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# **When the Rich Meet the Poor: Interactions with the Homeless in New York City**

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# When the Rich Meet the Poor: Interactions with the Homeless in New York City\*

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April 19, 2017

## Abstract

As inequality rises in the United States, the rich and poor are increasingly unlikely to interact with one another. We use data on “311” calls reporting homeless individuals in New York City between 2010 and 2016 to determine whether the rich are more likely to see or interact with the unsheltered homeless population. Calls reporting a homeless encampment to police and calls requesting social service assistance for a homeless individual are respectively 0.9 percent and 1.2 percent more frequent for every one percent increase in a neighborhood’s median income. These relationships are partly mediated by the concentration of subway station entrances in more affluent areas, suggesting that public transportation may play a role in bringing the rich and the homeless together. We also examine the response by police to encampment calls and by social service workers to assistance calls. Police response times are faster, and social service response times are slower in more affluent neighborhoods. To the extent that these responses disproportionately discourage interactions between the rich and the homeless, we find that they are attributable to broader measures of police efficiency across neighborhoods, and differences across, rather than within, the nonprofit organizations that respond to social service requests.

*JEL classification:* D31; I32; I38; K42; R12; R28

**Keywords:** Segregation; Inequality; Homelessness

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# 1 Introduction

At the same time that increasing attention is paid to growing levels of inequality in the United States, Americans are personally experiencing less inequality in their daily lives. Residential segregation based on income has increased every decade since 1970, with the rich becoming particularly isolated, mirroring the growth of income-based segregation in schools (Bischoff and Reardon 2014; Owens, Reardon and Jencks 2016). Meanwhile, research has indicated that interaction between the rich and poor matters. Access to more affluent neighborhoods improves long term outcomes for young children (Chetty, Hendren and Katz 2016; Chetty and Hendren 2016). And personally identifying with the poor can lead to more altruistic behavior by the rich (Batson et al. 1981; Small and Loewenstein 2003; Small, Loewenstein and Slovic 2007). Some suggest that the increasing isolation of the rich from the poor could be more severe, leading to the breakdown of institutions that promote a healthy society (Murray 2012).

Segregation along class lines may be uniquely avoided in the case of unsheltered homelessness, however. The unhoused do not have to pay the high rent in expensive housing markets, and the unsheltered homeless are not dependent on where others are willing to accept homeless shelters when choosing where to sleep. Indeed, the wealth of residents in a particular area may draw more unsheltered homeless individuals who can benefit from extensive transportation systems, generous city and social services, and private charity. Local ordinances regarding living outdoors may partly discourage unsheltered homelessness, but the wealthiest cities in the United States nonetheless retain highly visible unsheltered homeless populations. While unsheltered homelessness may be among the final vestiges of rich meeting poor in their daily lives, evidence of these interactions has to this point been anecdotal.

In order to understand where interactions occur and how authorities respond, we use novel data on calls made in New York City reporting the unsheltered homeless population. Specifically, we analyze over 75,000 calls to law enforcement or social service agencies to

either complain about or request assistance for homeless individuals, over the period 2010-2016. We first analyze the neighborhoods in which interactions occur. When controlling only for neighborhood population, we find that a one percent increase in median income is associated with 0.9 percent more complaints about encampments and 1.2 percent more requests for assistance. This pattern is not a function of differences in overall call rates, as “311” calls regarding non-homeless issues are associated with slightly lower levels of neighborhood median income. We next examine whether the relationship between neighborhood affluence and call frequency can be explained by the presence of subway stations or homeless shelters in affluent areas. Controlling for subway stations reduces the elasticity of calls with respect to median income by about 38 percent for encampment calls and 23 percent for assistance calls. Controlling for beds in homeless shelters and supportive housing for the formerly homeless increases the elasticity of both types of calls with respect to median income. Given that larger concentrations of beds are associated with greater call frequencies, this suggests that locating homeless services outside of affluent areas may reduce the likelihood of interactions between the rich and the unsheltered homeless population.

Next, we analyze the response by authorities to 311 calls to help determine whether disproportionate pressure is placed on unsheltered individuals to vacate affluent neighborhoods. We find that police response times to encampment calls are 33 percent faster in neighborhoods at the top decile of median income compared with neighborhoods at the bottom decile, after controlling for neighborhood population, temperature and time-related fixed effects. When controlling for police response time to non-homeless related “311” complaint calls this relationship weakens significantly, suggesting that differential overall police efficiency across neighborhoods plays a major role in explaining this result. Although apparently attributable to broader forces, our results nonetheless suggest that police actions place disproportionate pressure on unsheltered individuals to vacate more affluent areas.<sup>1</sup>

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<sup>1</sup>This assumes that police efforts discourage unsheltered homelessness rather than encourage it. Such an assumption is consistent with theories of broken windows policing, in which police efforts concentrate on removing perceived disorder to make neighborhoods safer (Wilson and Kelling 1982). Evidence from Los Angeles suggests that when applied to homeless encampments in particular (under Police Commissioner

Meanwhile, response times by social service workers to assist the homeless are 25 percent slower in neighborhoods at the top decile of median income compared with neighborhoods at the bottom decile. This association weakens considerably when controlling for differences in overall response times for the four separate nonprofit organizations that conduct outreach to the homeless. Thus, there is no evidence that city authorities exert pressure on any given organization to respond differently across neighborhoods within its jurisdiction. Whether slower social service response times in more affluent neighborhoods nonetheless disproportionately discourage interactions between the rich and the homeless depends on whether social service workers encourage or discourage unsheltered homelessness. The stated goal of outreach providers according to the city’s Department of Homeless Services website is to “engage street homeless individuals and encourage them to move from the streets into housing,” suggesting that slower responses in more affluent areas would create lesser pressure for unsheltered individuals to vacate these areas.<sup>2</sup> At the same time, efforts to assist individuals on the streets could make it easier to remain there, suggesting greater pressure on unsheltered individuals to vacate more affluent areas.

One contribution of this paper is to highlight an unexplored forum of colocation among people of different economic classes. A substantial literature has documented the evolving state of income diversity in neighborhoods in the United States, finding that income-based segregation has generally increased over the past several decades in conjunction with increased income inequality (Jargowsky 1996; Fischer 2003; Watson 2009; Bischoff and Rear-don 2014). Ganong and Shoag (2015) find that local land use regulations have contributed as well to income sorting across states. Others have found that the poor in particular are increasingly segregated from other classes (Abramson, Tobin and VanderGoot 1995; Lichter, Parisi and Taquino 2012). These studies focus on people with residences and thus exclude the unsheltered homeless. While the unsheltered homeless population is too small to af-

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William Bratton who has also served as New York City Police Commissioner between 2014 and 2016), this approach significantly reduced crime (Berk and MacDonald 2010).

<sup>2</sup>Website available at <https://www1.nyc.gov/site/dhs/outreach/street-outreach.page>.

fect these patterns, the visibility of those living on the streets may nonetheless represent a relevant source of contact with the poor from the perspective of the urban rich.

Another contribution of this paper is to analyze how public policy in particular shapes the locational choices of the poor. In other contexts, policy has either done little to reverse income-based segregation or has reinforced it. Public housing tenants live in neighborhoods with higher poverty rates than those in which unassisted low income tenants live (Newman and Schnare 1997). Housing units financed by the Low Income Housing Tax Credit have little or no effect on reducing concentrated poverty and may have greater welfare benefits when placed in low-income areas (Ellen, Horn and O'Regan 2016; Diamond and McQuade 2016). Recipients of tenant based housing vouchers live in neighborhoods with only slightly lower poverty rates than the neighborhoods in which they would have otherwise lived (Jacob and Ludwig 2012; Metzger 2014). Land use regulations have the consequence of increasing housing prices, which can drive out poor households but potentially increase homelessness (Edward L. Glaeser and Saks 2005; Raphael 2010; Ganong and Shoag 2015). In the case of unsheltered homelessness, we find evidence that local authorities exert disproportionate pressure on unsheltered individuals to vacate more affluent areas in response to "311" calls.

Finally, this paper contributes to a general literature on homelessness. Many have examined the determinants of homeless population sizes, finding that climate and housing prices are major factors (Bohanon 1991; Honig and Filer 1993; O'Flaherty 1996; Quigley, Raphael and Smolensky 2001; Byrne et al. 2013; Corinth 2017). Several have examined the determinants of homeless shelter populations in New York City and Philadelphia (Cragg and O'Flaherty 1999; Culhane et al. 2003; O'Flaherty and Wu 2006; O'Flaherty and Wu 2008). This is the first paper to study unsheltered homelessness within a geographic area using precise geospatial data, rather than aggregate counts at larger geographic levels. We provide new insights including that interactions with the unsheltered homeless population are more frequent in neighborhoods with higher median incomes, more public transportation and more homeless shelter and supportive housing beds. It is also the first paper to document city ac-

tions that directly confront unsheltered homeless individuals, including individual responses by the police and social workers.

This paper proceeds as follows. Section 2 describes the “311” call data. Section 3 analyzes the neighborhoods in which homeless interactions occur. Section 4 analyzes the response by authorities to homeless interactions. Section 5 discusses the results and policy implications. Section 6 concludes.

## 2 “311” Call Data

New York City maintains a “311 system” in which residents or others visiting the city can report on a large array of city conditions via phone, an app or a website. We refer to all reports, regardless of mode of submission, as calls. These calls range from complaining about the unsanitary condition of a building to reporting a faulty traffic signal. In total, there are almost 300 “complaint” types. The information collected via the 311 system is used by city employees to improve government services, and the data is publicly accessible. Since January 2010, approximately 14.3 million calls have been placed across all complaint types. Figure 1 shows the monthly time series. We focus on two specific types of calls—complaints about homeless individuals setting up encampments and requests for homeless assistance. The New York Police Department responds to complaint calls concerning homeless encampments, while homeless assistance calls get forwarded to the Department of Homeless Services, which dispatches social workers to locate the homeless individual and offer any needed assistance. Placing calls requires individuals to provide their exact location and to describe the individual about which they are calling, allowing for dispatched authorities to find the homeless individual in question.

Observed calls do not provide a random sample of where homeless individuals are located, of all instances in which residents or city visitors observe homeless people, or of all instances in which the community responds to homeless people in need of assistance. An observation is



only created when an individual perceived to be homeless and/or a homeless encampment is observed by another individual, and when that individual calls 311 or uploads the information via the 311 app.<sup>3</sup> We may expect, however, that by capturing interactions in which an individual exerted effort to either complain about an encampment or request assistance, we observe the interactions in which the caller is most bothered or concerned.<sup>4</sup> To the extent that these types of interactions are spatially correlated with less intensive interactions such as thoughts of concern, annoyance, conversation or simple observation that do not result in calls, our results will be informative about interactions involving the unsheltered homeless population in general.

Throughout our analysis, we distinguish between calls that are classified as complaint calls about homeless individuals establishing encampments and those that are classified as homeless assistance. There are several reasons for doing so. First, the mechanisms for submitting information varies. For complaints about encampments, the only way to submit information throughout the study period is to place a phone call to the 311 call center. Requests for homeless assistance, meanwhile, can be submitted by phone call or the 311 app, although only requests submitted via the 311 app can be observed prior to March 2016.<sup>5</sup> When a phone call is placed, the 311 operator classifies the call as one that pertains to either homeless assistance or a complaint about an encampment. A second important distinction is to whom the information is forwarded—complaint calls about encampments are forwarded to the police department while calls for assistance are forwarded to city’s Department of Homeless Services. Third, the type of call may reflect the motivation of the caller—compassion or concern may be more likely to motivate requests for homeless assistance, while annoyance may be more likely to motivate complaints about an encampment.

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<sup>3</sup>It is possible, although anecdotally rare, that an individual requests assistance for him or herself via the 311 system.

<sup>4</sup>It should be noted, however, that we do not observe 911 calls about homeless individuals, which may reflect the greatest levels of concern. There are also calls that the city categorizes as “inquires” that are not uploaded to the 311 database. These calls are determined not to merit inclusion in the categories for which they were submitted.

<sup>5</sup>See Figure A1 in the appendix for screen shots of the 311 app.

Figure 2 plots the monthly volume of encampment calls, which were tracked beginning in January 2010. Encampment call volume exhibits a predictable seasonal pattern, peaking in the summer months and ebbing in the winter months, likely reflecting fewer encampments actually present and/or fewer people making the effort to call 311 about individuals establishing encampments in the winter. Monthly call volumes also trend upward, especially in the years 2014 through 2016. This coincides with a new mayor, Bill de Blasio assuming office, although it is unclear whether the upward trend is the result of administration policies, such as perceived backing off of proactive policing, or other factors such as knowledge among city residents of the 311 system as a way to report homeless individuals (Stewart and Goodman 2015). For example, a number of media outlets published accounts of increasing homeless-related 311 calls beginning in August 2015, which in turn may have fueled a continual increase in call volume (Fanelli 2015). Another possible reason is a general increase in homelessness. As Figure 3 shows, the number of adults without children in city homeless shelters grew steadily over the sample period, growing by 87 percent between January of 2010 and December of 2016.<sup>6</sup> Of course, this could also reflect movement of a constant overall homeless population from the streets into shelters, potentially reflecting higher quality shelter options.

Figure 4 plots the monthly volume of homeless assistance calls between June 7, 2013 and March 14, 2016.<sup>7</sup> While assistance calls could be submitted via phone or the 311 app during this period, only requests submitted via the app include call location and thus are included in our analysis (and this figure). During this period, response times by social workers dispatched to the homeless individual are unavailable, and so these data are used only in our analysis of locations in which calls are placed. Figure 5 plots the monthly volume of homeless assistance calls between March 15, 2016 and December 31, 2016. These calls come from three sources, including (i) requests made via the 311 app, (ii) requests made via phone, and (iii) reports

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<sup>6</sup>The population of families in shelters is less relevant given that homeless counts generally find zero children in unsheltered locations.

<sup>7</sup>Assistance calls could be placed before this period but call locations and response times were not recorded and thus are not considered in our analysis.

from city employees dispersed to find unsheltered homeless individuals throughout the city as part of its new HOME-STAT (Homelessness Outreach and Mobile Engagement Street Action Teams) program. We are unable to distinguish between these sources, and therefore, an unknown subset of these calls do not reflect interactions between civilians and unsheltered homeless individuals. Thus, we do not use these calls for our analysis of locations in which calls are placed. However, unlike calls placed during the earlier period, we observe response times by social workers for these calls. Thus, we use these calls for analysis of response times by authorities to requests for assistance.

For each call, we observe the exact latitudinal and longitudinal coordinates from which it was placed. Figure 6 maps each encampment and assistance call placed in 2015. We also observe the exact time and date of each call. Figure 7 and Figure 8 show the distribution of each call type over each hour of the day. Calls are most frequent between the hours of 8:00am and 12:00pm, and are least frequent in the early morning hours. Finally, we observe the length of time it takes authorities to respond to each call and the outcome (for assistance calls, this is true only beginning March 15, 2016). Outcomes are listed in Table A1 in the appendix, along with the distribution of response times. For analysis of response times, we only include calls for which authorities were dispatched to the homeless individual. Figure 9 shows the distribution of response times for each call type restricted to calls with these outcomes. It is important to note that response times are based on the time between the call being placed and when the responding police officer or social service worker indicates that the issue has been resolved, which may occur somewhat later than the time at which the homeless individual was actually approached. However, as long as reported resolution times are not systematically different based on locational characteristics of the call, conclusions analyzing the difference in response times across characteristics will be unaffected.

### 3 Locations of Interactions

This section analyzes the locations of calls, focusing on characteristics of the neighborhoods in which calls are placed. We use data at the census tract level from the American Community Survey (ACS) five-year pooled sample over 2011-2015. Table 1 shows the average neighborhood characteristics of homeless encampment calls, homeless assistance calls, all non-homeless related 311 calls, and for the average New York City neighborhood (weighted by resident population). Notably, neighborhoods in which non-homeless 311 calls are placed are similar to the average New York City neighborhood. The average median neighborhood income across New York City neighborhoods is approximately \$58,000, while the average non-homeless 311 call takes place in a neighborhood with a median income of nearly \$57,000. Compared to the average city neighborhood, the average neighborhood in which non-homeless 311 calls occur has a similar poverty rate (18.4 percent versus 17.6 percent), percent of white residents (41 percent versus 43 percent), and a similar median monthly rent (\$1,346 versus \$1,341). Finally, the average neighborhood in which non-homeless 311 calls occur has 6.3 percent of households with annual incomes above \$200,000, compared to the average New York City neighborhood in which 6.6 percent of households have such incomes.

To the contrary, the average neighborhood in which a homeless-related 311 call is made is dramatically different from the average New York City neighborhood. For homeless encampment calls, the average median income is \$84,000, and for homeless assistance calls it is \$97,000. Respectively, for the average neighborhood in which encampment calls and assistance calls are made, poverty rates are 12 percent and 10 percent, the percent of households that are white is 57 percent and 62 percent, and median monthly rents are \$1,795 and \$1,998. 15.9 percent of households have annual incomes above \$200,000 in the average neighborhoods in which encampment calls are made, and 20.0 percent have such incomes in the average neighborhood in which assistance calls are made. In other words, the typical homeless-related 311 call is made in a neighborhood that is substantially less poor, more white, more expensive, and richer when compared to either where other 311 calls are made

or to the average New York City neighborhood. Figure 10 shows maps indicating 311 call volumes and median income by precinct; it is clear that homeless-related calls are concentrated in more affluent neighborhoods.

We next explore the determinants of call frequency to help understand why calls are more frequent in more affluent neighborhoods. Specifically, we aggregate all calls that occurred in a given census tract over the sample period for each call type, and regress call volumes on neighborhood-level covariates. Table 2 shows summary statistics for call volumes and covariates, including the number of subway stations and beds in homeless shelters and permanent supportive housing targeted to adults without children. Data on subway station locations come from the New York City Metropolitan Transportation Authority, and data on homeless shelter and supportive housing locations come from the U.S. Department of Housing and Urban Development. Figure 11 displays the locations of all subway stations as well as homeless service concentration by neighborhood. We also control for neighborhood population to account for higher propensities to report on homeless individuals when there are more residents nearby. Finally, because the variance of the number of calls of each type far exceeds its mean, we use a negative binomial regression that relaxes the constraint that mean and variance are equal in the case of Poisson regressions for count data.

Table 3 presents regression results for encampment calls. We use the logarithm of median income and the inverse hyperbolic sine transformation of the number of subway stations and homeless service beds. The inverse hyperbolic sine transformation approximates the logarithmic transformation while still being defined at zero, thus allowing us to treat estimates as elasticities. When controlling only for neighborhood population, a one percent increase in median income is associated with 0.89 percent more encampment calls. More subway stations and homeless service beds are also strongly and positively associated with more encampment calls. Moreover, subway stations have a strong mediating effect on the association between median income and encampment call frequency. Including subway stations reduces the elasticity between median income and encampment calls by 0.34. Homeless service beds

have the opposite effect, increasing the elasticity between median income and encampment calls by 0.06. Thus, the concentration of subway stations in affluent neighborhoods may help bring the rich and unsheltered homeless together, while locating homeless services in less affluent areas may modestly pull them apart.

Table 4 presents regression results for assistance calls. Results are very similar to those for encampment calls. The elasticity between median income and assistance calls is 1.19 when controlling only for population. Subway stations and homeless service beds are strongly associated with more assistance calls, and the same mediating patterns as observed with encampment calls are found. In this case, however, homeless services appear to be more important in pulling the rich and the homeless apart. Finally, Table 5 shows results for non-homeless related calls. Here, the association between call frequency and median income is much smaller and negative. The associations with shelter beds and subway stations are also much smaller but still positive. This suggests that the patterns we observe for homeless-related calls are not simply a reflection of where 311 calls in general are placed. Appendix Tables A2, A3 and A4 show results using ordinary least squares and replicate the same basic findings for each call type.

## 4 Response to Interactions

Having documented the types of neighborhoods in which homeless interactions take place as well as potential mechanisms that determine their locations, we next analyze how authorities respond to calls. Here we seek to determine whether city actions exert disproportionate pressure on unsheltered homeless individuals to vacate more affluent areas. Response times are available for all homeless encampment calls, which get forwarded to the police department, as well as for homeless assistance calls placed beginning in March 2016, which get forwarded to social service agencies. We restrict the sample to calls in which either a police officer or caseworker was actually dispatched to the homeless individual. This removes

14 percent of encampment calls from our sample; among these, 49 percent did not elicit a response because a description of the homeless individual was unavailable, and 10 percent were outside of the New York Police Department’s jurisdiction (other excluded call categories are shown in Table A1 in the appendix). Meanwhile, 11 percent of all assistance calls are removed in our main specification. Thus, nonrandom decisions to dispatch police officers and social workers to calls is unlikely to significantly bias estimates. Among those included in our sample, a non-negligible number of calls have response times exceeding 24 hours, and so we analyze median response times and employ quantile regression techniques that are robust to outliers. This allows us to avoid taking a stance on whether response times of these lengths are meaningful, except to the extent that they represent slower times than the median, potentially because authorities did not follow up with the homeless individual at any time.<sup>8</sup>

Figure 12 shows the median response times for neighborhoods in each decile of median income. For encampment calls, the median response time is 32 percent faster in neighborhoods in the highest income decile compared to neighborhoods in the lowest income decile. This pattern is reversed for assistance calls, for which the median response time is 37 percent slower when comparing the highest decile neighborhood to the lowest decile neighborhood. In the appendix, Figure A3 shows police response times for non-homeless calls by income decile, while Figure A4 and Figure A5 show response times using income groupings based on constant absolute dollar ranges.

We next examine the determinants of response times. We enter neighborhood median income as a continuous variable for some specifications, and for others, we include a set of dummies based on the decile of neighborhood income across all New York City neighborhoods weighted by their population. This allows us to examine non-linear associations between neighborhood affluence and response time. In addition to median income, we include proximity to the nearest subway station, daily maximum city-level temperature, hour of day

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<sup>8</sup>Results based on ordinary least squares that exclude calls with response times over 12 hours are shown in the appendix with similar results.

effects, and year-month effects as covariates.<sup>9</sup> Temperature data come from the National Oceanic and Atmosphere Administration, Global Summary of Day Data. For regressions predicting response times to encampment calls, we also include the median response time in a given neighborhood in a given month to all other calls to which the police department responds. This variable accounts for differences in police efficiency due to differences in staffing, officer quality and other factors that may affect police response to homeless encampment calls. The extent to which this measure of police efficiency mediates any relationship between neighborhood affluence and police response time can provide insights into mechanisms underlying this relationship. Fortunately, we observe 2.9 million calls to which the police respond, allowing us to control for police efficiency at the neighborhood-month level. For regressions predicting response times to assistance calls, we include a set of indicator variables based on the nonprofit organization assigned the particular call. The city contracts out to four separate nonprofit organizations that each have responsibility for homeless outreach in an entire borough, with one organization responsible for two boroughs.<sup>10</sup> These indicator variables can help determine whether any differential response times across neighborhoods is driven by differences across organizations or within organizations. Table 6 shows summary statistics for response times and covariates.

Table 7 presents quantile regression results for encampment calls. When controlling for temporal variables only, including year-month fixed effects, hour of day fixed effects and average daily temperature, there is a significant negative relationship between median income and response time. A one percent increase in neighborhood median income is associated with a response time that is 0.21 percent faster. Closer proximity to the nearest subway station reduces response times but only modestly mediates the relationship between response time and median income. Meanwhile, controlling for police efficiency in responding to all other

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<sup>9</sup>Figure A2a and Figure A2b in the appendix show the distribution of calls across distance to the nearest subway station.

<sup>10</sup>The Manhattan Outreach Consortium responds to calls in Manhattan, Common Ground responds to calls in Brooklyn and Queens, BronxWorks responds to calls in the Bronx, and Project Hospitality responds to calls in Staten Island.



complaints reduces the association between response time and median income substantially, suggesting that faster response times to encampment calls in more affluent neighborhoods is driven largely by police resource constraints or broader department priorities. A similar pattern emerges when allowing response times to more flexibly respond to neighborhood incomes. Response times are 33 percent faster in neighborhoods in the highest decile of median income compared to neighborhoods in the lowest decile, when controlling only for temporal factors. When controlling for proximity to the nearest subway station and police efficiency, response times are only 10 percent faster in the most affluent neighborhoods compared to the least.<sup>11</sup>

Table 8 presents quantile regression results for assistance calls. Here, the relationships for spatial variables are reversed.<sup>12</sup> On the basis of specification (2), a one percent increase in median income is associated with a 0.11 percent increase in response time. Closer proximity to the nearest subway station increases response times. Including fixed effects for the non-profit organization receiving the call almost completely eliminates the association between neighborhood median income and response time, suggesting that organizations themselves do not respond differentially to neighborhoods within their jurisdictions on the basis of affluence. When considering median income deciles, response times are 23 percent slower in the highest decile neighborhood relative to the lowest, which is again mediated by inclusion of indicator variables for the nonprofit organizations that respond to calls.<sup>13</sup>

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<sup>11</sup>Table A7 in the appendix shows encampment results based on the period from March 15, 2016 through December 31, 2016 in order to align with the same period used for assistance calls. Results are similar.

<sup>12</sup>Interestingly, response times to assistance are slower in colder temperatures. If the response of social service agencies is motivated by compassion, we would expect responses to be faster in colder weather when homeless individuals face greater health risks. However, our sample is based only on March 15 through December 31 of 2016, and so this result could reflect a trend of decreasing response times in the city that remains after controlling for month fixed effects.

<sup>13</sup>Table A8 in the appendix shows assistance results based on excluding calls in which the homeless individual could not be found, with results that are largely similar.

## 5 Discussion

In recent decades, class-based segregation across neighborhoods has grown. As a result, the rich and poor may have fewer opportunities to see or interact with one another. Homelessness, in theory, may be an exception. Higher housing prices have been theoretically and empirically linked to larger homeless populations. While homeless shelters can be built in lower income neighborhoods, there is less the city can directly do to locate unsheltered homeless individuals in less affluent neighborhoods. Moreover, greater access to public transportation and charitable services could further bring the rich and unsheltered homeless together.

Our results suggest that interactions with the unsheltered homeless population are indeed concentrated in more affluent neighborhoods. And subway stations appear to play an important role in doing so. This result is consistent with Glaeser, Kahn and Rappaport (2008) who find that the poor are attracted to cities in order to gain access to public transportation. Results for the homeless population could reflect preferences for access to public transportation or subway stations could proxy for other spatial characteristics such as more panhandling opportunities or access to local establishments. Given that non-homeless related 311 calls are much less strongly associated with subway stations, this result does not appear to be a function solely of where 311 calls are placed.

While unsheltered homelessness in theory and according to the evidence here bucks the trend of segregation between rich and poor, the unsheltered population represents only a small fraction of the poor. According to the latest annual homeless count conducted in January 2016, there were just over 176,000 people across the country found unsheltered in the United States, which amounts to less than one percent of all poor adults (U.S. Department of Housing and Urban Development 2016; Proctor, Semega and Kollar 2016). However, if unsheltered homeless individuals are extremely visible, they may constitute a relevant source of interaction with the poor from the perspective of the rich. Even in this case, it is important to note that the unsheltered homeless population is not representative of the broader poor

population. For example, 7 percent of unsheltered homeless people are children, compared to 34 percent of poor people; and 70 percent of unsheltered homeless people are male compared to 44 percent of poor people.

Another important caveat to these results is that we do not observe the identity of those placing calls about homeless individuals. For example, people commuting to work or visiting city parks in affluent areas, rather than residents of those areas, may be the people making 311 calls. Even in this case, however, the fact that these interactions take place in neighborhoods with high concentrations of richer households suggests that the rich are more likely to observe the homeless individuals who are the subject of calls than households living in less affluent neighborhoods. A final caveat is that analysis is based on reports of homeless individuals through New York City's "311" system, which may not be representative of interactions with the homeless across the city. We find, however, that non-homeless 311 calls are made in neighborhoods that are very similar to the average city neighborhood, and so it does not appear that people in less affluent neighborhoods are less likely to utilize the 311 system. Also, both complaint calls about encampments and homeless assistance calls are markedly higher in affluent neighborhoods. Thus, our findings do not seem to be explained by people in more affluent neighborhoods simply being more (less) compassionate, in which case we would expect assistance (complaint) calls to be higher but complaint (assistance) calls to be lower.

Aside from documenting a novel forum of colocation between rich and poor, this paper also documents city actions that may reinforce segregation between the rich and homeless. Reducing residential segregation on the basis of income and race has been a longstanding goal of housing policy, although one at which policies have often failed or even been counter-productive. Unsheltered homelessness appears to be an extreme phenomenon in which the rich and poor are brought together. From our analysis of the city's response to interactions, however, it appears that disproportionate police pressure is placed on unsheltered individuals to vacate more affluent neighborhoods. Meanwhile, social service workers are slower to

respond in more affluent areas. On the one hand, if the effect of their response is to bring the unsheltered homeless into shelter (consistent with the stated purpose of the city’s outreach efforts), then this would create disproportionate pressure on unsheltered individuals to remain in affluent areas. On the other hand, if their response makes it easier to live on the streets, then it would create disproportionate pressure on unsheltered individuals to vacate affluent areas.

While the patterns we document are important for understanding how city actions shape locational outcomes of unsheltered homeless individuals, they do not imply direct motivations for separating the unsheltered homeless population from those in more affluent neighborhoods. Our results for police response times are driven in large part by broader measures of police efficiency in responding to other calls, which could in turn be driven by fewer demands on police officers in affluent areas to more serious issues which do not get reported via the 311 system. Slower response by social service workers in more affluent neighborhoods is driven by differences in response times across, rather than within, nonprofit organizations. This suggests that city authorities do not exert pressure on any given organization to respond differently to calls in the more affluent neighborhoods within its jurisdiction.<sup>14</sup>

Regardless of motivation, whether differential response to unsheltered homelessness across neighborhoods is socially optimal depends on the costs of enforcement and assistance in different areas as well as any benefits or costs that accrue to homeless and non-homeless individuals. For example, if the rich are made disproportionately more compassionate from interactions with the homeless, it may be inefficient to drive homeless individuals from affluent neighborhoods. Moreover, the unsheltered homeless may particularly value the amenities of affluent neighborhoods including subway stations and charitable efforts. How these benefits should be weighed against the nuisance or health hazards from individuals sleeping in particular areas depends on their costs and society’s values.

Beyond the question of whether disproportionate pressure should be placed on unshel-

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<sup>14</sup>It is also possible that outreach providers that are slower in resolving 311 calls are more efficient in their general outreach efforts.

tered homeless individuals to vacate specific types of neighborhoods is the broader question of whether pressure to vacate the streets in general is socially optimal. Given that interactions are concentrated in more affluent areas, even a uniformly applied policy response that was effective in reducing unsheltered homelessness would decrease interactions between the rich and the poor. Any benefits from these interactions, however, are almost surely dwarfed by the large social costs of unsheltered homelessness. Such costs accrue from frequent use of emergency rooms, hospitals and jails (Culhane, Metraux and Hadley 2002). Encouraging unsheltered homelessness is an inefficient and inhumane way to bring the rich and poor together.

## 6 Conclusion

We use novel data from calls about the unsheltered homeless population in New York City to determine the types of neighborhoods in which interactions with the unsheltered homeless occur. We find that both complaint calls about encampments and assistance calls are more frequent in neighborhoods with higher median incomes. This relationship is partly mediated by the prevalence of subway stations, suggesting that public transportation plays an important role in bringing the rich and unsheltered homeless together. Patterns of response to interactions are documented as well. Police responses to encampment calls are faster, and social service responses to assistance calls are slower in more affluent neighborhoods. To the extent that city actions disproportionately discourage interactions between the rich and the homeless, they appear to be attributable to broader levels of police efficiency across neighborhoods, and differences across, rather than within, social service nonprofit organizations that conduct outreach to the homeless.

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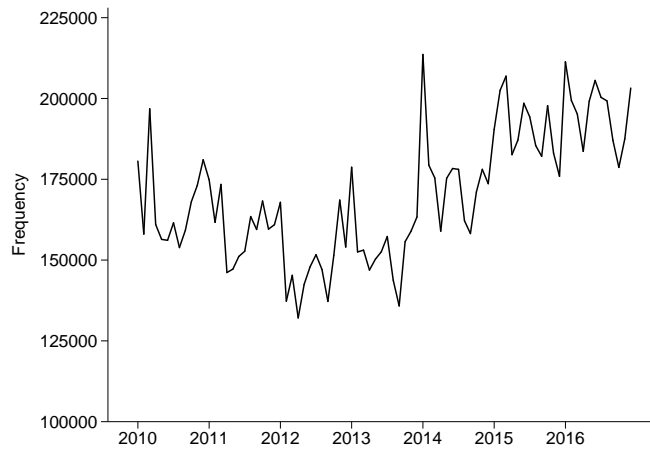


Figure 1: Monthly 311 calls: 2010–2016

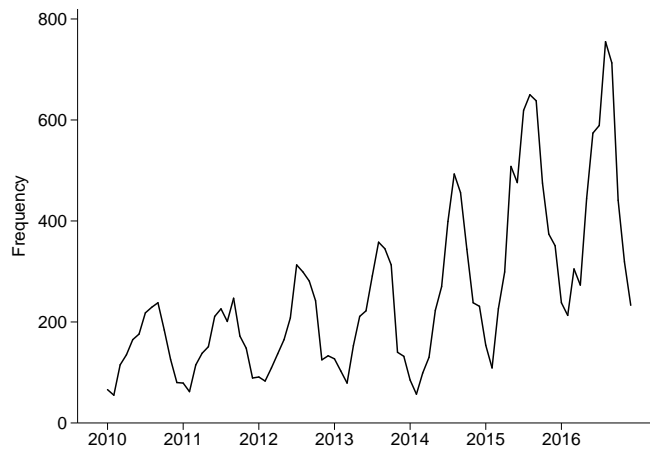


Figure 2: Monthly homeless encampment calls: 2010–2016

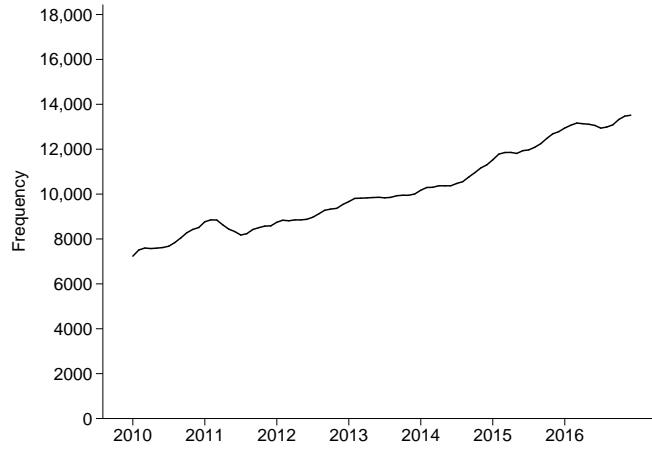


Figure 3: Average monthly population of adults without children in New York City shelters: 2010–2016

*Source:* New York City Department of Homeless Services

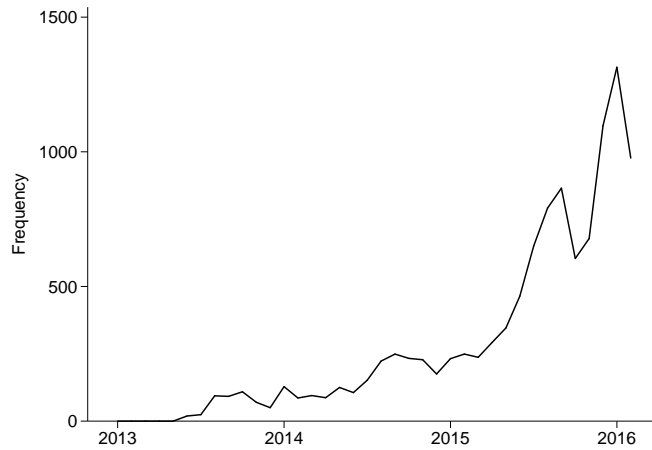


Figure 4: Monthly homeless assistance calls: June 2013–February 2016

Note: There were 1,516 assistance calls placed between March 1, 2016 and March 14, 2016 (not shown in the figure).

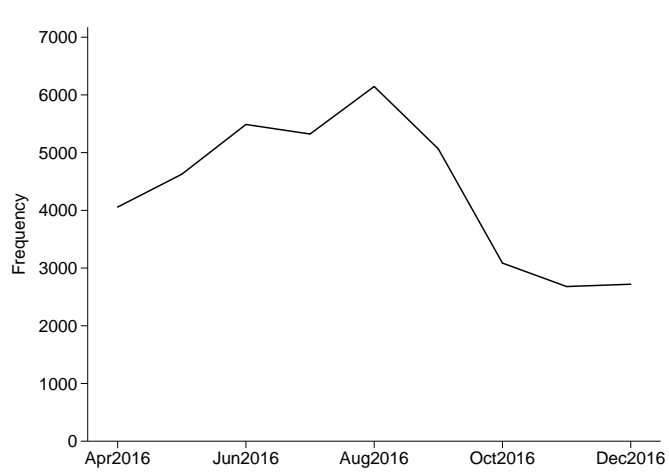
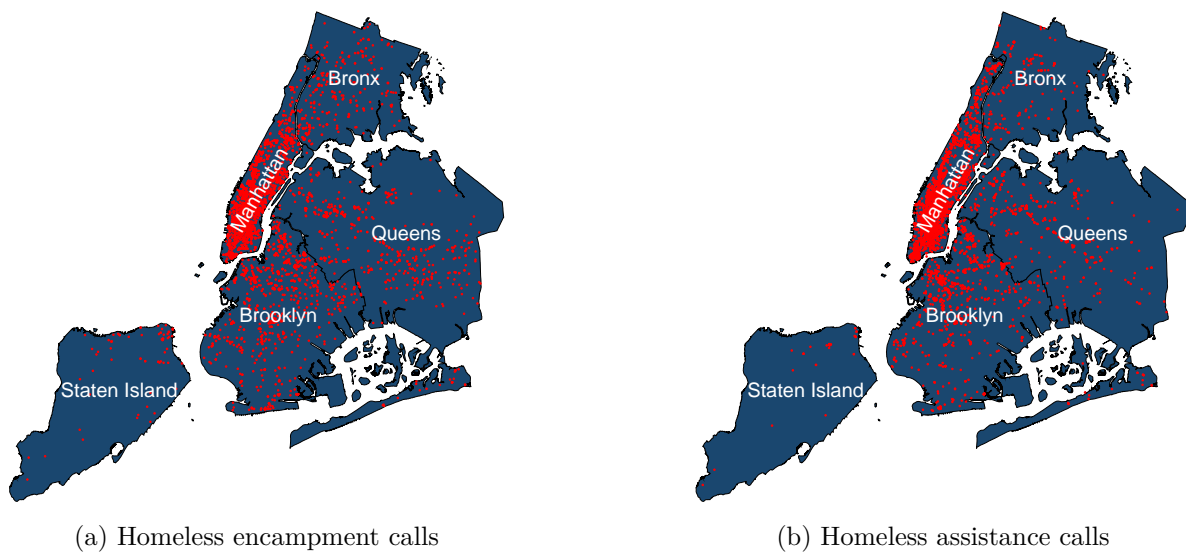


Figure 5: Monthly homeless assistance calls: April 2016–December 2016

Note: There were 2,104 assistance calls placed between March 15, 2016 and March 31, 2016 (not shown in the figure).



(a) Homeless encampment calls

(b) Homeless assistance calls

Figure 6: Locations of homeless encampment and assistance calls, 2015

Note: Each dot represents one call.

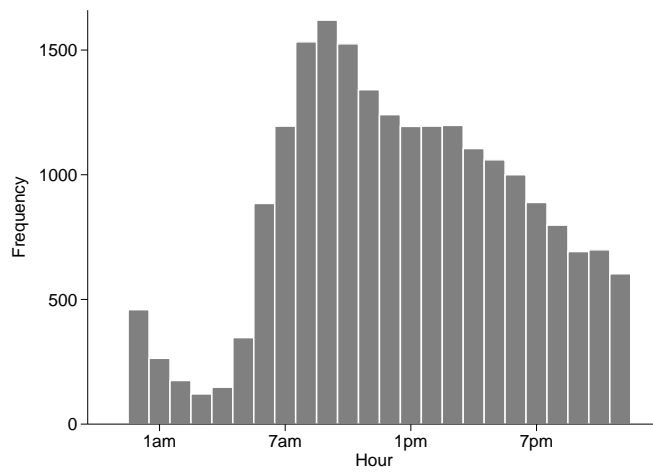


Figure 7: Homeless encampment call frequency by hour of day: 2010–2016

Note: All encampment calls, made between January 1, 2010 and December 31, 2016 are included.

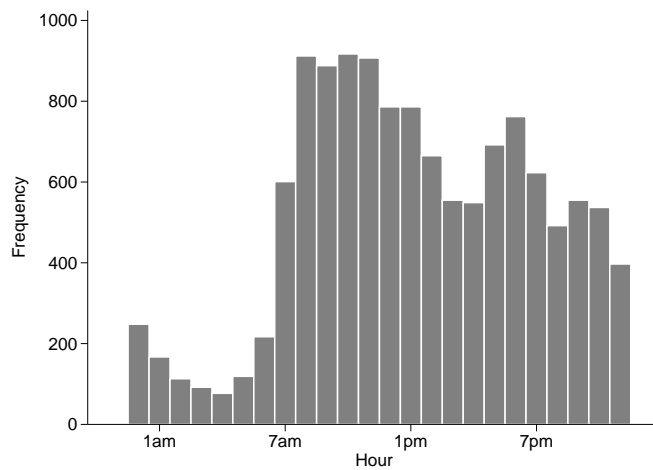


Figure 8: Homeless assistance call frequency by hour of day: 2013–2016

Note: All assistance calls made between June 7, 2013 and March 14, 2016 are included.

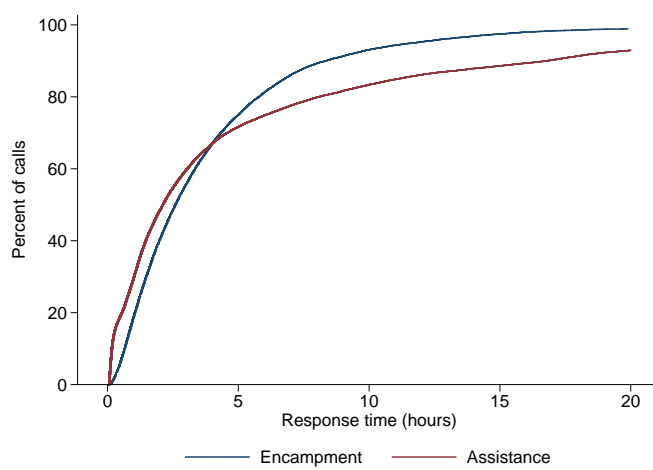
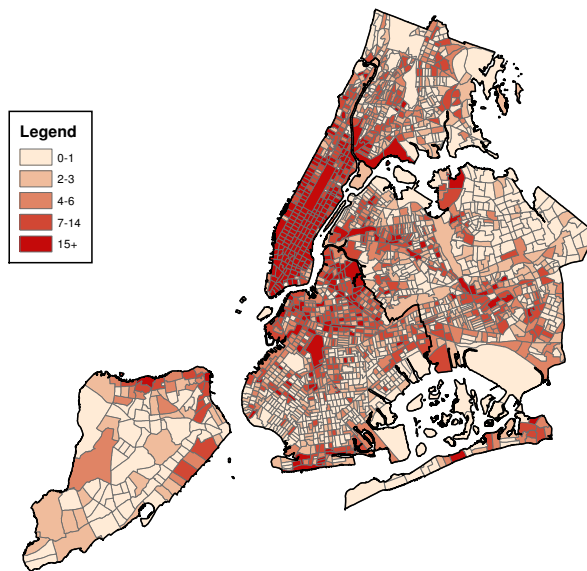
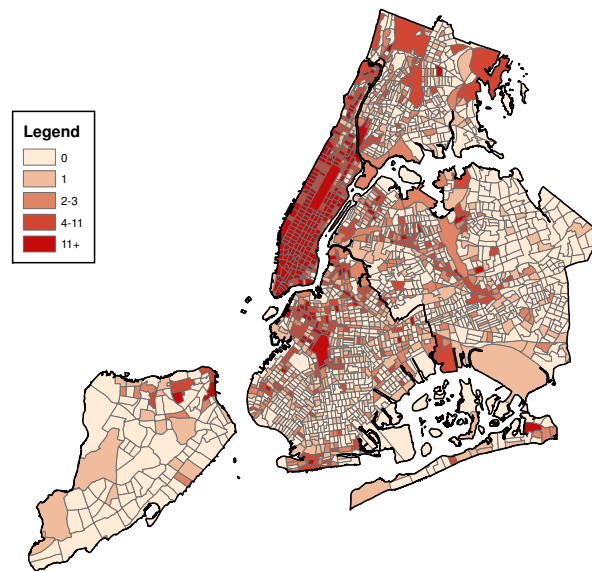


Figure 9: Cumulative distribution of response times by call type

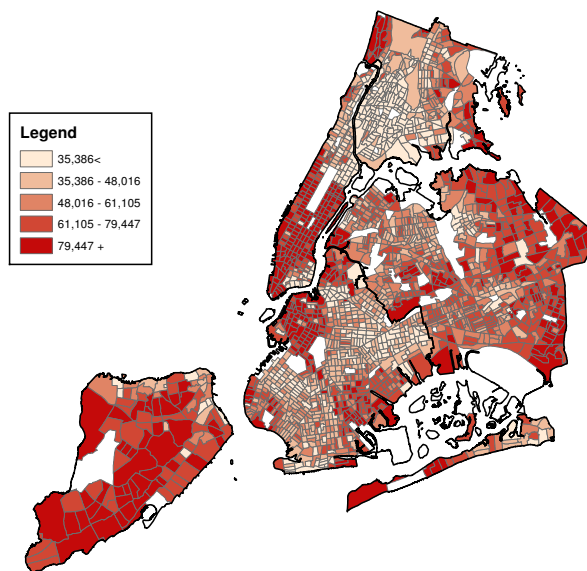
Note: Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.



(a) Homeless encampment calls



(b) Homeless assistance calls



(c) Median Income

Figure 10: Call frequency and median income by census tract

Note: All encampment calls, made between January 1, 2010 and December 31, 2016, are included. All assistance calls made between June 7, 2013 and March 14, 2016 are included. Median income is based on the 2011-2015 ACS pooled sample

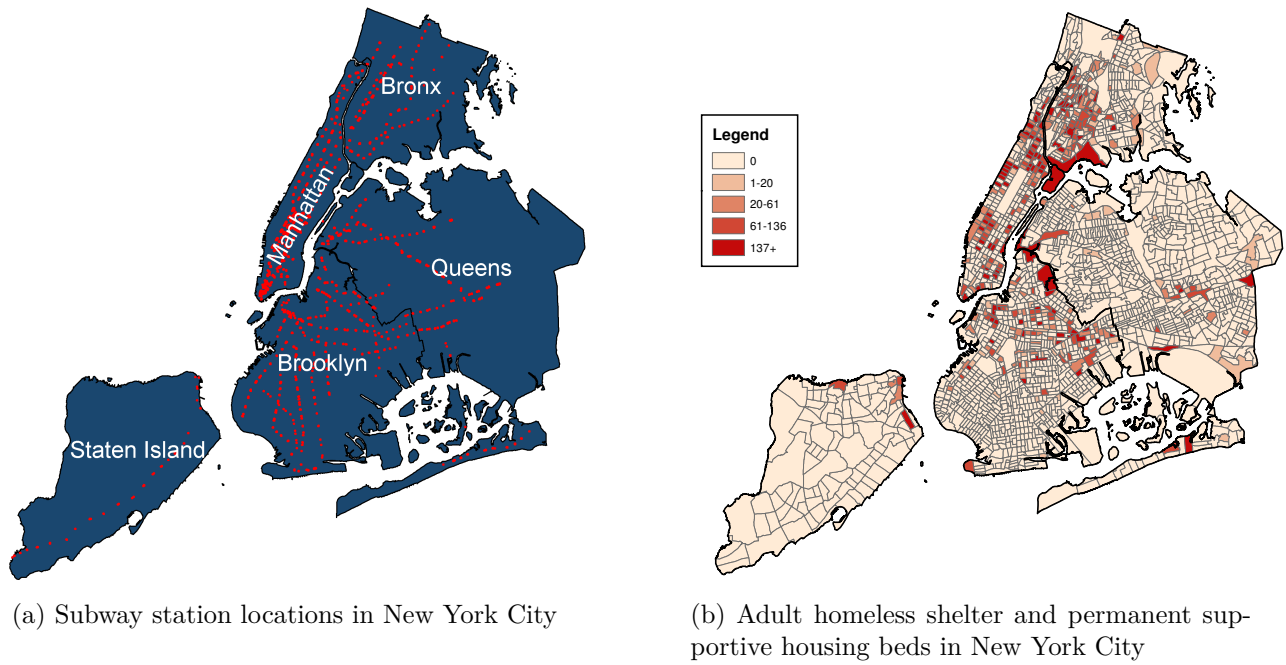


Figure 11: Subway stations and homeless services in New York City

Source: New York City Open Data, Subway Entrances; U.S. Department of Housing and Urban Development, Homeless Inventory Count, 2015

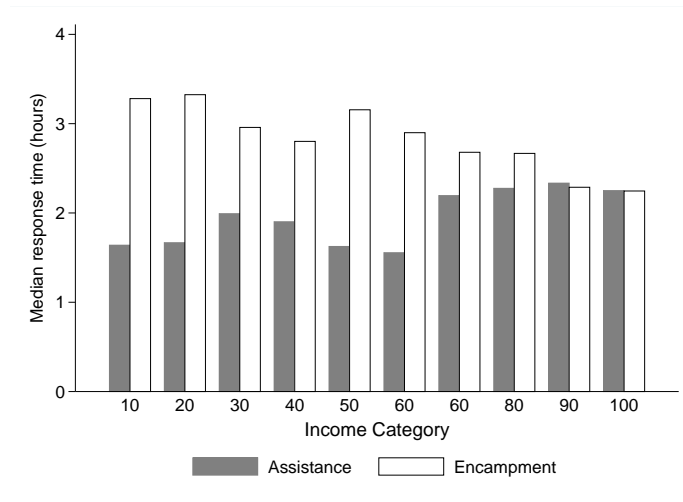


Figure 12: Median response time to homeless encampment and assistance calls by median income decile

Note: Income categories are expressed in percentiles. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.

Table 1: Neighborhood characteristics of “311” calls

	Encampment calls	Assistance calls	Non-homeless calls	NYC average
Median Rent (\$)	1,795	1,998	1,346	1,341
% in range (thousands of \$)				
0–10	9.1	8.3	11.1	10.6
10–15	4.8	4.3	6.4	6.2
15–25	8.5	7.5	11.1	10.9
25–35	6.9	5.9	9.4	9.2
35–50	9.1	7.7	11.9	11.8
50–75	13.1	11.9	15.7	15.7
75–100	10.3	10.1	10.7	10.9
100–150	13.9	14.6	12.0	12.5
150–200	8.3	9.6	5.3	5.5
>200	15.9	20.0	6.3	6.6
Median Income (\$)	83,893	96,572	56,507	58,188
Average Income (\$)	126,120	145,954	77,876	80,023
% Below Poverty Line	12.0	9.6	18.4	17.6
% White	57.0	62.4	40.6	43.3
% Black	16.6	11.8	26.9	24.5
% Hispanic	19.7	16.1	31.1	28.9

Note: All encampment calls, made between January 1, 2010 and December 31, 2016, are included. All assistance calls made between June 7, 2013 and March 14, 2016 are included. Non-homeless calls made between January 1, 2010 and December 31, 2016 are included. The average New York City neighborhood is based on the 2011-2015 ACS pooled sample, and all statistics are weighted based on neighborhood population. Median income estimates in two neighborhoods are top-coded at \$250,000.

Table 2: Summary statistics, neighborhood level variables

	Mean	Median	Std. dev.	Min	Max
Encampment calls	9.74	3	23.89	0	364
Assistance calls	5.69	0	18.71	0	206
Non-homeless calls	5,857.25	4,901	3,946.22	10	39,021
Population	3,888	3,550	2,240	0	28,926
Median income	59,283	5,4563	29,384	9,829	250,000
Subway stations	0.88	0	2.11	0	36
Homeless shelter and supportive housing beds	22.14	0	109.49	0	3,424

Note: There are a total of 2,167 neighborhoods. All encampment calls, made between January 1, 2010 and December 31, 2016, are included. All assistance calls made between June 7, 2013 and March 14, 2016 are included. All non-homeless related calls made between January 1, 2010 and December 31, 2016 are included. Median income estimates in two neighborhoods are top-coded at \$250,000.



Table 3: Negative binomial estimates: homeless encampment calls

	(1)	(2)	(3)	(4)
Median income	0.889*** (0.0844)	0.952*** (0.0796)	0.550*** (0.0858)	0.659*** (0.0823)
Population	0.390*** (0.101)	0.437*** (0.0761)	0.548*** (0.0740)	0.521*** (0.0716)
Homeless beds		0.230*** (0.0191)		0.180*** (0.0180)
Subway stations			0.673*** (0.0437)	0.586*** (0.0386)
$\ln(\alpha)$ constant	0.676*** (0.0396)	0.543*** (0.0371)	0.467*** (0.0445)	0.373*** (0.0460)
Observations	2103	2103	2103	2103
$R^2$	0.0247	0.0443	0.0553	0.0681

Dependent variable is the count of homeless encampment calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All encampment calls, made between January 1, 2010 and December 31, 2016, are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table 4: Negative binomial estimates: homeless assistance calls

	(1)	(2)	(3)	(4)
Median income	1.191*** (0.180)	1.431*** (0.118)	0.920*** (0.121)	1.095*** (0.112)
Population	0.258** (0.123)	0.366*** (0.0930)	0.579*** (0.0993)	0.561*** (0.107)
Homeless beds		0.271*** (0.0342)		0.179*** (0.0275)
Subway stations			0.984*** (0.0771)	0.888*** (0.0721)
$\ln(\alpha)$ constant	1.558*** (0.0533)	1.441*** (0.0479)	1.247*** (0.0650)	1.182*** (0.0710)
Observations	2103	2103	2103	2103
$R^2$	0.0268	0.0440	0.0709	0.0792

Dependent variable is the count of homeless assistance calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All assistance calls made between June 7, 2013 and March 14, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table 5: Negative binomial estimates: non-homeless calls

	(1)	(2)	(3)	(4)
Median income	-0.123*** (0.0271)	-0.0716*** (0.0276)	-0.182*** (0.0241)	-0.128*** (0.0252)
Population	0.565*** (0.0461)	0.559*** (0.0406)	0.579*** (0.0369)	0.567*** (0.0356)
Homeless beds		0.0809*** (0.00735)		0.0632*** (0.00590)
Subway stations			0.225*** (0.0166)	0.195*** (0.0142)
$\ln(\alpha)$ constant	-1.515*** (0.0503)	-1.625*** (0.0449)	-1.683*** (0.0433)	-1.756*** (0.0426)
Observations	2103	2103	2103	2103
$R^2$	0.0266	0.0329	0.0361	0.0402

Dependent variable is the count of non-homeless related calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All non-homeless related calls made between January 1, 2010 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table 6: Summary statistics, call-level variables

	Mean	Median	Std. dev.	Min.	Max.
<b>Duration (hours)</b>					
Complaint	4.50	2.58	33.33	0.09	2406.13
Assistance	10.94	2.10	52.01	0.03	4716.78
<b>Median income (dollars)</b>					
Complaint	84,252	77,396	44,486	10,746	250,000
Assistance	98,150	103,797	43,358	9,829	250,000
<b>Distance to nearest subway station (miles)</b>					
Complaint	0.25	0.14	0.43	0.00	4.99
Assistance	0.14	0.09	0.20	0.00	4.98
<b>Temperature (degrees Fahrenheit)</b>					
Complaint	70	74	16	15	100
Assistance	74	78	15	27	96
<b>Median police response to non-homeless calls (hours)</b>					
Complaint	2.60	1.87	25.09	0.16	2315.32

Note: Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.

Table 7: Median estimates: police response to homeless encampment calls

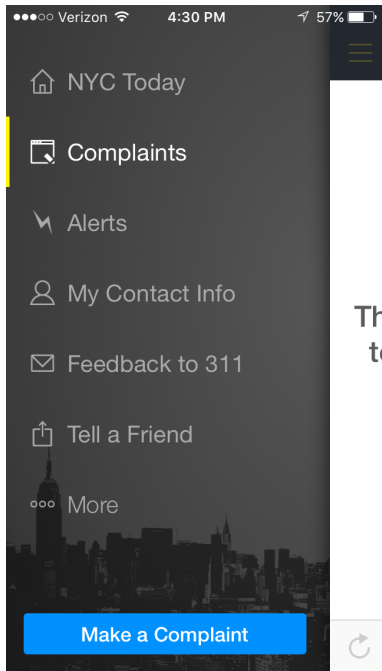
	(1)	(2)	(3)	(4)	(5)	(6)
Median income	-0.209*** (0.0160)	-0.173*** (0.0163)	-0.0869*** (0.0173)			
Temperature	0.0546 (0.0768)	0.0809 (0.0761)	0.0545 (0.0782)	0.0699 (0.0773)	0.118 (0.0763)	0.0825 (0.0754)
Distance to subway station		0.0771*** (0.00826)	0.0496*** (0.00858)		0.0824*** (0.00853)	0.0565*** (0.00853)
Median response to other calls			0.387*** (0.0189)			0.381*** (0.0184)
Income decile 2				0.0384 (0.0548)	0.0639 (0.0541)	0.0573 (0.0535)
Income decile 3				-0.0771 (0.0575)	-0.0732 (0.0568)	-0.00969 (0.0561)
Income decile 4				-0.130** (0.0568)	-0.120** (0.0561)	-0.0705 (0.0555)
Income decile 5				-0.0574 (0.0564)	-0.0170 (0.0558)	0.0205 (0.0551)
Income decile 6				-0.127** (0.0549)	-0.125** (0.0542)	-0.0804 (0.0537)
Income decile 7				-0.136** (0.0536)	-0.156*** (0.0530)	-0.0676 (0.0525)
Income decile 8				-0.178*** (0.0528)	-0.169*** (0.0523)	-0.0899* (0.0520)
Income decile 9				-0.334*** (0.0508)	-0.290*** (0.0502)	-0.158*** (0.0501)
Income decile 10				-0.329*** (0.0437)	-0.250*** (0.0435)	-0.104** (0.0436)
Observations	17,745	17,745	17,705	17,745	17,745	17,705
$R^2$	0.053	0.057	0.074	0.054	0.058	0.074

Dependent variable is the logarithm of response time to call. Logarithmic transformations of median income, temperature, distance to the nearest subway station, and median response time to other calls are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

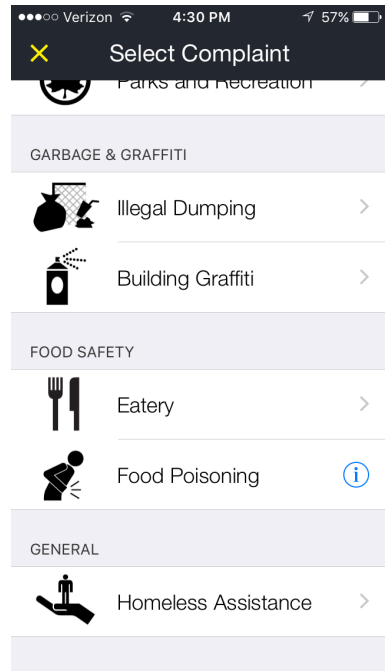
Table 8: Median estimates: social service response to homeless assistance calls

	(1)	(2)	(3)	(4)	(5)	(6)
Median income	0.117*** (0.0175)	0.111*** (0.0178)	0.0246 (0.0194)			
Temperature	-0.181** (0.0898)	-0.171* (0.0902)	-0.107 (0.0912)	-0.167* (0.0927)	-0.160* (0.0913)	-0.112 (0.0908)
Distance to subway station		-0.0203** (0.00942)	-0.00372 (0.00963)		-0.0250** (0.00976)	-0.00509 (0.00977)
Income decile 2				0.0534 (0.0705)	0.0568 (0.0697)	0.0723 (0.0694)
Income decile 3				0.119* (0.0721)	0.111 (0.0710)	0.174** (0.0709)
Income decile 4				0.176** (0.0800)	0.191** (0.0792)	0.230*** (0.0791)
Income decile 5				-0.0123 (0.0778)	-0.0240 (0.0767)	0.0406 (0.0769)
Income decile 6				0.0225 (0.0756)	0.0168 (0.0745)	0.136* (0.0750)
Income decile 7				0.316*** (0.0673)	0.323*** (0.0666)	0.301*** (0.0663)
Income decile 8				0.189*** (0.0613)	0.201*** (0.0607)	0.154** (0.0606)
Income decile 9				0.395*** (0.0566)	0.373*** (0.0558)	0.296*** (0.0561)
Income decile 10				0.247*** (0.0489)	0.232*** (0.0482)	0.129*** (0.0488)
Nonprofit indicators			X			X
Observations	35,259	35,259	35,259	35,259	35,259	35,259
$R^2$	0.0586	0.0587	0.0616	0.0600	0.0602	0.0627

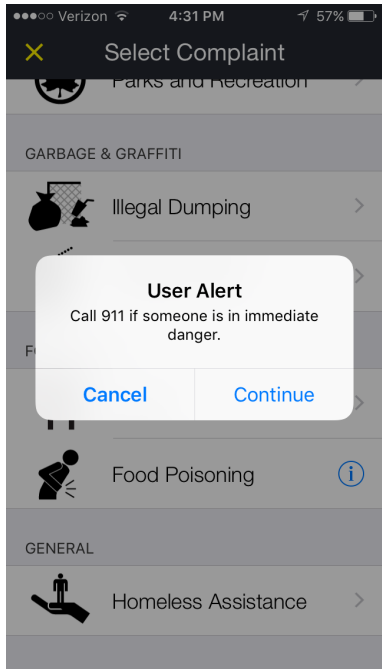
Dependent variable is the logarithm of response time to call. Logarithmic transformations of median income, temperature, and distance to the nearest subway station are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.



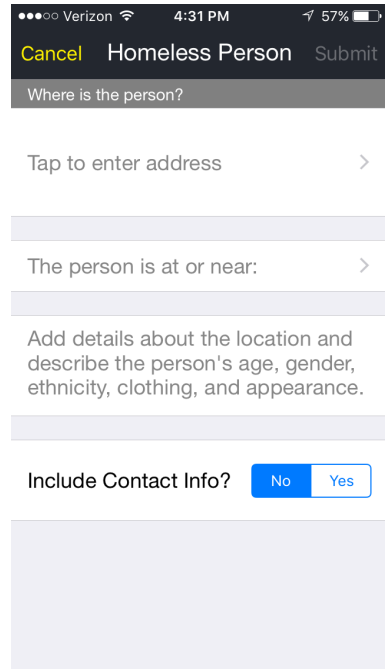
(a) Home screen



(b) Complaint selection screen



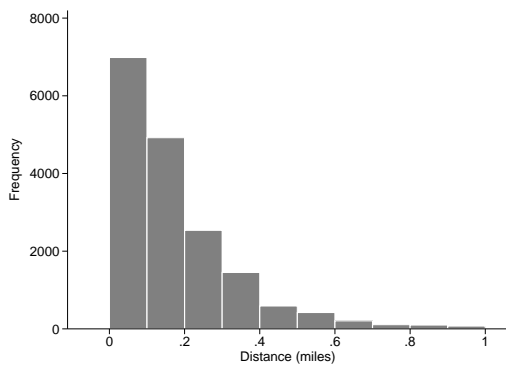
(c) Alert popup



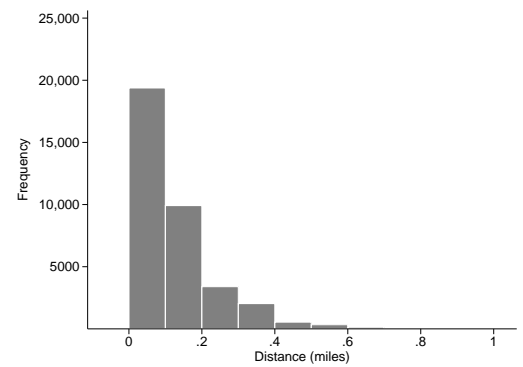
(d) Homeless assistance form

Figure A1: Screen shots from “NYC 311” app

Source: NYC 311 app, image captured on February 10, 2017



(a) Encampment calls



(b) Assistance calls

Figure A2: Frequency of encampment calls by distance to nearest subway station

Note: Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.

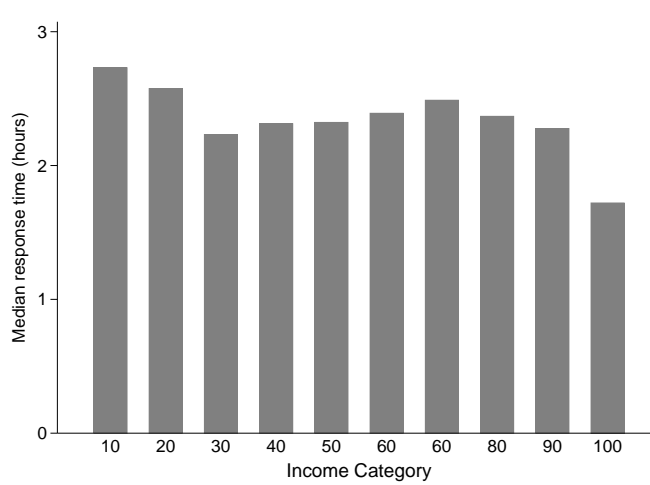


Figure A3: Median police response time to non-homeless related calls by median income decile

Note: Income categories are expressed in percentiles. All non-homeless calls, placed between January 1, 2010 and December 31, 2016, are included.

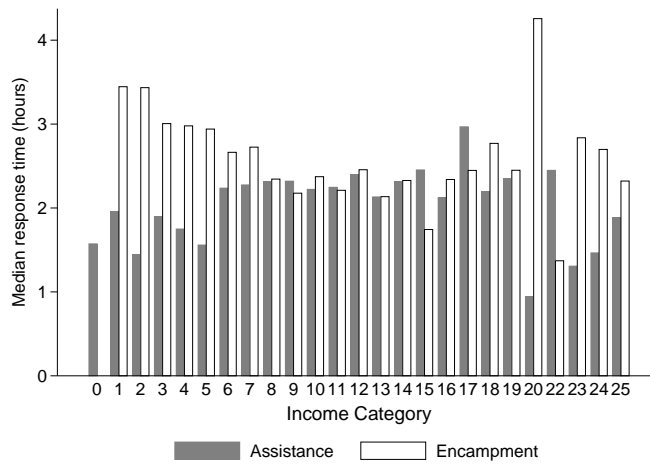


Figure A4: Median response time to homeless encampment and assistance calls by median income

Note: Income categories are in tens of thousands of dollars. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.

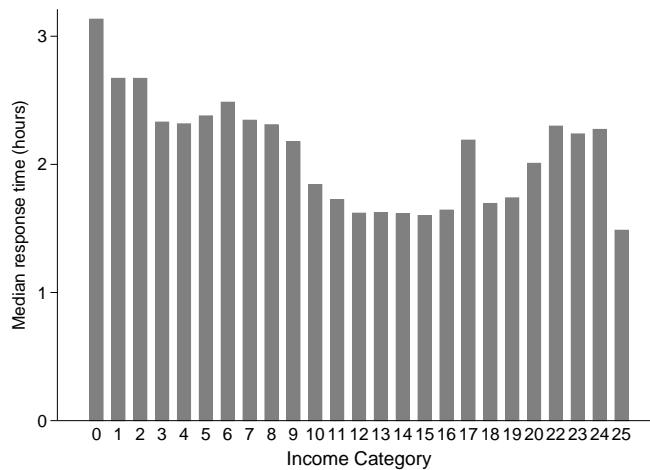


Figure A5: Median police response time to non-homeless related calls by median income

Note: Income categories are in tens of thousands of dollars. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.

Table A1: Call frequencies and distribution of response times by call outcomes

Outcome	Freq.	1%	5%	10%	25%	50%	75%	90%	95%	99%
<b>Encampment calls</b>										
Issued summons in response to complaint*	56	0.28	0.43	0.74	1.15	2.51	4.3	5.91	10.01	18.3
Made arrest*	26	0.16	0.39	0.47	0.86	1.75	3.37	7.02	7.91	8.91
Responded but person gone*	3,354	0.22	0.5	0.76	1.51	3.13	5.68	9.05	12.55	22.19
Responded and prepared a report*	44	0.27	0.44	0.62	1.1	2.15	3.87	6.02	6.78	11.85
Responded but action not necessary*	2,090	0.16	0.32	0.52	1.06	2.21	4.38	7.19	9.85	16.82
Responded and took action to fix condition*	6,741	0.18	0.4	0.59	1.1	2.14	4.19	7.09	9.62	16.95
Responded but no evidence of violation*	5,766	0.22	0.48	0.71	1.44	3.02	5.75	9.9	13.74	26.77
Responded but unable to gain entry*	196	0.18	0.5	0.75	1.4	3.05	5.13	9.1	12.85	20.68
Reviewed complaint and provided info	806	0.15	0.24	0.4	0.91	2.55	6.58	11.13	15.34	59.41
Not within NYPD jurisdiction	295	0.12	0.2	0.28	0.63	1.58	3.53	6	8.52	18.75
Request cannot be processed	442	0.11	0.15	0.22	0.57	1.57	3.79	6.97	9.76	23.48
No description available	1,463	0.16	0.33	0.46	0.95	1.92	3.75	6.6	8.9	16.45
<b>Assistance calls</b>										
Referred to NYPD	988	0.07	0.1	0.12	0.19	0.34	0.77	3.84	43.72	174.88
Not enough info	933	0.06	0.09	0.11	0.16	0.34	1.05	5.65	26.34	125.52
Referred to outside homeless outreach provider	12	0.15	0.15	0.18	0.21	0.37	0.96	2.94	15.88	15.88
Not within DHS jurisdiction	217	0.06	0.08	0.1	0.16	0.27	0.64	5.99	21.85	219.85
Sent mobile outreach response team	2	0.54	0.54	0.54	0.54	0.63	0.72	0.72	0.72	0.72
Will send mobile outreach team	10	0.16	0.16	0.16	0.2	0.39	0.5	0.98	1.47	1.47
Individual accepted service*	46	0.5	0.62	0.8	1.02	1.58	2.16	3.21	4.93	23.83
Individual found and assistance offered*	2,561	0.06	0.1	0.16	0.63	1.32	2.6	5.59	10.19	75.3
Mobile team arrived at location	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Assistance offered but not accepted*	8,383	0.42	0.63	0.78	1.15	2.05	4.18	12.58	21.15	140.64
Could not find individual*	25,804	0.05	0.08	0.12	0.51	2.3	7.38	17.97	37.84	219.5
Request submitted	36	0	0	0	0.01	0.01	0.01	0.02	0.02	0.02

Note: \* indicates outcome included in analysis of response to calls. In some cases, analyses exclude assistance calls with outcomes of “Could not find individual.” Encampment calls, made between January 1, 2010 and December 31, 2016, are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included.



Table A2: Ordinary least squares estimates: homeless encampment calls

	(1)	(2)	(3)	(4)
Median income	0.393*** (0.0702)	0.557*** (0.0682)	0.308*** (0.0606)	0.447*** (0.0599)
Population	0.646*** (0.0753)	0.555*** (0.0687)	0.538*** (0.0616)	0.477*** (0.0576)
Homeless beds		0.227*** (0.0153)		0.181*** (0.0137)
Subway stations			0.698*** (0.0361)	0.626*** (0.0340)
Observations	2103	2103	2103	2103
$R^2$	0.0771	0.167	0.237	0.292

Dependent variable is the inverse hyperbolic sine transformation of the count of homeless encampment calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All encampment calls, made between January 1, 2010 and December 31, 2016, are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A3: Ordinary least squares estimates: homeless assistance calls

	(1)	(2)	(3)	(4)
Median income	0.754*** (0.0738)	0.899*** (0.0715)	0.654*** (0.0604)	0.766*** (0.0590)
Population	0.590*** (0.0808)	0.509*** (0.0750)	0.464*** (0.0607)	0.415*** (0.0575)
Homeless beds		0.202*** (0.0177)		0.146*** (0.0150)
Subway stations			0.818*** (0.0387)	0.760*** (0.0370)
Observations	2103	2103	2103	2103
$R^2$	0.111	0.184	0.335	0.371

Dependent variable is the inverse hyperbolic sine transformation of the count of homeless assistance calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All assistance calls made between June 7, 2013 and March 14, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A4: Ordinary least squares estimates: non-homeless calls

	(1)	(2)	(3)	(4)
Median income	-0.0988*** (0.0261)	-0.0440* (0.0260)	-0.124*** (0.0241)	-0.0761*** (0.0244)
Population	0.682*** (0.0373)	0.651*** (0.0355)	0.650*** (0.0332)	0.628*** (0.0320)
Homeless beds		0.0762*** (0.00616)		0.0625*** (0.00563)
Subway stations			0.208*** (0.0140)	0.183*** (0.0131)
Observations	2103	2103	2103	2103
$R^2$	0.413	0.464	0.485	0.519

Dependent variable is the inverse hyperbolic sine transformation of the count of non-homeless related calls throughout the period. Logarithmic transformations of median income and population are made, and the inverse hyperbolic sine transformation of shelter beds and subway stations are made. All non-homeless related calls made between January 1, 2010 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A5: Ordinary least squares estimates: police response to homeless encampment calls

	(1)	(2)	(3)	(4)	(5)	(6)
Median income	-0.177*** (0.0119)	-0.151*** (0.0122)	-0.0921*** (0.0126)			
Temperature	0.0437 (0.0571)	0.0466 (0.0570)	0.0526 (0.0565)	0.0419 (0.0571)	0.0460 (0.0569)	0.0527 (0.0565)
Distance to subway station		0.0562*** (0.00623)	0.0412*** (0.00624)		0.0600*** (0.00639)	0.0448*** (0.00641)
Median response to other calls			0.257*** (0.0143)			0.254*** (0.0144)
Income decile 2				0.0101 (0.0411)	0.00780 (0.0410)	0.0199 (0.0406)
Income decile 3				-0.0341 (0.0430)	-0.0367 (0.0429)	-0.00464 (0.0425)
Income decile 4				-0.109*** (0.0424)	-0.117*** (0.0423)	-0.0763* (0.0420)
Income decile 5				-0.0199 (0.0421)	-0.0105 (0.0420)	0.0115 (0.0417)
Income decile 6				-0.0951** (0.0410)	-0.102** (0.0409)	-0.0735* (0.0407)
Income decile 7				-0.140*** (0.0401)	-0.158*** (0.0400)	-0.100** (0.0398)
Income decile 8				-0.140*** (0.0395)	-0.162*** (0.0395)	-0.0810** (0.0394)
Income decile 9				-0.270*** (0.0379)	-0.267*** (0.0378)	-0.167*** (0.0379)
Income decile 10				-0.270*** (0.0327)	-0.233*** (0.0329)	-0.130*** (0.0331)
Observations	16,906	16,906	16,872	16,906	16,906	16,872
$R^2$	0.0720	0.0765	0.0939	0.0730	0.0778	0.0945

Dependent variable is the logarithm of response time to call. Calls with response times greater than 12 hours are excluded. Logarithmic transformations of median income, temperature, distance to the nearest subway station, and median response time to other calls are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A6: Ordinary least squares estimates: social service response to homeless assistance calls

	(1)	(2)	(3)	(4)	(5)	(6)
Median income	0.0412*** (0.0124)	0.0405*** (0.0126)	0.0270** (0.0137)			
Temperature	-0.168*** (0.0642)	-0.168*** (0.0642)	-0.168*** (0.0642)	-0.168*** (0.0641)	-0.169*** (0.0641)	-0.169*** (0.0641)
Distance to subway station		-0.00254 (0.00667)	0.000554 (0.00675)		-0.0101 (0.00681)	-0.00663 (0.00687)
Income decile 2				0.109** (0.0479)	0.114** (0.0481)	0.120** (0.0482)
Income decile 3				0.268*** (0.0490)	0.268*** (0.0490)	0.280*** (0.0492)
Income decile 4				0.230*** (0.0552)	0.237*** (0.0554)	0.250*** (0.0557)
Income decile 5				0.123** (0.0527)	0.125** (0.0527)	0.144*** (0.0532)
Income decile 6				0.140*** (0.0510)	0.141*** (0.0510)	0.176*** (0.0517)
Income decile 7				0.389*** (0.0463)	0.395*** (0.0465)	0.391*** (0.0466)
Income decile 8				0.228*** (0.0420)	0.233*** (0.0421)	0.224*** (0.0423)
Income decile 9				0.315*** (0.0389)	0.314*** (0.0389)	0.298*** (0.0394)
Income decile 10				0.186*** (0.0335)	0.184*** (0.0335)	0.164*** (0.0343)
Nonprofit indicators			X			X
Observations	30,380	30,380	30,380	30,380	30,380	30,380
$R^2$	0.165	0.165	0.165	0.167	0.168	0.168

Dependent variable is the logarithm of response time to call. Calls with response times greater than 12 hours are excluded. Logarithmic transformations of median income, temperature, and distance to the nearest subway station are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included. Assistance calls made between March 15, 2016 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A7: Median estimates: police response to homeless encampment calls, March 15, 2016 through December 31, 2016

	(1)	(2)	(3)	(4)	(5)	(6)
Median income	-0.339*** (0.0339)	-0.286*** (0.0340)	-0.122*** (0.0374)			
Temperature	-0.167 (0.183)	-0.0413 (0.177)	-0.0638 (0.182)	-0.117 (0.177)	-0.0547 (0.184)	-0.0467 (0.184)
Distance to subway station		0.0879*** (0.0171)	0.0561*** (0.0177)		0.0730*** (0.0182)	0.0621*** (0.0183)
Median response to other calls			0.507*** (0.0382)			0.488*** (0.0396)
Income decile 2				0.0105 (0.120)	-0.0365 (0.124)	0.0135 (0.125)
Income decile 3				-0.282** (0.121)	-0.264** (0.125)	-0.0646 (0.126)
Income decile 4				-0.192 (0.117)	-0.256** (0.122)	-0.0198 (0.123)
Income decile 5				-0.124 (0.114)	-0.171 (0.119)	-0.0103 (0.119)
Income decile 6				-0.0649 (0.117)	-0.0711 (0.121)	-0.00565 (0.122)
Income decile 7				-0.264** (0.112)	-0.346*** (0.116)	-0.197* (0.117)
Income decile 8				-0.182 (0.111)	-0.258** (0.115)	0.00304 (0.117)
Income decile 9				-0.691*** (0.103)	-0.709*** (0.107)	-0.295*** (0.110)
Income decile 10				-0.573*** (0.0915)	-0.545*** (0.0956)	-0.181* (0.0993)
Observations	3,989	3,989	3,982	3,989	3,989	3,982
$R^2$	0.0480	0.0525	0.0815	0.0568	0.0602	0.0852

Dependent variable is the logarithm of response time to call. Logarithmic transformations of median income, temperature, distance to the nearest subway station, and median response time to other calls are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included. Encampment calls made between January 1, 2010 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.

Table A8: Median estimates: social service response to homeless assistance calls, excluding calls in which individual not found

	(1)	(2)	(3)	(4)	(5)	(6)
Median income	0.142*** (0.0193)	0.134*** (0.0202)	-0.0134 (0.0226)			
Temperature	-0.106 (0.0979)	-0.0823 (0.100)	-0.0461 (0.0960)	-0.103 (0.0969)	-0.0745 (0.0979)	-0.0634 (0.0966)
Distance to subway station		-0.0303*** (0.0103)	-0.0131 (0.00996)		-0.0312*** (0.0102)	-0.0142 (0.0102)
Income decile 2				0.0334 (0.0742)	0.0622 (0.0750)	0.0334 (0.0745)
Income decile 3				0.0764 (0.0735)	0.0919 (0.0743)	0.0302 (0.0735)
Income decile 4				-0.0153 (0.0841)	0.0286 (0.0850)	0.0163 (0.0845)
Income decile 5				-0.0207 (0.0747)	-0.00490 (0.0755)	0.0186 (0.0748)
Income decile 6				0.0400 (0.0762)	0.0500 (0.0770)	0.0898 (0.0771)
Income decile 7				0.0783 (0.0723)	0.102 (0.0731)	0.0342 (0.0727)
Income decile 8				0.147** (0.0682)	0.187*** (0.0690)	0.0271 (0.0691)
Income decile 9				0.229*** (0.0637)	0.235*** (0.0644)	0.0554 (0.0658)
Income decile 10				0.242*** (0.0546)	0.247*** (0.0553)	0.0101 (0.0578)
Nonprofit indicators			X			X
Observations	10,548	10,548	10,548	10,548	10,548	10,548
$R^2$	0.0425	0.0431	0.0525	0.0436	0.0442	0.0533

Dependent variable is the logarithm of response time to call. Logarithmic transformations of median income, temperature, and distance to the nearest subway station are made as well. All specifications include year-month and hour of day fixed effects. Only calls for which authorities were dispatched to the homeless individual are included, excluding calls in which the homeless individual was not found. Assistance calls made between March 15, 2016 and December 31, 2016 are included. Robust standard errors are shown in parentheses. \* indicates significance at the 10 percent level, \*\* at the 5 percent level, and \*\*\* at the 1 percent level.