Unequal Responsiveness in City Service Delivery: Evidence from 42 Million 311 Calls*

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Abstract

We assess unequal responsiveness to citizen demands for municipal goods and services using a dataset of about 42 million 311 requests from 13 large cities between 2011 and 2019. We report three findings. First, we find no evidence that cities respond to requests from whiter and more affluent neighborhoods faster than they do the *same* type of request from less white and affluent neighborhood, even when accounting for proxies of neighborhood need. On average, however, white, rich neighborhoods receive faster responses to their calls than non-white, poor neighborhoods. Additional analyses suggest that these disparities may not reflect deliberate bias on the part of cities in favor of the needs of whites and the rich, but rather that non-white and poor neighborhoods tend to ask for services that require more time and resources for the city to respond to. Our paper provides the most comprehensive and contemporary analysis to date of inequalities in U.S. city service delivery.

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Democratic government relies on the "responsiveness of the government to the preferences of its citizens, considered as political equals" (Dahl 1971, 1). Research evaluating whether this holds true or not in the U.S. has generally drawn two conclusions. First, federal and state policy tends to move in the same direction as public preferences (e.g., Caughey and Warshaw 2018; Erikson, Wright, and McIver 1993; Lax and Phillips 2012; Soroka and Wlezien 2010). At the same time, policy also appears more responsive to the preferences of whites and the wealthy than to the preferences of non-whites and the poor (e.g., Bartels 2008; Griffin and Newman 2007, 2008; Gilens 2012; Rigby and Wright 2011). Citizens therefore appear far from political equals in the eyes of policymakers.

Recent work has extended the investigation of unequal responsiveness to local governments, finding that the left-right ideology of local elected leaders best reflects the ideological preferences of whites and the rich (Schaffner, Rhodes, and La Raja 2020).[1] The limitation of these analyses is that areas where local governments have the most discretion arguably do not map neatly onto such an ideological spectrum. Rather, local governments are primarily responsible for providing and maintaining public goods and services — roads, water, streetlights, police and fire protection, and trash collection, among others — that we tend to conceive of as "good" rather than left or right. Indeed, as is often said, there is no Democratic or Republican way to pick up garbage. Consequently, empirical research on (unequal) responsiveness in local politics that focuses entirely on ideology is at best incomplete, and at worst, misleading (Anzia 2021).

Nevertheless, widespread racial and class-based segregation in most major cities coupled with scarce municipal resources means that opportunities abound for city officials to favor some racial and income groups over others in the allocation of essential goods and services. Consistent with this, some argue that wealthy, white neighborhoods are advantaged in service provision relative to poorer, non-white neighborhoods (e.g., Hajnal and Trounstine 2014).

This paper assesses whether city governments are more responsive to citizen *demands* for goods and services from white and rich neighborhoods than they are to demands from non-white and poor

[1] As with federal and state policy, local policy also moves with public preferences in the aggregate (Einstein and Kogan 2016; Tausanovitch and Warshaw 2014).

neighborhoods. Our analyses draw on an original dataset of about 42 million 311 requests from 13 large cities between 2011 and 2019. 311 is a government-sponsored phone number available in many U.S. cities; where available, 311 is the primary way that citizens can report issues in their community (i.e., a pothole or downed streetlight) and place requests for city services. The benefit of these data is that we can measure citizen demands in neighborhoods of different economic and racial compositions, and see whether how fast government responds to those demands depends on the composition of the neighborhood. Our dataset notably includes requests for *every* service provided in each city, and we test two distinct mechanisms through which inequalities in responsiveness could occur. We therefore address several limitations in the comprehensiveness and contemporary relevance of previous work on responsiveness that uses data on citizen-initiated requests for services (Clark et al. 2020; Jones et al. 1977; Mladenka 1981; Wichowsky, Shah, and Heideman 2022).

We report three key findings. First, *within* service areas, we find no evidence that cities respond to requests from whiter and more affluent communities faster than requests from less white and affluent neighborhoods. In other words, if a poor neighborhood and a rich neighborhood in the same city both ask for a streetlight to be fixed, both see their requests solved in the same amount of time.

On the other hand, averaging *across* service areas, cities respond to requests from the whitest and wealthiest neighborhoods faster than requests from the least white and poorest neighborhoods. Specifically, neighborhoods in the top terciles of the city's white population and income distribution receive about 4-6% faster response times — a difference of about 30-48 hours relative to the average wait time — than do neighborhoods in the bottom terciles. For race in particular, these gaps are even larger when comparing the very top and very bottom deciles (as large as a 4 day difference relative to the average), and when subsetting to the most common types of service requests in each city. These results suggest that inequalities in responsiveness emerge because rich and poor neighborhoods, and white and non-white and neighborhoods, ask for different services — services that vary in their average response time, and that tend to be longest for services more frequently requested by non-white, poor neighborhoods.

It does not appear, however, that cities *deliberately* prioritize fast responses to the set of services that tend to come from rich and white neighborhoods. First, we find that changes in demand by race and income do not correspond to changes in wait times: as a particular service is increasingly demanded by non-whites and the poor, the average wait time stay the same. Second, leveraging services common across cities, we find that variation in wait times across cities is unrelated to across-city variation in demand by neighborhood race and income for that service. Both findings ultimately suggest that inequalities in responsiveness reflect practical considerations: non-white and poor neighborhoods tend to ask for services that are simply more difficult for cities to respond to.

In some respects, our findings paint a more positive picture of city governments than others do (e.g., Trounstine 2018). Still, on average, citizens in white and affluent neighborhoods *do* receive faster 311 responses than those in non-white and poor communities. Consequently, our findings have potentially important implications for a variety of outcomes, including citizen trust in government and vote choice.

Inequalities in Local Public Goods Provision

Race and income appear to shape both the level and distribution of municipal public goods and services. For starters, racially diverse and segregated cities tend to invest less in public goods and services overall (Alesina, Baqir, and Easterly 1999; Glaser 2002; Hopkins 2009; Trounstine 2016). One explanation for this relationship is that diverse and segregated cities are also more diverse and polarized in their political preferences, leading to a lack of consensus on how to spend public funds and thus, underinvestment (Alesina, Baqir, and Easterly 1999). Citizens in more diverse contexts may be also be especially reticent to support investment in public goods because it means that members of other racial and ethnic groups will also benefit from those goods (e.g., Gilens 1996; Luttmer 2001).

To the extent that diverse and segregated cities do invest in public goods, they do so primarily to the benefit of white and affluent neighborhoods and exclusion of non-white and less affluent neighborhoods. Trounstine (2018) shows that segregated cities have historically provided less public water access to Black and renter neighborhoods than non-Black and non-renter neighborhoods. These relationships remain as of just 30 years ago. Historical accounts similarly document the lack of quality public goods and services in non-white and poor neighborhoods. For instance, Abrams (1955, 74-75) concludes that:

> Garbage collections, building inspections, street maintenance, and other city services are less satisfactory than in other areas. The abnormal number of rat bites in Harlem, for example, may be ascribed not only to lack of proper upkeep but to the ready supply of uncollected garbage in the streets. Southern cities and some in the North omit street paving and sidewalks in Negro sections.

Perhaps as a consequence, white and wealthy residents tend to view city services much more favorably than relative to non-whites and the poor (e.g., Aberbach and Walker 1970; DeHoog, Lowery, and Lyons 1990; Hajnal and Trounstine 2014; Schuman and Gruenberg 1972). Indeed, across 26 cites, Hajnal and Trounstine (2014) show that Blacks are much less satisfied with city police, fire, libraries, and schools than are whites. But once objective measures of neighborhood conditions and service quality are accounted for, these gaps disappear (DeHoog, Lowery, and Lyons 1990; Hajnal and Trounstine 2014). This suggests that differential satisfaction likely reflects variation in public goods provision by race and income.[2]

These studies establish that public goods and services are more numerous and of higher quality in white and affluent neighborhoods than they are in non-white and less affluent neighborhoods. But we cannot know from these studies whether city *responsiveness* to demands for goods and services depends on neighborhood race and income. Put another way, when residents of different neighborhoods explicitly ask cities to perform a service in their area, does the city respond to those requests differently? If so, are observed differences related to the demographic profile of the

[2] Subjective evaluations of city services tend to reflect objective conditions (e.g., Holbrook and Weinschenk 2020), and capture citizens' interactions and experiences with city officials and services (e.g., Kelly 2003; Kelly and Swindell 2002; Percy 1986).

neighborhoods? Answering such questions requires data on citizen demands (by demographics), and on whether and how government responded to those demands (Trounstine 2010).

We conceptualize responsiveness in a very literal sense: when a direct request for government service is made by a resident, how does government respond?[3] Several scholars have examined this kind of responsiveness using data on citizen-initiated requests for goods and services. Researchers tend to measure responsiveness in two ways with these data: whether the city responds favorably to the request at all, and how fast the city responds to the request (conditional on having responded). Just one study finds clear evidence of racial and economic inequalities: in Milwaukee, both high-poverty and Black neighborhoods receive slower responses to their requests than to low-poverty and white neighborhoods (Wichowsky, Shah, and Heideman 2022).

The more common finding, however, is that race and income are not systematically related to whether or how fast city officials respond to service requests (Jones et al. 1977; Mladenka 1981; Nivola 1978; Vedlitz and Dyer 1984).[4] If inequalities in response times do emerge, they appear "unpatterned" as it relates to race and income (see also Jones et al. 1978; Mladenka 1980). For example, Vedlitz and Dyer (1984)'s study of Dallas shows that the city is more likely to respond to requests for street maintenance in high-income neighborhoods, but more likely to respond to requests for trash collection in low-income neighborhoods. Others suggest racial- or income-based differences in response times to requests for service are so small in magnitude so as to be virtually unnoticeable (Clark et al. 2020).

Though these papers provide a direct test of responsiveness, they are limited in three important ways. First, with two exceptions (Clark et al. 2020; Wichowsky, Shah, and Heideman 2022), each is now more than four decades old. Second, most focus on just one city at a time, and within a city, just one or two service areas and a limited number of citizen contacts placed over short period

[3]This conceptualization is distinct from more general evaluations of responsiveness as how closely public policy corresponds with public preferences (Manin, Przeworski, and Stokes 1999). Especially in the American politics literature, responsiveness entails mapping liberalness of opinion to liberalness of policy (Erikson, Wright, and McIver 1993). In our context, while demand via formal request may imply preference, preference does not necessarily imply demand.

[4]Audit experimental work also suggests that city housing officials are actually *more* likely to respond to requests for information about how to apply for public housing if the requestor is Black rather than white (Einstein and Glick 2017).

of time: Jones et al. (1977) examines only environmental-related requests in Detroit, Mladenka (1981) studies just 2,000 citizen contacts, and Vedlitz and Dyer (1984) examine citizen requests in Dallas in 1975. Though Clark et al. (2020) study 15 cities over an 11-year period, they limit their analysis to seven services *common* to all cities in the study. By prioritizing comparability of services across cities, their analysis may exclude service areas unique to particular cities but that may be the most relevant and perhaps even most common in those cities (e.g., requests for snow removal requests in Boston).

And third, as we detail below, there are several ways that inequalities in responsiveness may emerge. Some papers test whether there are inequalities in responsiveness *within* a given type of service (Clark et al. 2020; Vedlitz and Dyer 1984). Others pool across service areas, and assess whether average responsiveness varies by neighborhood race and income (Jones et al. 1977; Mladenka 1981; Wichowsky, Shah, and Heideman 2022). No study does both.[5]

We address each of these limitations. Like others, we use data on citizen demands for service requests that also document how government responded to those requests. Unlike others, we assess responsiveness — and each of the particular ways that it can emerge — using data that covers *every* service area offered by each of 13 large cities over a recent nine-year period. We can therefore offer the most exhaustive, generalizable, and time relevant test yet of racial- and income-based inequalities in responsiveness to demands for goods and services.

Two Pathways to Unequal Responsiveness

Before proceeding to our data and analysis, we detail two, non-mutually exclusive mechanisms through which inequalities in how cities respond to citizen demands for good and services may emerge. First, cities may respond faster or slower to requests from whiter and more affluent communities than they do the *same* type of request from less white and affluent neighborhoods (Clark

[5] Another perennial challenge in this literature is that the nature of citizen demands may be correlated with the underlying needs of neighborhoods, which may be difficult or impossible to measure. We address this point in robustness checks of our main results.

et al. 2020).[6] For instance, if a white neighborhood and a non-white neighborhood both report an overflowing sewer, the city could fix the sewer in the white neighborhood before the sewer in the non-white neighborhood, or vice-versa. Inequalities can therefore emerge *within* service types. We define this form of inequality as follows, where i denotes city and j a given service category:

$$\mathbb{E}[\text{Wait Time}_{ij} \mid \text{Poor}_i, \text{Service}_{ij}] \neq \mathbb{E}[\text{Wait Time}_{ij} \mid \text{Rich}_i, \text{Service}_{ij}]$$

$$\mathbb{E}[\text{Wait Time}_{ij} \mid \text{Non-White}_i, \text{Service}_{ij}] \neq \mathbb{E}[\text{Wait Time}_{ij} \mid \text{White}_i, \text{Service}_{ij}]$$

Second, cities may simply respond faster to rich and white neighborhoods on average than they respond to poor and non-white neighborhoods, or vice-versa. Here, inequalities emerge *across* service types.

Key to this pathway is that the type of demands placed on government differ by neighborhood race and income. There are two reasons to suspect this may be the case. First, objective conditions often differ between neighborhoods of different racial and economic compositions. Low-income and non-white neighborhoods tend to have more graffiti, broken windows, and litter than wealthier neighborhoods and areas with more white residents (Thornton et al. 2016). Poorer areas also tend to have less clean streets (Neckerman et al. 2009).

Second, several studies show that need is the primary predictor of whether citizens in a given neighborhood place service requests or not (Minkoff 2016; Thomas 1982; Vedlitz, Dyer, and Durand 1980). For instance, Minkoff (2016)'s analysis of 311 usage in New York City shows noise complaints are more common in more commercial areas, presumably because these areas are in fact noisier. The relationship between needs and calls means that differential neighborhood conditions and needs are likely to be reflected in which goods and services particular neighborhoods ask for. That is, poorer and less white neighborhoods should be more likely to ask for graffiti removal than more affluent and white neighborhoods because they have greater need for it.

Given differences in demand by race and income then, inequalities may emerge if, on average, the types of service requests that tend come from one neighborhood receive faster responses than

[6]This pathway is identical to that examined in audit experimental studies (e.g., Butler and Broockman 2011; Einstein and Glick 2017).

do the types of requests that come from the other neighborhood. Mladenka (1981, 706) finds evidence of this in his study of Chicago:

> White wards accounted for 56 percent of all street and traffic complaints in the city whereas predominately black wards accounted for only 12 percent. White wards receive a slightly lower level of bureaucratic response to citizen-initiated contacts because residents of these wards are more likely to communicate grievances about streets and traffic and because these service complaints are less likely to be accorded a favorable level of response.

Mathematically, we can define this pathway as follows, where i again denotes city:

$$\mathbb{E}[\text{Wait Time}_i \mid \text{Poor}_i] \neq \mathbb{E}[\text{Wait Time}_i \mid \text{Rich}_i]$$
$$\mathbb{E}[\text{Wait Time}_i \mid \text{Non-White}_i] \neq \mathbb{E}[\text{Wait Time}_i \mid \text{White}_i]$$

Across-service inequalities could emerge in one of two ways. First, city governments may respond faster to the kinds of demands that come from rich and white neighborhoods than those that come from poor and non-white neighborhoods (or vice-versa) because they are deliberately designed to do so. In other words, bias may be institutionalized in the service call response system. For instance, in Mladenka (1981)'s analysis of traffic complaints in Chicago, he argues that the reason street and traffic complaints are less likely to receive a favorable response is because the city devotes too few resources to address these issues. As a result, unequal responsiveness (in favor of Black neighborhoods) emerges in Chicago because of calculated underinvestment in the service areas most demanded by white neighborhoods.

But it could also be the case that the kinds of service requests that come from rich and white neighborhoods are simply easier for cities to respond to, while those that come from poor and non-white communities are more difficult (or vice-versa). For instance, graffiti removal likely requires much less time and far fewer resources than does filling a pothole or trimming an overgrown tree. If poor and non-white neighborhoods tend to ask for pothole repairs, and rich, white neighborhoods tend to ask for graffiti removal, average wait times between the neighborhoods would be unequal. But, it would not reflect a deliberate expression of pro-white or pro-rich bias on the part of government. Rather, it would reflect the fact that, from a practical standpoint, it is genuinely easier to remove graffiti than it is to fix a pothole. We revisit these two possibilities later in the manuscript.

Data

As noted, evaluating unequal responsiveness requires two pieces of data: (1) citizen demands for goods and services by race and income; and (2) how government responded to those demands. One data source meeting both of these criteria are 311 call logs. 311 is a government-sponsored phone number that provides access to non-emergency municipal services. It offers citizens a way to communicate with their local government about issues in their community, making them the "eyes and ears" of the city. Citizens can call 311 to request a variety of city goods and services, including road and traffic light repairs, trash collection, and graffiti removal. For these reasons, several scholars have used 311 data to measure citizen demand for goods and services (e.g., Christensen and Ejdemyr 2020; Clark et al. 2020; Levine and Gershenson 2014; Minkoff 2016; White and Trump 2018; Wichowsky, Shah, and Heideman 2022).

Though city 311 systems vary, in every city, citizens can call 311 directly. In some, citizens can also report issues online or via a smartphone application. Requests can be filed 24 hours a day, seven days a week. Every city requires that citizens both describe the problem and the exact location of the problem, meaning that each request can be easily geolocated to particular neighborhoods. In some cities (e.g., Boston and San Francisco), callers can include a photo of the problem along with their written description. In most cities, calls are routed to a central command center before city employees direct the call to the appropriate city agency or department. City workers then investigate the report and (if needed) fix the issue. Once fixed, city workers will mark the request as closed in the 311 log.

Given these features, 311 data are well-suited to assess responsiveness: we can see how quickly cities respond to demands for good and services from neighborhoods of different racial and economic composition. We sought to collect 311 data for each of the 30 largest cities in the U.S. for as many years as possible up through the end of the 2019. To be included, a city must of course have 311 or a 311-equivalent and make their call log publicly-available. Some cities, such as Indianapolis and Seattle, do not currently have 311. Others, like Fort Worth, do not make 311 data available to the public. Among those that have 311 and provide public access to the call log, the city must report four pieces of information to be included in our analysis: the date and time the request was made, the kind of request made, the location of the request was placed in latitude and longitude, and the date and time that the request was closed by the city. Of the top 30 cities, 13 meet these criteria.[7]

Table 1: **Summary of Requests by City**

City	First Request	Last Request	# of Requests	# of Service Areas
New York	01/01/2011	12/31/2019	18,120,677	250
Los Angeles	08/05/2015	12/31/2019	3,361,604	12
Houston	11/09/2011	12/31/2019	2,511,901	281
Philadelphia	12/08/2014	12/31/2019	1,059,372	59
Dallas	10/01/2013	12/31/2019	2,458,952	495
Austin	01/01/2014	12/31/2019	846,964	138
San Francisco	01/01/2011	12/31/2019	3,227,431	95
Denver	01/01/2011	12/31/2013	553,409	195
Nashville	07/17/2017	12/31/2019	230,505	187
Washington, DC	01/01/2011	12/31/2019	2,381,132	278
Boston	07/01/2011	12/31/2019	1,359,081	50
Memphis	01/01/2016	12/31/2019	825,427	176
Baltimore	01/01/2011	12/31/2019	5,411,317	328

Table 1 summarizes the 311 data for each city, with cities listed in order of their current population.[8] In total, the dataset includes just over 42 million unique 311 calls across 2,544 unique service areas. Demand is clearly highest in New York City, though demand does not appear to be a linear function of population. Indeed, Baltimore residents placed nearly 5.5 million requests over the nine-year period, double that of a residents in a much larger city like Houston. There is also

[7]Many cities were excluded because they did not meet one of these data requirements. For example, Chicago includes open and close dates, but not times, while Phoenix, San Antonio, Columbus, El Paso, and Memphis do not include latitude and longitude.

[8]Denver's data end in 2013 because calls post-2013 include long-form descriptions of the problem, but not general service categories that we rely on here to categorize calls and that are used prior to 2014 in Denver.

variation in the number of unique goods and services requested in each city. As noted, previous studies using citizen contact data often examine just a handful of service areas. In our data, the average number of services offered by a city is 195, meaning that most other work is severely limited in scope. The clear benefit of our data is that we can retain the uniqueness of each city's service needs and demands while still generalizing patterns in unequal responsiveness across cities.

Moreover, we note that provided service categories are often specific, not general, such that cities often make subtle distinctions between seemingly related problems. For instance, in Austin, "Loose Dog" and "Vicious Dog" are separate service categories. Importantly for our analysis of within-service inequality, this suggests that these categories at least coarsely correspond to the nature of the particular problem, assuaging some concern that requests listed under the same category may be of different severity or require different resources from the city. Indeed, Washington, DC has separate service categories for snow and ice on roadways and bridges versus snow and ice on sidewalks, which would likely require mobilization of snowplows versus crews with shovels, respectively. Likewise, in Baltimore, there are separate service categories for "Fallen Limbs" and "Downed Trees."

Our main dependent variable is wait time, defined as the number of hours between when the request was placed and when the city closed the request. Larger values therefore indicate a longer wait time. The median wait time is about 48 hours, but the mean is 610 (25 days). For this reason, we log-transform wait times in our analysis. We assume that city officials close requests in real-time, such that we can accurately measure how long it took the city to fix the reported issue. City governments use 311 data as a performance metric and as one way determine how to best spend city resources, and so these wait times should be accurate, or else they become a useless performance metric. Indeed, closing requests in any way but in real-time would provide imprecise information and could lead cities to spend resources inefficiently.

One way to check the veracity of the reported close dates is by looking for peculiar "clustering" that may suggest city officials close calls in large batches rather than in real-time. We do so in three ways. First, Figure A1 simply counts the number of requests closed by hour (rounded) in each city.

If the closing dates given in the data reflect some internal process that a city uses to "clear the deck," then we may expect to see that all calls tend to be closed at the same time, perhaps for example, at 9 AM at the start of business or 5 PM at the close of business. We do not find too much evidence of this. With a few exceptions – e.g., in Baltimore, there is a cluster of calls closed at midnight, while in New York, a very large batch were closed at 6 AM — calls seem to closed throughout the day, with most cities closing calls fairly equally throughout the latter half of the day. Figures A2 and A3 repeat this analysis for each of day of the week (i.e., Monday, Tuesday, etc.) and day of month (i.e., the 1st, 15th, etc.). In analyzing the day of the month that calls are closed, three cities stand-out for outliers: Denver, Philadelphia, and Washington, DC. DC in particular raises some concerns, as many calls appear to be closed on the 1st of the month. But in general, we do not see such consistent patterns in the data to suggest that the close dates in the data are wholly inauthentic.[9]

Though we feel comfortable using the reported close dates to create measures of responsiveness, we also use a second dependent variable available in a handful of our cities that side-steps concerns about real-time record-keeping — the *expected* wait time. Six cities — Baltimore, Boston, Dallas, Houston, Philadelphia, and Washington, DC — assign a due date to every 311 call.[10] We subtract the open date from the due date, giving us the number of hours the city expects to take to respond to the demand. The average expected wait time is larger than average wait times in our full sample (703 versus 610 hours).

Due dates are assigned to each call as they are placed. Indeed, most cities' 311 call log system assign due dates automatically based on the service being requested. Because of this, they should be much less prone to user-error on the part of city officials. There are additional benefits to this measure. For one, it allows for a comparison of how fast cities *intended* to respond relative to how fast they actually responded. It also offers another window into the pathways to inequality outlined above. For example, analysis of expected wait times tests for the "worst case scenario" of

[9]Aggregating across cities, we also show that patterns of clustering do not appear strongly related to the race or income composition of the neighborhood making the call (Figures A4-A9).

[10]We exclude New York because they assigned due dates for just 39% of calls.

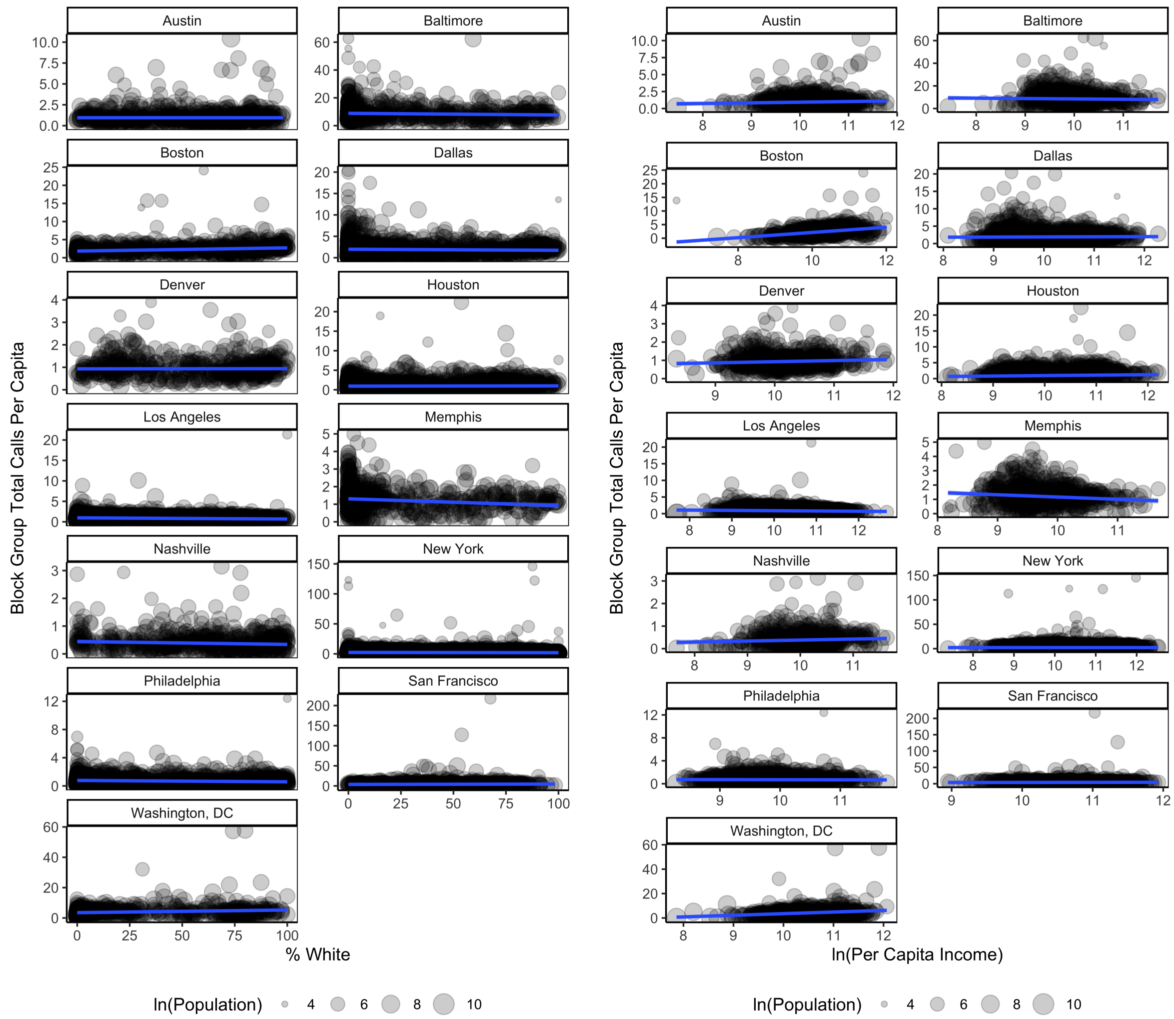
within-service inequalities — should we find differences in expected wait times by neighborhood demographics within service types, then such inequalities may be baked in to the 311 service delivery system. It would mean that how cities assign due dates for each type of service depends on where the request comes from.

To measure the racial and income composition of the neighborhood from which each call originated, we use data from the 2006-2010 American Community Survey (ACS). In particular, we use information on the percent non-Hispanic white and per capita income at the block-group level. Block groups are one of the lowest levels of geographic aggregation in the Census, each containing between 600 and 3,000 people. Assessing responsiveness at the block group level therefore provides one of the most granular analyses possible. Rather than use the continuous measures provided in the ACS, our primary analyses use demographic terciles; that is, we place each block group into its within-city percent white and per capita income tercile, and merge these indicators to our call log using the latitude and longitude for the location of the service request.[11] Using terciles in our analysis permits us to easily test for nonlinearities in the relationship between neighborhood composition and wait times.

A natural question is which neighborhoods tend to use 311. By city, Figure 1 regresses the total number of calls placed per capita by block group pooled over the entire period of study against block group (a) percent white and (b) per capita income, with the line of best fit shown in blue. In our data, representation in 311 calls appears fairly equal across neighborhood types; the average resident of richer or majority-white neighborhoods calls with similar frequency to the average resident in poorer or majority non-white neighborhoods. Where differences emerge (e.g., for income in Boston and Washington, DC), they are miniscule in magnitude. In this way, our data are reassuringly consistent with other work using Boston's 311 data (Feigenbaum and Hall 2016), but also highlight the usefulness of a multi-city approach as patterns of 311 participation in Boston (and DC) are clearly different than most other large cities (at least those in our data).

[11] The correlation between income and race terciles is 0.64, indicating that more white neighborhoods tend to also be wealthier neighborhoods, and vice-versa.

Figure 1: **311 Usage by Neighborhood Race and Income**

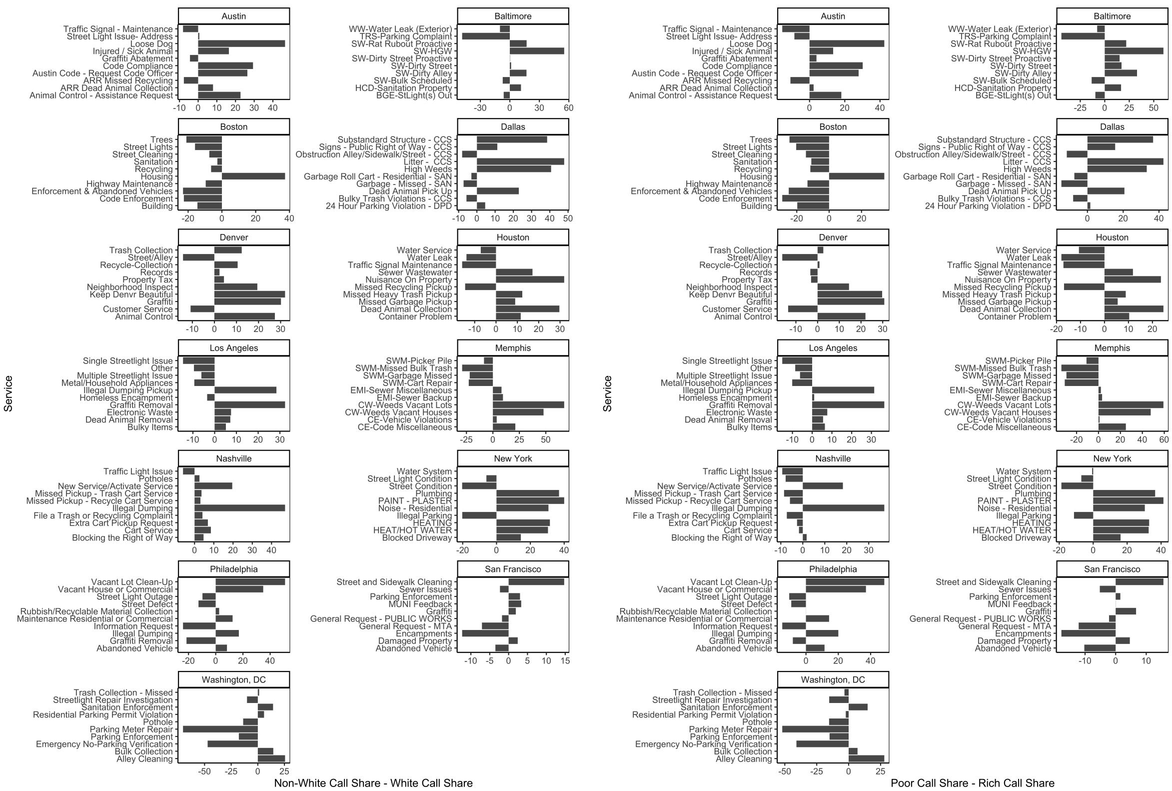


(a) Race

(b) Income

A second important descriptive question is whether the *types* of demands placed on government differ by neighborhood race and income. For each city-service area, we pool over time and calculate the share of calls requested by each block group third, and then subtract the share from the top tercile from the share coming from the bottom tercile. Consequently, positive values indicate that the service is requested more by poor, non-white neighborhoods, while negative values indicate greater demand among wealthier, white neighborhoods. Due to the number of unique city-services in our dataset, we present information for only the top 10 service areas by volume within each city.

Figure 2: **Types of 311 Demands by Neighborhood Race and Income**



(a) Race

(b) Income

Figure 2 plots the results for (a) race and (b) income, respectively. In every city, we find differences the kinds of requests being placed by different neighborhoods. In Dallas, reports of litter and weeds were much more likely to come from non-white neighborhoods, while white neighborhoods were more likely to call about missed garbage collection and street obstructions. These differences are also often quite large in magnitude, too. For instance, in Los Angeles, the share of calls about illegal dumping and graffiti removal from wealthy neighborhoods is over 30 percentage points higher than the share from less wealthy neighborhoods. Neighborhoods of different compositions clearly place different demands on government. These patterns of differential demand raise the possibility of across-service inequalities in wait times. That is, they suggest that cities could be more responsiveness to some groups than others simply by providing faster responses to the types of services that those neighborhoods request.

Taken together, or call-level dataset documents both the racial and income composition the neighborhood making the request, and how long it took government to respond to that request. We observe relative equality in the use of 311 across neighborhoods, and we also observe clear variation in the types of neighborhoods that tend to request each service. Below we outline our research design for assessing whether different neighborhoods receive different response times to the requests that they place.

Specifications

Recall the first possible pathway to inequality in responsiveness: that cities may respond to requests from whiter and more affluent communities faster (or slower) than they do the *same* type of request from less white and affluent neighborhoods. We test this mechanism with the following equation estimated using ordinary least squares:

$$\textit{ln(Wait Time)}_{ijl} = \beta_1 \textit{Middle}_{ik} + \beta_2 \textit{Bottom}_{ik} + \gamma_{jl} + \epsilon_{ijl} \tag{1}$$

where $\textit{ln(Wait Time)}_{ijl}$ is the log-transformed wait time (or expected wait time) in hours for call i in city-service area j placed in month-year l. $\textit{Middle}_{ik}$ is equal to 1 if the call i originated from the middle third of city $k's$ city percent white or per capita income distribution, and $\textit{Bottom}_{ik}$ is equal to 1 if call i originated from the bottom third of city $k's$ percent white or income distribution (making the top tercile our reference category). γ_j are city-service-month-year fixed effects.[12] ϵ_{ijl} is the error term.

This fixed effects structure means that β_1 and β_2 give the average estimated difference in wait times between the given group and the top tercile *within* cities, service area, month, and year.

[12]Standard errors are clustered by block group.

Put another way, the specification allows us to discern — *among calls for the same service in a given city placed in same month-year* — whether wait times for the bottom third of neighborhood race and income are shorter or longer than they are for the top third of neighborhood race and income. The equation implicitly estimates a separate regression for each city-service-month-year combination, and the coefficients are a weighted average of these separate regressions. A positive β_1 would suggest that cities tend to respond faster to calls from the top tercile than to calls for the same type of service from the bottom tercile.

Cities may also respond faster to requests from rich and white neighborhoods than poor and non-white neighborhoods *on average*. As noted, this could occur if neighborhoods of different racial and income compositions place different demands on government, and if different service areas take different amounts of time to respond to average.

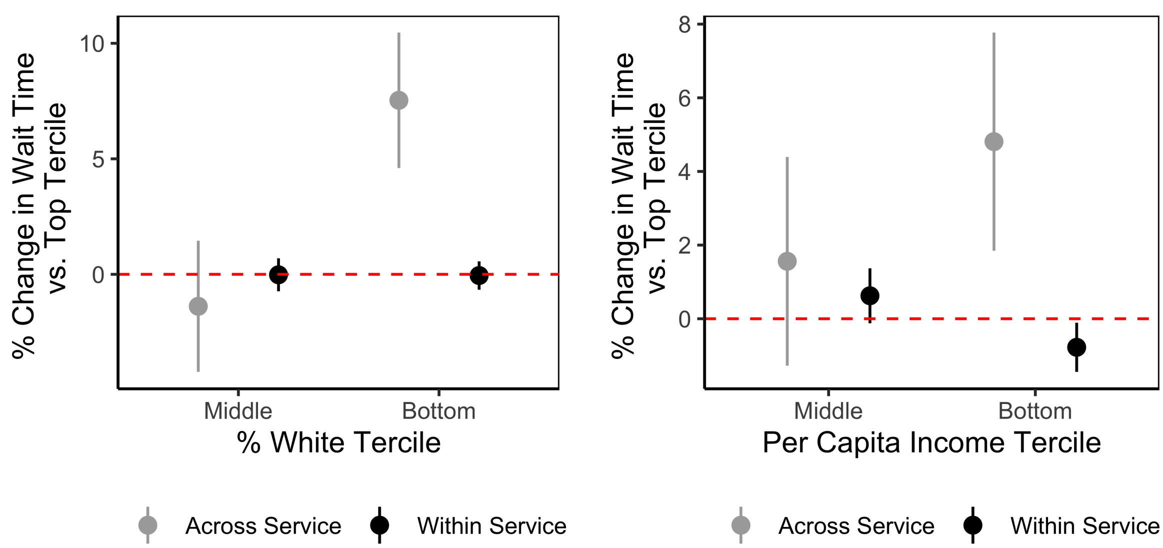
We test this second possibility using a slightly revised version of Equation 1. The difference is that we include city-month-year fixed effects instead of city-service-month-year fixed effects. Replacing city-service indicators with city means that we are now testing whether, within cities and during the same month and year, less white and poorer neighborhoods receive a slower or faster response to their demands than they do whiter and wealthier neighborhoods, on average pooling across all service areas.

Results

Figure 3 shows the results for our main dependent variable, wait time in hours, for neighborhood (a) race and (b) income, respectively. As indicated in Equation 1, the top tercile of neighborhood race and income is the reference group, and so effects for each of the two remaining terciles should be interpreted as relative to the top tercile. The gray points show the effects across-services, while the black points show the effects within-services. 95% confidence intervals for each estimate are included. Because our outcomes are log-transformed, coefficients should be interpreted as the percent difference in wait times relative to the wait times for the top tercile.

We find no substantive relationship between neighborhood race and wait times, or neighborhood income and wait times, *within* service areas. This suggests that, given a particular service request — e.g., a request for trash collection or graffiti removal — cities respond equally as fast regardless of whether the request originated from a white or non-white neighborhood, or from a rich or poor neighborhood. In fact, for income, to the extent that differences do emerge, it is the poorest neighborhoods (i.e., bottom tercile) that tend to benefit with shorter wait times relative to the wealthiest neighborhoods. Substantively, though, these effects are small. These findings are thus consistent with those in Clark et al. (2020), and suggest that response times depend on the time and resources needed to respond to a demand, and that the time and resources needed does not vary by neighborhood race or income.

Figure 3: **Effects of Neighborhood Race and Income on Wait Times**



(a) Race

(b) Income

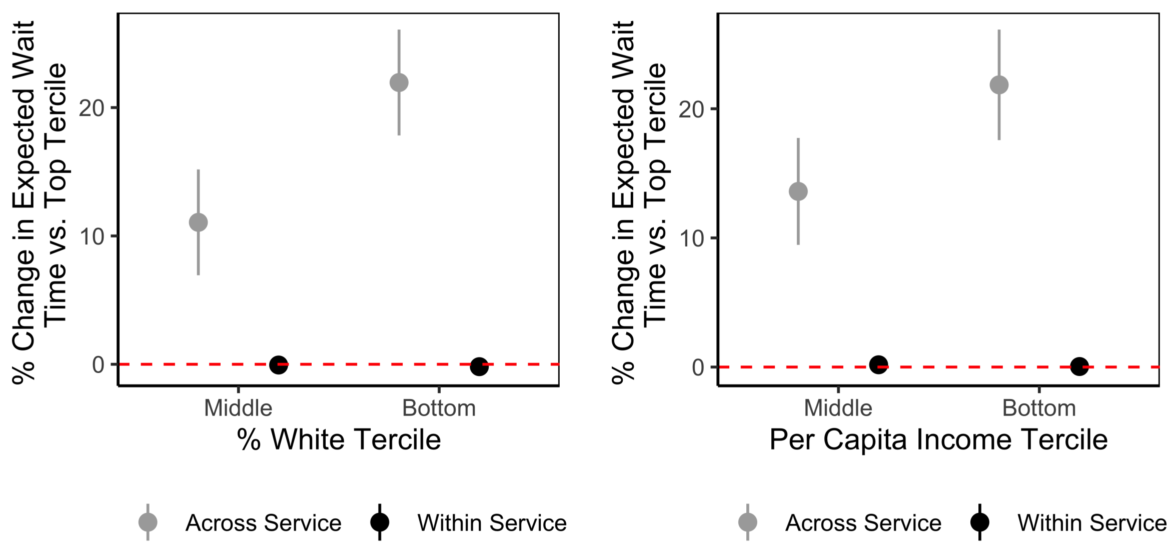
However, looking *across* service area, we find large and statistically significant differences in wait times across both neighborhood race and income. These differences are particularly large for race. On average, service requests from neighborhoods in the bottom tercile of a city's percent white distribution are responded to 7.5% slower than are requests from the city's top tercile. Recall that the mean wait time is 610 hours, or 25 days. This suggests that neighborhoods in the bottom tercile of the white population wait just over 46 hours longer — almost 2 days — than do neighborhoods in the top tercile, on average. Effects for income are slightly smaller in magnitude.

These effects emerge because of what we show in Figure 2: neighborhoods of different racial and economic compositions make different service demands of government. The raw data illustrate this point. For example, in Washington, DC, calls for alley cleaning overwhelming come from non-white neighborhoods, while calls for parking meter repairs come from white neighborhoods. Furthermore, wait times for alley cleaning are much longer than wait times for meter repairs: in April 2018, for instance, the mean wait time for alley cleaning was 351 hours (15 days) while the wait time for parking meter repairs was 208 hours (9 days). Our results suggest that what we see in DC with alley cleaning and parking meter repairs is the norm in city politics: service demands that tend to come from more white and affluent neighborhoods are responded to faster than the types of service demands that come from less white and affluent neighborhoods. This may be because those demands are simply more difficult for cities to respond to, or because cities deliberately prioritize (in terms of the speed at which they respond) the types of requests that tend to come from white, wealthy neighborhoods. Indeed, one can imagine that repairing a parking meter requires less equipment and especially less personnel than cleaning an alleyway. We explore this further below.

Figure 4 re-estimates these models using *expected* wait time as the dependent variable. We find a very precise null effect of neighborhood race and income on expected response times, holding services constant. It suggests that cities internally assign due dates on the basis of the service category — and absolutely nothing else. However, very large inequalities emerge across service areas, ones even larger than we observe when considering wait times. Here, expected wait times for requests from neighborhoods in the bottom tercile of race and income are about 21% longer than expected wait times for requests from the top tercile of neighborhood race and income. Substantively, this amounts to about a 6 day difference relative to the average expected wait time. This confirms again that there are compositional differences in the types of services being requested.

The fact that the across-service gaps are larger for expected wait times than realized wait times suggests that the types of services that cities expect to take longer to respond to do not take quite as long as anticipated. The normatively positive news then is that cities do not appear to shirk even further beyond expected, resource-based differences. Still, while expected disparities are greater than actual disparities, actual disparities still exist.

Figure 4: **Effects of Neighborhood Race and Income on Expected Wait Times**



(a) Race

(b) Income

Robustness Checks

Taken together, we conclude that responsiveness to demands for city goods and services is unequal in a particular way: needs and demands differ by neighborhood race and income, and cities appear to prioritize white and wealthy demands by responding faster to their requests. In this section, we report on a series of robustness checks and extensions of these main results.

Controlling for Neighborhood Needs. As mentioned, a key limitation of 311 data is that we cannot measure the objective needs of different neighborhoods; we do not observe the on-theground problems a neighborhood faces independent of the 311 calls they place. This means that the service categories provided in the data — however detailed they may be, as discussed earlier — may not alone adequately account for the nature of the problem in different neighborhoods, complicating our within-service area analysis. For whatever reason, requests in certain neighborhoods may represent more pressing needs than the same request placed in other neighborhoods. If so, the equal wait times we observe within service areas may actually indicate that neighborhoods with bigger issues may not be getting the representation they deserve. This is especially concerning if we believe the probability of calling 311 conditional on fixed problem severity increases as a neighborhood become wealthier and whiter. Put differently, less white or poorer neighborhoods may have a higher tolerance for certain problems; when calls *do* occur in these neighborhoods, they reflect more serious problems, making the insignificant difference in wait times not indicative of equal representation.[13]

There are two particular ways in which needs may differ and that could confound our results. First, neighborhoods may make the same request, but responding to it requires different resource allocation from the city. This could be because of the scale of the problem (e.g., large versus small pothole), or because problems reported in certain neighborhoods require a greater mobilization of city resources to respond to (e.g., more personnel). Second, neighborhoods may make the same request, and the city costs necessary to fix the problem may be the same, but the downstream impact of the problem may be greater in some neighborhoods than in others (e.g., a pothole located in a major intersection versus a quiet residential street).

We adjust for these factors with three control variables: (1) the distance to the city center (in miles) for each call; (2) block group population density as given in the ACS; and (3) block

[13] One might also be concerned that the probability of making a 311 request varies between neighborhoods independent of problem severity. Problems could be of equal severity on average, but more numerous in poorer or less white neighborhoods, making the observed similarity in calls rates shown in Figure 1 a result of a lower probability of logging a complaint. Ultimately, we view this as a limitation on the theoretical scope of the paper rather than on the robustness of our empirical finding. We study representation conditional on a request being made: how do cities respond when a citizen makes a service request? Certainly, problems that go unreported are still problems and can speak to broader representational questions of cities, but such questions are beyond the scope of this paper given the data we bring to bear.

group walkability.[14] The first is meant to account for the differential monetary and time costs a city may face in attending to needs in the center of a city as opposed to the the periphery. The latter two are meant to capture the "busyness" of a neighborhood and therefore the scope of the potential consequences should a problem go unaddressed for too long. Tables A1 and A2 re-estimate the models reported in Figures 3 and 4, respectively, to include these additional variables. Across the board, our results remain completely unchanged: we still observe no neighborhood racial and income-based gaps in responsiveness within service areas, and while the magnitude of the effects are weaker in models using wait times as the outcome, we also still see some across-service inequalities in responsiveness by both race and income. These results give us greater confidence that differences in need by neighborhood do not affect our findings about the relative equality in responsiveness within types of services.

Deciles of Neighborhood Race and Income. We also re-estimate our models using neighborhood race and income deciles, rather than terciles. These results are presented in Table A3 and A4 for wait times and expected wait times, respectively. When using deciles, we find substantively larger inequalities in across-service responsiveness for neighborhood race relative to our main models using terciles. Here, averaging across service areas, cities respond about 16.4% faster to calls placed by the top decile relative to calls placed by the bottom decile — a difference of just over 4 days relative to the average wait time. The inequalities uncovered in the main analysis appear concentrated at the tails of the city's racial distribution. Again, though, this pro-white bias disappears in tests that account for the service being requested.

The findings regarding income are more mixed: the largest across-service area gaps appear to be between the top decile of income and the 2nd and 3rd deciles. Looking at the within-service models, some of these inequalities persist, though to a lesser degree. At the same time, small disparities between the top decile and 5th through 9th deciles emerge.

[14] We use a walkability index constructed by the U.S. Environmental Protection Agency. It reflects each block group's built environment, and captures the likelihood of walking being used as a mode of travel. Inputs to the index include proximity to transit stops, intersection density (which accounts for road connectivity), and diversity of land uses (e.g., employment to household mix). Higher values indicate more walkable neighborhoods. City centers and main streets tend to score highest, while rural or suburban residential areas score lowest.

Subsetting to the Top 10 Service Areas by City. A strength of our analysis is that we can assess unequal responsiveness across the entire range of goods and services that citizens request in each city. We may wonder though whether the results hold among the most common request types within each city. We therefore subsetted the data to the top 10 service areas (pooled over-time) in each city. Doing so drops about 2/3 of all calls from the data; as shown in Figure 2, these are precisely the service areas for which we observe large differences in how frequently neighborhoods of different kinds place requests. The results are in Tables A5 and A6. Across both race and income, we find that the magnitude of the inequality in responsiveness increases substantially when pooling across service areas, yet still non-existent within-service areas.

City-by-City Results. Our main models allow us to draw conclusions about responsiveness averaged across cities, but there may also be important heterogeneity across cities. In Figures A10 and A11, we present results for both outcomes city-by-city. Most cities mirror the aggregate patterns. Just one — Baltimore — shows no bias of any form. Austin, Los Angeles, and San Francisco are three outliers. In these cities, the direction of unequal responsiveness is reversed: they are more responsive to poorer and less white neighborhoods than they are to richer and more white neighborhoods on average. In Los Angeles, this is even true within service areas.

Alternative Time Fixed Effects. Our main specifications use month-year as the time dimension in our fixed effects, meaning that we evaluate variation in responsiveness by neighborhood race and income among demands placed in the same month and year. Tables A7-A10 use even more fine-grained fixed effects for time: open week and open date. The results are substantively and statistically similar. Even among calls placed on the same exact day, we still find that neighborhoods in the bottom tercile of race and income receive slower responses on average relative to the top tercile. Again, however, once we account for the service being request, there are no racial or income-based differences in wait times, actual or expected.

Exploring Mechanisms Behind Across-Service Inequalities

As noted earlier, within-city, across-service area inequalities may emerge in one of two ways. First, city governments may respond faster to the kinds of demands that come from rich and white neighborhoods because the bureaucracy is deliberately designed to do so. In this case, we may think of the bias as institutionalized. Alternatively, it could be the case that the kinds of service requests that come from rich and white neighborhoods are simply easier for cities to respond to for practical reasons (e.g., less personnel required).

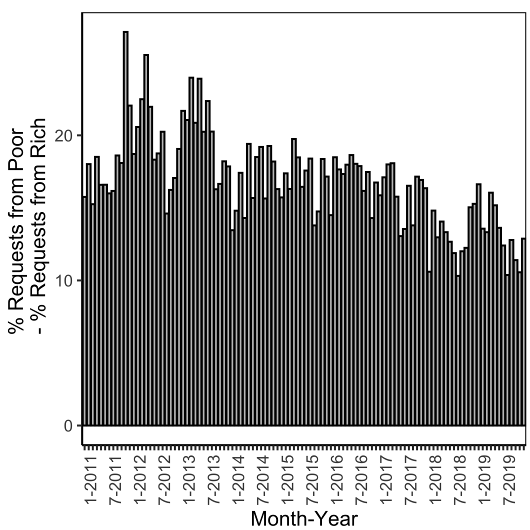
Offering direct evidence to adjudicate between these two possibilities is made difficult by the sheer number of unique services that we study — 2,544 in total. A comprehensive analysis would require information about administrative procedures for each of these service areas, a data effort clearly beyond the scope of this (and perhaps any) study. Though detailed analyses of a very small subset of services in one or two cities may be possible, our interest throughout this paper has been generalizing patterns of unequal responsiveness across cities and service areas. Thus, we turn to two aggregate-level analyses testing observable implications of these distinct mechanisms.

First, we leverage over-time changes in demand for each service by neighborhood race and income. The logic is as follows: if the biases we observe are institutionalized in the city response system — meaning that cities tend to deliberately prioritize fast responses to services demanded by white and wealthy neighborhoods — it should be the case that cities respond to increasing demand for a service among non-white and poor neighborhoods (relative to demand from white and affluent neighborhoods) by increasing wait times for that service. Conversely, as whites and the rich increasingly demand a particular service (relative to non-whites and the poor), wait times should decrease.

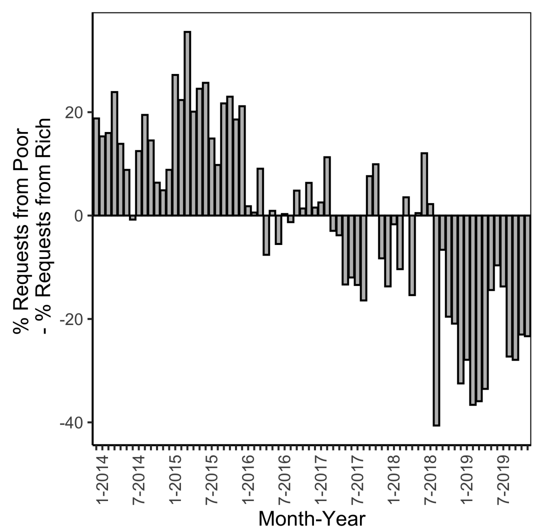
We test this possibility in the following way. For each city-service and month-year combination in our data, we calculate the average wait time as well as the share of all requests that came from the top third and bottom third of neighborhood race and income. We subtract the share of calls coming from the top third from the share coming from the bottom third, giving us a measure of *differential demand* where positive values indicate that poor/non-white neighborhoods requested that service more than rich/white neighborhoods did in that particular month-year.

Figure 5 plots the over-time, within-service variation in demand that our analysis relies on. Consider (a) street and sidewalk cleaning in San Francisco. In every month-year in our data, the poorest neighborhoods demand street cleaning more so than do the wealthiest neighborhoods — i.e., there are no negative values in the data. Yet, variation in the magnitude of this differential demand exist. For instance, in December 2011, low-income demand was about 22 percentage points higher than demand from white neighborhoods (45.28% of calls versus 23.23%). In March 2018, this gap was half as large. If inequality in responsiveness is deliberate or institutionalized, wait times should be longer in December 2011 than March 2018.

Figure 5: **Examples of Differential Demand by Month and Neighborhood Income**



(a) San Francisco — Street and Sidewalk Cleaning



(b) Austin — Graffiti Abatement

Demand for services by race and income may also change more fundamentally over-time. Figure 5 also shows significant variation in requests for graffiti abatement in Austin (b) from month-to-month. For portions of the period of study, requests for graffiti removal were overwhelmingly placed by low income neighborhoods. At other times, these patterns are reversed. Again, if cities base response times on demand by neighborhood demographics, average wait times for graffiti removal in Austin should be longer in months where demand is greater among the poor than the rich. Given the potential for more dramatic changes in demand as with graffiti removal in Austin, we also estimate models where we replace our continuous measure of differential demand with an indicator variable taking on the value 1 if non-white/poor neighborhoods demanded the service more than white/rich neighborhoods in that month-year, and 0 otherwise. Doing so allows us to assess whether and how average wait times change as a service "flips" from a non-white/poor need to a white/rich need, and vice-versa.

Table 2 regresses average wait times on both measures of differential demand (continuous and binary) with fixed effects for city-service and month-year.[15] Across the board, we find no statistically significant evidence that changes in demand by neighborhood race and income are related to changes in average (or expected) wait times.[16] These results cast some doubt on the idea that cities are deliberately prioritizing the needs of white and wealthy neighborhoods. Specifically, they suggest that city officials are not pulling the levers of the city bureaucracy to redirect resources in response to changes in compositional demand.[17] Put another way, they suggest that different problems require different amounts of time for the city to address — amounts that do not change depending on which neighborhoods are predominantly demand that service at a given point in time.

[15]We include the total number of calls made for that service and in that month-year as regression weights.

[16]We also estimate these models using lagged demand/need in the prior month-year. These results are presented in Table A11 and are substantively similar.

[17]Because city budgets are set annually, it may be difficult or even impossible for city officials to actually reallocate resources in response to month-to-month changes in demand, as we estimate in Table 2. In Table A12, we estimate the effect of how year-to-year changes in demand affect response times. These models still show null effects of variation in neighborhood demand on average wait times.

Table 2: **Effects of Change in Differential Demand by Month on Wait Times**

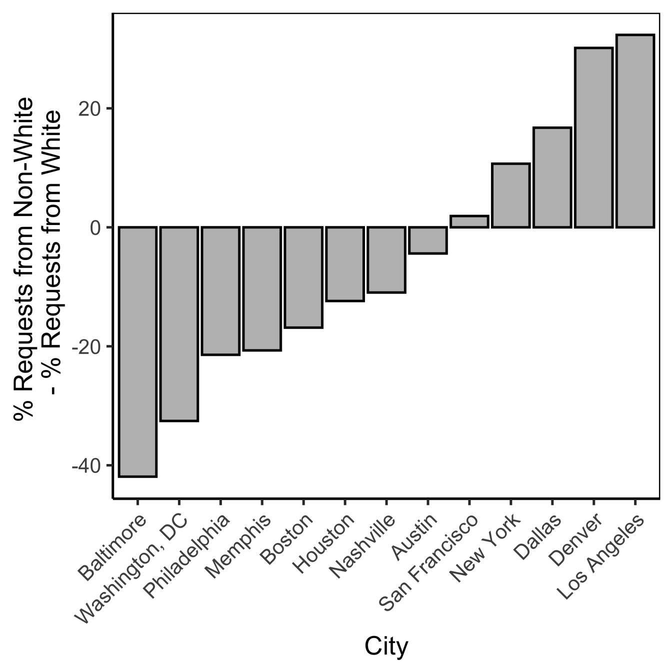
	DV: ln(Mean Wait Time)				*DV: ln(Mean Expected Wait Time)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-White - White	-0.002				0.001			
	(0.002)				(0.001)			
Non-White Need		0.014				0.035		
		(0.054)				(0.045)		
Poor - Rich			0.0004				0.0005	
			(0.002)				(0.0010)	
Poor Need				0.028				0.049^{+}
				(0.054)				(0.029)
City-Service FEs	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	110,579	110,579	110,579	110,579	69,134	69,134	69,134	69,134
R^2	0.857	0.857	0.857	0.857	0.763	0.763	0.763	0.763

Notes: Time refers to month-year. Standard errors are clustered by city-service. Observations are weighted by the total number of calls. $^{+}p<0.10$

Our second analysis draws on a subset of services *common* across cities.[18] While each city call log has requests unique to the city — e.g., coyote disturbances in Austin — many cities are responding to similar issues. It seems reasonable to assume that response times for the same service should be *relatively* similar across cities; at the very least, the average time to response across cities should reflect the average difficulty of responding to the issue across municipalities. We therefore examine whether variation in wait times across cities for a particular (common) service type is a function of variation in demand for that service across cities.

For each common service area, we calculate the average wait times and differential demand (measured in the same way as above) in each city and month-year. Figure 6 shows variation in demand for graffiti removal by city and neighborhood race. We see significant variation in both where such requests tend to come from in each city, and in the magnitude of differences in demand. If cities deliberately design their 311 response system to prioritize white and rich needs, wait times for graffiti removal should longest in Los Angeles, and shortest in Baltimore.

Figure 6: **Differential Demand for Graffiti Removal by City and Neighborhood Race**



[18]We applied a very conservative approach to identifying common service areas. For instance, while "Streetlights" in one city and "Streetlight Investigation and Repair" in another are collapsed into a common service category, "Loose Dog" in one and "Aggressive Dog" in another would not be. In total, we found 79 common services covering about 65% of total calls.

Similar to the previous analysis, we regress average wait times on differential demand, but here include fixed effects for each common service-month-year.[19] The estimates thus capture whether differential demand explains across-city differences in wait times for the same common service area in the same month-year. Table 3 shows the results. Here too, we find no statistically significant relationships between demand and average wait times, or demand and expected wait times.[20] Whether cities take more or less time than average to respond to calls for a particular service appears unrelated to whether demand in that city tends to come whites or non-whites, or the rich or the poor. Combined, our two analyses of aggregate demand and wait times lead us to draw an important normative conclusion: cities may not deliberately prioritize the needs of white, wealthy neighborhoods.

[19]This analysis uses across-city variation. Therefore, we normalize average wait times by dividing each average common-service wait time by the average wait time across all common services in that city. This accounts for that fact that some cities may be slower or faster than others generally.

[20]As before, we also estimate models using lagged demand (Table A13). The results are the same.

Table 3: **Effects of Differential Demand on Wait Times: Across Cities, Within Common Service**

	DV: ln(Mean Wait Time)				*DV: ln(Mean Expected Wait Time)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-White - White	0.002				-0.0007			
	(0.002)				(0.004)			
Non-White Need		-0.017				-0.087		
		(0.075)				(0.134)		
Poor - Rich			0.002				-0.002	
			(0.002)				(0.004)	
Poor Need				0.020				-0.116
				(0.088)				(0.144)
Common Service-Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	23,883	23,883	23,883	23,883	14,670	14,670	14,670	14,670
R^2	0.602	0.601	0.603	0.601	0.648	0.651	0.649	0.653

Notes: Time refers to month-year. Standard errors clustered by city-common service. Observations weighted by the number of calls.

Discussion and Conclusion

We provide the most comprehensive evaluation of unequal responsiveness in U.S. city service delivery. For a given type of service request, we find no evidence that response times depend on the racial or income makeup of the neighborhood placing the request. Yet, we find strong evidence that, on average, cities respond faster to requests from white and affluent neighborhoods than they do requests from non-white and less affluent neighborhoods. At the same time, we suggest that these differences primarily reflect the fact that non-white and poor neighborhoods tend to request services that take the city more time and effort to respond to.

Still, we caution against reading our paper as a ringing endorsement of city governments. For one, the across-service inequalities that we do observe may still be "institutionalized" given that cities have historically tended to underinvest generally in public goods and services in non-white and poor neighborhoods (Trounstine 2018). Previous underinvestment may also be compounded by contemporary underinvestment beyond 311 (e.g., through how today's city officials choose to distribute the general city budget). Consequently, non-white and poor neighborhoods are left with more significant, severe, and costly issues to call 311 about — issues that necessarily take the city more time to respond to. This is of course speculative; we cannot assess this claim with the data at hand.

Though 311 is the main way that citizens in most major cities communicate with local government, it is not without limitations as a method of studying local responsiveness. For one, because our data only allow us to observe *when* cities close a service request, we do not know in what way they responded to each request. It is possible that cities close requests without actually fixing the reported problem, and that they do this more frequently in non-white and poor neighborhoods than they do in white and affluent neighborhoods (or vice-versa), perhaps even within service areas. We also cannot know, conditional on fixing the problem, the quality of the service provided. These are important questions that future research should explore.

Moreover, our results can only speak to representation via 311. The claims we make are about inequalities in responsiveness conditional on direct requests being made of city government —

just as researchers interested in how *expressed* mass preferences (via public opinion surveys) over federal healthcare or immigration policy correspond to federal policy in those areas. We are well-equipped to address how how quickly to cities respond to articulated needs, which itself is situated within the broader question of how well cities attend to neighborhood needs more generally. It may be, though, the any inequalities or equalities in responsiveness via 311 are offset or undone through goods and service provision more generally (e.g., as mentioned above, through the city budget).

Finally, while our analysis focuses on how demographic characteristics shape 311 responsiveness, it is worth noting that the distribution of government resources generally has also been shown to reflect political characteristics (e.g., Kriner and Reeves 2015). Though 311 calls are ostensibly handled by unelected bureaucrats rather than elected officials, there is in fact evidence that elected officials and their incentives influence how fast bureaucrats respond to these calls (Christensen and Ejdemyr 2020). As a result, it seems reasonable that responsiveness may also vary by a neighborhood's level of electoral support for the mayor or local city councilor. Merging our 311 data with precinct-level voting returns could shed light on this question.

Public goods provision affects how citizens vote in local elections (Burnett and Kogan 2017). Given this, the fact that citizens in neighborhoods of different racial and economic composition are not entirely political equals in how cities respond to requests for goods and services could have large implications for local democracy, broadly speaking — even as city governments appear to be responding to these calls primarily using bureaucratic, technical-rational criteria rather than in purposefully and overtly discriminatory ways.

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Supplementary Appendix for "Unequal Responsiveness in City Service Delivery: Evidence from 42 Million 311 Calls"

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June 11, 2023

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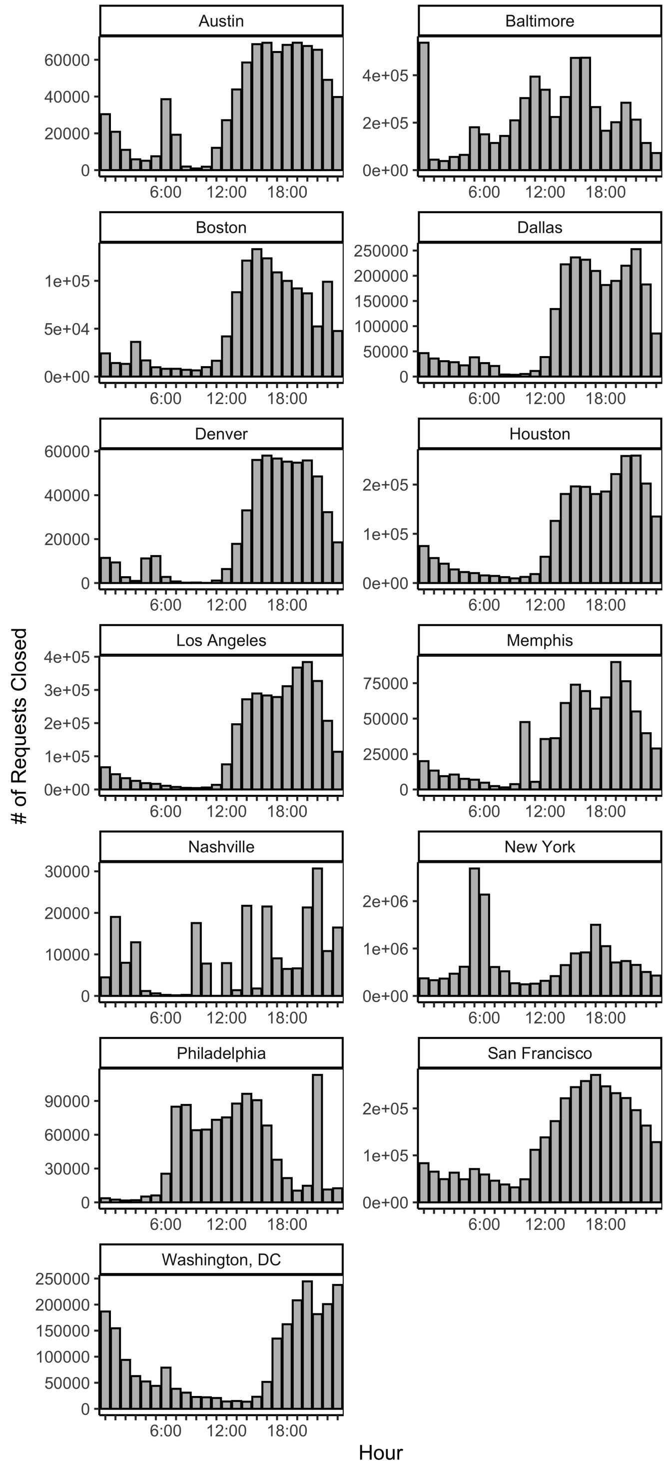


Figure A2: **Clustering of Closing Dates by Day of Week and City**

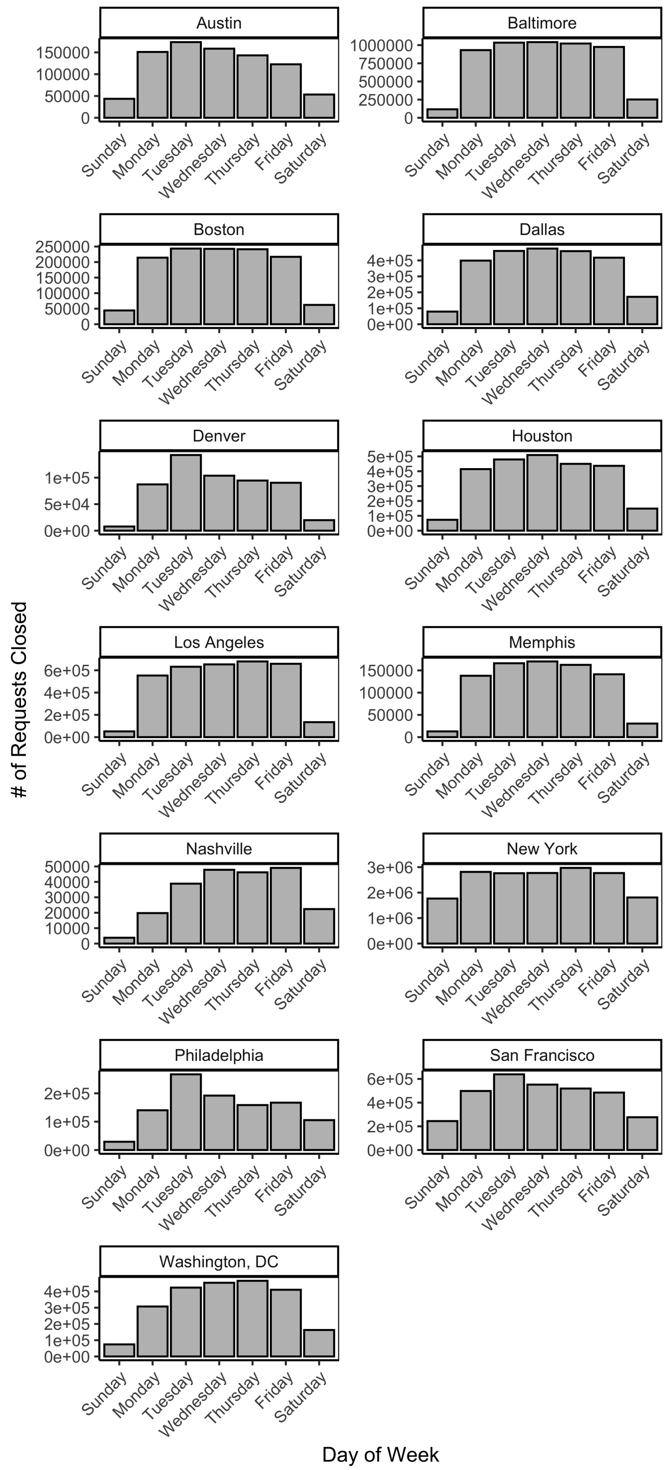


Figure A3: **Clustering of Closing Dates by Day of Month and City**

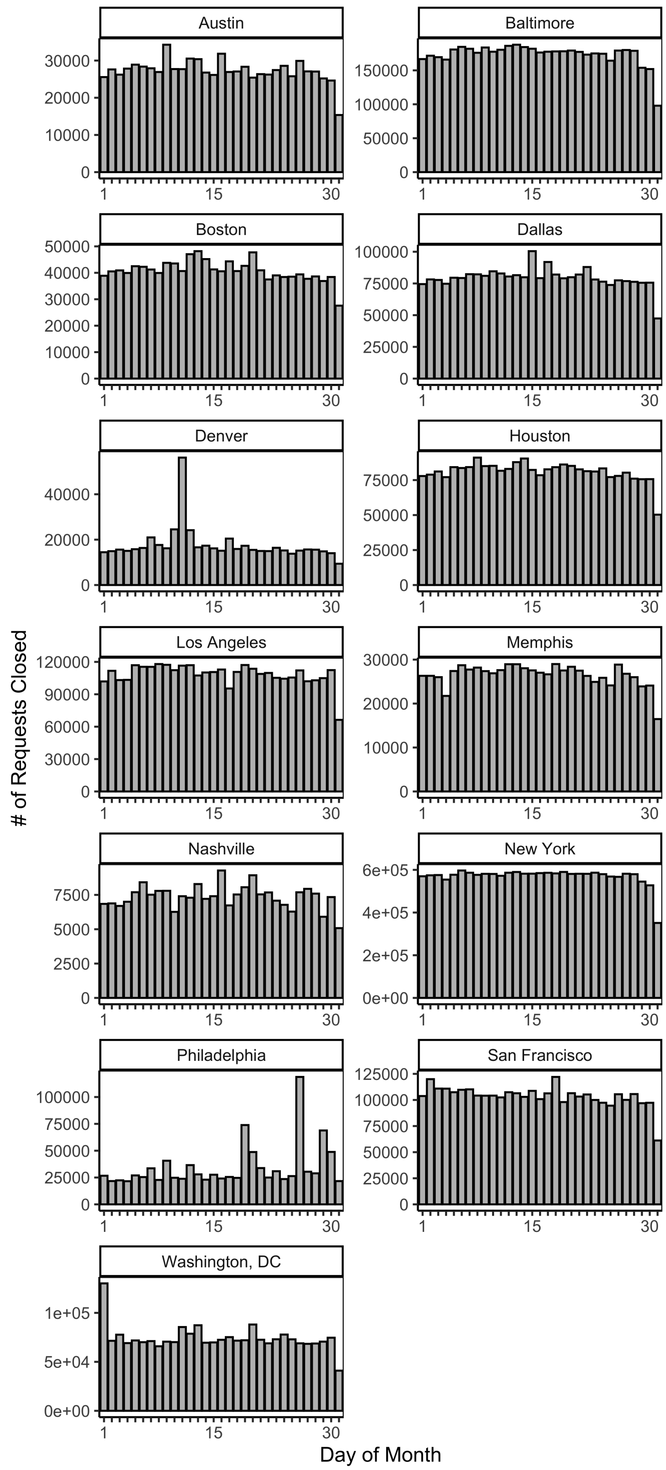


Figure A4: **Clustering of Closing Dates by Hour and Neighborhood Race**

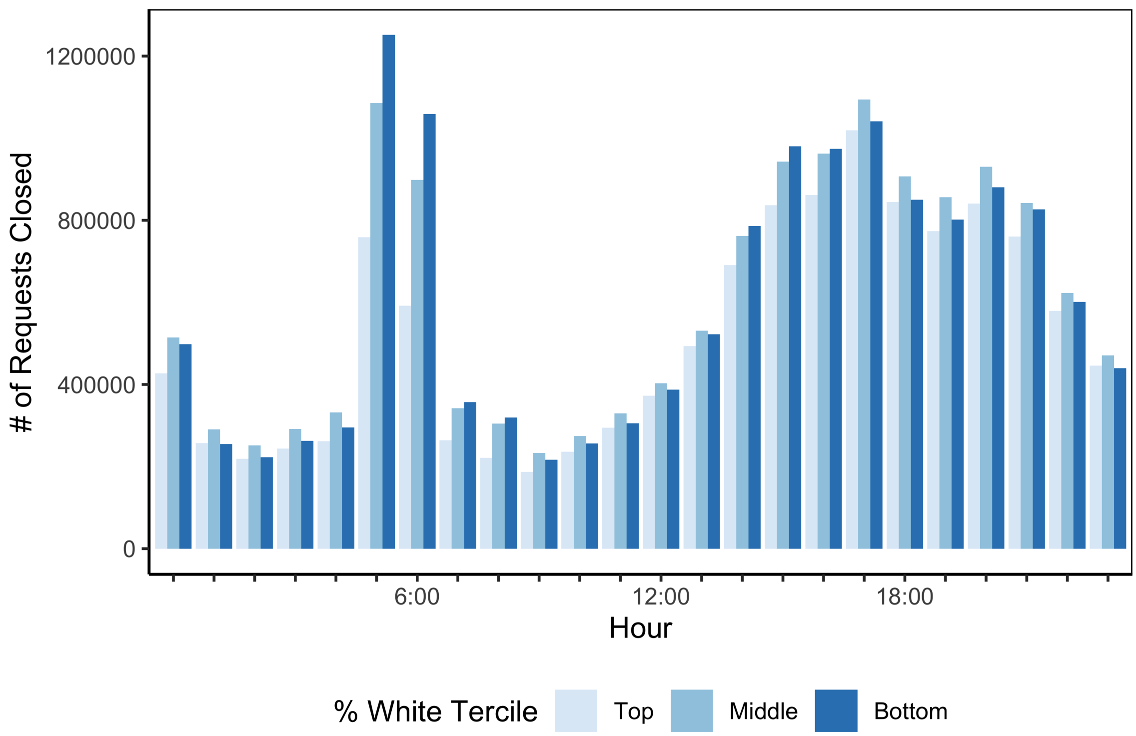


Figure A5: **Clustering of Closing Dates by Hour and Neighborhood Income**

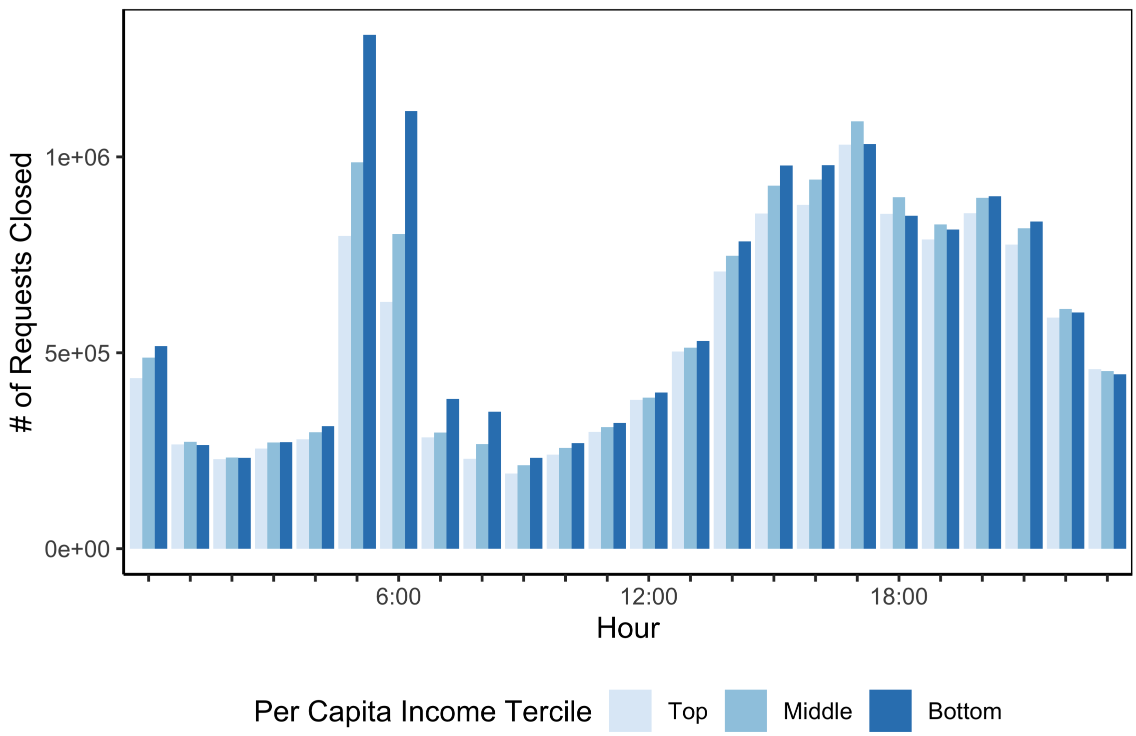


Figure A6: **Clustering of Closing Dates by Day of Week and Neighborhood Race**

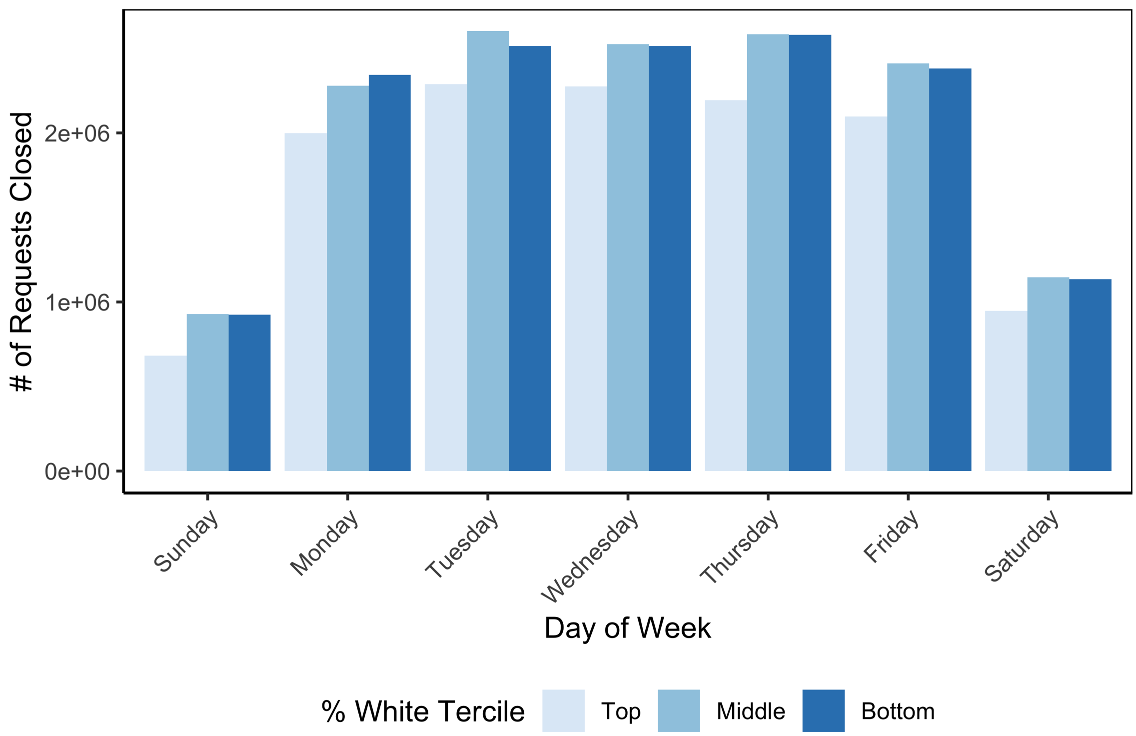


Figure A7: **Clustering of Closing Dates by Day of Week and Neighborhood Income**

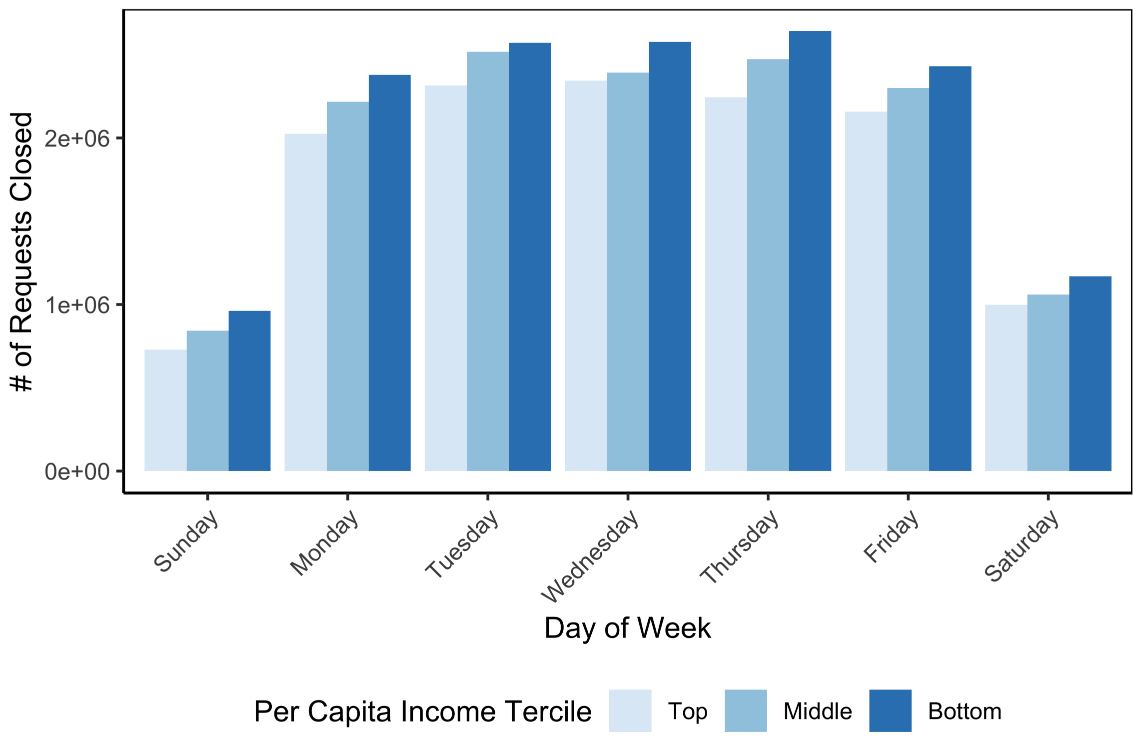


Figure A8: **Clustering of Closing Dates by Day of Month and Neighborhood Race**

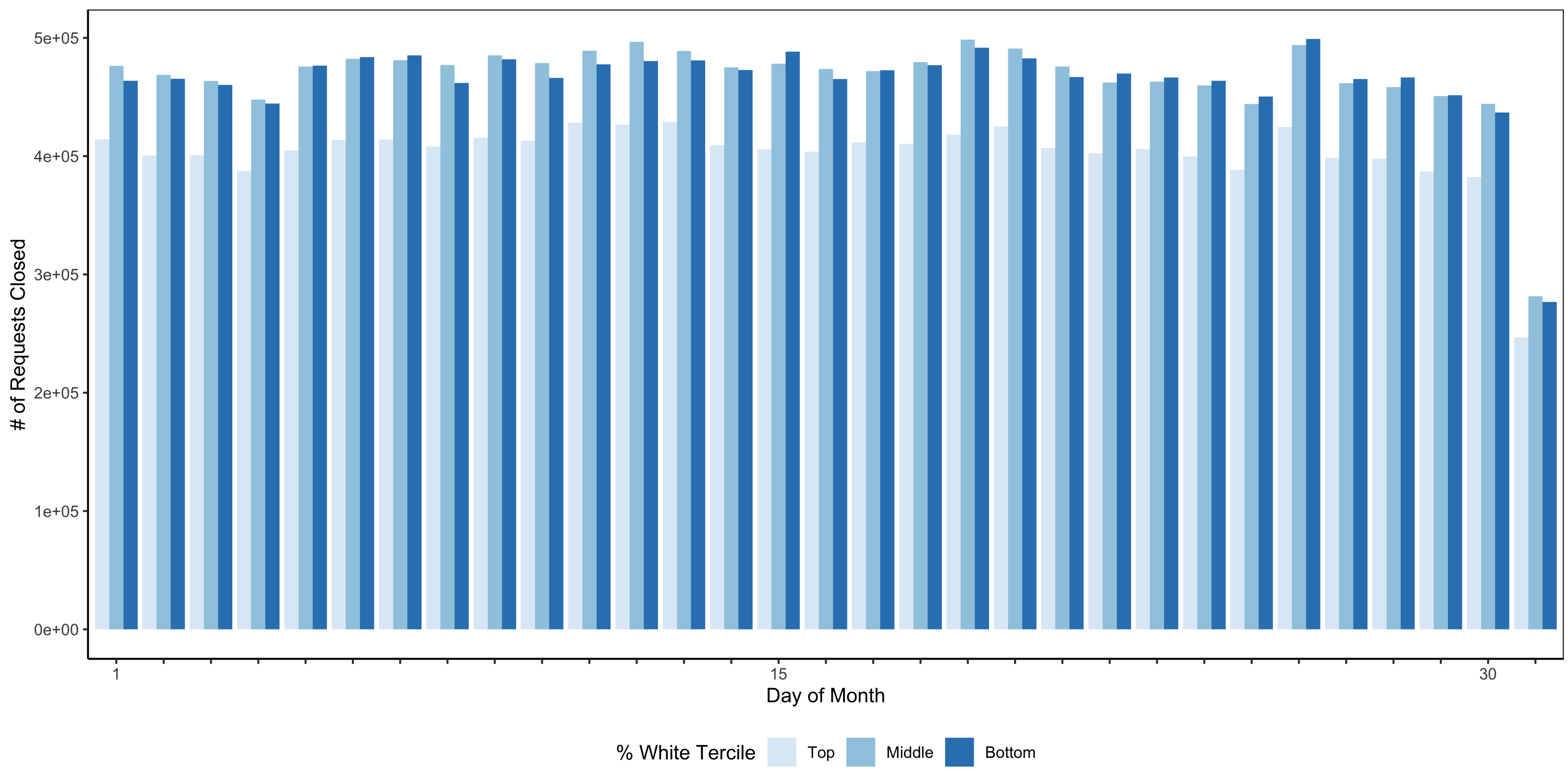


Figure A9: **Clustering of Closing Dates by Day of Month and Neighborhood Income**

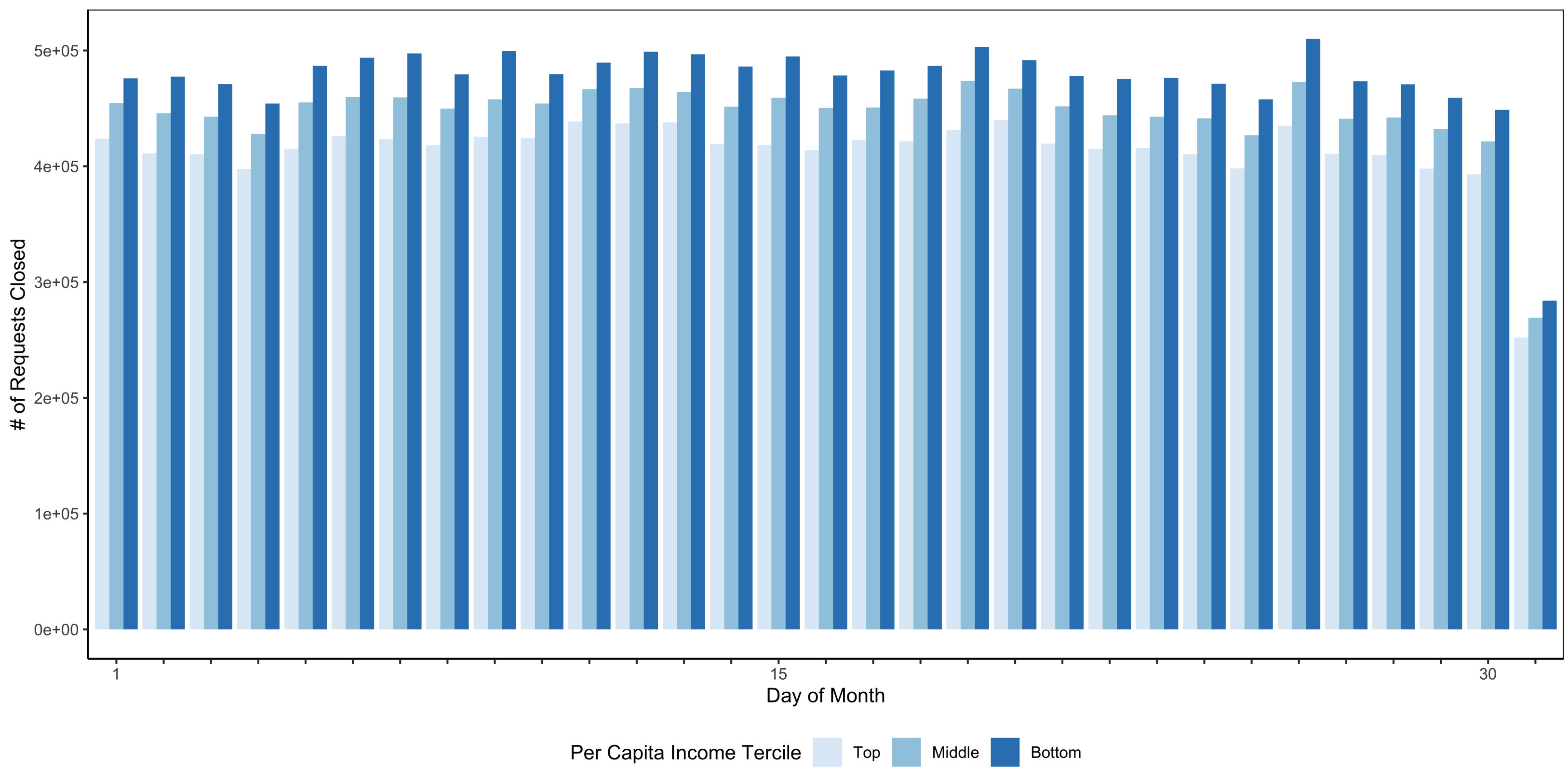


Table A1: **Effects of Neighborhood Race and Income on Wait Times: Controlling for Unmeasured Need**

	DV: ln(Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	-0.025^{+}	0.002	0.002	0.008*
	(0.014)	(0.004)	(0.013)	(0.004)
Bottom	0.052***	0.004	0.025^{+}	-0.001
	(0.013)	(0.003)	(0.013)	(0.003)
ln(City Center Distance)	0.021*	0.009***	0.023**	0.009***
	(0.008)	(0.002)	(0.008)	(0.002)
ln(Pop. Dens.)	0.021**	-0.016***	0.021**	-0.015***
	(0.007)	(0.002)	(0.007)	(0.002)
Walkability Index	-0.016***	0.002**	-0.017***	0.002**
	(0.003)	(0.0006)	(0.003)	(0.0006)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	41,107,325	41,107,040	41,106,792	41,106,507
R^2	0.114	0.650	0.114	0.650

Notes: Time refers to month-year. Standard errors clustered by block group. $^{+}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A2: **Effects of Neighborhood Race and Income on Expected Wait Times: Controlling for Unmeasured Need**

	DV: ln(Expected Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	0.104***	-0.0007	0.132***	0.002+
	(0.018)	(0.0010)	(0.017)	(0.0009)
Bottom	0.211***	-0.002*	0.210***	-0.0003
	(0.017)	(0.0009)	(0.018)	(0.0009)
ln(City Center Distance)	-0.031**	6.85×10^{-5}	-0.035**	0.0001
	(0.011)	(0.0006)	(0.011)	(0.0006)
ln(Pop. Dens.)	-0.0008	0.004***	-0.007	0.004***
	(0.013)	(0.0006)	(0.013)	(0.0006)
Walkability Index	-0.004	2.94×10^{-5}	-0.006	0.0001
	(0.004)	(0.0002)	(0.004)	(0.0001)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	14,437,586	14,437,585	14,437,054	14,437,053
R^2	0.111	0.916	0.111	0.916

Notes: Time refers to month-year. Standard errors clustered by block group. $^+$p<0.10; *p<0.05; **p<0.01; ***p<0.001

Table A3: **Effects of Neighborhood Race and Income on Wait Times: Deciles**

	DV: ln(Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Decile				
9th	0.016	0.003	0.047	0.020***
	(0.018)	(0.005)	(0.037)	(0.005)
8th	0.041	0.009+	-0.019	0.034***
	(0.037)	(0.005)	(0.018)	(0.006)
7th	-0.020	0.021***	0.025	0.036***
	(0.018)	(0.006)	(0.017)	(0.006)
6th	-0.005	0.006	0.004	0.031***
	(0.019)	(0.007)	(0.018)	(0.008)
5th	0.011	-0.002	0.041*	0.029***
	(0.018)	(0.006)	(0.017)	(0.005)
4th	0.038+	0.003	0.034+	0.014*
	(0.019)	(0.005)	(0.019)	(0.006)
3rd	0.065***	0.007	0.100***	0.018**
	(0.019)	(0.005)	(0.018)	(0.006)
2nd	0.066***	0.011*	0.051**	0.012*
	(0.019)	(0.005)	(0.020)	(0.006)
1st	0.164***	-0.004	0.021	0.009
	(0.020)	(0.005)	(0.024)	(0.006)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	41,111,241	41,110,956	41,110,708	41,110,423
R^2	0.114	0.650	0.114	0.650

Notes: Time refers to month-year. Standard errors clustered by block group. $^{+}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A4: **Effects of Neighborhood Race and Income on Expected Wait Times: Deciles**

	DV: ln(Expected Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Decile				
9th	0.029	-0.004*	0.125*	0.0002
	(0.021)	(0.002)	(0.056)	(0.002)
8th	0.088	-0.003+	0.075***	-0.0009
	(0.057)	(0.002)	(0.021)	(0.002)
7th	0.068***	-0.004**	0.161***	-0.0007
	(0.020)	(0.002)	(0.018)	(0.002)
6th	0.143***	-0.003	0.206***	0.003
	(0.020)	(0.002)	(0.019)	(0.002)
5th	0.197***	-0.002	0.220***	0.0007
	(0.017)	(0.002)	(0.019)	(0.002)
4th	0.212***	-0.002	0.241***	0.003
	(0.020)	(0.002)	(0.018)	(0.002)
3rd	0.215***	-0.003+	0.291***	0.0004
	(0.018)	(0.002)	(0.018)	(0.002)
2nd	0.265***	-0.005**	0.290***	8.29×10^{-5}
	(0.018)	(0.001)	(0.019)	(0.002)
1st	0.323***	-0.004**	0.304***	-0.003
	(0.018)	(0.001)	(0.024)	(0.002)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	14,437,586	14,437,585	14,437,054	14,437,053
R^2	0.112	0.916	0.111	0.916

Notes: Time refers to month-year. Standard errors clustered by block group.+p<0.10; *p<0.05; **p<0.01; ***p<0.001

Table A5: **Effects of Neighborhood Race and Income on Wait Times: Top 10 City-Service Areas**

	DV: ln(Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	0.052***	0.004	0.076***	0.007
	(0.013)	(0.005)	(0.012)	(0.005)
Bottom	0.163***	0.005	0.112***	-0.009+
	(0.013)	(0.005)	(0.014)	(0.005)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	23,532,391	23,532,391	23,532,096	23,532,096
R^2	0.163	0.624	0.162	0.624

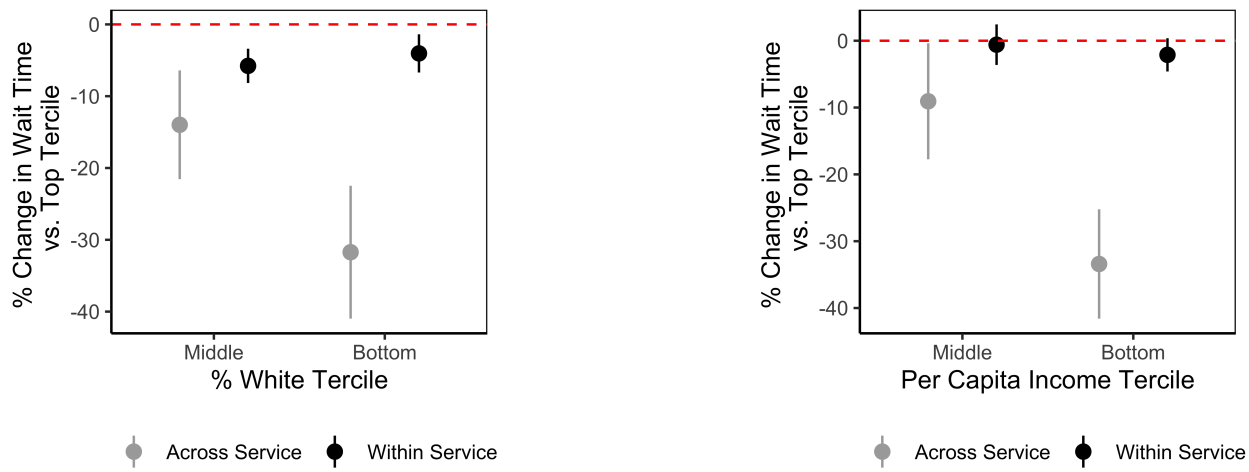
Notes: Time refers to month-year. Standard errors clustered by block group. $^{+}$p<0.10; ***p<0.001

Table A6: **Effects of Neighborhood Race and Income on Expected Wait Times: Top 10 City-Service Areas**

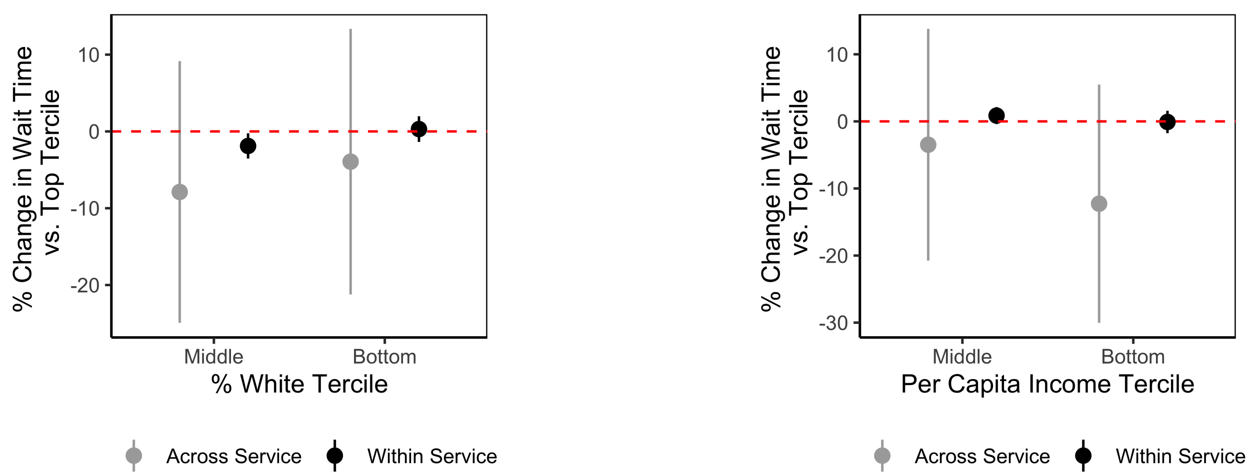
	DV: *ln(Expected Wait Time)*			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	0.160***	-0.001	0.212***	0.003+
	(0.015)	(0.002)	(0.014)	(0.001)
Bottom	0.327***	-0.003*	0.323***	0.0008
	(0.015)	(0.001)	(0.015)	(0.001)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	7,873,783	7,873,783	7,873,488	7,873,488
R^2	0.16415	0.88705	0.16428	0.88705

Notes: Time refers to month-year. Standard errors clustered by block group. $^{+}p<0.10$; $^{*}p<0.05$; $^{***}p<0.001$

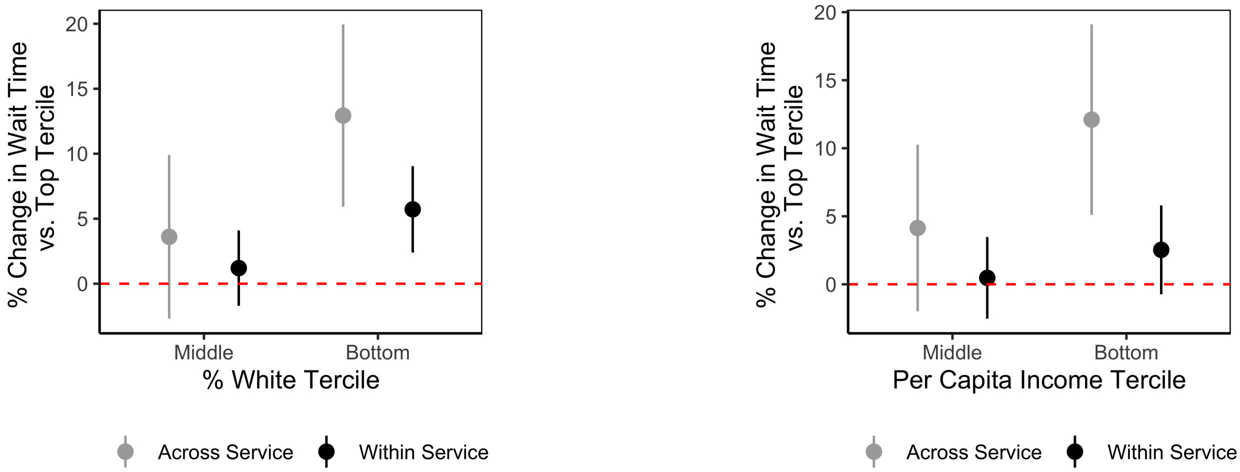
Figure A10: **Effects of Neighborhood Race and Income on Wait Times: City-by-City**



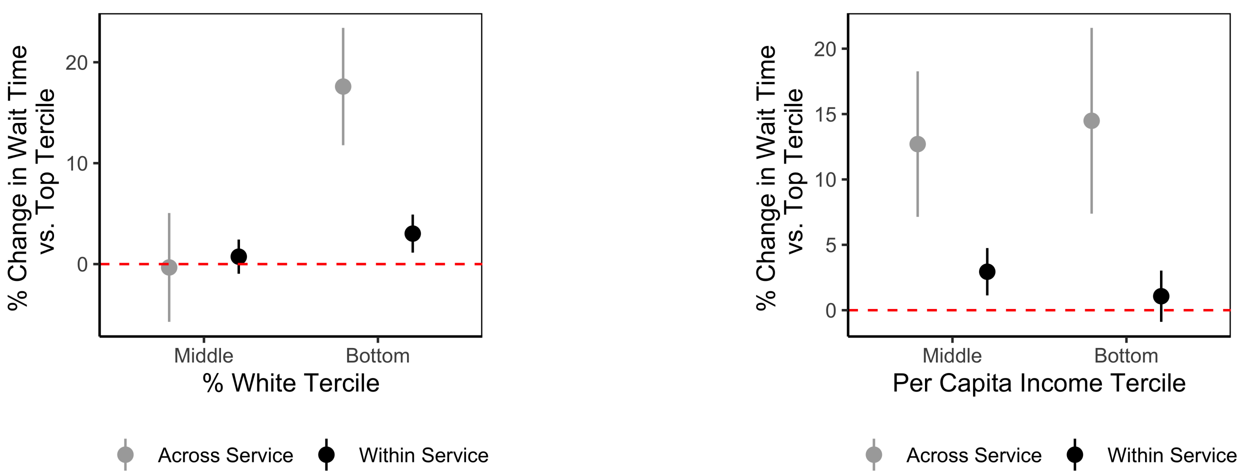
(a) Austin



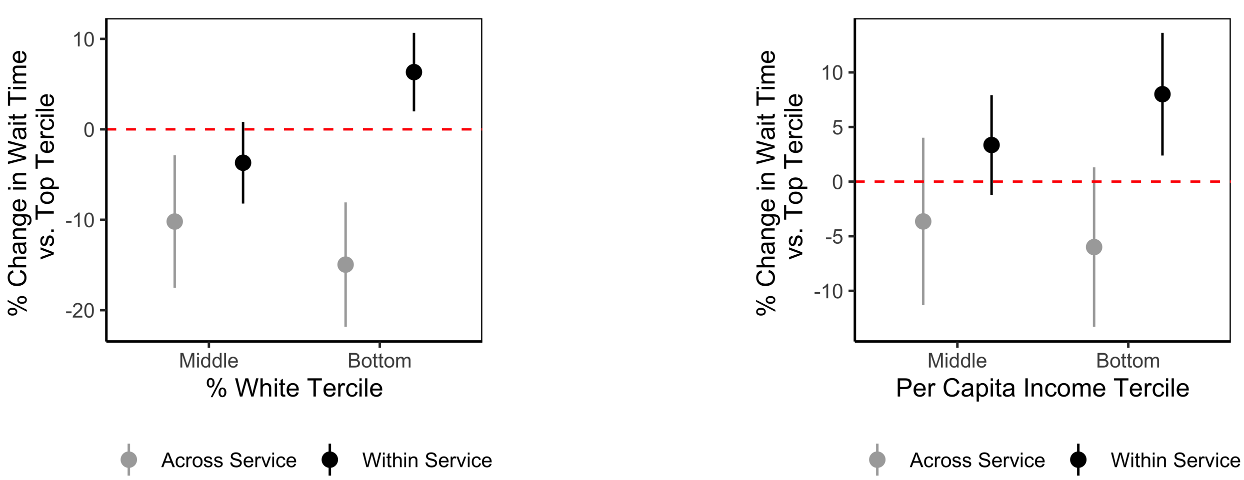
(b) Baltimore



(c) Boston



(d) Dallas



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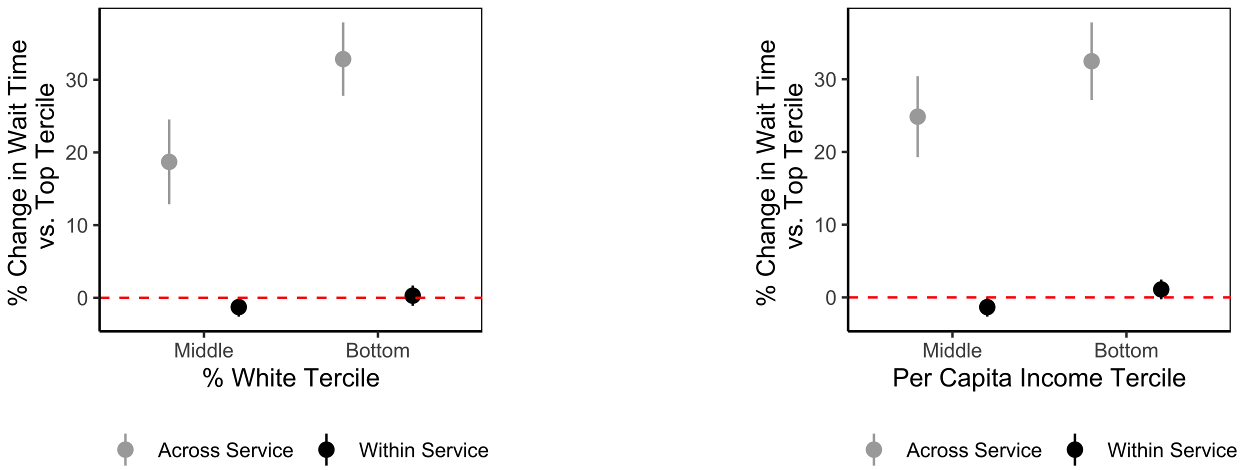
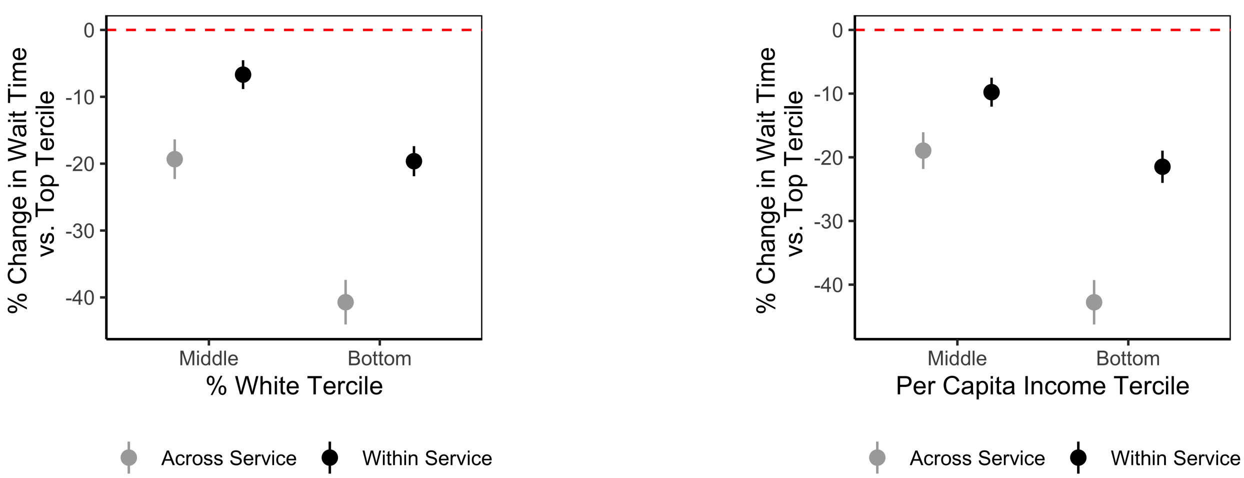
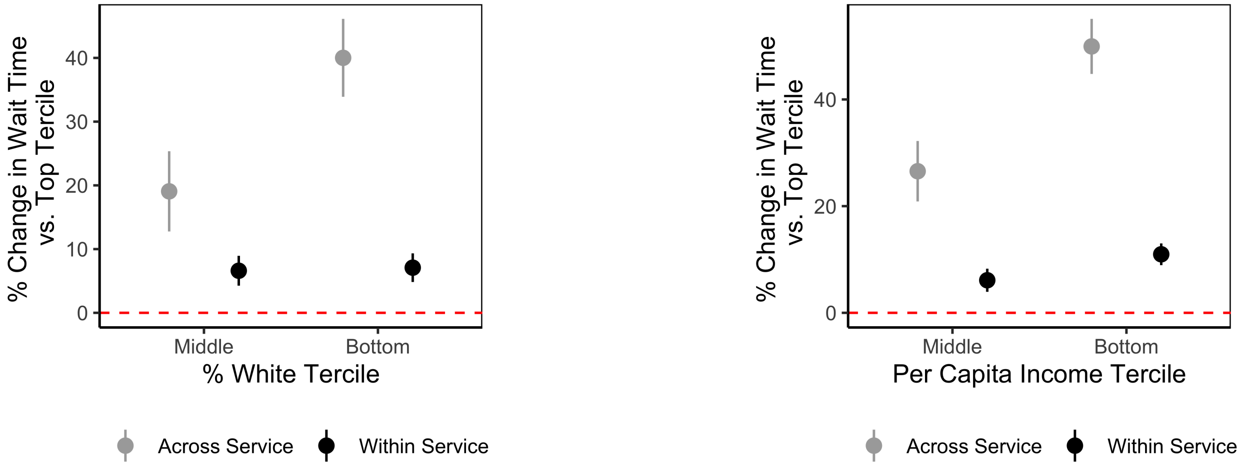


(f) Houston



(g) Los Angeles



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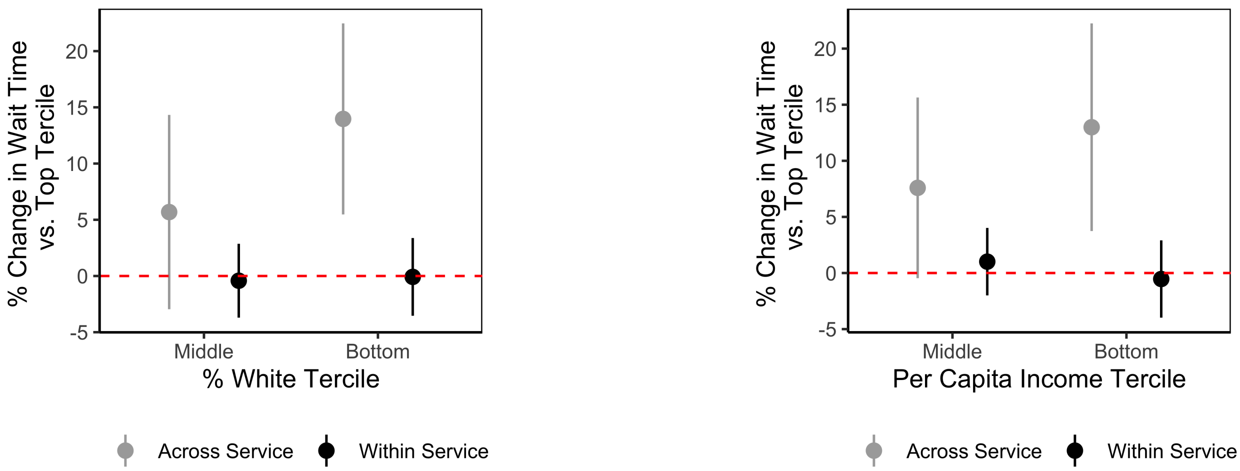

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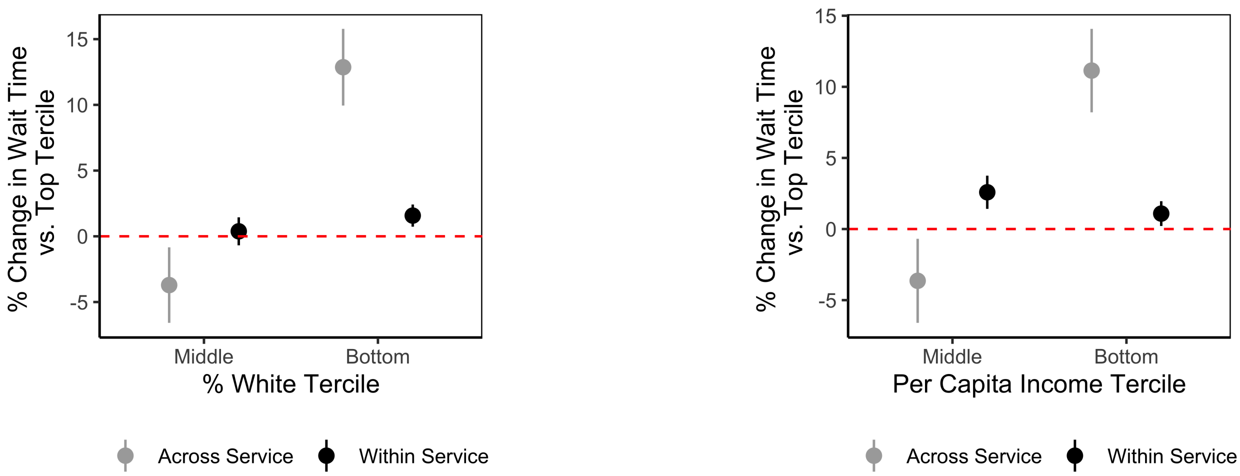

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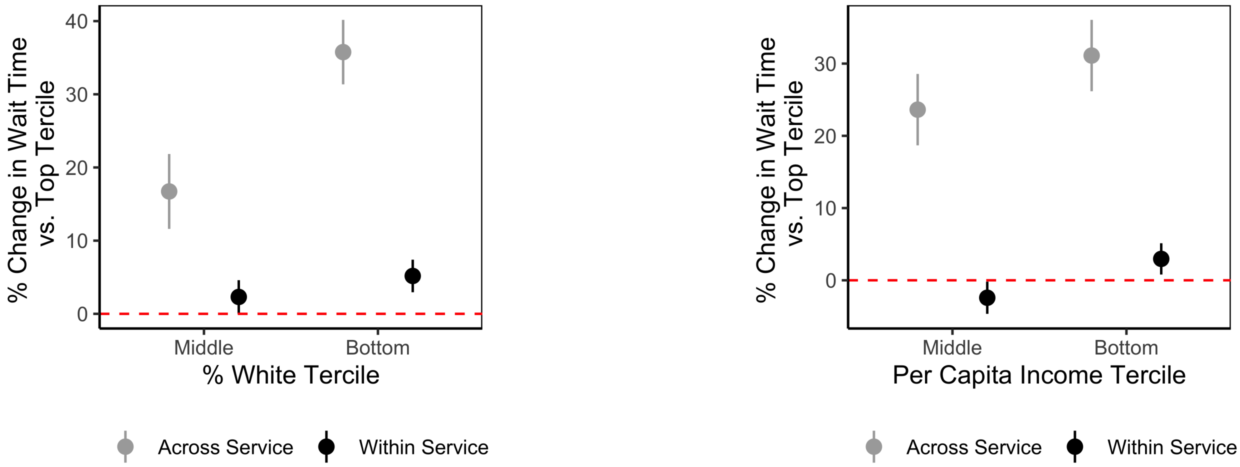

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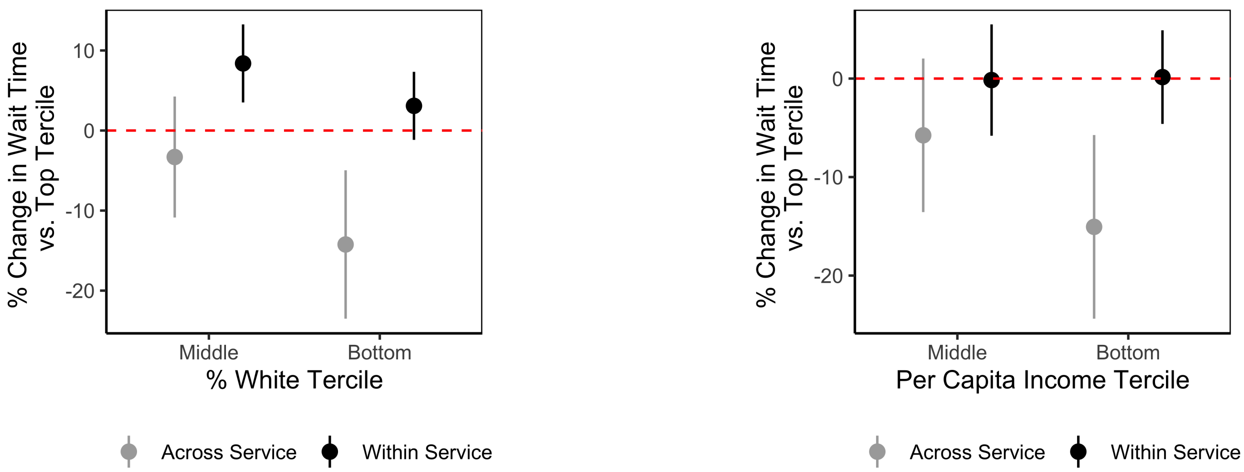

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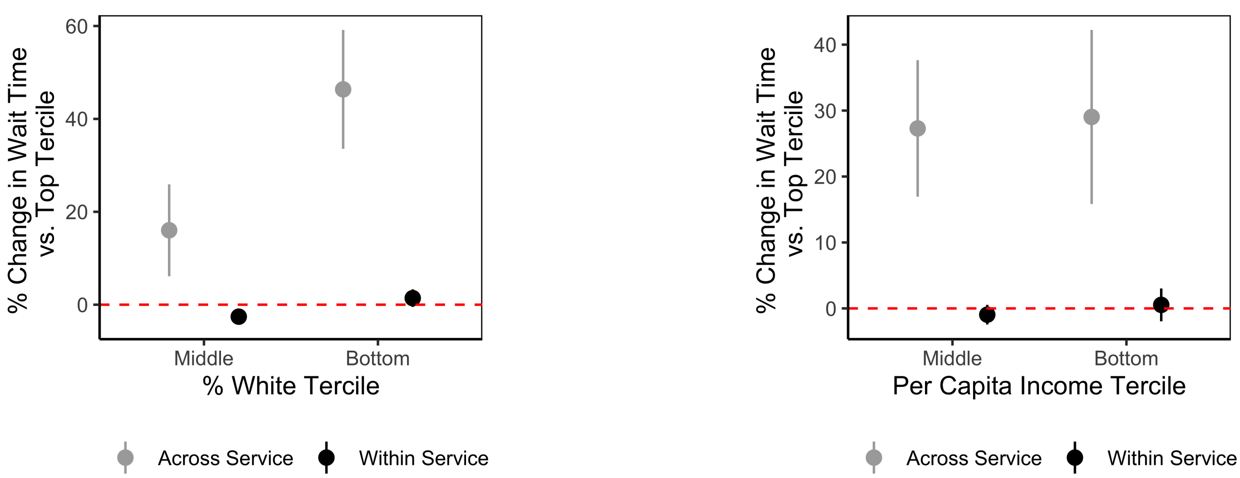
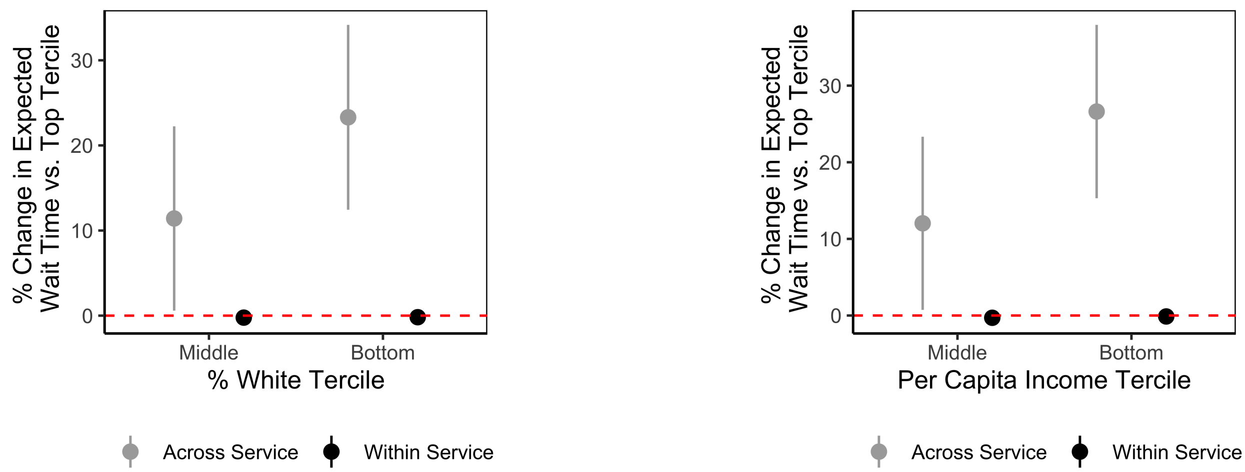
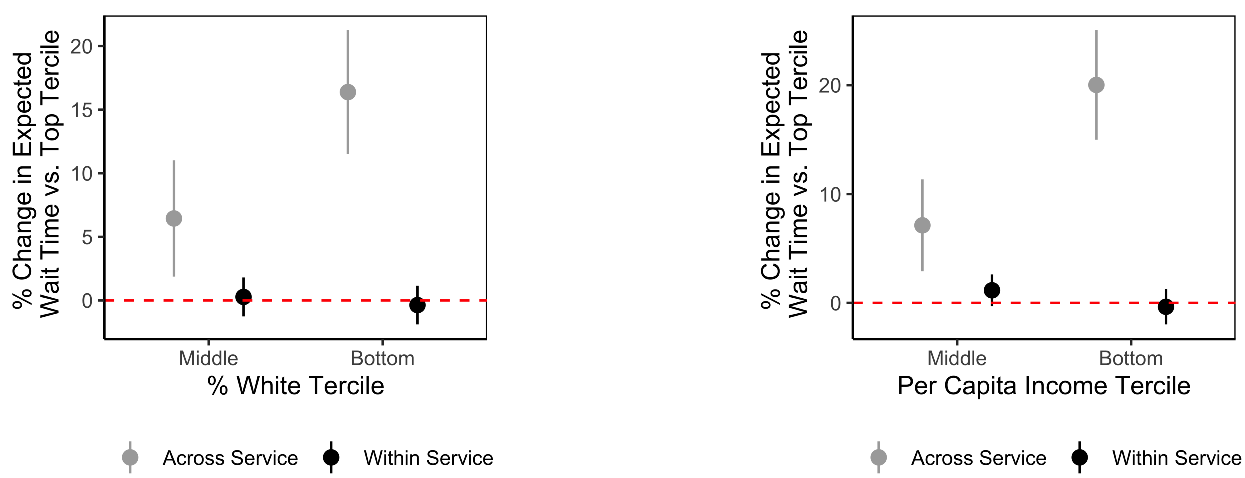


(m) Washington, DC

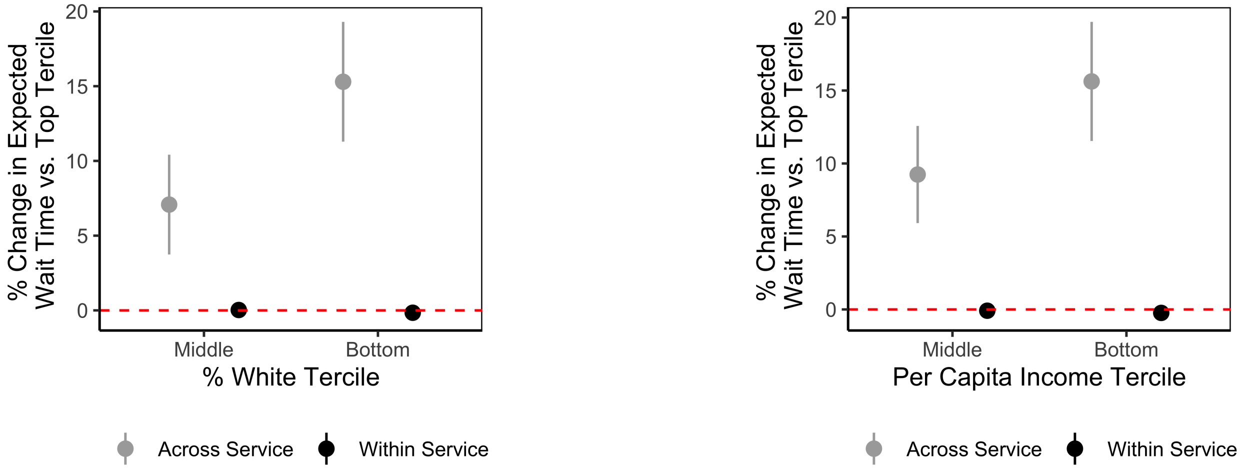
Figure A11: **Effects of Neighborhood Race and Income on Expected Wait Times: City-by-City**



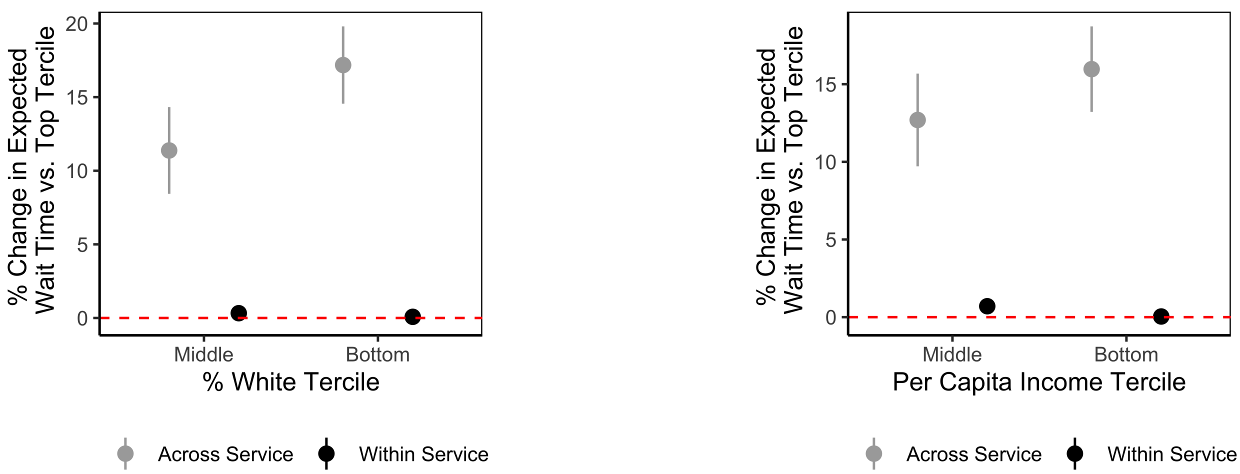
(a) Baltimore



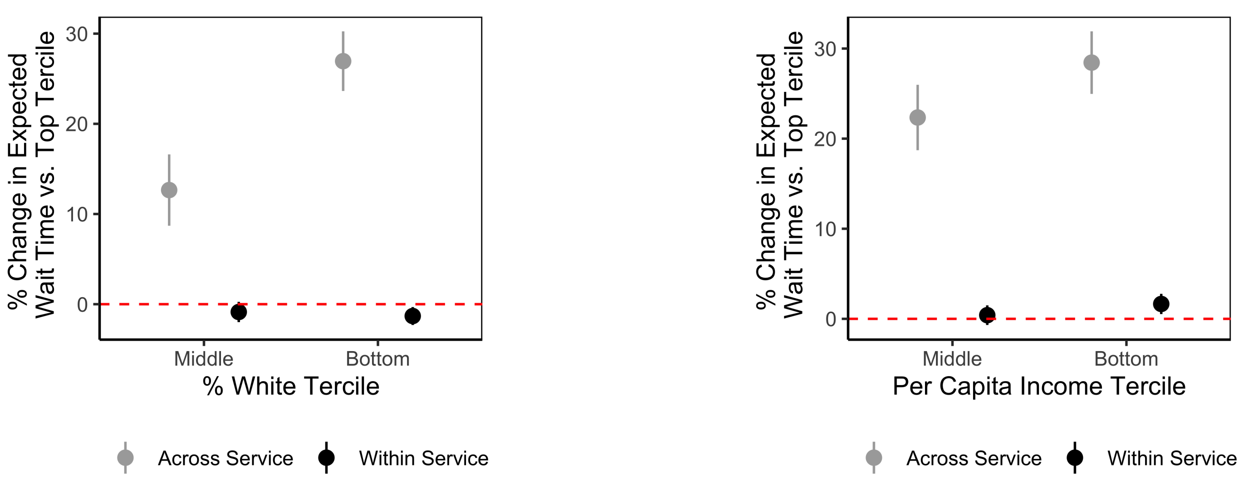
(b) Boston



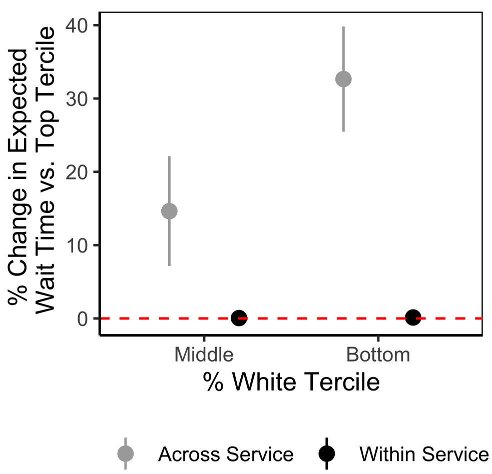
(c) Dallas

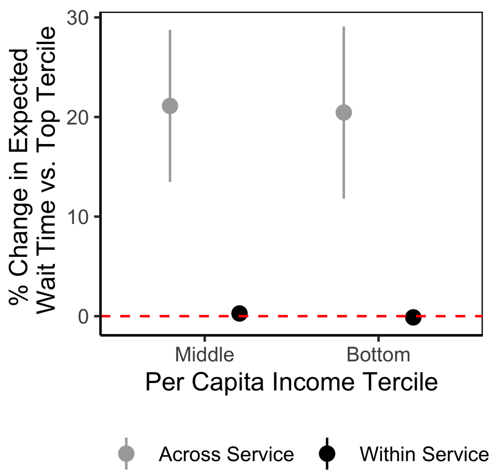


(d) Houston



(e) Philadephia





(f) Washington, DC

Table A7: **Effects of Neighborhood Race and Income on Wait Times: Week Fixed Effects**

	DV: ln(Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	-0.013	0.0004	0.015	0.007^{+}
	(0.014)	(0.004)	(0.014)	(0.004)
Bottom	0.075^{***}	0.0009	0.048^{**}	-0.006^{+}
	(0.015)	(0.003)	(0.015)	(0.003)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	41,111,241	41,110,956	41,110,708	41,110,423
R^2	0.117	0.661	0.116	0.661

Notes: Time refers to week. Standard errors clustered by block group. $^{+}$p<0.10; **p<0.01; ***p<0.001

Table A8: **Effects of Neighborhood Race and Income on Expected Wait Times: Week Fixed Effects**

	DV: ln(Expected Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	0.110***	-0.0005	0.135***	0.002*
	(0.021)	(0.0009)	(0.021)	(0.0009)
Bottom	0.219***	-0.002+	0.217***	0.0004
	(0.021)	(0.0009)	(0.022)	(0.0009)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	14,437,586	14,437,585	14,437,054	14,437,053
R^2	0.116	0.919	0.116	0.919

Notes: Time refers to week. Standard errors clustered by block group. $^{+}p<0.10$; $^{*}p<0.05$; $^{***}p<0.001$

Table A9: **Effects of Neighborhood Race and Income on Wait Times: Date Fixed Effects**

	DV: ln(Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	-0.005	0.004	0.018	0.009^{*}
	(0.014)	(0.004)	(0.014)	(0.004)
Bottom	0.085^{***}	0.006^{+}	0.055^{***}	-0.002
	(0.015)	(0.003)	(0.015)	(0.003)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	41,111,241	41,110,956	41,110,708	41,110,423
R^2	0.133	0.691	0.133	0.691

Notes: Time refers to date. Standard errors clustered by block group. $^{+}p<0.10$; $^{*}p<0.05$; $^{***}p<0.001$

Table A10: **Effects of Neighborhood Race and Income on Expected Wait Times: Date Fixed Effects**

	DV: ln(Expected Wait Time)			
	% White		*Per Capita Income*	
	(1) Across	(2) Within	(3) Across	(4) Within
Middle	0.107***	0.0005	0.133***	0.002**
	(0.021)	(0.0008)	(0.021)	(0.0008)
Bottom	0.215***	0.001+	0.212***	0.003**
	(0.021)	(0.0008)	(0.022)	(0.0009)
City-Time FEs	✓		✓	
City-Service-Time FEs		✓		✓
Observations	14,437,586	14,437,585	14,437,054	14,437,053
R^2	0.128	0.933	0.128	0.933

Notes: Time refers to month-year. Standard errors clustered by block group. $^+p<0.10$; $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A11: **Effects of Changes in Lagged Differential Demand on Wait Times**

	DV: ln(Mean Wait Time)				*DV: ln(Mean Expected Wait Time)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-White - White$_{t-1}$	-0.0007				0.0008			
	(0.001)				(0.0009)			
Non-White Need$_{t-1}$		0.016				0.029		
		(0.051)				(0.046)		
Poor - Rich$_{t-1}$			0.0008				0.0006	
			(0.001)				(0.0009)	
Poor Need$_{t-1}$				0.036				0.055
				(0.050)				(0.038)
City-Service FEs	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	108,119	108,119	108,119	108,119	67,777	67,777	67,777	67,777
R^2	0.858	0.858	0.858	0.858	0.764	0.764	0.764	0.764

Notes: Time refers to month-year. Standard errors clustered by city-service. Observations are weighted by the total number of calls.

Table A12: **Effects of Changes in Differential Demand by Year on Wait Times**

	DV: ln(Mean Wait Time)				*DV: ln(Mean Expected Wait Time)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-White - White	-0.003				0.005			
	(0.005)				(0.003)			
Non-White Need		0.072				0.135		
		(0.114)				(0.112)		
Poor - Rich			0.006				0.003	
			(0.006)				(0.003)	
Poor Need				0.016				0.022
				(0.135)				(0.049)
City-Service FEs	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	12,120	12,120	12,120	12,120	7,578	7,578	7,578	7,578
R^2	0.889	0.889	0.889	0.889	0.767	0.766	0.766	0.766

Notes: Time refers to year. Standard errors clustered by city-service. Observations are weighted by the total number of calls.

Table A13: **Effects of Lagged Differential Demand on Wait Times: Across Cities, Within Common Service**

	DV: ln(Mean Wait Time)				*DV: ln(Mean Expected Wait Time)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-White - White$_{t-1}$	0.001				-0.0007			
	(0.002)				(0.003)			
Non-White Need$_{t-1}$		-0.016				-0.098		
		(0.075)				(0.135)		
Poor - Rich$_{t-1}$			0.002				-0.002	
			(0.002)				(0.003)	
Poor Need$_{t-1}$				0.017				-0.129
				(0.088)				(0.144)
Common Service-Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	23,809	23,809	23,809	23,809	14,634	14,634	14,634	14,634
R^2	0.602	0.601	0.603	0.601	0.648	0.652	0.649	0.654

Notes: Time refers to month-year. Standard errors clustered by city-common service. Observations are weighted by the total number of calls.