of urban built environment on actual cross-class interactions, I use cellphone GPS data from Moro et al. 2021. This data contains device locations from 4.5 million users in 11 major US cities: Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York City, Philadelphia, San Francisco, Seattle, and Washington DC. Each device owner's socioeconomic status is estimated based on the median household income of their census block (determined by the location of their device between 10:00pm and 6:00am). These data enable the recording of visits to every place of interest (POI) within the 11 cities. These records allow Moro et al. (2021) to construct a measure of *experienced economic segregation* at the POI level. A POI where individuals from different socioeconomic backgrounds frequently interact will have low experienced economic segregation, while a POI dominated by one socioeconomic group - such as an upscale restaurant - will exhibit high experienced economic segregation.

Lastly, to determine the influence of increased cross-class interactions, I use a measure termed *friending bias* from Chetty et al. (2022a). At an individual level, friending bias is the share of high-socioeconomic status (high-SES) friends that a low socioeconomic status (low-SES) individual has, conditional on the economic distribution of individuals they are exposed to (Chetty et al. 2022b). By controlling for the individuals' exposed socioeconomic distributions, friending bias is largely a measure of internal willingness or ability to create cross-class relationships. Friending bias is derived from Facebook friendship data of 21 billion friendships between people aged 25 and 44 years old. Chetty et al. find that friending bias is strongly correlated with upward economic mobility.

Combining friending bias and geographic mobility data with rich demographic data at the ZIP code level allows me to characterize how features of the urban built environment influence actual cross-class interactions, and in turn, how these interactions reduce cross-class friending bias.

I find that each of the three features of the urban built environment I measure are associated with lower levels of experienced economic segregation. Consistent with my hypothesis, lower levels of experienced economic segregation are also associated with lower cross-class friending bias, suggesting that urban form may be an important mechanism through which cross-class interactions can reduce friending bias. I find that a one standard deviation increase in street intersection density, entertainment place density, and employment entropy are associated with a 0.084, 0.206, and 0.109 standard deviation decrease in experienced economic segregation respectively. Furthermore, a one standard deviation decrease in experienced economic segregation is associated with a 0.103 standard deviation decrease in cross-class friending bias. These relationships hold when controlling for a diverse set of demographics and when including city fixed effects. Thus, these results hold both within cities and across cities. Additionally, by employing an instrumental variables approach, I provide suggestive evidence of a causal relationships between experienced economic segregation and friending bias, wherein a one standard deviation decrease in experienced economic segregation leads to a 0.928 standard deviation decrease in cross-class friending bias.

Related Literature This paper contributes to three areas of economic research. First, and most directly, I build on social capital research pioneered by Robert Putnam, James Coleman, and Pierre Bourdieu (Carroll and Stanfield 2003). There has been a lot of research about the effects of social capital: Beaman (2012) examines the relationship between between social network size and labor market outcomes, and Aral and Nicolaides (2017) show that social networks influence how socially contagious physical exercise can be. Glaeser and Redlick (2008) study the relationships between social capital and human capital in the context of migration. Eagle et al. (2010) show that social network diversity is associated with the economic development of communities. Sacerdote (2011) examines peer effects in education. Alesina et al. (1999) show that ethnic fragmentation is negatively associated with public spending on education, roads, and sewers. Chetty et al. (2022a), using the data I utilize in this paper, provide evidence that social capital is a strong predictor of upward economic mobility. However, there is much less research about the determinants of social capital. There are two broad theories of social capital generation in the literature. The first emphasizes group sizes and finds that larger groups tend to form more same-type ties, and more ties per capita than smaller groups (Currarini et al. 2009). The second emphasizes social structuring. For instance, Feld (1982) finds that relationships tend to form within foci of activities that are disproportionately homogeneous, leading to greater homogeneity in the social ties that are developed within these groups. This paper builds on the later theory by asking if heterogeneous *interactions* are associated with more heterogeneous social networks.

Second, I build on Gordon Allport's famous work in *The Nature of Prejudice* about contact theory (Allport 1954), which posits that cross-group interactions can reduce cross-group prejudice under certain conditions[2]. Previous research has studied variation in university roommates (Rao 2019, Corno et al. 2022, Boisjoly et al. 2006, Laar et al. 2005), army groups (Carrell et al. 2019, Finseraas and Kotsadam 2017), and school classmates (Scacco and Warren 2018). However, these settings focus on particular subsets of the population, and are therefore prone to external validity concerns. Thus, these results may not generalize to everyday experienced interactions. In this paper, I explore random interactions in urban areas with heterogeneous populations. Given the relative difficulty of forming social bonds through chance encounters in cities as opposed to more structured social settings such as college campuses, this research is of particular significance.

Lastly, I contribute to urban design literature pioneered by Jane Jacobs. This field primarily looks at the effects of urban form on a variety of outcomes. For example, both Harari (2020) and Batty (2008) examine how city shape impacts urban functions. Glaeser and Sacerdote (2000) study the relationships between housing structure and social connection and crime rates. Bento et al. (2005) look at how urban form affects commuting and driving behaviour. This paper further examines the effects of urban form with modern fine grain data. This paper is also relevant to policy discussion at a neighborhood or city level surrounding

[2]Pettigrew and Tropp (2006) and Paluck et al. (2019) provide meta-analyses of contact theory.

urban design and planning.

The remainder of the paper is organized as follows: Section 2 describes the data. Section 3 explores particular cities in the data. Section 4 explains the methods and analyzes the results. Section 5 concludes.

2 Data

To test the hypothesis that urban design influences random cross-class interactions, and that those interactions lead to lower cross-class friending bias, I draw upon four primary sources of data: (1) urban built environment data from the Environmental Protection Agency (EPA); (2) mobile device location data from Cuebiq, a location intelligence and measurement platform; (3) Chetty et al.'s measure of cross-class friending bias derived from social network data of 21 billion Facebook friendships; and (4) demographic data from census records and other publicly available data sets. Summary statistics are provided for all data sources in Appendix A.

2.1 Urban Built Environment

To quantify the three measures of the urban built environment theorized to increase cross-class interactions, I use the *Smart Location Database* (SLD) from the Environmental Protection Agency (EPA)[3]. The SLD was designed to measure the built environment and transit accessibility. The database contains over 90 attributes of urban form and location efficiency for nearly all U.S. census block groups. Some characteristics included in the dataset are: total housing units, average distance to nearest transit stop, and number of jobs (broken down by job type). To aggregate the data at the ZIP code level I use a ZIP to census block group crosswalk provided by the Department of Housing and Urban Development. This allows me to analyze the data with the other datasets, which are already at the ZIP code level.

[3]https://www.epa.gov/smartgrowth/smart-location-database-technical-documentation-and-user-guide

The three attributes in the data set that I use as measures of urban form are: (1) street intersection density; (2) entertainment employment density; and (3) employment entropy.

Intersection Density To create the measure of street intersection density the EPA uses HERE Maps street network data[4]. Using this data the EPA classify all street facilities into three types: (1) automobile; (2) multi-modal; and (3) pedestrian. Then, the network data is used to identify intersections between all three types of street facility. The total number of intersections in a ZIP code is the sum of all intersections found in the network data. Street intersection density for ZIP code i is defined as follows:

$$D_i = \frac{I_i}{A_i} \tag{1}$$

Where I_i and A_i are the number of intersections and total land area in square miles of ZIP code i respectively. Street intersection density is a proxy for Jacobs' theorized urban design of small city blocks. Here, higher street intersection density indicates smaller city blocks. The average intersection density for all American ZIP codes is 44 intersections per square mile, and the average intersection density for all ZIP codes in Middlesex County, Massachusetts is 95 intersections per square mile. To contextualize these values, the ZIP code containing Harvard Square in Cambridge, Massachusetts (ZIP code 02138) has an intersection density of 342 intersections per square mile. Interestingly, the ZIP code with the second highest intersection density in the U.S (811 intersections per square mile) is the ZIP code containing Stanford University's campus (ZIP code 94305).

Entertainment Place Density To measure entertainment place density, the EPA uses employment data from the US Census' Longitudinal Employer-Household Dynamics (LEHD)

[4]The HERE maps street network data is a collection of digital maps, traffic information, and location-based services designed to provide accurate and up-to-date information for businesses and individuals. Website: https://www.korem.com/product/here-map-data/

Origin-Destination Employment Statistics (LODES) database from 2017[5]. This dataset contains employer locations and number of jobs broken down by wages and job characteristics. The EPA maps these job characteristics to an employment classification using the North American Industry Classification System (NAICS). The selected classifications are: retail, office, industrial, service, entertainment, education, health, and public administration. In the data, entertainment jobs are defined to be jobs in industries with NAICS codes 71 or 72. These represent the *arts, entertainment and recreation* and *accommodation and food services* sectors respectively. These sectors include places such as: theatres, public parks, athletic stadiums, museums, gyms, bowling alleys (NAICS code 71); and restaurants, cafes, bars, nightclubs, and hotels (NAICS code 72). Food services (restaurants, bars) are included with the entertainment classification, grocery stores are included with the retail classification. For more information on employment classification, see appendix A.2.2. The SLD then uses total job counts for each employment classification per square mile of land to measure employment density by employment classification. It is important to note that this data contains the location of the employer and not the home location of the employee, and is therefore a measure of ZIP code industry composition and not a measure of where the residents of a ZIP code are employed. Using employment density as a proxy for place-type density requires an assumption that places with a higher density of, for example, retail jobs, will also have a corresponding higher density of retail places. This assumption ignores any variance in the number of employees that different places employ. Employment density would be a perfect proxy for place density if all places employed the same number of people. The average entertainment place density for all U.S. ZIP codes is 0.32 entertainment jobs per square mile, and the average entertainment place density for all ZIP codes in Middlesex County, Massachusetts is 0.6 entertainment jobs per square mile. The ZIP code containing Harvard Square in Cambridge, Massachusetts (ZIP code 02138) has an entertainment place density of 7.55 entertainment jobs per square mile. The ZIP code with the highest entertainment place

[5]https://lehd.ces.census.gov/data/

density in the U.S. is the ZIP code directly surrounding Rockefeller center in Manhattan, New York City (ZIP code 10020) with an entertainment place density of 146 entertainment jobs per square mile.

Employment Entropy Lastly, to measure mixed primary-use buildings, I again draw upon the SLD's employment data. The SLD contains a measure of *employment entropy* which quantifies the variation in employment within a given ZIP code. To create this measure, the EPA uses the Shannon Equitability Index[6], used to measure the evenness of species in a community, on the eight employment classifications specified above. Employment entropy is calculated as follows:

$$E_i = \frac{-H_i}{\log(8)} \tag{2}$$

Where log(8) is a normalization factor for the eight employment classifications, and H is calculated as:

$$H_i = \sum_c p_{ci} * \ln(p_{ci}) \tag{3}$$

Where p_{ci} is the share of total jobs in employment classification c (for example retail jobs) in ZIP code i. Employment entropy will vary between zero and one, with higher values indicating greater entropy. In a ZIP code dominated by one industry, or one employment type, employment entropy will be very low. Whereas in a ZIP code with similar numbers of jobs across employment classifications, employment entropy will be very high.

While employment entropy is not a perfect proxy for mixed primary-use buildings, it indicates that within a confined region (ZIP code) there are multiple different types of places. Jacobs' primary motivation for mixed primary-use buildings was that they attract a variety of people at a variety of times to one place. Higher employment entropy achieves

[6] https://www.statology.org/shannon-diversity-index/

the same effect, but relies on the assumption that the variety of place types within a ZIP code bring different people together in a similar way. This assumption would be violated if, for instance, the variety of places within the ZIP code were geographically segregated, and visitors to the different places did not encounter one another. However, given the small size of ZIP codes it is unlikely that different place types will be so geographically segregated such that pedestrians visiting different places will never cross paths. See appendix A.2.2 for more information on how employment entropy is calculated. The average employment entropy for all U.S. ZIP codes is 0.55, and the average employment entropy for all ZIP codes in Middlesex County, MA is 0.59. Harvard Square in Cambridge, MA (ZIP code 02138) has an employment entropy of 0.48, and Greenwich Village in Manhattan, New York City has an employment entropy of 0.59.

2.2 Experienced Income Segregation

To measure experienced cross-class interactions I use data from Moro et al. (2021). This data was provided to them by Cuebiq[7], a location intelligence and measurement platform through their Data for Good program. Cuebiq's data consists of randomized GPS locations from mobile devices from 11 cities between October 2016 and March 2017. The 11 cities represented in the data are: Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York City, Philadelphia, San Francisco, Seattle, and Washington DC. The data consists of 67 billion GPS locations from 4.5 million users. Using these GPS locations, each mobile device is assigned a home census block based on the device's most common location between 10:00pm and 6:00am. Income is assumed to be the median household income of the home census block as per the 2012-2016 5-year American Community Survey (ACS).

Experienced economic segregation is calculated for every place of interest (POI) within the 11 cities. Every time a device visits a POI, the total time it spends at the POI and the imputed household income from above are recorded. Experienced economic segregation

[7]https://www.cuebiq.com/

is then calculated for each POI as the proportion of the total time that devices from each household income quartile spend at the POI. This is then normalized by $\frac{2}{3}$ to fit a $0 - 1$ range.

For a place α, S_α is the segregation of α:

$$S_\alpha = \frac{2}{3} \sum_q |\tau_{q\alpha} - \frac{1}{4}| \tag{4}$$

Where q is an income quartile, and $\tau_{q\alpha}$ is the share of time spent at place α by individuals in income quartile q.

$$\tau_{q\alpha} = \frac{T_{q\alpha}}{T_\alpha} \tag{5}$$

Where T_α is the total time spent at place α, and $T_{q\alpha}$ is the total time spent at place α by individuals in income quartile q.

If one quarter of the total time spent at a POI is by each income quartile, experienced economic segregation would be zero ($\frac{2}{3}[0 + 0 + 0 + 0] = 0$). Conversely, if 100% of the total time spent at a POI is by just one income quartile, experienced economic segregation would be one ($\frac{2}{3}[\frac{3}{4} + \frac{1}{4} + \frac{1}{4} + \frac{1}{4}] = 1$). More details for how experienced income segregation was calculated can be found in the paper by Moro et al. (2021).

I use a reverse geocoding method to retrieve the address and ZIP code of every POI from the dataset. I then aggregate all POIs within a given ZIP code with a mean weighted by the number of visits to each POI to calculate the experienced economic segregation for each ZIP code in the 11 cities.

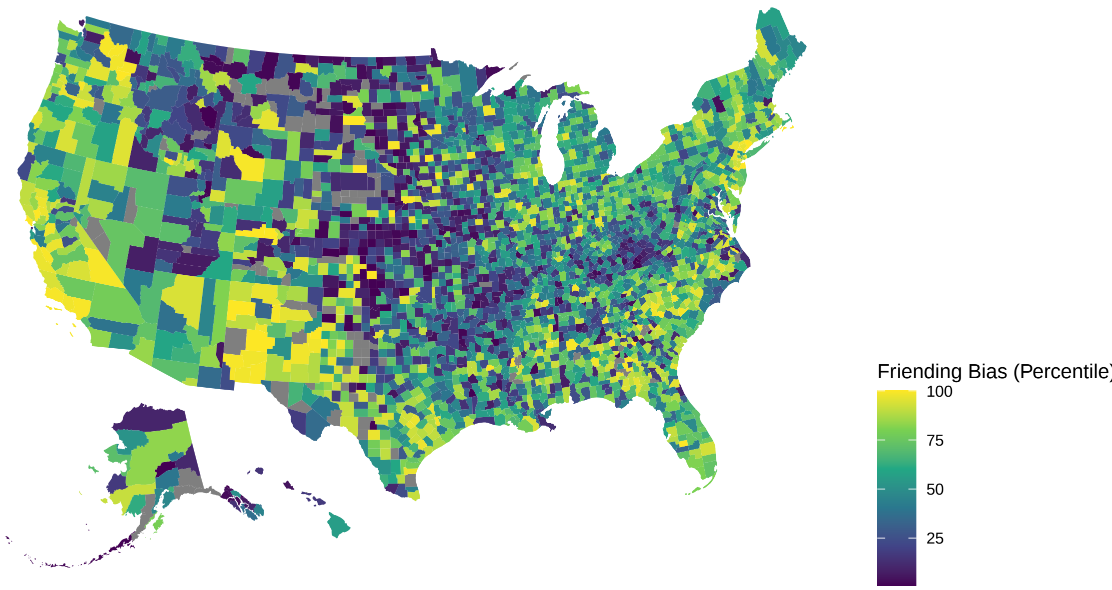
2.3 Friending Bias

To quantify cross-class bias, I use a measure of friending bias from Chetty et al. (2022a). They use data from 21 billion Facebook friendships between 72.2 million users aged 25-44, representing 84% of the US population of that age. The data represents Facebook members with at least 100 friends, with a US zip code, and who were active in the previous 30 days. Each user is assigned to a home census block based on their ZIP code. A model was constructed to predict each individual's socioeconomic status (SES) that combines measures such as median household income in an individual's census block, and self-reported educational attainment. More information for how SES is imputed can be found in their paper (Chetty et al. 2022a). Individuals are categorized as either above median SES (high-SES) or below median SES (low-SES), determined by the national distribution of SES.

Chetty et al. then leverage their proxy for SES to observe social network patterns between individuals from different parts of the SES distribution. They create a measure of cross-class bias termed friending bias that can be understood, at an individual level, as the share if high-SES friends that a low-SES individual has, conditional on the socioeconomic distribution of individuals they are exposed to. This can be conceptually understood as the difference between the share of high-SES friends in an individual's social network and the share of high-SES friends the individual would have were they to randomly select friends from the distribution of people they are exposed to. At a regional level, friending bias is the mean individual friending bias of all low-SES members of the region. Data for friending bias is available at both the ZIP code and county levels.

To help interpret the scale of the measure, Middlesex County in Massachusetts has a friending bias of 0.06. This indicates that the average low-SES individual from Middlesex County has a social network that contains 6% fewer high-SES friends than if they had randomly selected their friends from the people they are exposed to. Friending bias in Middlesex county is approximately 0.05 standard deviations above the national mean friending bias of 0.057. Figure 1 displays how friending bias varies nationally.

Figure 1: The Geography of Friending Bias in the U.S.

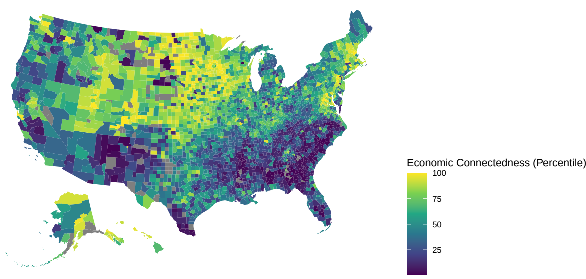


Notes: Friending bias mapped across the U.S. at the county level. The values plotted are percentile values.

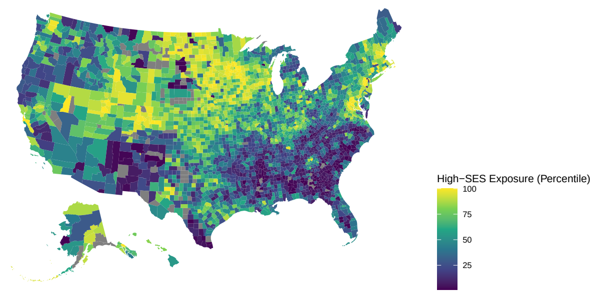
One helpful interpretation of friending bias is as one of two key determinants of *economic connectedness*. Economic Connectedness is defined, at an individual level, as the share of high-SES friends that a low-SES individual has. At a regional level economic connectedness is the mean individual economic connectedness of all low-SES individuals within the region. Economic connectedness can be decomposed into friending bias and *high-SES exposure*. High-SES exposure is simply the share of high-SES individuals that a low-SES individual is exposed to. The product of friending bias and high-SES exposure yields economic connectedness. Chetty et al. find that approximately half of the national variance in economic connectedness comes from high-SES exposure and half from friending bias.

The decomposition of economic connectedness into friending bias and high-SES exposure is also helpful for policy consideration: A project designed to change the economic distribution of the individuals within a region will focus on high-SES exposure, whereas policy designed to increase cross-class relationships between people of an existing region will focus on friending bias. This paper hypothesizes that urban built environment influences the likelihood of cross-class interactions, and that those interactions reduce cross-class bias, and is therefore interested in friending bias. Figure 2 displays how economic connectedness and high-SES exposure vary nationally.

Figure 2: The Geography of Economic Connectedness and High-SES Exposure in the U.S.



(a) Economic Connectedness



(b) High-SES Exposure

Notes: Economic connectedness and high-SES exposure mapped across the U.S. at the county level. The values plotted are percentile values.

2.4 Demographics

To more precisely analyze the relationships between urban form, cross-class interactions, and cross-class bias, I use a rich set of demographic data at the ZIP code level. I obtain population, population density, median household income, unemployment, and racial composition data from the American Community Survey (ACS) five year estimates from 2017-2021.

Population density is measured in people per square mile. Median household income is measured in 2021 inflation adjusted dollars. Unemployment rates are the share of unemployed individuals of the civilian ZIP code population aged 16 or above. Racial composition data is broken down into the shares of the total population that are: White, Black, Asian, American Indian and Alaska Native, Native Hawaiian, two or more races, and some other race[8]. I create a measure of racial diversity following US census standards by using Simp-

[8]https://www.census.gov/newsroom/press-kits/2022/acs-5-year.html

son's index. This can conceptually be understood as the probability that two people chosen at random from the population will be from different racial groups. This index is calculated as follows:

$$S_i = 1 - \sum_g \frac{P_{gi}(P_{gi} - 1)}{N_i(N_i - 1)} \tag{6}$$

Where S_i is the racial diversity index for region i, and P_{gi} is the population of group g in region i. N_i is the total population of region i.

Appendix B presents the relationships between these demographics and experienced economic segregation and friending bias.

3 City Case Studies

In this section, I narrow the scope of analysis to 2 cities to better illustrate the relationships between urban form, experienced economic segregation, and friending bias. These cities are Detroit and Seattle. By isolating individual cities, which are more recognizable and easily understood, this section can provide a more interpretable understanding of patterns in the data.

To aggregate the data at the city level, I follow a two-step process. First, I map each zip code in the data to its associated major metropolitan area. Next, I take a population weighted mean of all three urban form measures, experienced economic segregation, and friending bias for each zip code in a given city. This approach creates aggregated measures of the variables of interest for all 11 cities in the dataset, allowing me to observe broader trends in the data and facilitate meaningful comparisons across cities.

3.1 Detroit

To investigate broad patterns between the urban built environment, experienced economic segregation, and friending bias at the city level, I first explore the city of Detroit. Among the 11 cities in the dataset, Detroit exhibits the lowest aggregate values for all three urban form measures.

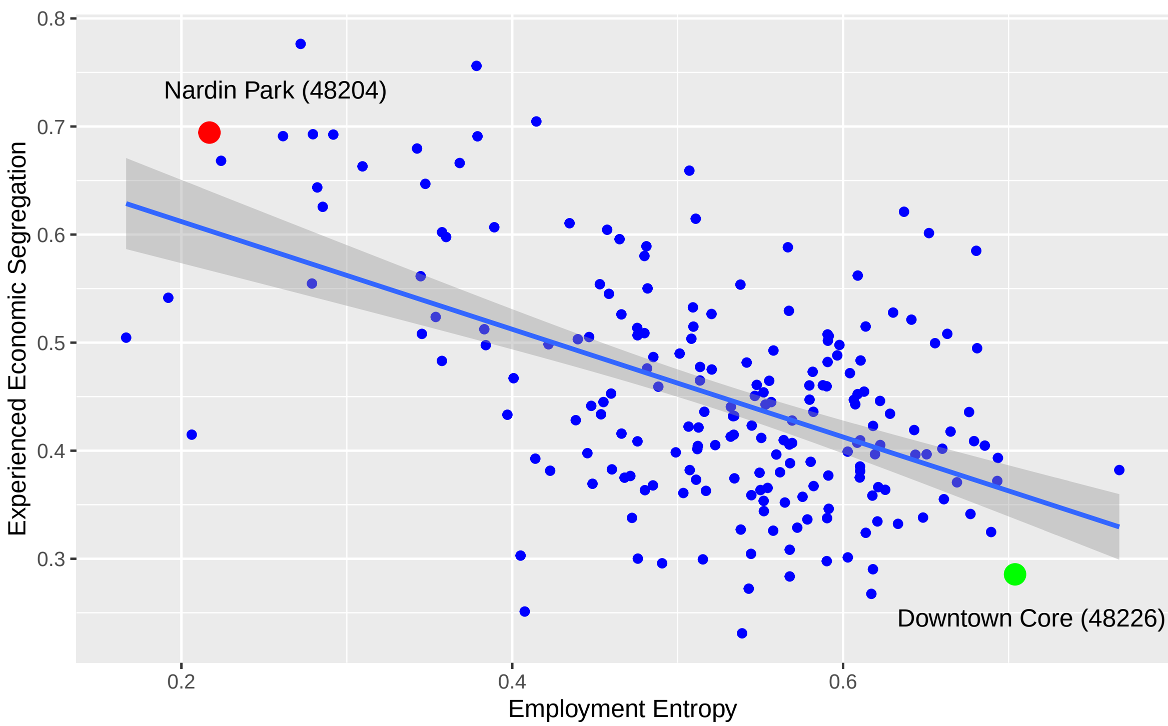
To illustrate, employment entropy in Detroit is 1.4 standard deviations below the average aggregated employment entropy across all 11 cities, and 2.8 standard deviations below employment entropy in San Francisco, the city with the highest employment entropy. Additionally, intersection density and entertainment place density in Detroit are 1.6 and 1.1 standard deviations below the average aggregated values across all 11 cities respectively.

Consistent with the hypothesis, Detroit also exhibits high levels of experienced economic segregation. With the exception of New York City (which has many unique characteristics), Detroit exhibits the highest level of aggregated experienced economic segregation among the 11 cities in the dataset. This pattern supports the hypothesis that the urban built environment could be a mechanism in shaping experienced economic segregation, and motivates further exploration of the relationship between these variables.

To illustrate the relationship between the urban built environment and experienced economic segregation within Detroit, I study the neighborhood of Nardin Park (containing ZIP code 48204), located approximately seven miles northwest of downtown Detroit. This is a low-income suburb, with a median annual household income of $\$22,000$. It is also heavily reliant on cars, and has few amenities that promote cross-class interactions. The employment entropy in Nardin Park is 0.22, which is 2.8 standard deviations below the average employment entropy in Detroit of 0.52. Nardin Park also exhibits low levels of entertainment place density and intersection density. These disparities could be contributing to the neighborhood's high level of experienced economic segregation of 0.7, which is 2.3 standard deviations above the average experienced economic segregation in Detroit of 0.45.

Interestingly, the neighborhoods within Detroit that exhibit the highest values of the urban form measures also tend to have lower experienced economic segregation. This highlights that the urban built environment is linked to experienced economic segregation both within and between cities. For instance, ZIP code 48226, which contains Detroit's major downtown area, exhibits close to the highest values for all urban form measures in Detroit. In this neighborhood of downtown Detroit, the experienced economic segregation is only 0.29, which is 1.6 standard deviations below the average experienced economic segregation in Detroit of 0.45. Figure 3 presents the negative relationship between employment entropy and experienced economic segregation for all ZIP codes in Detroit.

Figure 3: Employment Entropy and Experienced Economic Segregation in Detroit

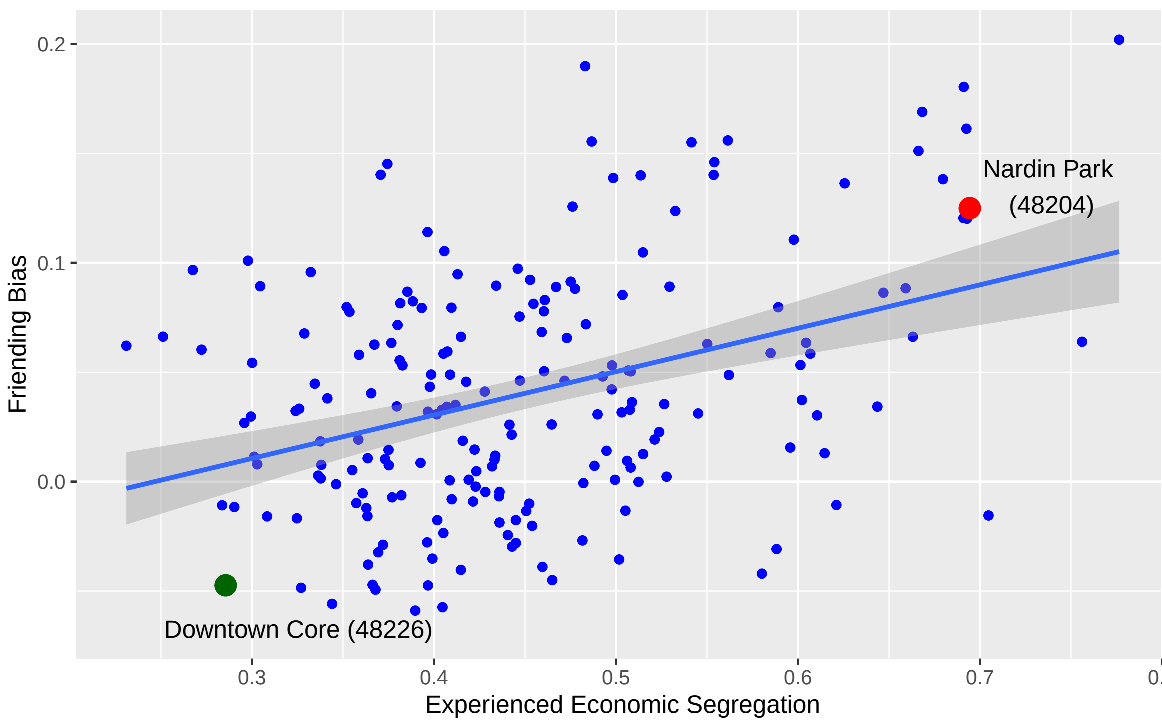


Notes: Scatter plot between employment entropy and experienced economic segregation at the ZIP code level in Detroit. The sample contains 205 ZIP codes in the Detroit metropolitan area.

In addition to the observed relationship between urban form and experienced economic segregation, ZIP codes in Detroit also display a relationship between experienced economic segregation and friending bias. Examining the same two ZIP codes as above helps to highlight this pattern. Nardin Park, a neighborhood with low levels of urban form and high levels of experienced economic segregation, also exhibits high levels of cross-class friending bias. Friending bias in Nardin Park is 1.5 standard deviations above the average ZIP code in

Detroit. Similarly, the neighborhood in Detroit's downtown core, with high levels of urban form and low levels of experienced economic segregation, exhibits a level of friending bias 1.6 standard deviations *below* the average ZIP code in Detroit. Figure 4 plots experienced economic segregation and friending bias for all ZIP codes in Detroit. These observed patterns provide preliminary evidence supporting the hypothesized correlational chain from urban form to experienced cross-class interactions to cross-class friending bias.

Figure 4: Experienced Economic Segregation and Friending Bias in Detroit



Notes: Scatter plot between experienced economic segregation and friending bias at the ZIP code level in Detroit. The sample contains 205 ZIP codes in the Detroit metropolitan area.

3.2 Seattle

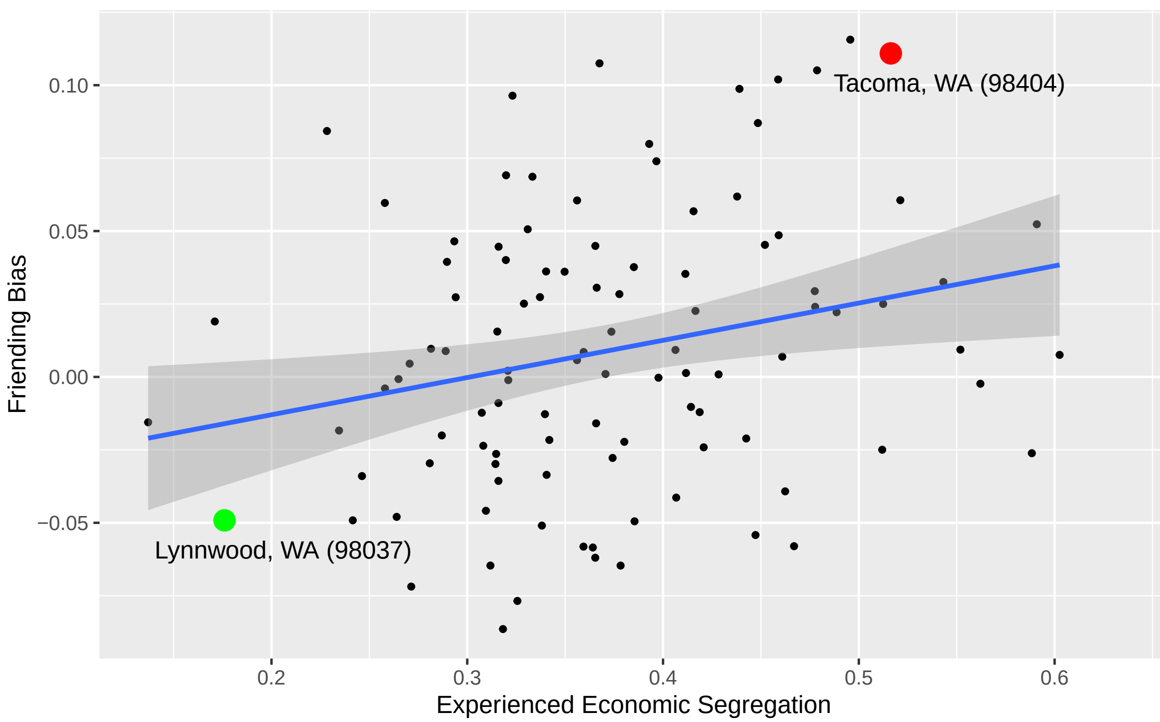
Seattle serves as another city that illustrates the relationships between urban form, experienced economic segregation, and friending bias. Out of the 11 cities in the dataset, Seattle exhibits the lowest aggregated levels of both experienced economic segregation and friending bias, thus providing a compelling example of the second stage of the hypothesized correlational chain.

Experienced economic segregation and friending bias in Seattle are 1.7 and 1.9 standard deviations below the mean of the 11 cities. These findings imply a positive relationship between experienced income segregation and friending bias at the city level, consistent with the second stage of the hypothesized correlational chain.

In addition to the city-level relationship between experienced economic segregation and friending bias, it is also illustrative to examine this relationship at the ZIP code level within the city of Seattle. ZIP codes in Seattle with higher levels of experienced economic segregation tend to have higher levels of friending bias. One example of this relationship can be seen in Lynnwood, Washington's ZIP code 98037, located approximately 15 miles north of downtown Seattle. This is a relatively middle class neighborhood, with a high degree of racial diversity. Notably, this ZIP code displays low levels of both experienced economic segregation and friending bias. Experienced economic segregation is 2.1 standard deviations below the average ZIP code in Seattle, and friending bias is 1.2 standard deviations below the average ZIP code in Seattle. Additionally, this ZIP code exhibits high levels of all three urban form measures, consistent with the first stage of the hypothesized correlational chain. For instance, street intersection density and employment entropy are 0.1 and 0.7 standard deviations above Seattle's averages.

Another example that illustrates the relationship between experienced economic segregation and friending bias within Seattle is ZIP code 98037, located south of Seattle in Tacoma, Washington. This neighborhood exhibits high levels of both experienced economic segregation and friending bias, with values 1.5 and 2.2 standard deviations above Seattle's average ZIP code respectively. This ZIP code looks demographically similar to Lynnwood, Washington with lower middle-class levels of household income, and a high degree of racial diversity. Interestingly, this ZIP code also exhibits low levels of urban form, with entertainment place density and employment entropy 0.4 and 1.9 standard deviations below the average ZIP code in Seattle. These findings provide evidence that experienced economic segregation and friending bias could be linked within cities, and that urban form may be an important determinant of experienced economic segregation. Furthermore, the demographic similarities between these two ZIP codes suggest that these patterns could persistent when controlling for demographic distributions. Figure 5 displays the positive relationship between experienced economic segregation and friending bias for all ZIP codes in Seattle.

Figure 5: Experienced Economic Segregation and Friending Bias in Seattle

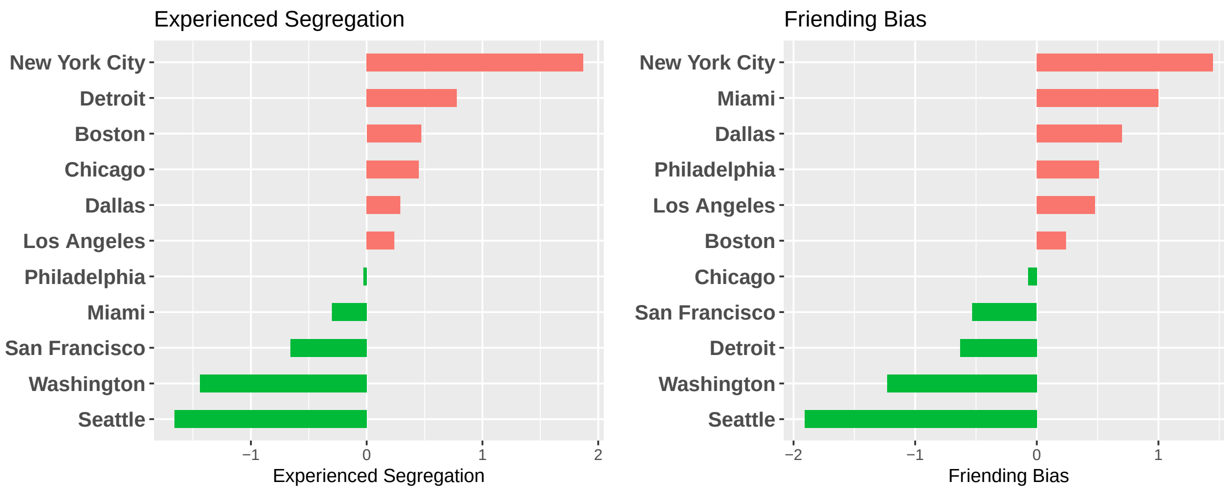


Notes: Scatter plot between experienced economic segregation and friending bias at the ZIP code level in Seattle. The sample contains 106 ZIP codes in the Seattle metropolitan area.

3.3 Across City Comparisons

In the previous subsections I observed broad patterns in the data that support the hypothesized correlational chain in both Detroit and Seattle. In addition to these within-city analyses, it is also helpful to observe city-level patterns between all 11 cities in the dataset. Figure 6 displays a ranking of normalized values of experienced economic segregation and friending bias in the 11 cities, and Figure 7 plots experienced economic segregation and friending bias. These figures provide a high-level overview of patterns between experienced economic segregation and friending bias across levels across the 11 cities.

Figure 6: Ranked Experienced Economic Segregation and Friending Bias for 11 Cities

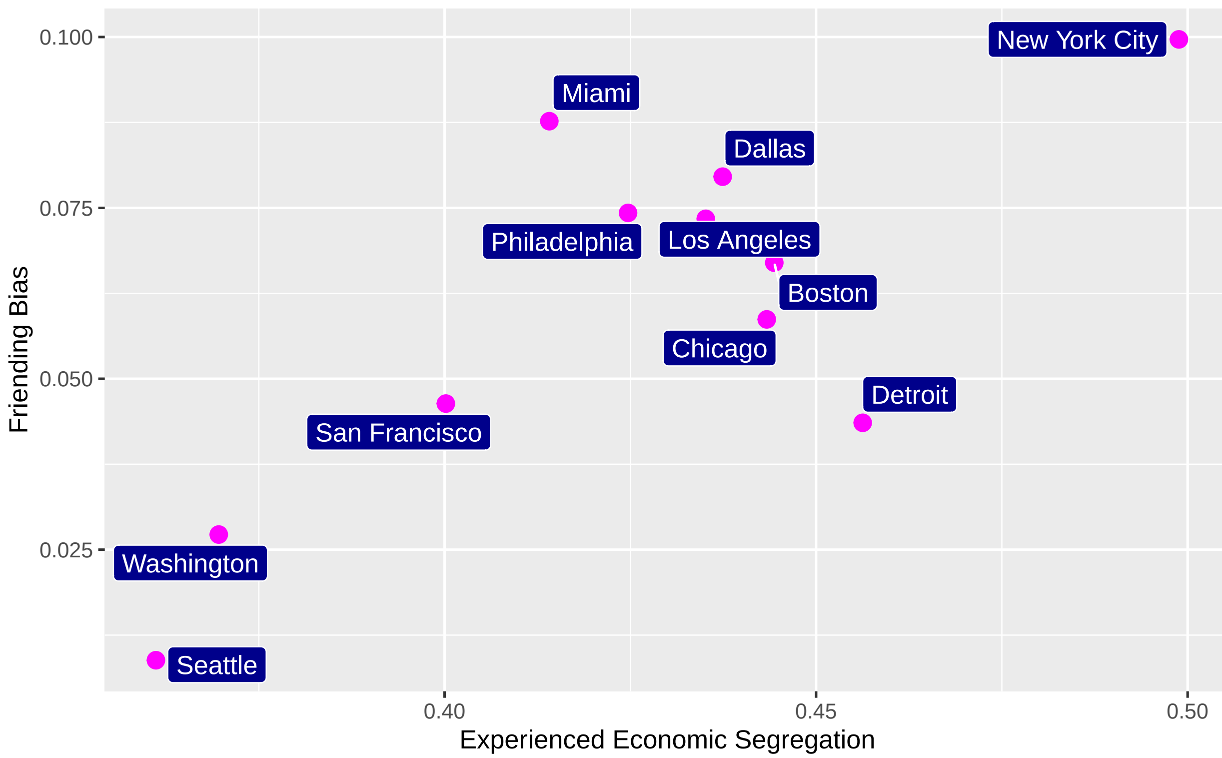


(a) Experienced Economic Segregation

(b) Friending Bias

Notes: Population weighted aggregated values of experienced economic segregation and friending bias at the city level, standardized to a z-score. The 11 cities are ranked on these aggregated values.

Figure 7: City Level Experienced Economic Segregation and Friending Bias



Notes: Plot of aggregated values of experienced economic segregation and friending bias at the city level for the 11 cities in the dataset.

Figures 6 and 7 reveal that Seattle exhibits the lowest aggregated levels of experienced income segregation and friending bias, while New York City exhibits the highest levels of both. Detroit exhibits the second highest aggregated values of experienced economic segregation. Furthermore, Figure 7 illustrates a generally positive relationship between experienced economic segregation and friending bias at the city level.

Both Detroit and Seattle offer insights that contribute to a deeper understanding of the data. Both cities provide concrete examples of the hypothesized correlational chain, which will be empirically tested in the following section. Additionally, analyzing city-level patterns across all cities further supports the second stage of the hypothesized correlational chain. These findings imply that we can anticipate meaningful results both within and across cities, potentially motivating policy at various levels of government.

4 Results

In the following section, I outline my methodology and present the results of the analyses. In the first subsection, I empirically test the hypothesis that urban form is associated with experienced cross-class interactions. In the second section, I examine the downstream effects of experienced cross-class interactions on cross-class friending bias. When combined, these two analyses allow me to validate the hypothesized correlational chain from urban built environment, to experienced cross-class interactions, to cross-class friending bias.

4.1 Urban Form and Experienced Economic Segregation

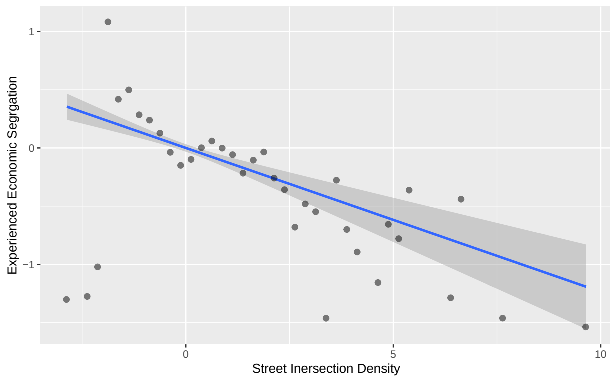
In this subsection, I examine the extent to which the urban built environment might influence experienced economic segregation. I standardize all three measures of urban form and experienced economic segregation to mean 0 and standard deviation 1 such that all estimates can be interpreted in terms of standard deviations. The initial regression of experienced economic segregation on urban form is as follows:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \epsilon \tag{7}$$

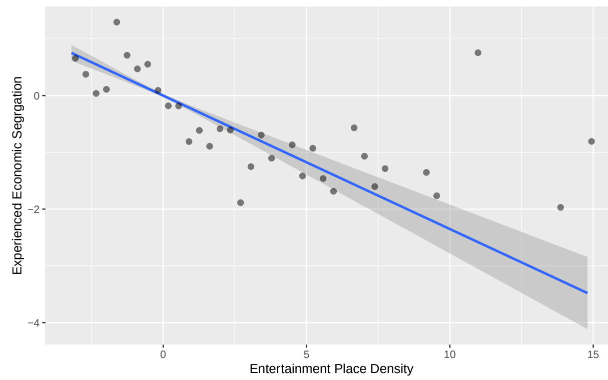
Where the dependent variable Y_i represents experienced economic segregation of ZIP code i, the independent variable X_i represents one of three measures of urban form, Z_i is a vector of control variables, and ϵ is an error term. I perform this regression with no controls, a simple set of controls (median household income and population density), and with a full set of controls including all demographics described in section 2.4. To capture within-city variation, I also perform the regression using city fixed effects. Because individual mobility behaviour is influenced by a complex set of endogenous factors, this exercise is purely descriptive, and does not imply causation. Figure 8 displays the results of this regression with the full set of controls for the three urban form measures. I use a binned scatter plot with 50 bins to allow for easier interpretation of the data.

Figure 8: Urban Form and Experienced Economic Segregation

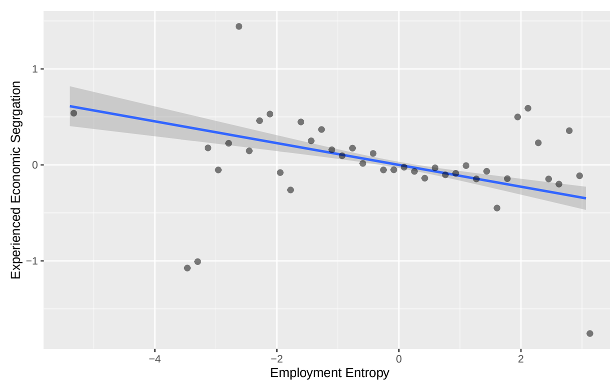
Panel A: Intersection Density and Experienced Economic Segregation



Panel B: Entertainment Place Density and Experienced Economic Segregation



Panel C: Employment Entropy and Experienced Economic Segregation



Notes: Binned scatter plots between three measures of urban form and experienced economic segregation at the ZIP code level, controlling for all demographic variables described in section 2.4, excluding city fixed effects. Number of bins in all panels = 50. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

Figure 8 shows the relationships between the urban form measures and experienced economic segregation. Column 1 of Table 1 presents the raw association between the urban forms and experienced economic segregation. Columns 2 and 3 of Table 1 present an equivalent regression as column 1, but include a set of basic controls (column 2) and a comprehensive set of controls (column 3). When including the full set of controls, the estimates indicate that a one standard deviation increase in street intersection density[9], entertainment place density,

[9]Figure 8: panel A presents a binscatter plot between intersection density and experienced economic segregation with 50 bins. The three points with the lowest intersection densities are significantly below the estimate. However, one city is not exclusively driving these lower values. Of the 185 ZIP codes below the 6th percentile of intersection densities, 18%, 18% and 16% are from Washington DC, New York City, and Dallas respectively.

and employment entropy are associated with a 0.124, 0.235, and 0.113 standard deviation decrease in experienced economic segregation respectively. Within the Boston metropolitan area, a one standard deviation increase in street intersection density is approximately equivalent to moving from North Cambridge (Porter Square, Alewife Station, ZIP code 02140) to East Cambridge (Cambridgeside, Kendall Square, ZIP code 02141). A one standard deviation increase in entertainment place density is approximately equivalent to moving from Brookline (High Street Hill, Fisher Hill, ZIP code 02445) to Cambridge's Central Square (including Cambridgeport, MIT, ZIP code 02139). Lastly, a one standard deviation increase in employment entropy is approximately equivalent to moving from West Somerville (Tufts, Union Square, ZIP code 02144) to Back Bay (Newbury Street, Boston Public Garden, ZIP code 02116). Similarly, a one standard deviation decrease in experienced economic segregation is equivalent to moving from a ZIP code with *no integration* (i.e., all places are visited by people within a single income quartile) to a ZIP code where 92% of visitors are from one income quartile and the remaining 8% are from another quartile. Column 4 of Table 1 introduces city fixed effects, and coefficients imply a one standard deviation increase in street intersection density, entertainment place density, and employment entropy correspond with a 0.110, 0.209, and 0.131 standard deviation decrease in experienced economic segregation respectively. These estimates do not significantly differ from the results without city fixed effects, suggesting that the observed relationships are robust to the inclusion of city-specific characteristics. Entertainment place density is consistently the strongest predictor of experienced economic segregation, independent of incorporating city fixed effects.

Table 1: Urban Form and Experienced Economic Segregation

	Dependent variable:			
	Experienced Economic Segregation			
Panel A				
Intersection Density	-0.039^{**}	-0.144^{***}	-0.124^{***}	-0.110^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
R^2	0.002	0.075	0.151	0.225
Panel B				
Entertainment Place Density	-0.117^{***}	-0.243^{***}	-0.235^{***}	-0.209^{***}
	(0.018)	(0.023)	(0.022)	(0.021)
R^2	0.014	0.092	0.170	0.241
Panel C				
Employment Entropy	-0.229^{***}	-0.161^{***}	-0.113^{***}	-0.131^{***}
	(0.017)	(0.019)	(0.019)	(0.020)
R^2	0.053	0.078	0.148	0.228
Dep. Var. Mean	0	0	0	0
Dep. Var. S.D.	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087

*p<0.1; **p<0.05; ***p<0.01

Notes: Regression coefficients for experienced economic segregation on three measures of urban form: street intersection density, entertainment place density, and employment entropy. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

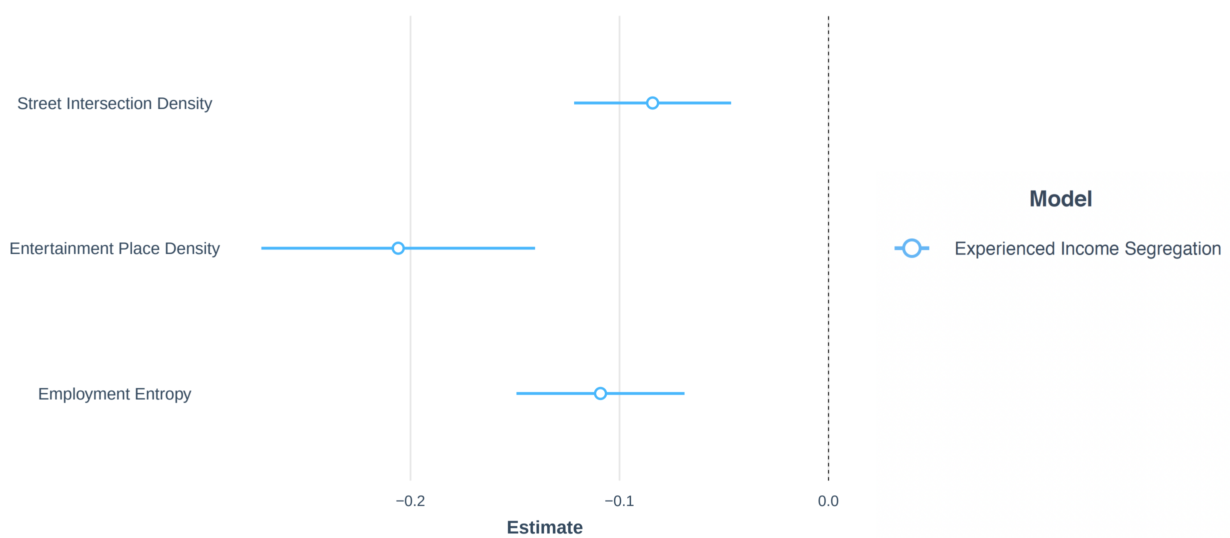
4.1.1 Multivariate: Urban Form and Experienced Income Segregation

Given the high collinearity of the three urban form measures (see Appendix A.2.1), it is important to understand their collective relationship with experienced economic segregation. Thus, in this section I conduct a multivariate OLS regression that incorporates all three urban form measures. This regression is given by:

$$Y_i = \beta_0 + \beta_1 \boldsymbol{X_i} + \beta_2 Z_i + \epsilon \tag{8}$$

Where $\boldsymbol{X_i}$ now represents a vector containing all three urban built environment measures. Z_i and ϵ are operationally identical to Equation 7. This multivariate OLS regression is intended to investigate the individual effects of different urban forms on experienced economic segregation, and to compare the relative magnitudes of these effects. Figure 9 plots the resulting coefficients from this regression for the three urban form measures controlling for the full set of demographic controls.

Figure 9: Urban Form and Experienced Economic Segregation



Notes: Coefficient plots of experienced economic segregation against three urban form measures from a multivariate OLS regression including the full set of control variables. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

Table 2: Urban Form and Experienced Economic Segregation

	Dependent variable:			
	Experienced Economic Segregation			
	(1)	(2)	(3)	(4)
Street Intersection Density	-0.065^{***}	-0.125^{***}	-0.084^{***}	-0.084^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Entertainment Place Density	-0.088^{***}	-0.199^{***}	-0.206^{***}	-0.179^{***}
	(0.018)	(0.023)	(0.022)	(0.022)
Employment Entropy	-0.237^{***}	-0.160^{***}	-0.109^{***}	-0.131^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Dep. Var. Mean	0	0	0	0
Dep. Var. S.D.	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.067	0.122	0.183	0.255

*p<0.1; **p<0.05; ***p<0.01

Notes: Multivariate regression coefficients for experienced economic segregation on three measures of urban form: street intersection density, entertainment place density, and employment entropy. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

The multivariate OLS regression reveals statistically significant negative relationships between all three urban form measures (intersection density, entertainment place density, and employment entropy) and experienced economic segregation. Column 1 of Table 2 displays the results of this regression independent of any demographic control variables. Columns 2 and 3 of Table 2 present the estimates for the regression when controlling for a simple set and full set of demographic controls respectively. With the full set of controls, the estimates indicate that a one standard deviation increase in intersection density, entertainment place density, and employment entropy are associated with a 0.084, 0.206, and 0.109 standard deviation decrease in experienced economic segregation respectively. Consistent with the univariate OLS regressions above, the results of the multivariate analysis indicate that entertainment place density remains the strongest predictor of experienced economic segregation. Additionally, the inclusion of city fixed effects maintains statistical significance for all three urban form measures, with entertainment place density remaining the strongest predictor of experienced economic segregation.

The results of these analyses provide support for the first stage of the hypothesized correlational chain, which posits that urban form influences experienced cross-class interactions. Specifically, I find that three forms of the urban built environment are negatively associated with experienced economic segregation. This result is consistent with Jane Jacobs' theoretical arguments that certain forms of urban design, such as small city blocks, and mixed primary-use buildings, can help foster cross-group interactions.

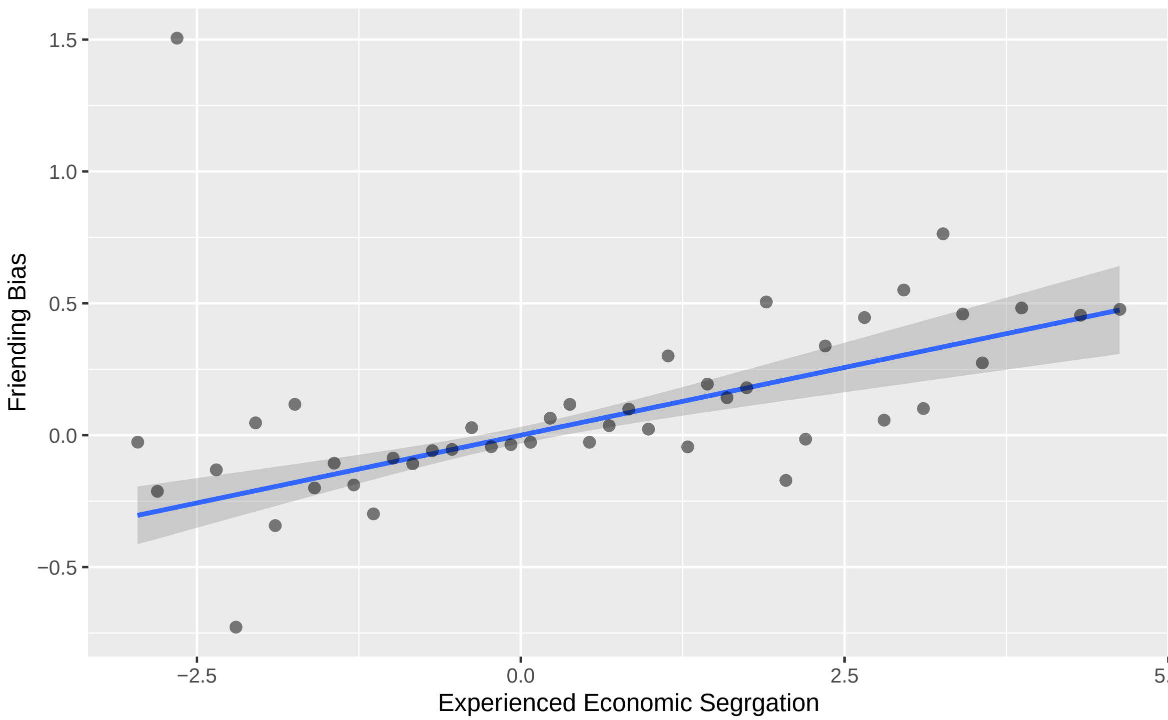
4.2 Experienced Economic Segregation and Cross-Class Bias

In this section I examine the relationship between experienced economic segregation and friending bias. All variables are again standardized to mean 0 and standard deviation 1 so coefficients can be understood in terms of standard deviations. The regression of friending bias on experienced economic segregation is given by:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \epsilon \tag{9}$$

Where Y_i represents the friending bias of ZIP code i, and X_i represents the experienced economic segregation of ZIP code i. Consistent with the previous section, $_1$ represents a vector of controls, and ϵ represents the error term. I again perform this regression with no controls, with simple controls, with a full set of controls, and including city fixed effects to account for unobserved heterogeneity across cities. Figure 10 displays the results of this regression with the full set of controls. I again use a binned scatter plot with 50 bins to facilitate easier interpretation.

Figure 10: Experienced Economic Segregation and Friending Bias



Notes: Binned scatter plot of cross-class friending bias on experienced economic segregation at the ZIP code level. Number of bins = 50. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

Figure 10 displays a clear positive relationship between experienced economic segregation and friending bias. Columns 1, 2, and 3 of Table 3 present the resulting coefficients from regressions with no controls, simple controls, and full controls respectively. Column 4 presents the estimate when including city fixed effects. A one standard deviation decrease in experienced economic segregation is associated with an decrease of between 0.057 and 0.103 standard deviations depending on the specification of controls. To help interpret these results, a one standard deviation change in friending bias is approximately a change of 0.08. If, for example, an individual's social network was 50% high-SES friends, and they were exposed to 50% high-SES individuals, then a one standard deviation decrease in friending bias would is equivalent to replacing 8% of the low-SES friends with high-SES friends. The average Facebook user has approximately 200 friends[10], so this change would result in approximately 16 more high-SES friends. This one standard deviation decrease in friending bias would be equivalent to moving from East Cambridge (Cambridgeside, Kendall Square, ZIP code 02141; friending bias = -1.05) to Harvard Square (ZIP code 02138; friending bias $= -1.13$).

[10] https://pewinternet.tumblr.com/post/23177613721/facebook-a-profile-of-its-friends-in-light-of

Table 3: Experienced Economic Segregation and Friending Bias

	Dependent variable:			
	Friending Bias			
Experienced Economic Segregation	0.208***	0.068***	0.103***	0.057***
	(0.019)	(0.018)	(0.018)	(0.018)
Population Density		0.063***	−0.031*	−0.111***
		(0.017)	(0.017)	(0.018)
Median Household Income		−0.472***	−0.382***	−0.427***
		(0.019)	(0.022)	(0.024)
Population			0.118***	0.157***
			(0.019)	(0.019)
Racial Diversity			0.200***	0.216***
			(0.019)	(0.020)
Unemployment Rates			0.016	0.012
			(0.021)	(0.021)
Constant	0.004	−0.050***	−0.064***	−0.188
	(0.018)	(0.017)	(0.016)	(0.474)
Dep. Var. Mean	0	0	0	0
Dep. Var. S.D.	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	2,814	2,811	2,811	2,811
R^2	0.042	0.220	0.279	0.332

*p<0.1; **p<0.05; ***p<0.01

Notes: OLS regression coefficients for friending bias on experienced economic segregation. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

These results verify the second stage of the hypothesized correlational chain that increased cross-class interactions can reduce cross-class friending bias. This is consistent with Allport's contact theory that cross-group interactions can reduce cross-class bias.

4.2.1 Instrumental Variables Estimates on Friending Bias

Despite the strong correlations between experienced economic segregation and friending bias outlined above, concerns may remain about factors that influence both measures. In this section, I describe my approach to generating plausibly exogenous variation in experienced economic segregation.

Instrumental Variables Approach The instrumental variable approach I employ aims to use urban form as an instrument to estimate the causal effect of experienced economic segregation on friending bias by exploiting the causal effect of urban form on experienced economic segregation.

Under the assumption of constant treatment effects, my IV approach requires three conditions: relevance, independence, and exclusion. The strong relationships between the three urban form measures and experienced economic segregation outlined in section 4.1 provide prima facie evidence of instrument relevance, though I formally present the first stage relationships in Tables 4 and 6. Independence requires that the potential outcomes (the friending bias that a given area would have exhibited with more or fewer cross-class interactions) is orthogonal to urban form. Although there are plausible reasons that this condition may not be satisfied - for instance, if a third variable, such as racial diversity, influences both urban form (through blockbusting or construction of housing projects) and friending bias (fewer cross-class friendships) - this assumption seems fairly reasonable. Finally, the exclusion restriction requires that urban form does not affect friending bias except through its effects on cross-class interactions. I now discuss this assumption in greater detail.

Exclusion Restriction At one level, this assumption is intuitive: Facebook friendships largely represent people known from real life, and these real life friendships arise from physical interactions. However, the assumption that *all* of the effects of the urban form measures on friending bias operate exclusively through cross-class interactions - the outcome variable in the first-stage regressions - requires that the instrument does not have *any* direct spillovers, negative or positive, onto friending bias. Therefore, a more nuanced consideration of the mechanisms by which each of the three urban form measures influence friending bias is required.

The exogeneity assumption for intersection density is justifiable for two reasons. First, intersection density is largely a function of historical construction, which is driven by topology, land use patterns, and technical innovation, such as transportation technology. Once established, street networks are unlikely to change in the short term, as they underpin the structure and operation of the city (Marshall 2004). As such, it is reasonable to claim that intersection density is independent of Facebook social network patterns. Furthermore, given strict urban zoning laws and construction restrictions, changes in intersection density are generally unlikely or will be small in magnitude. Second, even if intersection density did change today, there is no obvious channel through which it will influence Facebook friendships other than experienced interactions. Changes in intersection density could potentially influence other aspects of urban life such as car traffic congestion. However, car traffic itself is unlikely to be directly related to Facebook friendships since individuals do not typically form social connections while driving. Therefore, changes in intersection density are unlikely to influence Facebook social networks through this channel. Other effects of intersection density on urban life are similarly unrelated to Facebook friendships. Thus, intersection density likely satisfies the exogeneity condition and can be used as a valid instrument for estimating the causal effect of experienced interactions on Facebook social networks.

While the exogeneity assumption for intersection density is relatively robust, concerns may arise regarding the relationships between employment patterns (entertainment place density, and employment entropy) and Facebook networks that do not operate through experienced interactions. This assumption would be violated if, for instance, entertainment places create online communities where individuals who have not met in real life can establish friendships on Facebook, thereby bypassing then need for experienced interactions. Such spillovers from employment patterns onto friending bias could be very complex and may violate a narrow exclusion restriction.

To address these concerns, I proceed in this section in two stages. First, I instrument solely with intersection density, given its robust argument for exogeneity. Second, I instrument on all three urban form measures. Together, the three pieces of evidence I present - OLS estimates, intersection density instrument estimates, and three urban form measures instrument estimates - tell a consistent story, even if none are fully free from concerns of exogeneity.

Instrument: Intersection Density Table 4 presents the first-stage coefficient estimates with intersection density as the sole instrument. Column 1, 2, 3, and 4 present results with no controls, a simple set of demographic controls, a full set of demographic controls, and a full set of demographic controls with city fixed effects. All three specifications indicate that intersection density strongly predicts experienced economic segregation. A one standard deviation increase in intersection density is associated with a $0.11 - 0.14$ standard deviation decrease in experienced economic segregation, depending on choice of specification. All specifications that include demographic controls exhibit F-statistics above the conventional threshold of 10, indicating that intersection density is a sufficiently strong instrument for experienced economic segregation. These results mirror the results from section 4.1. Specifically, the estimates are identical to the OLS estimates presented in panel A of Table 1.

Table 4: First Stage Least Squares Regressions

	Dependent variable:			
	Experienced Economic Segregation			
	(1)	(2)	(3)	(4)
Intersection Density	-0.039^{**}	-0.144^{***}	-0.124^{***}	-0.110^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.002	0.075	0.151	0.225
F Statistic	4.783^{**}	83.732^{***}	90.999^{***}	46.928^{***}

*p<0.1; **p<0.05; ***p<0.01

Notes: Stage 1 IV regression coefficients of experienced income segregation on intersection density. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

Table 5 presents 2SLS estimates of experienced economic segregation on friending bias, with intersection density as the sole instrument. Again, column 1, 2, 3, and 4 present results with no controls, a simple set of demographic controls, a full set of demographic controls, and a full set of demographic controls with city fixed effects. A one standard deviation decrease in experienced economic segregation, as predicted by intersection density, is associated with a $0.13 - 1.15$ standard deviation decrease in friending bias, depending on choice of specification. Controlling for a full set of demographics, and including city fixed effects achieves statistical significance for this relationship at the 0.01 level. Figure 11, which for consistency and ease of comparison mirrors the OLS specification of Figure 10 (that is, a full set of controls), shows the estimate of the effect of experienced economic segregation on friending bias. These results are consistent with the hypothesis that experienced economic segregation has a causal effect on cross-class friending bias.

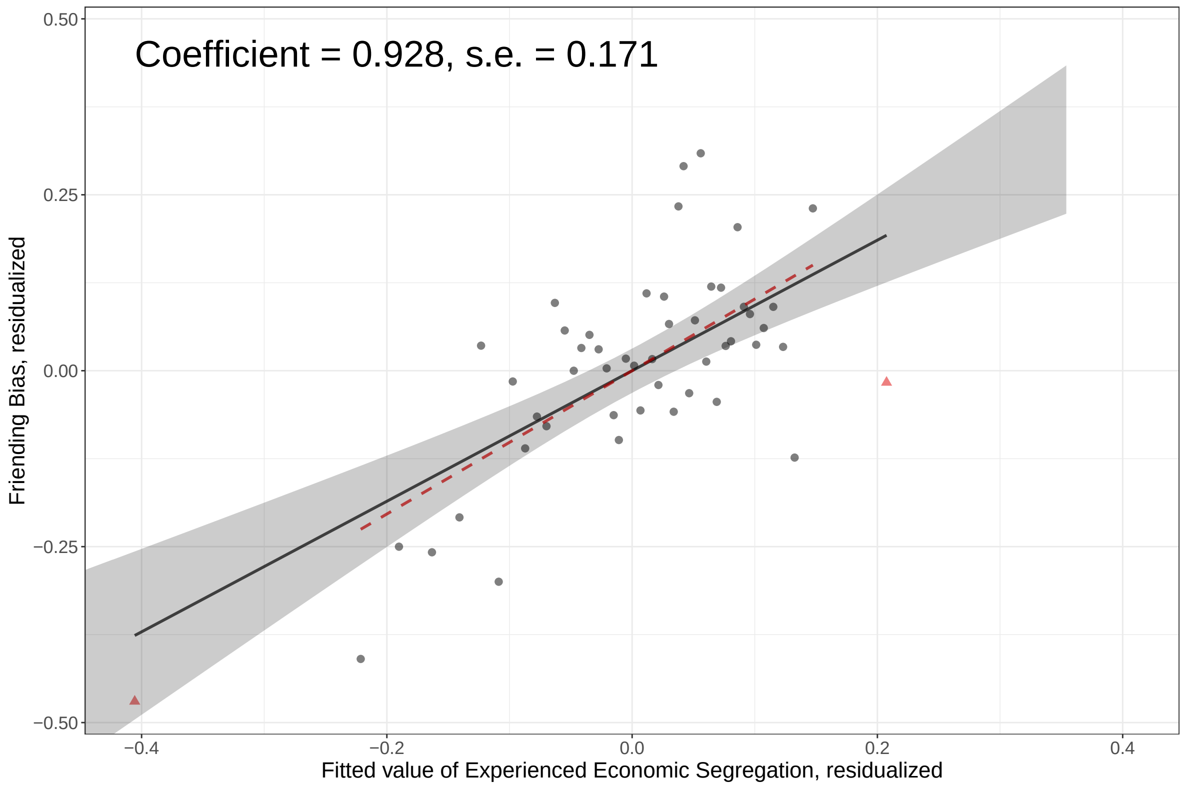
Table 5: Second Stage Least Squares Regressions

	Dependent variable:			
	Friending Bias			
	(1)	(2)	(3)	(4)
Experienced Economic Segregation (Predicted)	0.213***	0.132	0.928***	1.148***
	(0.019)	(0.125)	(0.192)	(0.269)
Population Density		0.056**	−0.156***	−0.192***
		(0.022)	(0.037)	(0.033)
Median Household Income		−0.453***	−0.253***	−0.186***
		(0.042)	(0.042)	(0.070)
Population			0.130***	0.141***
			(0.025)	(0.029)
Racial Diversity			0.340***	0.443***
			(0.041)	(0.064)
Unemployment Rate			−0.235***	−0.325***
			(0.064)	(0.089)
Constant	0.004	−0.047***	−0.031	
	(0.018)	(0.018)	(0.023)	
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	2,814	2,811	2,811	2,811
R^2	0.044	0.216	−0.257	−0.514

*p<0.1; **p<0.05; ***p<0.01

Notes: Two-stage least squares estimates of friending bias on experienced economic segregation, instrumented by intersection density. All variables are standardized to a z-score

Figure 11: Experienced Economic Segregation and Friending Bias



Notes: Binned scatter plot of stage 2 IV regression of cross-class friending bias on experienced economic segregation, instrumenting with street intersection density, at the ZIP code level. Number of bins = 50. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details). Red triangles are used to indicate the top and bottom 2.5% of the data by fitted values; the red dotted line indicates the regression fit after dropping observations in the top and bottom 2.5% of fitted values

Instruments: Urban Form Measures Here, I proceed with an analogous instrumental variable approach using all three urban form measures as instruments. As explained above, due to potential exclusion restriction violations, the results of this exercise should be interpreted as speculative, and I do not imply a causal relationship between experienced economic segregation and friending bias.

Table 6 presents the first-stage coefficient estimates with all four urban form measures as instruments. The four columns are analogous to the previous section. These results indicate that all three urban form measures strongly predict experienced economic segregation. A one standard deviation increase in intersection density, entertainment place density, and employment entropy area associated with 0.08, 0.21, and 0.11 standard deviation decreases in experienced economic segregation. Additionally, F-statistics for all specifications are above the threshold of 10, implying instrument relevance. These results are identical to the multivariate OLS estimates presented in Table 2.

Table 6: First Stage Least Squares Regressions

	Dependent variable:			
	Experienced Economic Segregation			
	(1)	(2)	(3)	(4)
Intersection Density	-0.065^{***}	-0.125^{***}	-0.084^{***}	-0.084^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Entertainment Place Density	-0.088^{***}	-0.199^{***}	-0.206^{***}	-0.179^{***}
	(0.018)	(0.023)	(0.022)	(0.022)
Employment Entropy	-0.237^{***}	-0.160^{***}	-0.109^{***}	-0.131^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.067	0.122	0.183	0.255
F Statistic	74.372^{***}	85.244^{***}	86.276^{***}	49.979^{***}

*p<0.1; **p<0.05; ***p<0.01

Notes: Stage 1 IV regression coefficients of experienced income segregation on three urban form measures: intersection density, entertainment place density, and employment entropy. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

Table 7 presents 2SLS estimates of experienced economic segregation on friending bias, with all three urban measures as instruments. Again, column 1, 2, 3, and 4 present results with no controls, a simple set of demographic controls, a full set of demographic controls, and a full set of demographic controls with city fixed effects. A one standard deviation decrease in experienced economic segregation, as predicted by the three urban form measures, is associated with a $0.18 - 0.26$ decrease in cross-class friending bias depending on choice of specification. This relationship is statistically significant at the 0.01 level regardless of specification.

The IV estimates tend to be larger than the corresponding OLS estimates by a factor of two to four. One explanation for this pattern is measurement error, which is inherent in my measure of experienced economic segregation given the noisy nature of cellphone mobility data. This noise exists for a variety of reasons. First, it is derived from a sample of the population over a selected time period and may not be entirely representative of the urban population. Second, device locations are recorded on regularly spaced time intervals and may not fully capture individual-level mobility. Finally, socioeconomic status is calculated as the median in the device's home census block and therefore does not reflect any variation in socioeconomic status within the census block. By instrumenting with urban form, which is partially based on census employment data, this measurement error in experienced economic segregation is reduced, potentially explaining the larger estimates from IV versus OLS analyses.

To examine the robustness of my instrumental variable approach, it is useful to note that the corresponding OLS estimates in Table 3 are very sensitive to city fixed effects. Moving from column 3 to 4 (excluding vs including city fixed effects) of Table 3 sees the OLS estimate drop by approximately one half. These changes in the OLS estimates suggest that some of the positive relationship between experienced economic segregation and friending bias could, for example, be explained by the fact that cities with lower friending bias simply have more places that attract people from different socioeconomic groups. By contrast, the corresponding IV estimates in Table 7 remain stable with the inclusion of city fixed effects. This stability suggests that the instruments successfully isolate exogenous variation in experienced economic segregation that is orthogonal to such confounding factors across cities.

Figure 12 presents the estimates of the effects of experienced economic segregation on friending bias controlling for the full set of demographic variables. This, as with Figure 11, is meant to mirror the OLS results from Figure 10 with an instrumental variables approach. Consistent with my hypothesis, these results provide evidence, albeit descriptive, that experienced economic segregation is associated with cross-class friending bias in American cities.

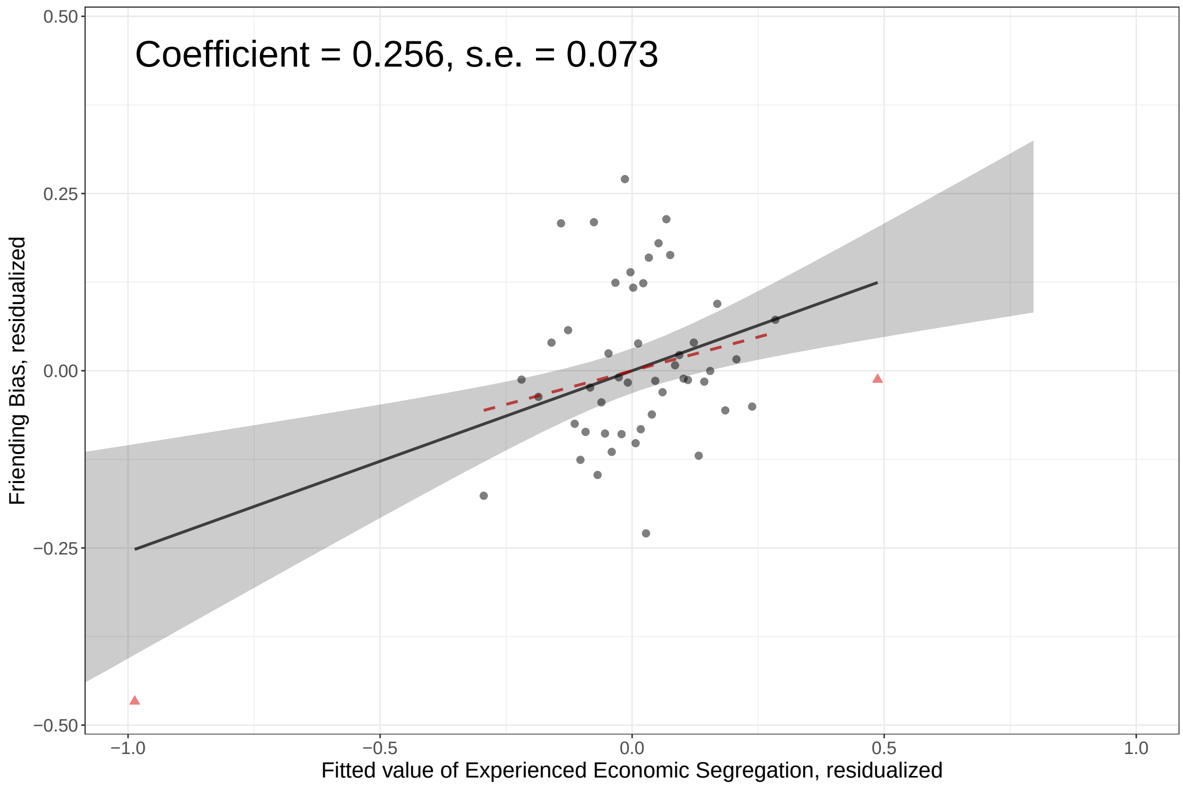
Table 7: Second Stage Least Squares Regressions

	Dependent variable:			
	Friending Bias			
	(1)	(2)	(3)	(4)
Experienced Economic Segregation (Predicted)	0.181*** (0.020)	0.177*** (0.066)	0.256*** (0.076)	0.213*** (0.083)
Population Density		0.050*** (0.018)	−0.054*** (0.021)	−0.123*** (0.019)
Median Household Income		−0.440*** (0.027)	−0.358*** (0.025)	−0.392*** (0.030)
Population			0.120*** (0.019)	0.155*** (0.019)
Racial Diversity			0.226*** (0.023)	0.249*** (0.027)
Unemployment Rate			−0.030 (0.031)	−0.037 (0.033)
Constant	0.005 (0.019)	−0.045*** (0.017)	−0.058*** (0.017)	
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	2,814	2,811	2,811	2,811
R^2	0.029	0.209	0.260	0.315

*p<0.1; **p<0.05; ***p<0.01

Notes: Two-stage least squares estimates of friending bias on experienced economic segregation, instrumented by three urban form measures: intersection density, entertainment place density, and employment entropy. All variables are standardized to a z-score.

Figure 12: Experienced Economic Segregation and Friending Bias



Notes: Binned scatter plot of stage 2 IV regression of cross-class friending bias on experienced economic segregation, instrumenting all three urban form measures, at the ZIP code level. Number of bins = 50. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details). Red triangles are used to indicate the top and bottom 2.5% of the data by fitted values; the red dotted line indicates the regression fit after dropping observations in the top and bottom 2.5% of fitted values

5 Discussion and Conclusion

The persistence of American economic inequality is cause for great concern. The likelihood of climbing the American socioeconomic ladder is far below what the *Land of Opportunity* should promise. Recent research by Chetty et al. found that cross-class friendships are the strongest known predictor of upward economic mobility. By combining this research with theories of urban design and social capital by Jane Jacobs and Gordon Allport respectively, I develop a hypothesis for reducing cross-class friending bias. Following Jacobs' theories, I hypothesize that certain forms of the urban built environment can increase unplanned cross-class interactions. These urban forms are small city blocks and mixed primary-use buildings. Additionally, I posit that entertainment places are conducive to cross-class interactions through their inherent social nature, and therefore increased entertainment place density should also increase unplanned cross-class interactions. Next, I use Allport's contact hypothesis to posit that increased cross-class interactions should reduce inter-class friending bias as they meet Allport's criteria of equal footing. Using urban built environment, mobile phone GPS location, and Facebook social network data, this paper empirically tests the hypothesized correlational chain from urban form to experienced cross-class interactions to inter-class friending bias.

There are two primary results from my analyses corresponding to the two stages of the hypothesized correlational chain. First, I explored the effects of the three urban built environment measures on experienced economic segregation. I find that all three urban forms negatively correlate with experienced economic segregation. These results hold when controlling for a vast set of demographic data the ZIP code level. Furthermore, they remain consistent when including city fixed effects. Second, I test the effects of experienced economic segregation on cross-class friending bias. I find that a 10% decrease in experienced economic segregation associates with a 0.54% decrease in friending bias. If a given person has 200 friends, this decrease will be equivalent to replacing one low-SES friend with a high-SES friend.

Broader Implications The consistency of the results when including and excluding city fixed effects motivates policy discussion at both the neighborhood and city levels. As new metropolitan areas are built, or plans are developed to improve existing urban areas, the effects of urban form on social dynamics should be considered. This paper provides evidence that smaller city blocks, increased primary building uses, and more entertainment places will all decrease experienced economic segregation. Despite these results, there are likely diminishing returns for all three urban forms. Indeed, as entertainment place density increases it is directly at odds with employment entropy. Additionally, there is a practical ceiling on how small city blocks can get. This paper also provides no stance on what negative effects are associated with the urban forms. For example, increase entertainment place density could be associated with higher levels of crime, create congestion effects, or displace amenities that provide other benefits.

Open areas for research There are two primary directions for further research. First, replicating these results along other axes of segregation would allow for consideration of more outcome variables. This paper focused on cross-class segregation and bias, with upward economic mobility as the motivation. Similar research could be conducted motivated by racial, ethnic, or gender based disparities. Second, this paper isolated three forms of urban built environment. Further research could expand on this by considering other urban forms that influence experienced economic segregation. Some such forms could be public transit access, quality or availability of public parks, general walkability, or mixed building ages. Expanding research along more axes of urban form would allow for increased understanding of the effects urban form on social behaviour.

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Appendix

A Summary Statistics

A.1 Demographics

Table 8: Summary Statistics for ZIP Code Level Demographic Data

Statistic	N	Mean	St. Dev.	Min	Median	Max
Population	23,088	13,722.710	15,789.140	0	6,697.5	122,814
Population Density (ppl/mi^2)	23,088	1,586.327	5,393.217	0.000	127.738	143,683.100
Racial Diversity (Simpson's Index)	23,086	0.246	0.196	0.000	0.189	0.792
Household Income (1000s of USD)	22,970	56.513	23.226	7.167	51.502	244.527
Unemployment Rate	23,088	0.043	0.024	0.000	0.039	0.558

Notes: Summary statistics for ZIP code level demographic data. Sample contains all ZIP codes available in the U.S. Data was obtained from the American Community Survey five year estimates from 2017-2021.

A.2 Urban Design

Table 9: Summary Statistics for ZIP Code Level Urban Design Measures

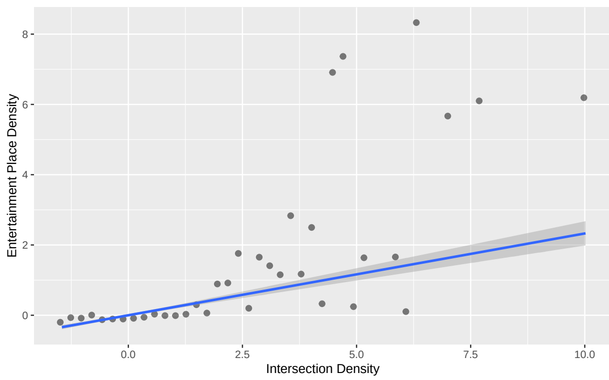
Statistic	N	Mean	St. Dev.	Min	Median	Max
Street Intersection Density	23,075	44.041	54.595	0.004	21.078	836.363
Employment Entropy	23,075	0.552	0.107	0.000	0.560	0.947
Entertainment Place Density	23,075	0.324	2.362	0.000	0.028	146.378

Notes: Summary statistics for ZIP code level urban built environment data. Sample contains all ZIP codes available in the U.S. Data was obtained from the Environmental Protection Agency's Smart Location Database.

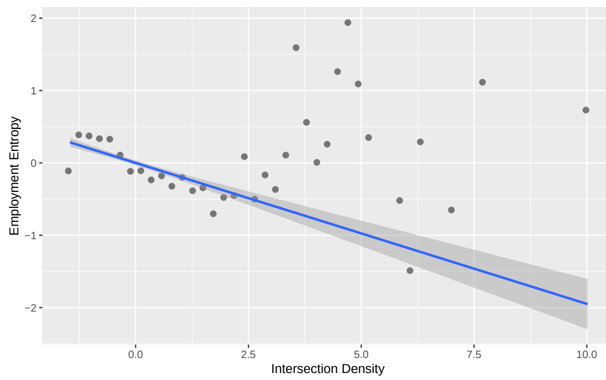
A.2.1 Urban Form Collinearity

Figure 13: Urban Form Collinearity

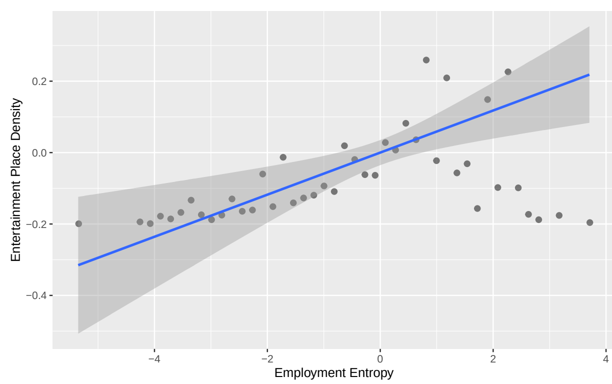
Panel A: Intersection Density and Entertainment Place Density



Panel B: Intersection Density and Employment Entropy



Panel C: Employment Entropy and Entertainment Place Density



Notes: Binned scatter plots between the three measures of urban form at the ZIP code level. Number of bins in all panels = 50. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

A.2.2 Employment Classifications

The eight employment classifications are specified below:

Table 10: Employment Classifications

Classification	NAICS Sectors
Retail Jobs	44, 45
Office Jobs	51, 52, 53, 55
Industrial Jobs	11, 21, 22, 23, 31-33, 42, 48-49
Service Jobs	54, 56, 81
Entertainment Jobs	71, 72
Education Jobs	61
Healthcare Jobs	62
Public Admin Jobs	92

Notes: Eight employment classifications used in the EPA's Smart Location Database, mapped to their corresponding NAICS sectors.

A.2.3 Place Type Density

Table 11: Summary Statistics for ZIP code Employment Density

Statistic	N	Mean	St. Dev.	Min	Median	Max
Density of Retail Jobs	3,100	0.667	2.747	0.0002	0.252	106.299
Density of Office Jobs	3,000	1.133	11.613	0.000	0.116	458.344
Density of Industrial Jobs	3,100	0.835	3.240	0.001	0.278	92.987
Density of Service Jobs	3,100	2.069	13.543	0.0003	0.300	340.594
Density of Entertainment Jobs	3,100	1.012	5.060	0.000	0.225	146.378
Density of Education Jobs	3,100	0.644	3.711	0.000	0.131	121.230
Density of Healthcare Jobs	3,100	1.089	3.684	0.000	0.258	81.197
Density of Public Admin Jobs	3,100	0.443	5.535	0.000	0.016	188.140

Notes: Summary statistics for ZIP code level employment density by employment classification. Sample contains all ZIP codes available in the U.S. Data was obtained from the Environmental Protection Agency's Smart Location Database.

A.2.4 Employment Entropy

Employment Entropy is calculated as follows:

$$-E/(\ln(8))$$

Where:

$$E = (\text{Retail Jobs}/\text{Total Jobs}) * \ln(\text{Retail Jobs}/\text{Total Jobs}) +$$

$$(\text{Office Jobs}/\text{Total Jobs}) * \ln(\text{Office Jobs}/\text{Total Jobs}) +$$

$$(\text{Industrial Jobs}/\text{Total Jobs}) * \ln(\text{Industrial Jobs}/\text{Total Jobs}) +$$

$$(\text{Service Jobs}/\text{Total Jobs}) * \ln(\text{Service Jobs}/\text{Total Jobs}) +$$

$$(\text{Entertainment Jobs}/\text{Total Jobs}) * \ln(\text{Entertainment Jobs}/\text{Total Jobs}) +$$

$$(\text{Education Jobs}/\text{Total Jobs}) * \ln(\text{Education Jobs}/\text{Total Jobs}) +$$

$$(\text{Healthcare Jobs}/\text{Total Jobs}) * \ln(\text{Healthcare Jobs}/\text{Total Jobs}) +$$

$$(\text{Public Admin Jobs}/\text{Total Jobs}) * \ln(\text{Public Admin Jobs}/\text{Total Jobs})$$

A.3 Experienced Income Segregation

Table 12: Summary Statistics for Zip Code Experienced Economic Segregation in 11 cities

Statistic	N	Mean	St. Dev.	Min	Median	Max
Experienced Income Segregation	3,100	0.439	0.108	0.086	0.423	0.939

Notes: Summary statistics for ZIP code level experienced economic segregation. Sample contains all ZIP codes available from the Cuebiq dataset from 11 major metropolitan areas (see section 2.2 for details).

A.4 Cross-Class Bias

Table 13: Summary Statistics for ZIP Code Friending Bias

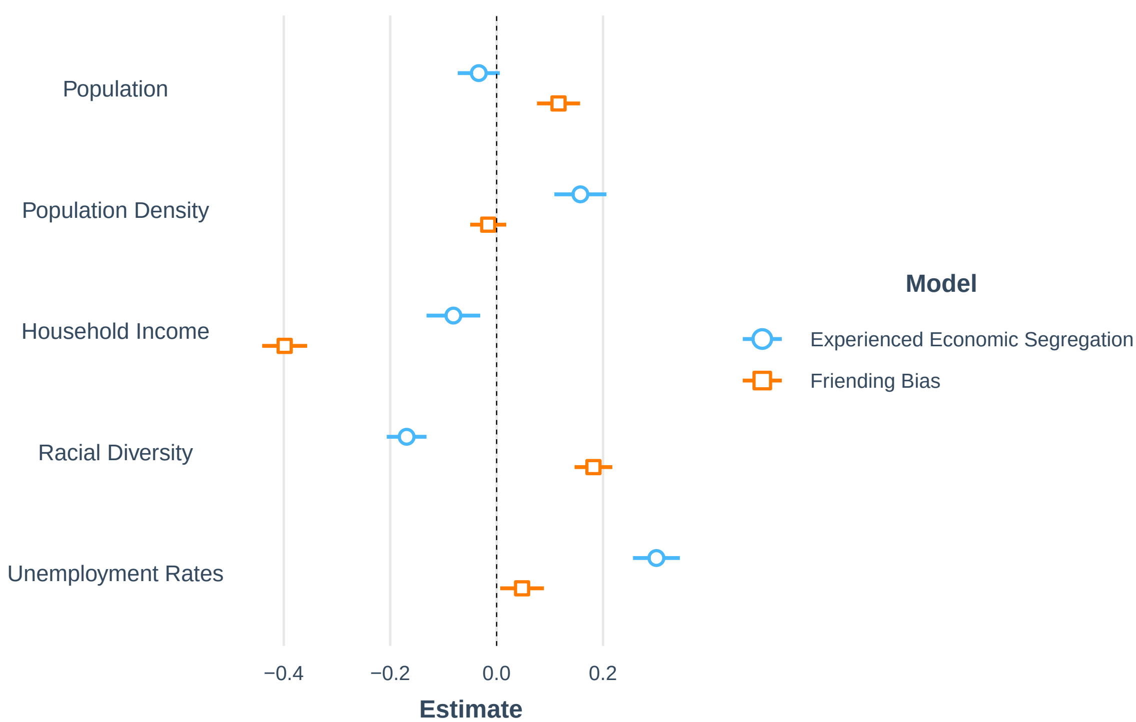
Statistic	N	Mean	St. Dev.	Min	Median	Max
Friending Bias	18,379	0.057	0.072	−0.143	0.049	0.520
Economic Connectedness	19,028	0.883	0.219	0.235	0.876	1.708
Exposure	18,379	1.005	0.239	0.171	1.007	1.750

Notes: Summary statistics for ZIP code level social capital measures. Sample contains all ZIP codes available from the Facebook social network data from Chetty et al. (2022a).

B Interaction Effects: Demographics

Within the set of ZIP codes contained in the 11 cities, I explore the relationships between demographic data and urban form, experienced economic segregation, and friending bias. This will allow me to better understand how all variables vary nationally. All variables are scaled to mean 0 and standard deviation 1, so coefficients can be interpreted in standard deviations. I run OLS regressions of all variables on all demographics and present the results in Tables 14 and 15. Figure 14 and 15 plot the resulting coefficients from these regressions for experienced economic segregation and friending bias (Figure 14) and urban form (Figure 15).

Figure 14: Demographics and Experienced Economic Segregation and Friending Bias



Notes: Coefficient plots of experienced economic segregation and friending bias against all demographic variables. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

Alesina and La Ferrara (2000) provide one explanation for the negative relationship between racial diversity and friending bias.

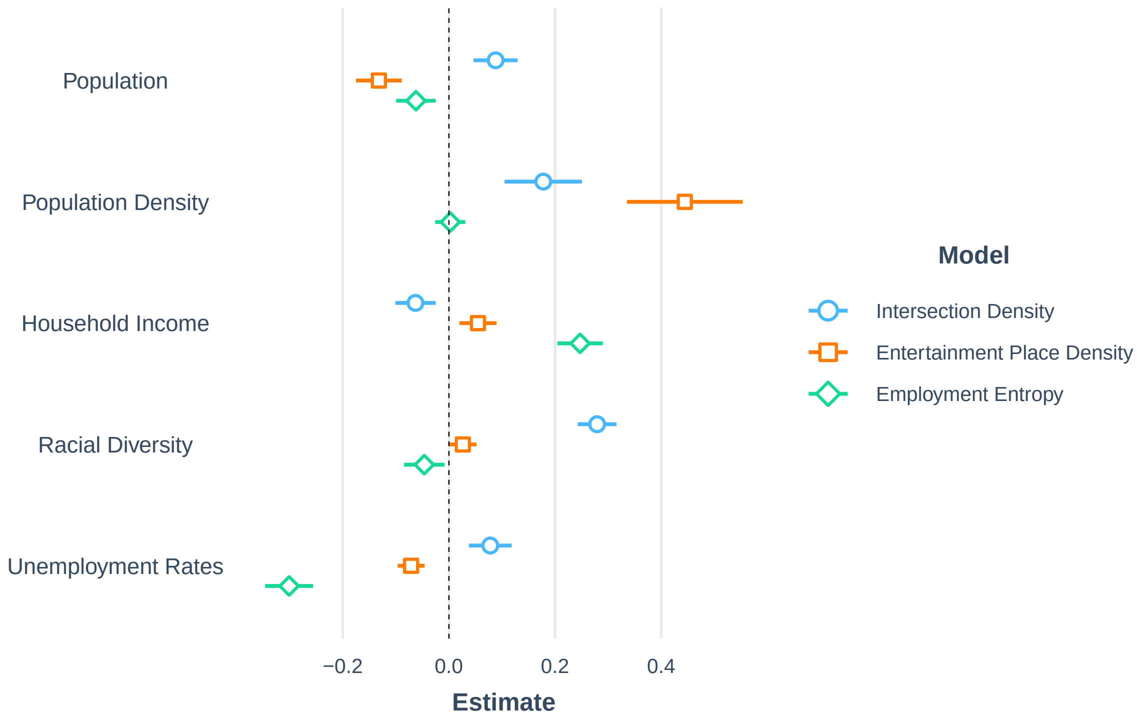
Table 14: Demographics and Experienced Economic Segregation and Friending Bias

	Dependent variable:	
	Experienced Economic Segregation	Friending Bias
Population	-0.034^{*}	0.116^{***}
	(0.020)	(0.019)
Population Density	0.157^{***}	-0.016
	(0.018)	(0.017)
Median Household Income	-0.081^{***}	-0.398^{***}
	(0.021)	(0.022)
Racial Diversity	-0.169^{***}	0.182^{***}
	(0.019)	(0.019)
Unemployment Rates	0.300^{***}	0.048^{**}
	(0.021)	(0.021)
Constant	0.001	-0.068^{***}
	(0.017)	(0.016)
Mean	0	0
Std. Dev	1	1
Observations	3,087	2,811
R^2	0.139	0.270
Adjusted R^2	0.138	0.269
Residual Std. Error	0.928 (df = 3081)	0.855 (df = 2805)
F Statistic	99.526^{***} (df = 5; 3081)	207.833^{***} (df = 5; 2805)

*p<0.1; **p<0.05; ***p<0.01

Notes: Regression coefficients for experienced economic segregation and friending bias on all demographic variables. All variables are standardized to a z-score.

Figure 15: Demographics and Urban Form



Notes: Coefficient plots of three measures of urban form: intersection density, entertainment place density, and employment entropy against all demographic variables. All variables are standardized to a z-score. The sample is from ZIP codes in 11 major metropolitan areas (see section 2.2 for details).

Table 15: Demographics vs Experienced Economic Segregation and Friending Bias

	Dependent variable:		
	Intersection Density	Entertainment Place Density	Employment Entropy
	(1)	(2)	(3)
Population	0.088***	−0.132***	−0.062***
	(0.019)	(0.016)	(0.018)
Population Density	0.178***	0.444***	0.002
	(0.017)	(0.015)	(0.017)
Median Household Income	−0.063***	0.055***	0.247***
	(0.019)	(0.017)	(0.019)
Racial Diversity	0.279***	0.026*	−0.046***
	(0.018)	(0.016)	(0.018)
Unemployment Rates	0.078***	−0.071***	−0.301***
	(0.019)	(0.017)	(0.019)
Constant	−0.002	−0.009	0.002
	(0.016)	(0.013)	(0.015)
Observations	3,087	3,087	3,087
R^2	0.234	0.238	0.265
Adjusted R^2	0.233	0.237	0.264
Residual Std. Error (df = 3081)	0.869	0.750	0.856
F Statistic (df = 5; 3081)	188.731***	192.292***	222.724***

*p<0.1; **p<0.05; ***p<0.01

Notes: Regression coefficients for three urban form measures: intersection density, entertainment place density, and employment entropy on all demographic variables. All variables are standardized to a z-score.

C Intersection Density and Experienced Economic Segregation

Table 16: Intersection Density and Experienced Economic Segregation

	Dependent variable:			
	Experienced Economic Segregation			
Intersection Density	-0.039^{**}	-0.144^{***}	-0.124^{***}	-0.110^{***}
	(0.018)	(0.019)	(0.019)	(0.019)
Population Density		0.158^{***}	0.179^{***}	0.099^{***}
		(0.018)	(0.019)	(0.019)
Median Household Income		-0.218^{***}	-0.089^{***}	-0.135^{***}
		(0.018)	(0.020)	(0.022)
Population			-0.023	0.007
			(0.020)	(0.020)
Racial Diversity			-0.135^{***}	-0.151^{***}
			(0.020)	(0.021)
Unemployment Rates			0.310^{***}	0.313^{***}
			(0.021)	(0.020)
Constant	0.000	-0.001	0.0003	0.761^{*}
	(0.018)	(0.017)	(0.017)	(0.442)
Mean	0	0	0	0
Std. Dev	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.002	0.075	0.151	0.225

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: Regression coefficients for experienced economic segregation on street intersection density Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

D Entertainment Place Density and Experienced Economic Segregation

Table 17: Entertainment Place Density and Experienced Economic Segregation

	Dependent variable:			
	Experienced Economic Segregation			
Entertainment Place Density	-0.117^{***}	-0.243^{***}	-0.235^{***}	-0.209^{***}
	(0.018)	(0.023)	(0.022)	(0.021)
Population Density		0.215^{***}	0.262^{***}	0.181^{***}
		(0.020)	(0.020)	(0.021)
Median Household Income		-0.163^{***}	-0.068^{***}	-0.109^{***}
		(0.018)	(0.020)	(0.022)
Population			-0.065^{***}	-0.033^{*}
			(0.020)	(0.020)
Racial Diversity			-0.163^{***}	-0.177^{***}
			(0.019)	(0.020)
Unemployment Rates				-0.726^{*}
				(0.441)
Constant	0.000	-0.003	-0.002	0.882^{**}
	(0.018)	(0.017)	(0.016)	(0.438)
Mean	0	0	0	0
Std. Dev	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.014	0.092	0.170	0.241

*p<0.1; **p<0.05; ***p<0.01

Notes: Regression coefficients for experienced economic segregation on entertainment place density. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.

E Employment Entropy and Experienced Economic Segregation

Table 18: Employment Entropy and Experienced Economic Segregation

	Dependent variable:			
	Experienced Economic Segregation			
Employment Entropy	−0.229***	−0.161***	−0.113***	−0.131***
	(0.017)	(0.019)	(0.019)	(0.020)
Population Density		0.110***	0.158***	0.075***
		(0.018)	(0.018)	(0.019)
Median Household Income		−0.121***	−0.053**	−0.099***
		(0.019)	(0.021)	(0.022)
Population			−0.041**	−0.010
			(0.020)	(0.020)
Racial Diversity			−0.174***	−0.190***
			(0.019)	(0.020)
Unemployment Rates			0.266***	0.265***
			(0.021)	(0.021)
Constant	0.000	−0.00001	0.001	0.747*
	(0.017)	(0.017)	(0.017)	(0.442)
Mean	0	0	0	0
Std. Dev	1	1	1	1
Simple Controls	No	Yes	Yes	Yes
Full Controls	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	3,100	3,087	3,087	3,087
R^2	0.053	0.078	0.148	0.228

*p<0.1; **p<0.05; ***p<0.01

Notes: Regression coefficients for experienced economic segregation on employment entropy. Column 1 includes no controls, column 2 includes simple controls (population density and median household income), column 3 includes full controls described in section 2.4, column 4 includes full controls and city fixed effects. All variables are standardized to a z-score.