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**New Faces Changing Spaces: How Gentrification Shapes
Individual Demand for Policing**

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**New Faces Changing Spaces: How Gentrification Shapes
Individual Demand for Policing**

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Report

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Abstract

New Faces Changing Spaces: How Gentrification Shapes Individual Demand for Policing

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How does gentrification impact individual demand for policing? Previous research finds that gentrification is associated with more calls to the police but cannot show which residents make these calls or evaluate explanations for why these calls occur. My novel individual-level approach allows me to test common assumptions and ethnographic findings about gentrification and policing. Using a within-subject design that matches 2014-2021 voter file data with administrative police records from Austin, TX, I show that gentrifiers make more calls to the police than long-term residents in gentrifying neighborhoods and that this increasing call volume is associated with the act of moving. Specifically, I show that wealthier, white gentrifiers demand more policing as they move into spaces with relatively higher levels of poverty and more non-white residents regardless of changes in crime. These findings challenge the common assumption that crime alone drives demand for policing, instead highlighting the impact of poverty and race in shaping individual political behavior in gentrifying contexts.

Table of Contents

Introduction	5
Background & Theory	10
Argument & Hypotheses	16
The Case: Austin, TX	18
Data	21
Dependent Variables	22
Explanatory Variables	23
Estimation Strategy	28
Findings	29
Who Calls the Police in Gentrifying Neighborhoods?	29
Movement into Gentrifying Areas and Greater Demand for Policing	31
Neighborhood Racial Composition and Gentrifier Demand for Policing	36
Conclusion & Implications	40
A Appendix	42
A.1 Matching Call data to Voter File	42
A.2 OMP Call Classification	43
A.3 Multi-unit property analysis	44
A.4 Austin Census Tracts by Gentrification Status	48
A.5 Sample Distribution of Observations by Mover Categories	48
A.6 Details on BISG Method	48
A.7 Analysis 1	49
A.8 Analysis 2	52
A.9 Analysis 3	56
Works Cited	59
Vita	65

Introduction

Every Sunday, Chicano Park, on the East side of Austin, TX, transforms into a hub for brightly-colored lowriders and vintage cars blasting loud-music out of their stereos and occasional plumes of white smoke. After a few loops of the park, the drivers, mostly Black and Latino men in their twenties and thirties, park their cars, pull out barbeque grills and join families and friends to pass the rest of the afternoon in the park. These Car Club gatherings have been taking place every Sunday since the nineties, but recently, residents of The Weaver, a newly-constructed luxury apartment complex located near the park have lodged numerous complaints. While The Weaver’s website promises renters access to a “community that is rich in history and tradition,” at a recent gathering, a white tenant pleaded with police officers to disband the celebration, calling it ‘scary’ (Holley 2021). This tension between long-term residents and newer residents over the use of neighborhood space is not unique to Austin. Cities across the country are grappling with increased demand for policing by newer residents to gentrifying areas.

Gentrification is traditionally defined as “the in-migration of middle-and upper-income households into existing lower income urban neighborhoods” (Griffith 1996, p. 241). As is the case in Austin’s East Side, gentrification typically brings greater numbers of more affluent, largely white residents (gentrifiers) into lower-income, previously disinvested neighborhoods that are often majority Black or Latino (Hyra 2008; Wyly and Hammel 2008; Ellen and O’Regan 2011). Scholars argue that this influx of more socially privileged and empowered into disadvantaged neighborhoods often leads to increased policing (Sharp 2014; Laniyonu 2018) particularly driven by citizen demand (Beck 2020; Harris, Rigolon, and Fernandez 2020; Herring 2019). However, there is considerable disagreement between scholars about why these increased demands occur.

In this paper, I argue that gentrifiers increase their demand for policing when they move into more impoverished and nonwhite spaces. While conventional wisdom predicts that increased gentrifier demand for policing is solely a response to heightened crime, prior

qualitative work finds that gentrifiers often demand policing to curb behaviors they link to criminality or neighborhood disorder such as homelessness, late-night gatherings in public spaces, or unauthorized home repairs. Furthermore, this response is often highly racialized, as largely white gentrifiers' perceive the mere presence of non-white residents as evidence that a neighborhood is dangerous absent objective measures of safety. Adjudicating between differing explanations of gentrifier behavior is important because in determining whether gentrifier calls to police are tools for enhanced personal safety in the face of greater crime or a method for gentrifiers to weaponize the police to surveil the behavior of the often low-income, non-white traditional residents of gentrifying neighborhoods. Using voter file data and administrative call records, I am able to identify specific types of movers into gentrifying spaces and the number of calls to the police that they make over time. I find that gentrifiers are more likely to demand policing than long-term residents of gentrifying neighborhoods and that they increase their calls to the police after moving into a gentrifying space net changes in violent crime. I also find support for the racial threat hypothesis in that gentrifiers increase their demand at greater levels when moving into neighborhoods with higher proportions of Black and Latino residents.

The most common explanation for a rise in demand for policing is that it is a response by gentrifiers to crime. Given the correlation between poverty and crime (Sharkey, Besbris, and Friedson 2017; Gaitán-Rossi and Velázquez Guadarrama 2021), movement into previously disadvantaged neighborhoods may expose gentrifiers, typically accustomed to the lower rates of crime associated with more affluent neighborhoods, to higher rates of crime. Furthermore, construction of new housing complexes or upscale businesses may increase the potential for property crime within developing areas. As a response, gentrifiers could demand greater policing both in reaction to specific crimes and in an effort to prevent future crime by increasing police surveillance of the area.

Alternatively some evidence suggests that increased gentrifier demand for policing is less a response to objective changes in crime and more a reaction to perceived poverty or cross-class

interactions in gentrifying neighborhoods. Within local politics, more affluent residents often wield political power to maintain and increase the economic status of their property and the surrounding neighborhoods (Einstein, Glick, and Palmer 2019; Yoder 2020; Hankinson 2018; Pleger 2017). In this scenario, gentrifiers may engage police to respond to more visible signs of poverty, such as homelessness, graffiti, or abandoned vehicles in an attempt to improve the appearance of their surroundings and the socio-economic status within the neighborhood.

Similarly, theories of racial threat predict that it is privileged whites' response to more ethno-racial diversity within neighborhoods that drives greater demand for policing. Since gentrification often brings large numbers of white residents into historically majority Black or Latino neighborhoods, racial threat theories predict that white gentrifiers will perceive gentrifying neighborhoods as 'disordered, dangerous, or more prone to criminal activity irrespective of objective measures of crime in the area. These racial stereotypes then generate a heightened demand for policing. Ultimately, which of these three explanations is more correct has implications for both how gentrification occurs (Hwang and Sampson 2014) and resulting social and political behavior (Enos 2016; Michener 2013).

Empirical tests of the sources and trajectory of demand for policing in gentrifying neighborhoods are both rare and limited in their ability to explain which residents demand policing in gentrifying neighborhoods and whether this demand is a result of movement into gentrifying spaces. The vast majority that investigate the link between gentrification and citizen demand for policing are either qualitative case studies of a single neighborhood (Muñiz 2015; Parekh 2015; Pattillo 2010) or quantitative studies that use census tracts or neighborhoods as their unit of analysis (Legewie and Schaeffer 2016; Beck 2020; Collins, Stuart, and Janulis 2022). While qualitative case studies provide rich detail about individual-level mechanisms, they are highly specific, limited to only a single neighborhood or a small number of individuals. Previous quantitative work that has been confined to the aggregate-level, suffers from issues related to ecological inference. At a base level, these studies are unable to identify what type of residents within gentrifying neighborhoods make calls to the police. More-

over, they cannot evaluate how distinct neighborhood-level conditions such as changes in crime, socio-economic status and racial composition vary with gentrifier demand for policing. Therefore, an individual-level analysis is necessary in order to establish relative levels of demand by residents within gentrifying neighborhoods and test competing explanations for why gentrifiers demand for policing.

To address these limitations, I test how gentrification leads to increased demand for policing. I conduct this test within the city of Austin, TX, one of the most rapidly gentrifying cities in the country (Kimble 2022; Maciag 2015). Leveraging large-scale administrative data on 310,393 voters between 2014-2021, I use household addresses to identify distinct types of within-city movers. This allows me to compare the behavior of gentrifiers, individuals or households that move from wealthy neighborhoods into gentrifying spaces, to other types of urban movers and non-movers, including long-term residents of gentrifying neighborhoods. Matching these addresses to over 2 million 911 calls and 311 requests from the same time period, allows me to test 1) if gentrifiers make more calls to the police relative to long-term residents of gentrifying areas, 2) if gentrifiers increase their demand for policing after into a gentrifying area net changes in crime, and 3) if gentrifiers make more calls when moving into predominantly non-white spaces.

I find evidence that gentrifiers make more calls to the police than long-term residents in gentrifying spaces. I then show that moving into gentrifying tracts leads to increased calls to the police net changes in crime. Gentrifiers are also especially likely to increase their demand for order maintenance policing, the policing of low-level, non-violent behaviors such as homelessness, loitering, or public intoxication. I further find that this behavior is most pronounced among gentrifiers moving into spaces with high proportions of Black and Latino residents.

This paper establishes citizen demand for policing as a component of the entrenched relationship between policing and gentrification. Building on the work of sociologists, it explicitly links changes in demand to the perceptions and preferences of gentrifiers providing

evidence that gentrifier demand is not exclusively tied to threats of violence to themselves or their property, but to a discomfort with living among greater poverty and non-white residents. These findings have tremendous consequences for the traditional residents of gentrifying neighborhoods, heightening the risk of police encounters for lower-income, particularly Black and Latino residents in their everyday lives. They also shed light on how processes of gentrification may further entrench racial and class inequalities in urban centers as long-term residents face not only the threat of economic displacement, but also increased surveillance and criminalization. Ultimately, demand for policing is a key element to the politics of gentrification as it helps explain how newer residents cultivate power and control within gentrifying contexts.

Background & Theory

Since the 1950s, U.S. cities have experienced high levels of deindustrialization, weakening traditional manufacturing and heavy industry. Facing financial constraints that necessitate a robust tax base (Peterson 1981), city governments have increasingly focused on building urban amenities to attract and satisfy a certain “creative class” of urban professional workers and accompanying jobs. As opportunities for employment in cities have increased, demand for housing in or near city centers has increased among professional workers leading to the in-movement of young, higher-earning, well-educated, professionals or creatives into previously lower-income neighborhoods, a process commonly known as gentrification (Florida 2002; Griffith 1996; Wyly and Hammel 2008). Although there are many ways to understand gentrification, most traditional descriptions define it as a class-based phenomenon, where higher-income residents move into less affluent neighborhoods.

These traditional descriptions however, largely ignore, especially in the U.S. context, the persistent marginalization, segregation, and discrimination that leaves urban Black and Latino communities with little access to political or economic power and vulnerable to the tastes, preferences, and demands of white, wealthy residents (Betancur 2002). Gentrifying urban spaces typically see not only a rise in the proportion of the population holding college degrees, working professional jobs, and with higher incomes than the median income of the neighborhood (Brown-Saracino 2009; Robinson 1995; Wyly and Hammel 2008; Zuk et al. 2018), but also a rise in the white population (Smith 1996). This process is not always straightforward, for instance, Hwang and Sampson (2014) finds that the likelihood of neighborhood gentrification is attenuated by the Black population in the area. Even taking this into account, gentrifiers’ racial and socio-economic characteristics make them distinct from traditional residents of gentrifying areas, who due to systemic racism, poverty, and institutional dis-investment are often less likely to hold college degrees, have lower incomes, and are often people of color.

As new residents move into gentrifying spaces, scholars have found concurrent increases

in policing, especially the policing of homelessness, or behaviors such as loitering, or public intoxication. This type of policing practice, commonly referred to as order maintenance policing (OMP), most often deployed in neighborhoods that have been politically or socially construed as disordered and is designed to intervene in low-level activity before it escalates to more serious crime. Yet the people and neighborhoods who are routinely the targets of these practices become functionally criminalized via heightened contact with police even as no criminal activity has transpired at the point of contact.

As a consequence of gentrifying neighborhoods' previous institutional disinvestment and poverty, municipal governments deploy OMP to protect the new investment and residents of these spaces which they think of as disordered (Sharp 2014). Laniyonu (2018) finds that gentrification is associated with a rise in OMP, in the form of stops under New York City's Stop and Frisk Policy. Within the context of Los Angeles, Collins, Stuart, and Janulis (2022) determine that gentrifying tracts experience a greater number of citations compared with other tract types. Taking a broader perspective, Sharp (2014) demonstrates that across 100 American cities, there is a strong and positive relationship between growth in the proportion of the population who can be classified as members of the "creative" class and order maintenance arrests. Overall, OMP practices bring civilians into more frequent contact with police, the impact of which can be seen in heightened stops, citations, and arrests that follow from these practices.

One explanation for this rise in policing and OMP in gentrifying neighborhoods is increased citizen demand. Legewie and Schaeffer (2016) find that calls to New York's 311¹ hot-line increase during gentrification and Laniyonu (2018) finds slight increases in 311 calls in neighborhoods adjacent to gentrifying spaces. Beck (2020) and Sahn, Lerman, and Mooney (Working paper) find that 311 calls to the police increase as a neighborhood's middle-class population increases and as the proportion of white residents grows. However, there remains a dearth of knowledge on the relationship between citizen-initiated policing and gentrification

¹311 is a non-emergency phone system through which citizens, typically in cities, can make complaints, request services, or access information from their local government

especially at a more granular level.

While one might expect an increase in calls to be linked to the in-migration of gentrifiers to a neighborhood, empirical work has investigated patterns only at the aggregate level. This presents potential problems as an exclusively aggregate-level analysis cannot identify the source of the calls and thus cannot determine whether the differential characteristics between gentrifiers and traditional residents of gentrifying neighborhoods yield distinct behavioral outcomes. Examining only neighborhood-level trends could lead observers to conclude that all residents are making equal demands and thus assume that that increased demand reflects a universal decline in neighborhood safety. Missing the variation in individual-level behavior could therefore lead to imprecise or unsuitable policy responses that misinterpret the factors driving increased demand.

The most common assumption for why gentrifiers demand policing is that it is a direct response to heightened levels of crime in gentrifying neighborhoods. Due to the high correlation between poverty and crime (Sharkey, Besbris, and Friedson 2017; Gaitán-Rossi and Velázquez Guadarrama 2021), movement into gentrifying areas may expose gentrifiers to higher rates of crime. This increased direct exposure to more crime, whether it be crimes against persons, property or society, is the most common explanation for these calls.

In contrast, findings from ethnographies of gentrifying neighborhoods provide alternative explanations: that increased demand for policing is a result of gentrifiers' response to the greater levels of poverty and larger non-white populations, particularly Black residents in their new neighborhoods. Qualitative research finds that class differences between gentrifiers and long-term residents often characterizes differences in the attitudes of residents toward their neighborhoods. Long-term residents often spend most or all of their lives in the same neighborhood and devote time and energy to mingling with their neighbors, while newcomers typically report being drawn to the neighborhood to make financial gains on their homes and do not mention a desire to get to know their neighbors nor spend any time among the community (Cybriwsky and Levy 1980). These distinct community histories and ties yield

different conceptions of public safety and the use of public space generating conflicts between newer and older residents. These newer residents, more likely to have higher levels of trust in the police and be accustomed to greater responsiveness from public officials, then turn to police to remedy these conflicts. In Pattillo (2010)’s work on gentrification in Chicago, she links myriad sources of conflict—where to barbecue, fixing cars on the street, porch sitting, honking horns, unauthorized home repairs and others—to increases in gentrifier demand for the informal and formal policing of the behavior of long-term residents.

Alongside class and also directly linked to it, race has also been shown to be a salient force in driving local political behavior. The racial threat hypothesis, first proposed by Blalock (1967), posits that members of the dominant group—in this context—white gentrifiers, will perceive increases in the size and proportion of the black population nearby as threatening and will take action to reduce this threat. Research finds support for this hypothesis especially in the case of urban politics. Investigating the issue of public housing in urban spaces, Enos (2016), finds that after the demolition of a public housing complex in Chicago reduced the number of Black residents near a predominantly white neighborhood, white voter turnout in local elections declined. There is also a plethora of evidence that White perceptions of racial threat influence a wide range of political attitudes from immigration policy (Hopkins 2010; Campbell and Citrin 2006; Ha 2010) to busing (Bobo 1983) and affirmative action (Tolbert and Grummel 2003). Hamel and Wilcox-Archuleta (2022) find that even the presence of higher numbers of Black workers in a neighborhood during daytime hours is associated with more conservative voting behaviors and racial attitudes among whites who live in the same neighborhood.

Moreover, in their research on gentrification in the Tr  me district of New Orleans, Parekh (2015) interviews two residents on their attitudes towards neighborhood safety. June, an African American woman in her forties working two jobs to raise her children, describes how the purportedly “nosy grandmothers sitting on their porches” were constantly watching what was going on in the street. For June, this meant that criminal activities were thwarted

by the surveillance created through the eyes of a network of older women. Meanwhile Ellen, “a middle-class, single White woman who had recently bought a home in Treme after having lived in Metairie, a predominantly White New Orleans suburb, for most of her life,” describes how she “was fearful of going out on the street, and she felt afraid when she saw ‘too many’ people hanging out on their porches.” (Parekh 2015, p. 209). Parekh (2015) highlights the racialized nature of the Ellen’s perceptions, noting that the use of public space by residents “led Ellen to feel fearful not only since she was unfamiliar with it, but also because of the blackness of the bodies she encountered in public space” (p. 210). This evidence suggests that gentrifiers’ perceptions of their neighborhoods are heavily influenced by racial biases and a sense of threat, and thus moving into more non-white spaces could generate an increased demand for policing among white gentrifiers.

Despite ample qualitative evidence, quantitative empirical tests of the association between gentrification and individual demand for policing are both rare and limited. The vast majority of studies that investigate the link between gentrification and citizen demand for policing are either qualitative case studies of a single neighborhood (Parekh 2015; Pattillo 2010; Freeman 2005) or quantitative studies that use census tracts or neighborhoods as their unit of analysis (Legewie and Schaeffer 2016; Beck 2020; Collins, Stuart, and Janulis 2022). While ethnographic case studies provide rich detail about individual-level mechanisms, a more systematic analysis can assess the extent to which some of these findings travel to different neighborhoods and explain the behavior of a large sample of individuals.

Previous quantitative work has been confined to the aggregate-level, using gentrifying neighborhoods as the unit of analysis. This work suffers from issues related to ecological inference in that it is unable to test specific causal mechanisms underlying gentrifier demand for policing. Often this work relies on the theory that increased numbers of gentrifiers are the reason behind increased demand for policing, but it is unable to directly test this argument nor is it able to test the competing explanations outlined above for why gentrifiers may be increasing their demand for policing. In this paper, I conduct an analysis that allows me

to both systematically analyze the behavior of gentrifiers and test competing explanations for why gentrifiers may increase their demand for policing. Substantively, this provides insight into the relationship between gentrification and policing and how the race and class-based nature of urban spaces shapes individual political behavior. From a methodological standpoint, this paper develops an approach to identifying movers within urban spaces that can be applied in a variety of ways to study how neighborhood context and movement itself shape urban politics.

Argument & Hypotheses

Drawing on the existing literature on gentrification and policing, I expect that within gentrifying neighborhoods, gentrifiers will exhibit a greater demand for policing than long-term residents of these neighborhoods.

H1: *Gentrifiers will make more calls to the police than long-term residents within gentrifying tracts.*

In addition to demanding greater policing than long-term residents in gentrifying neighborhoods, I argue that gentrifiers' movement into gentrifying areas is associated with increases in individual demand for policing. Gentrifiers, accustomed to residing in more affluent, whiter neighborhoods, perceive gentrifying neighborhoods as spaces of greater disorder or chaos linked to more visible signs of poverty or to racial stereotypes of areas with greater proportions of non-white residents. Furthermore, qualitative research establishes that gentrifiers are likely to engage police in ways that are distinct from long-term residents of the same spaces, because as ascriptively privileged citizens, they have a different relationship to police. Thus gentrifiers will demand greater policing to remedy said perceived disorder, and because factors such as a class or race may structure individual perceptions of threat or danger for gentrifiers, I expect that more objective measures of the level of crime will not fully account for increased calls to the police. I further expect that these dynamics will be most apparent in requests for order maintenance policing (OMP) style intervention, as they aim to clean up neighborhoods and preempt crime, rather than responding to actualized criminal behavior.

H2: *Gentrifiers will increase their calls to the police after moving into a gentrifying tract net changes in crime.*

H2a: *Gentrifiers will increase their calls related to order maintenance policing after moving into a gentrifying tract net of changes in crime.*

Finally, because both gentrification and policing are highly racialized, I expect the racial context of gentrifying neighborhoods to impact gentrifier demand for police, specifically for

white gentrifiers. When white gentrifiers enter more nonwhite spaces, particularly those with substantial populations of Black and or Latino residents, this activates racial bias and prejudice increasing their sense of the neighborhood as dangerous and disordered. To remedy this sense of fear and establish control within these spaces, they increase their demand for policing.

***H3:** Gentrifiers who move into tracts with higher proportions of Black and Latino residents will increase their calls to police.*

The Case: Austin, TX

I test my hypotheses in the context of Austin, TX. While previous studies of gentrification have primarily focused on New York City, Chicago, Washington, D.C. and San Francisco, Austin provides the opportunity to study a context that 1) has gentrified more recently, and rapidly (Bresnan 2021), and 2) where gentrification is particularly racialized. In the past 30 years, the population of Austin has doubled, growing from under 500,000 residents in 1993 to over 1 million in 2023 (City of Austin Population History). Previously a smaller city characterized by the presence of the state capitol, military families, and those who are university-affiliated, the local economy now boasts the biggest companies in the world such as Dell, Google, and IBM, and most recently, Tesla. Rapid population and economic growth has increased the cost of living dramatically especially with regard to housing. In the past 10 years alone, the median household income for a family of four in the Austin area has risen from \$73,200 to \$122,300 (City of Austin) and median housing prices have doubled, from \$220,000 to \$501,507 (Texas A&M Real Estate Center 2022). These drastic changes have made Austin a prime example of a rapidly gentrifying urban area (Marin 2022; McGlinchy 2022; Delco 2019).

Like many other urban contexts, gentrification in Austin is particularly concentrated in historically Black and Latino majority neighborhoods, largely located just east and southeast of downtown. However, the racialized nature of gentrification is particularly powerful in the context of Austin. As Austin began to experience population growth in the early 20th century, city officials came together to develop a city plan that would connect the many disparate communities that made up the city at that point and determine where, when, and how much to allocate certain city resources. The result was Austin's 1928 Master Plan, a plan that fundamentally shaped the growth of Austin over the next century and "institutionalized racism in the capital city" (PBS 2021). The plan determined that despite the existence of Black communities in all sections of the city, from Clarksville to Wheatsville, African Americans should be forced to live in only one section of the city, "east of East Avenue

and south of the City Cemetery,” (present-day east and southeast of IH-35) and then zoned that area as the location for “undesirable industry” (Council 1928). In order to push Black residents out of their original neighborhoods and into the East side, the city government denied these neighborhoods city services, from public schools to utilities. Eventually the city built I-35 right through some of the communities closest to downtown, placing a literal divider between West and East Austin. As a result of these decisions and other practices of racial segregation such as racial covenants and redlining, Austin’s East Side saw high levels of poverty and institutional disinvestment.

This history forms the bedrock of gentrification in Austin today. For years, Black and Latino residents of the communities on the East side fought to clean up their neighborhoods, closing polluting plants such as Tank Farm, Browning Ferris Industries, and the Holly Power Plant (PBS 2021). This combined with the city’s “Smart Growth Plan” and investment in central city areas incentivized private developers to build new housing close to downtown and drew wealthy, largely white individuals, to increasingly move into historic Black and Latino communities on Austin’s east side (KUT 2021). This combined with the historical legacy of the City’s 1928 Plan and intentional segregation has resulted in the high levels of displacement of Black residents in Austin, even when compared to other gentrifying areas. Among the 10 fastest growing cities in the U.S., Austin was the only one to see a net loss in Black residents (KUT 2021). The concentration of Black residents on Austin’s east side makes the negative consequences of gentrification particularly harmful to Black residents.

Both Austin’s rapid development and its racial segregation make it a particularly apt case study for the impact of gentrification on gentrifier behavior. The speed at which Austin is gentrifying means that one can find variation within a smaller time frame as opposed to needing data across multiple decades. Furthermore, the concentration of Black and Latino residents in East Austin, allows for a measure of how the racial composition of gentrifying areas impacts gentrifier demand for policing.

Practically, Austin also provides the necessary data with which to conduct an individual-

level analysis. The availability of 311 and 911 administrative call data with location information alongside the TX voter file provides the key pieces in order to carry out my procedure linking police calls to addresses and identifying urban movers.

Data

In order to assess the impact of gentrification on individual household demand for policing, I create a dataset of calls to the police matched to voter file addresses. To create this I use the following data from the years 2014-2021: voter file data from Travis County, TX, publicly available 311 request records, 911 call data provided by the Austin Police Department and American Community Survey (ACS) data. To create my final dataset, I geocode the voter file data, sum the 311 and 911 call data by unique address, and then match the addresses of the voter file data to the addresses where the 311 requests and 911 calls originated for each year. After matching, I use voter id numbers and addresses to identify individuals who moved within Austin from one year to another. Next, I subset the data into three year windows in order to measure changes in the number of calls between the first year in the set and the final year for individuals who remained in the same neighborhood over the three year period and those who moved in the intervening year.² Finally, I restack each of these 3 year bins, including an indicator for the range of years, into a final dataset of 855,293 observations including 38,532 within city movers. For about 56% of the sample, these observations represent individual voters, and for the remaining 44%, they represent households with more than one registered voter. This allows me to evaluate the behavior at the individual and household-level before and after moving into a gentrifying tract.

There are a few limitations to this approach. The first is that not all of the call data matches with residential addresses. Many requests are made from non-residential addresses such as businesses or public buildings. Others do not have specific addresses but rather just street names e.g. “Corner of South Lamar and Barton Springs Rd.” or directional references. Across the eight years, there was an average matching rate of 38.08% for 311 requests and 27.3% for 911 calls.³

A second key limitation is that the call data does not distinguish between distinct units

²For more details on distribution of mover categories see Table A5

³For a more detailed description the matching process see Appendix A

in multi-unit housing complexes. Even if a call is from a multi-unit property and matches a street address in the voter file, I cannot assume that the call originated from that address given that there are multiple distinct units in the building. Therefore, for my primary analysis, I use only calls that can be traced to single-unit properties. However, in order to test whether similar patterns emerge for multi-unit properties, I conduct a separate analysis on calls from multi-unit properties. The results comport with those derived from the main analysis, and can be found in Appendix A.3.

Dependent Variables

My dependent variable is demand for policing. I conceptualize this variable as citizen-initiated 911 calls and 311 requests related to policing. To identify 311 requests related to policing, I hand-code requests including in the measure those that are routed directly to the Austin Police Department as well as order maintenance (OMP) demands such as noise complaints or reports of neighborhood code or environmental violations, those that represent attempts by residents to “clean-up” their neighborhood or monitor the behavior of their neighborhoods.⁴ This is meant to distinguish 311 requests that represent a demand for neighborhood surveillance from other types of more mundane requests such as inquiries into the recycling pick-up or reports of traffic stop-light outages.

To measure the change in individual demand for policing, I calculate the difference between between the number of calls from an individual address in the final year and the first year of the three year window. For instance, if the three year window was 2017-2019, an individual’s change in demand for policing would be the difference between the number of calls made in 2019 and the number made in 2017. This allows me to compare changes in the behavior of movers, those that moved neighborhoods in the intervening year, 2018, with non-movers, those that remained in the same neighborhood over the entirety of the three year period. Lastly, because I use a negative binomial regression to account for overdispersed,

⁴For full list of OMP related Requests see Table A1

count data, I transform the dependent variable into an individual's *increase* in total calls instead of change, so that the dependent variable does not include any negative values.

Explanatory Variables

Gentrifiers

My key explanatory variable is gentrifier, a binary variable with the values of 0 or 1. To create this variable, along with the other classes of residents I use for comparison, I use 2014-2021 ACS data to determine the socio-economic status of the tracts individuals moved between. I first borrow Laniyonu (2018)'s criteria for classifying which census tracts undergo processes of gentrification, classifying tracts that were eligible and ineligible to gentrify in 2014. Tracts that were below both the median household income and median rent of all tracts city-wide in 2014 are classified as eligible to gentrify. I then place the tracts into three categories based on changes in the % of population with a college degree and median rent. Those classified as ***gentrifying*** are in the top tercile of all gentrification eligible tracts for increases in the aforementioned variables, or have seen increases in median rent greater than the median increase across all city tracts.⁵ Tracts that were eligible to gentrify in 2014, but by 2021 did not meet the threshold to be included in the gentrifying category are classified as ***low SES***. Finally, tracts that were never eligible to gentrify are classified as ***high SES***.⁶

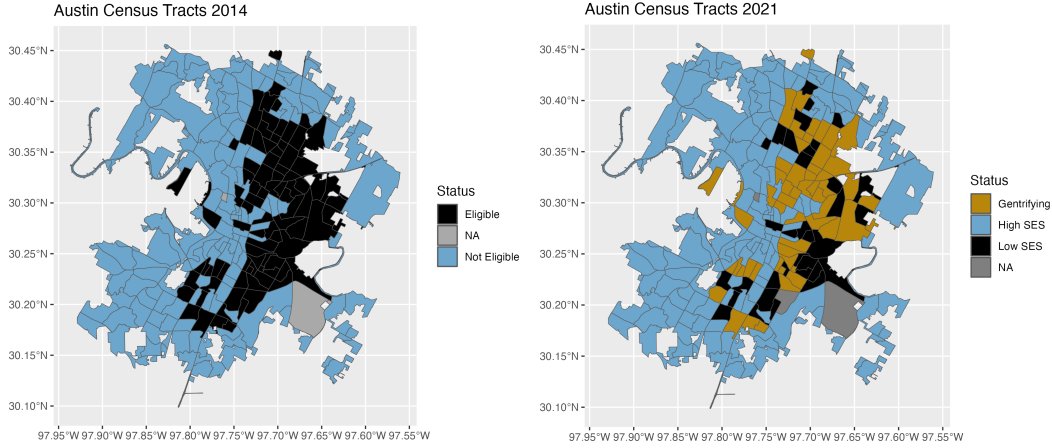
Figure 1 maps the gentrification status of each tract in 2014 and 2021. As the figure demonstrates, the vast majority of gentrification eligible tracts in 2014 lay to the east and southeast of downtown Austin, historically majority Black and Latino neighborhoods. From the 2021 map, it is clear that the bulk of gentrification has occurred on the east side of Austin with some occurring north of the city downtown as well. Tracts colored gold, that are gentrifying, are clustered to the east, northeast, and southeast areas of the city. Low SES

⁵Laniyonu (2018)'s measure classifies only tracts in the top tercile of changes in median rent and % college educated as gentrified, however I include the second criteria to capture tracts that are in the earlier stages of gentrification

⁶Among all of the census tracts within the Austin city limits, 21.81% were ***gentrifying***, 15.23% were ***low SES***, and 62.10% were ***high SES*** tracts. For more details see Table A4

tracts are also largely located to the East of the city, but abut nearby gentrifying tracts. This suggests a type of spatial diffusion in processes of gentrification and hints that neighborhoods that still have higher levels of poverty currently, may soon be targets for gentrification.

Figure 1: Gentrification in Austin 2014-2021



To create my final independent variable, I then use the gentrification status of each tract in Austin, to code three types of within-city movers. The criteria for each of the types is listed below, ⁷. Each category is measured with a binary 0 or 1 variable and each of the categories are mutually exclusive.

Table 1: Mover Type Classifications

Mover Category	Original Tract	New Tract
Gentrifier	ineligible to gentrify (high SES)	gentrifying, or low SES
Increase SES	eligible to gentrify (low SES)	high SES
No SES Change	ineligible to gentrify (high SES)	high SES
	eligible to gentrify (low SES)	gentrifying or low SES

Gentrifiers, following the traditional class-based definition in the literature, are higher-income individual households that move into previously lower-income neighborhoods.

⁷For sample distribution Table A5

Table 2 presents the average demographic characteristics of gentrifiers as compared to other types of movers and non-movers in the sample. Following the literature on gentrification, on average, gentrifiers are younger, and move from whiter neighborhoods with lower poverty and into more non-white neighborhoods with higher rates of poverty. Ultimately, this is a class-based measure, categorizing individual movement through changes in socioeconomic class.

Table 2: Average Sample Characteristics across Household Type

Characteristics	Gentrifiers	Increase SES	No Change	Non-movers
Household Age	42	44	47	55
Female Households	24%	25%	22%	21%
White Households	69%	63%	73%	70%
Black Households	1%	1%	1%	2%
Latino Households	10%	18%	11%	15%
Multi-Race Households	18%	15%	12%	10%
Change % Poverty	6%	-13%	-2%	-1%
Change % Nonwhite	16%	-10%	2%	0%
Change Crime Rate	21	-73	-13	-8

Crime

My next key explanatory variable is crime. One of the biggest alternative explanations for the rise in gentrifier demand for policing is that they are moving into areas with higher crime rates. As the statistics in Table 2 demonstrate, there is on average higher crime rates in gentrifiers' new neighborhoods compared to their original neighborhoods. Therefore, in order to fully account for the effect of crime, I include several controls in the model related to the prevalence of certain types of crime as well as conduct a sensitivity analysis with violent crime as the bounding variable. First, I hand code the crime data based on the type of crime committed. Following the FBI's Uniform Crime Reporting,⁸ I distinguish first between violent crime and nonviolent crime, and then between three types of crime 1) crimes against persons; 2) crimes against property; and 3) crimes against society. The three types

⁸FBI UCR Codes

of crime categories are exclusive (that is a crime cannot fall into both the crimes against person category and the crimes against property category), but there is overlap between the two buckets, that is, there are crimes in all three categories that are considered non-violent. Thus in my models, I include controls for changes in the number of violent crimes (relative to non-violent crime), and changes in the number of property crimes (relative to crimes against society and crimes against persons). This allows me to control for changes in the different types of crimes that may be occurring in gentrifying neighborhoods or that individuals may perceive to be occurring. Finally, I use min-max normalization to scale the crime variables between 0,1 to ensure that the units are standardized along with other independent variables in the regression.

% Black and Latino

My final main explanatory variable is the % of the population that is Black and Latino. For gentrifiers and other categories of movers, this is the % Black and Latino of the tract they move into, whereas for non-movers it is the % Black and Latino of their census tract in the third year of the three year window. I measure this using ACS data from the corresponding year, for instance, if the window is 2015-2017, the % Black and Latino is captured by ACS data from 2017.

I include both individual household-level controls and tract-level controls. For individual households, I control for the the median household age, whether the household is entirely female, mixed gender, or all male, and household race (white, Black, Latino, Asian or multi-race). Since the TX voter file does not include information about racial or ethnic background, I employ Bayesian Improved Surname Geocoding (BISG) which uses an individual’s surname and location to estimate the probability that they are of a given racial category (DeLuca and Curiel 2023; Barreto et al. 2022). I then impute the race or ethnicity of the individual based on the probability of each racial category,⁹ and because for 44% of the sample, I

⁹For more details about the BISG method see A.6 Details on BISG Method

am working at the household level, for addresses with multiple registered voters, I code the household as a racial category only if all members of the household are of the same racial group. Racially mixed households are coded as multi-racial. In addition to these individual-level characteristics, I include controls at the tract level. Since my dependent variable captures differences in total calls, I control for the changes in the following ACS variables at the census-tract level: % homeownership, unemployment rate, % in poverty, population. For each of these continuous variables, I use min-max normalization scaling all variables between 0,1 to ensure that the units are standardized along with other independent variables in the regression. Finally, for the full sample models, I control for each of the three-year windows by including a binary 0 or 1 to indicate each of the time-spans over which changes in calls were measured i.e. 2015-2017, 2016-2018 etc.

Estimation Strategy

I use negative binomial regression models to test my hypotheses. The use of negative binomial regression models allows for the estimation of my dependent variables which are discrete counts, number of calls to the police, and accounts for the over-dispersion in my data. For full results of likelihood ratio tests used to determine model suitability in contrast to Poisson models, see A.7 Analysis 1, A.8 Analysis 2, A.9 Analysis 3.

I use the following negative binomial regression model to test all of my hypotheses, changing the dependent variable and for my racial moderation analysis, including interaction terms.

$$\begin{aligned} \text{Log}(Y_i) = & \beta_0 + \beta_1 \text{gentrifier}_i + \beta_2 \text{movercategories}_i + \beta_3 \text{crime}_i + \\ & \beta_4 p_black_latino_i + \beta_5 \text{individualcontrols}_i + \beta_6 \text{neighborhoodcontrols}_i \end{aligned} \quad (1)$$

Where for analysis 1, Y_i is the total number of calls to police in the last year of the three-year window for individual i , for analyses 2 and 3, Y_i it is the increase in calls to police between the first and last year of the three-year window for individual. $gentrifier_i$ is my key explanatory variable, $movercategories_i$ are individuals/households i in the other mover categories, (only included in analyses 2 and 3). $crime_i$ is the change in violent crime and property crime between the first and last year of the three-year window for individual (for analysis 1, it is the tract-level violent crime and property crime in the last year of the three-year window.) $p_black_latino_i$ is the percent of the total population in a census tract in the final year of the three-year window that is comprised of Black and Latino residents. $individualcontrols_i$ are individual household i characteristics, and $neighborhoodcontrols_i$ are the changes in neighborhood-level census variables between the first and last year of the three-year window for individual i (for analysis 1, they are tract-level census variables in the last year of the three-year window). For my third analysis, I include the following interaction terms $\beta_5 p_black_latino_i * gentrifier_i$ and $\beta_6 p_black_latino_i * movercategories_i$.

Findings

Who Calls the Police in Gentrifying Neighborhoods?

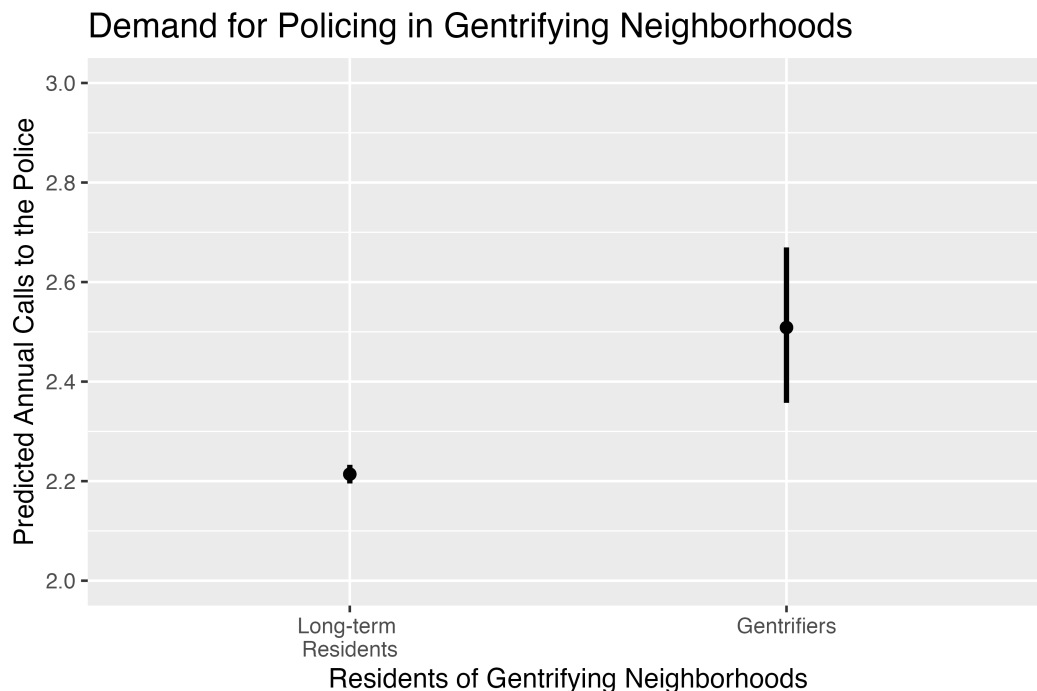


Figure 2: Individual Demand for Policing in Gentrifying Neighborhoods. X-axis are the different types of residents in gentrifying tracts. Y-axis is the predicted number of calls to police. Estimates from fully-specified negative binomial models with controls at means. 95% CIs displayed.

My first analysis compares the demand for policing between gentrifiers and long-term residents within gentrifying neighborhoods. Figure 2 plots the predicted annual calls to the police for gentrifiers vis-a-vis long-term residents.¹⁰ The predicted calls to the police for gentrifiers is 2.51 calls per year as compared to 2.2 calls for longer-term residents. This means that gentrifiers make about 14% more calls to the police per year than long-term residents. These results demonstrate support for *hypothesis 1*, gentrifiers demand greater policing compared to long-term residents of gentrifying neighborhoods. Even taking into account neighborhood socio-economic conditions, racial demographics, and crime rates, gentrifiers are still significantly associated with greater numbers of calls to the police than

¹⁰For results from fully-specified model see Table A6

long-term residents.

Furthermore these results provide evidence that gentrifiers do appear to behave differently than long-term residents, bringing quantitative empirical findings to previous findings from qualitative work indicating that gentrifiers' lack of historical ties to the neighborhood, expectations about the use of public space and sense of unease or threat, manifest themselves in greater calls to the police relative to longer-term residents. Finally, to the extent that gentrifying neighborhoods see an increase in calls to the police, these results provide evidence that the increase may well be tied to the propensity of newer residents, gentrifiers, to demand higher levels of policing than traditional residents.

While these results support the theory that within gentrifying spaces, gentrifiers demand greater policing than long-term residents, it is still unclear the extent to which these findings are a result of gentrifiers simply being more likely to call the police than the types of residents who traditionally have lived in gentrifying areas or whether movement into gentrifying area shapes individual demand for policing. Additionally, the results do not rule out the possibility that greater calls is simply a "mover effect," the result of being a newcomer to a neighborhoods. My next analysis evaluates these potential explanations by testing the relationship between movement into different types of neighborhoods and changes in demand for policing.

Movement into Gentrifying Areas and Greater Demand for Policing

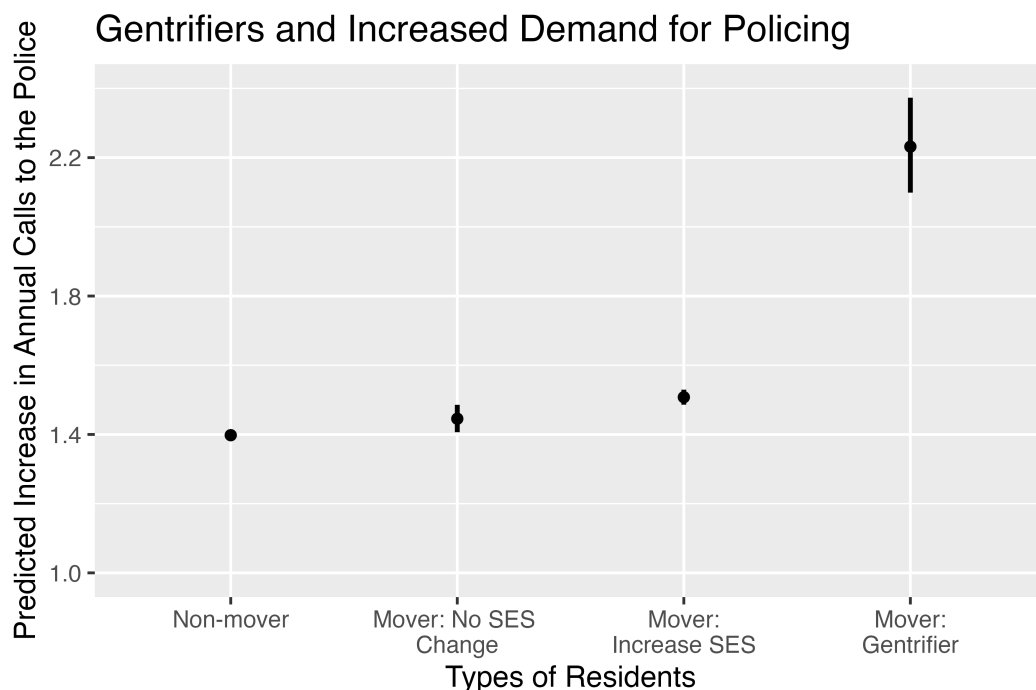


Figure 3: Movement and Increased Gentrifier Demand for Policing X-axis are the different categories of residents. Y-axis are the predicted annual increases in calls to the police. Estimates from fully-specified negative binomial regression models. 95% CIs displayed.

In order to more fully assess the relationship between neighborhood conditions and demand for policing, I conduct a second analysis testing the influence of movement into gentrifying tracts on individual increases in calls to the police. As the results in Figure 3 demonstrate, movement from a more affluent tract into a gentrifying tract (Mover: Gentrifier) is strongly and significantly associated with an increase in demand for policing net changes in crime.

¹¹ In support of *hypothesis 2*, gentrifiers have a predicted increase of 2.04 police calls after moving into a gentrifying tract net of changes in crime. This predicted increase in calls is relative to both other types of urban movers and relative to individuals and households who did not move over the same period of time. No SES change Movers, those who moved from one tract to another of similar socio-economic status, have the next largest predicted increase in calls of 1.50 followed by increase SES movers, those who moved from less affluent

¹¹For full model results see Table A7. For sensitivity analysis with the bounding variable as the change in violent crime rate see Figure A3

tracts into more affluent areas, with a predicted increase of 1.43 calls. Finally non-movers, individuals who remained in their same address over the same three-year period, had a predicted increase of 1.38 calls.

These results demonstrate that movement into a gentrifying context influences individual demand for policing. While on average, individual households of all types saw a predicted increase in calls to the police over the same time period, gentrifiers saw the greatest predicted increase, 36% more calls than the next closest category. They also indicate a lack of support for the theory that increasing calls is simply a result of movement into a new neighborhood. While both no SES change movers and increase SES movers have slightly greater expected increases in calls than non-movers, these increases are not on par with those predicted for gentrifiers. Thus while moving may make one slightly more likely to call the police, the results show that moving into a gentrifying neighborhood has a uniquely powerful influence on increasing individual demand for policing.

The findings from this analysis also indicate that moving into a gentrifying area is positively and significantly associated with increased calls to the police even when taking into account changes in crime. Results from the fully-specified model include controls for changes in violent crime and changes in property crime. As the results indicate, changes in violent crime are most prognostic for increasing calls to the police, however, even when controlling for these changes in violent crime, there is a significant relationship between gentrifiers and increasing demand for policing. Moreover, when conducting a sensitivity analysis with changes in violent crime as the bounding variable, I find that in order to attenuate the influence of gentrifiers on increases in demand for policing, an omitted variable would need to be 34 times as influential as changes in violent crime. This demonstrates the robustness of the finding that movement by gentrifiers into gentrifying areas is significantly correlated with increases in calls to the police.

Table 3 displays the incident rate ratios (IRRs) for the likelihood that gentrifiers increase their annual police calls relative to other types of residents. These IRRs provide further

support for *hypothesis 2* indicating that gentrifiers are 2.5 times more likely to increase their annual police calls than non-movers over the same period of time, about 2.4 times as likely as increase SES movers and about 2 times as likely as no SES change movers. These indicident rate ratios further demonstrate that gentrifiers are more likely to increase their calls even relative to other types of urban movers suggesting that it is not movement alone that is responsible for greater demand for policing, but rather the context of the areas individuals move into.

Table 3: Gentrifier Likelihood of Increasing Calls to Police

Gentrifiers Relative to	exp(Est.)	2.5%	97.5%
Non-movers	2.52	2.34	2.72
No SES Change Movers	2.06	1.90	2.24
Increase SES Movers	2.41	2.17	2.69

In order to further analyze differences in call behavior between gentrifiers and other urban residents, I run additional models with the dependent variables as increases in the following: 311 requests, 311 requests related to order maintenance (311 OMP), 911 calls, and 911 calls related to order maintenance (911 OMP). This allows for a deeper understanding of the nature of gentrifier demand for policing as it relates to the mode of police contact, 311 vs. 911, and the type of request, whether or not gentrifiers make increased order maintenance-related requests.

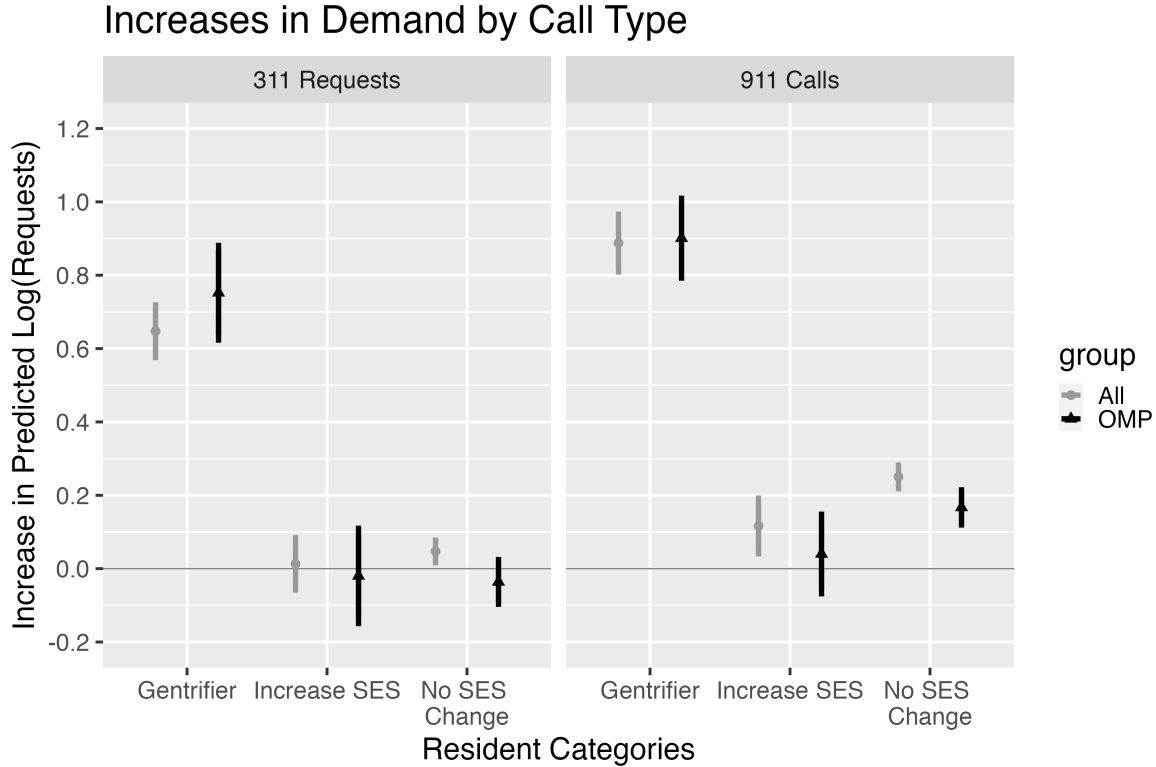


Figure 4: Increase in 311 and 911 Requests by Type Across Mover Categories. X-axis are the different resident categories. Y-axis are the increases in predicted annual log requests. Panels represent 311 and 911 requests. Circles and light gray error bars denote estimates for all types of requests. Triangles and black error bars denote estimate for OMP requests. Estimates from fully-specified negative binomial regression models. 95% CIs displayed.

The panel on the left plots the increase in predicted log 311 requests by request type for each type of mover. These results demonstrate that not only are gentrifiers likely to increase the number of 311 requests they make, but there is an even stronger relationship between gentrifiers and increased 311 requests related to order maintenance policing.¹² For gentrifiers, this represents an increase in not only demand for government services often associated with 311 requests but in particular, a demand for policing of certain behaviors within the neighborhood that are related to perceived disorder. This adds to the evidence presented in previous studies of gentrification and policing which finds a particularly strong relationship between OMP and gentrification. Interestingly, this same relationship does not exist for other types of movers. The influence of no SES change movers on increases in log

¹²For full model results, see Table A8

311 requests is significant but very small compared to gentrifiers, and there are null effects for increases in log 311 OMP requests. For increase SES movers, there are null effects for both increases in 311 requests and increases in OMP 311 requests.

Turning to 911 calls, the right panel plots the estimates for predicted log 911 calls by call type for each mover category. As compared to 311 requests, gentrifiers are even more likely to increase their 911 calls, however their increases in 911 calls and 911 omp calls are more similar than for 311 requests. Regarding other types of urban movers, there is a positive and significant relationship between both increase SES and no SES change movers and increases in 911 calls but once again, these correlations are far weaker than for gentrifiers. No SES change movers do see a positive and significant association with increased 911 OMP calls however this increase is slightly smaller than for overall 911 calls as compared to gentrifiers where the increase for OMP calls is slightly greater.

Overall, dis-aggregating between the mode and type of call provides greater insight into the not just gentrifier demand for policing, but the nature of that demand. Gentrifiers' propensity to increase both 311 requests and 911 calls indicates that they simultaneously demand greater government services and resources as well as greater surveillance by police within their new neighborhoods. The correlation between movement into a gentrifying area and order maintenance-related requests further supports previous empirical evidence highlighting the strong relationship not only between gentrification and rises in policing, but particularly the rise in order maintenance policing.

The other main theoretical explanation for increased demand in policing is that it is a result of racial biases linked to gentrifiers reaction to increased racial diversity within gentrifying neighborhoods. Within the U.S. context, there is a strong correlation between class and race suggesting that the findings from Analysis 2 about the influence of changes in neighborhood SES are likely also reflective of changes in racial demographic composition. However, in order to test this more precisely, I conduct a third analysis to analyze how neighborhood racial demographic context shapes gentrifier demand for policing.

Neighborhood Racial Composition and Gentrifier Demand for Policing

My third analysis tests how neighborhood racial demographic composition shapes gentrifier demand for policing. Understanding gentrification as a process that often brings white residents into contact with Black or Latino residents, and given the established relationship between perceived racial threat and white political behavior, I test whether gentrifiers' increased demand for policing is exacerbated when moving into heavily non-white spaces.

To assess the effect of neighborhood racial context on gentrifier demand for policing, I first test the correlation between the percent of the population that is Black and Latino and increases in demand for policing among gentrifiers. This allows for a better understanding of how demand for policing within gentrifying neighborhoods varies by racial demographic composition.

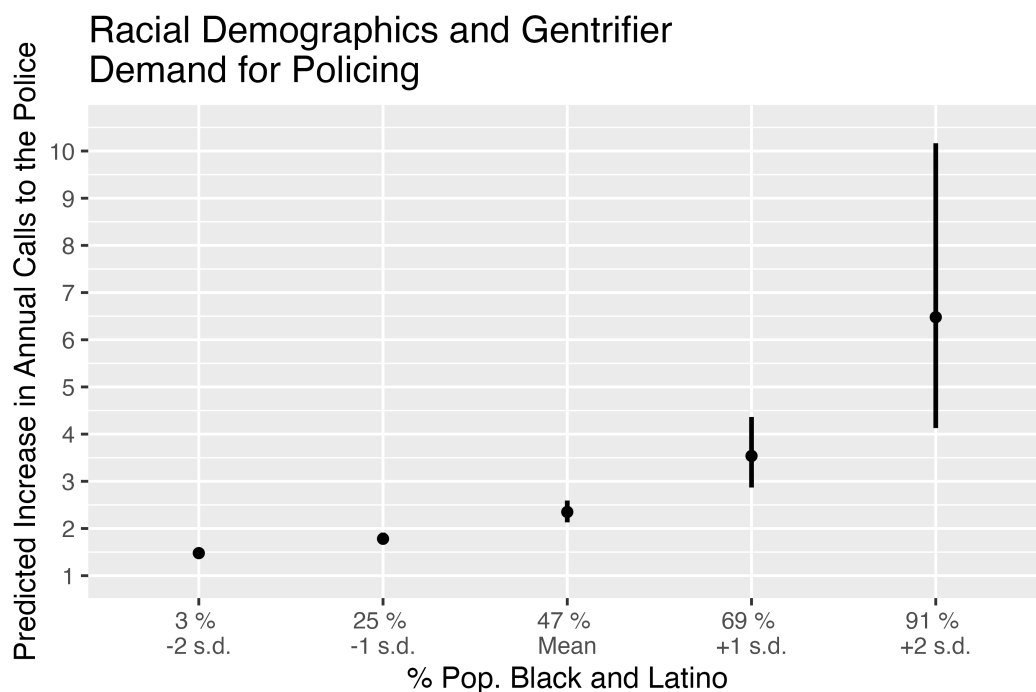


Figure 5: Among Gentrifiers: Influence of Neighborhood Racial Composition on Demand for Policing X-axis is the % of the population that is Black and Latino. Y-axis is the predicted increase in annual calls to police. Estimates from fully-specified negative binomial regression models. 95% CIs displayed.

Figure 5 displays the results from this test, indicating support for *hypothesis 3*, that gentrifiers that move into neighborhoods with greater proportions of Black and Latino residents demonstrate greater demand for policing.¹³ For example, gentrifiers who move into a neighborhood that has mean % of the population that is Black and Latino (47%) have a predicted increase of 2.35 calls per year compared to those who move into a neighborhood that is 1 standard deviation above the mean % Black and Latino (67%) who have a predicted increase of about 3.5 calls per year. Thus moving into a neighborhood that is majority Black and Latino can create even larger increases in gentrifier calls to the police. This evidence supports the theory that gentrifiers, largely white households within my sample, associate greater Black and Latino populations with greater levels of neighborhood disorder or danger and respond by calling the police. Additionally, because my measure of gentrifiers is a class-based measure, these findings show that changes in neighborhood socio-economic status do not fully account for increases in gentrifier demand for policing and that the movement by gentrifiers into more nonwhite spaces, heightens already increased levels of demand.

The results in Figure 5 suggest that movement into more nonwhite spaces plays a role in amplifying gentrifier demand for policing, however, it remains unclear whether this is a story specific to gentrification or whether all movers increase their demand for policing upon moving into neighborhoods with greater proportions of Black and Latino residents. To evaluate the influence of racial demographic composition on demand for policing for gentrifiers relative to other types of residents, I conduct moderation analyses interacting the % Black and Latino in one's neighborhood¹⁴ with each resident type among racial subgroups.

¹³For full model results see Table A9

¹⁴For movers, this represents the % Black and Latino of the neighborhood they moved into while for non-movers, it is the percent of the neighborhood they have lived in over the three-year period

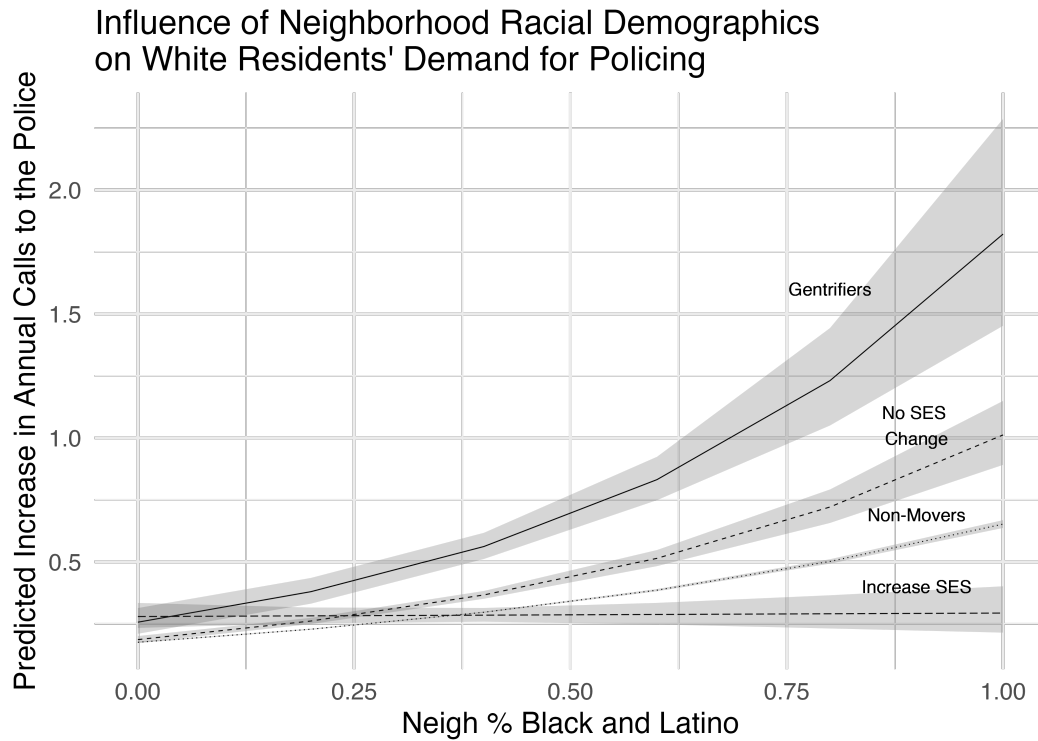


Figure 6: Influence of Neighborhood Racial Composition by White Resident Type on Demand for Policing X-axis is the % of the population that is Black and Latino. Y-axis is the predicted increase in annual calls to police. Estimates from fully-specified negative binomial regression models. 95% CIs displayed.

Figure 6 displays interaction plots for the moderation analysis among white households. The interaction plots reveal that for all white households regardless of mover status, living in a more nonwhite neighborhood increases annual calls to the police, however the marginal effects are greatest for gentrifiers. Interestingly when I conduct the same analysis among non-white households, I find null results for the interaction term coefficient for gentrifiers¹⁵, indicating that movement into nonwhite spaces is a significant predictor for increased demand for policing only among white households.

The effect of racial demographic composition on demand for policing could be a consequence of the fact that of each of the resident types, the neighborhoods gentrifiers move into have on average the greatest percentage of % Black and Latino residents relative to each of the other resident types.¹⁶ Therefore, it could be the case that all white residents behave

¹⁵See Table A10

¹⁶The mean % Black and Latino for gentrifiers is 42%, while for increase SES movers it is 41%, for no

similarly in regards to demanding more policing after moving into nonwhite areas, but that gentrifiers are most likely to move into more nonwhite neighborhoods. It could however, also be the case that the personal attitudes and characteristics of white gentrifiers in particular activate racial biases and animate greater demand for policing when moving into nonwhite spaces. Regardless of the precise mechanism behind this increased demand, the results from this analysis indicate that the relationship between gentrification and policing is racialized with white gentrifiers greatly increasing their demand for policing after moving into more non-white spaces.

SES change movers it is 34%, and for non-movers it is 37%

Conclusion & Implications

This paper examines whether and how gentrifiers increase their demand for policing in gentrifying neighborhoods. By introducing a novel, individual-level approach to the analysis of gentrification and policing, I pinpoint the source of increased demand for policing in gentrifying neighborhoods and establish the impact of neighborhood-level poverty and ethno-racial composition on gentrifier behavior.

Contrary to conventional wisdom, increased demand for policing by gentrifiers is not simply a response to crime. Instead exposure to higher levels of poverty and more Black and Latino residents animates gentrifier demand for policing. More specifically, not only are gentrifiers more likely to demand policing in gentrifying neighborhoods than long-term residents, but they increase their demand upon movement into gentrifying contexts, particularly those related to OMP. By increasing their 311 requests and 911 calls when moving into gentrifying neighborhoods, gentrifiers simultaneously demand greater public and private attention and investment while policing who receives said benefits.

This paper thus takes an important step in empirically establishing that gentrifier demand for policing is a component of increased policing in gentrifying areas. It also contributes to the robust body of literature on the impact of geographic and racial context on the individual-level behavior of urban residents with a particular emphasis on how processes of gentrification shape individual political behavior.

More broadly, this research suggests that as dis-invested areas see greater investment, development and profits, the majority of the benefits will likely accrue to these gentrifiers, individuals who on average already hold more wealth than the long-term residents of gentrifying areas. Thus, increases in 311 and 911 calls in gentrifying neighborhoods contribute to the ongoing accumulation of resources for wealthier, newer residents and thus reinforce the economic and class hierarchies in urban spaces.

A rise in calls to the police also carry pernicious consequences for Black and Latino residents. There are numerous examples of how majority Black and Latino neighborhoods

face heightened risk of police searches (Zhao and Messner, 2019), use-of-force (Omori and Stoler 2022), and risks of fatal encounters (Mitchell and Chihaya 2022). This is coupled evidence that Black and Latino individuals are also at greater risk for being stopped and arrested when living nearby or moving through majority white spaces (Gaston 2019; Zhao and Messner 2019). Gentrification brings both of these forces to bear, as processes often take place in areas that were once home to predominantly Black or Latino residents but now have substantial numbers of white residents. Gentrifiers' propensity to demand policing heightens the risk of police encounters for Black and Latino residents which, even when routine, carry with them the risk of arrests, use-of-force, or even death (Schwartz and Jahn 2020; Ross, Winterhalder, and McElreath 2021).

Long-term residents of color in gentrifying spaces already face the threat of displacement due to rising costs in their neighborhood, but with increasing numbers of gentrifiers entering the neighborhood, they also face the threat of increased policing and surveillance. As neighborhoods gentrify and people of color are pushed outside of city centers, this reinforces existing disparities from residential racial segregation and has the power to create new racial boundaries. Ultimately, demand policing within gentrifying neighborhoods has downstream consequences for the maintenance of racial and socio-economic hierarchies in urban spaces.

A Appendix

A.1 Matching Call data to Voter File

Within Travis County

- Unique Voters: 860,173
- 860,173 unique vuids (unique voters)
- 456,530 311 requests linked to addresses out of 1,185,223 total requests (about 39%)
- 1,492,721 911 calls linked to addresses out of 5,522,289 (about 27% of total pool)
- Of the 311 requests, 374,355 came from single-unit addresses (about 82%)
- Of the 911 calls, 970,269 came from single-unit addresses (about 65%)
- Max number of 311 requests in a year from a single unit address was 46.
- Max number of 911 calls in a year from a single unit address was 84.

Since I am working with call data from the Austin Police Department, I restrict the voters to only those within the city of Austin. Within the the city of Austin, there are 342,570 voters with unique addresses. Of these 342,570 voters, about 80,000 (23%) made at least one call to the police between 2014-2021.

A.2 OMP Call Classification

Table A1: Requests and Calls Classified as OMP

311 OMP Requests	911 OMP Calls
APD Routed Requests	ALCOHOL CONSUMPTION ORDINANCE
APH - Graffiti Abatement	SUSPICIOUS ODOR OR NOISE
Austin Code - Request Code Officer	SLEEP/PUBLIC PLACE
Austin Code - Code Complaint	VIOL OF PARK CURFEW
DSD - Environmental Complaint	LOITER IN PARK
DSD - Outdoor Venue Complaint	OBSCENITY
Graffiti Abatement	Disturbance
Loose Dog	Mischief / Vandalism
Graffiti Abatement	Public Intoxication
Loud Commercial Music	Suspicious Person or Vehicle
Parking Violation Enforcement	Trespass
Residential Parking Permit Enforcement	CRIMINAL MISCHIEF
Loud Music	CRIMINAL TRESPASS
ATD - Parking Violation Enforcement	UNREASONABLE NOISE
	POSS ALCOHOL AGE 17-20
	GRAFFITTI
	LITTERING
	CURFEW VIOLATION
	VIOL CITY ORDINANCE SOUND
	NOISE VIOLATION
	CIVIL DISTURBANCE/DEM
	VIOLATION CAMPING ORDINANCE
	Prowler
	Check Welfare

A.3 Multi-unit property analysis

Up to this point, all the prior analyses were about changes in behavior among individuals who live in single-unit properties. The location of the 311 and 911 data often does not contain unit or apartment numbers when the requests come from properties with multiple units. Therefore in order to make claims about an individual's change in behavior, I separated out those who live at an address with only one unit (and who one can assume with more confidence actually made the request) from those who live a multi-unit properties. For the 311 requests, only about 18% of all requests came from multi-unit properties, but for 911 Calls, about 35% came from multi-unit properties suggesting the need to analyze changes in the aggregate level in calls linked to these properties.

For this analysis, I calculate the total number of 311 requests and 911 calls and 311 omp requests and 911 omp calls made from a multi-unit property in 2014. I then match the property address to the call data from 2015-2021 to see if it appears again and how many calls appear each year. Finally, I subtract the total calls of each prior year from each subsequent year and assess the avg. increases in calls from 2014-2021 as well as the raw increase in calls between 2014 and 2021. Positive changes represent overall increases in total calls while negative or no change are coded as zero. The DVs are then the avg. increase and total increase in police calls between 2014-2021. My key independent variables are the type of neighborhood that the multi-unit property is located in: a gentrified neighborhood, a low SES (gentrification eligible but did not gentrify), and high SES (not eligible to gentrify). For my first model with the DV as average increase in police calls, I run a robust OLS regression. For my second model with the DV as the raw increase in police calls, I run a negative binomial regressions since my DV is a non-negative count variable, but my data is over-dispersed.

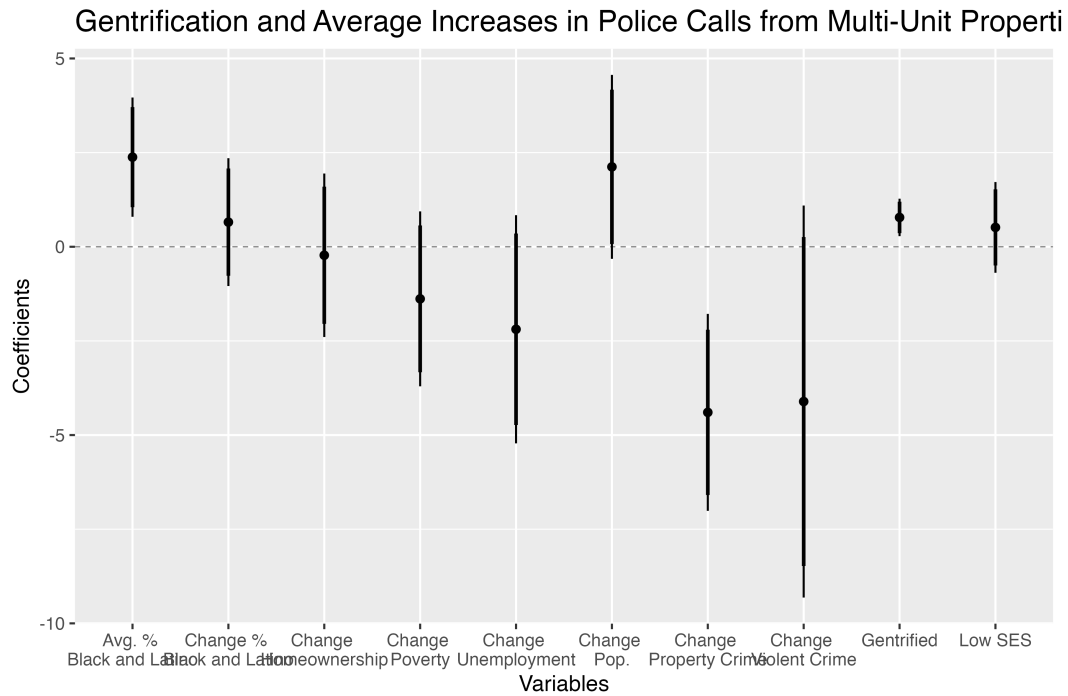


Figure A1: Multi-unit Properties and Average Increases in Calls to the Police X-axis are each of the variables in the model. Y-axis are coefficient estimates for the increase in number of calls to police. Estimates from fully-specified OLS models. 95% CIs displayed.

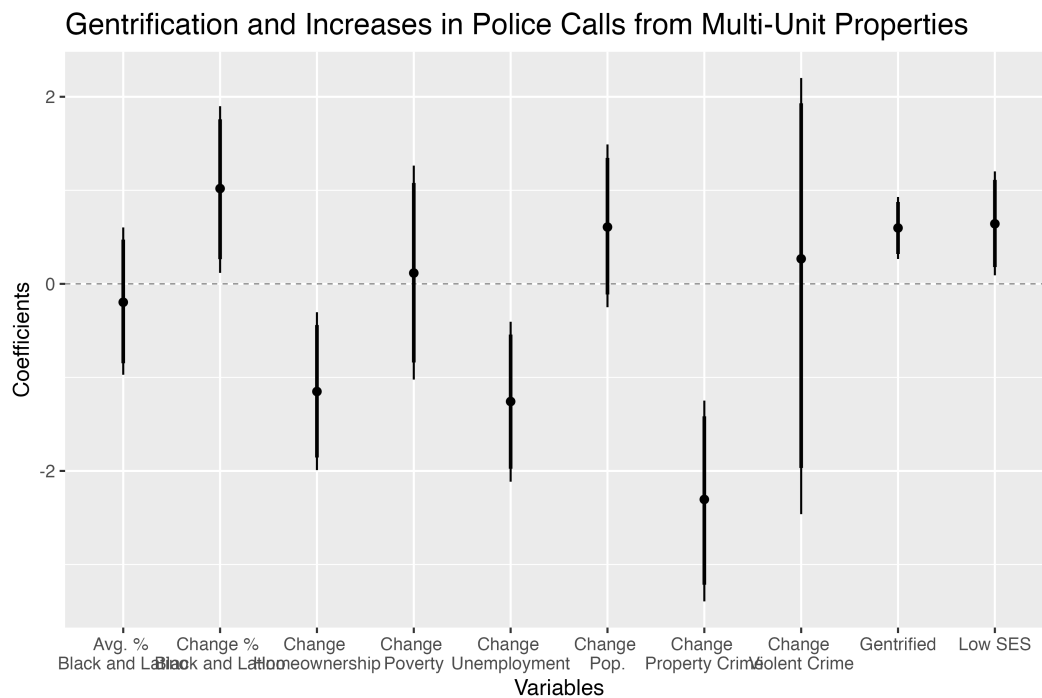


Figure A2: Multi-unit Properties and Increases in Calls to the Police X-axis are each of the variables in the model. Y-axis are coefficient estimates for the increase in the expected number of log(calls to police). Estimates from negative binomial regression models. 95% CIs displayed.

Table A2: Multi-unit Properties and Average Increases in Calls to the Police (2014-2021)

	Avg. Increase in Police Calls
Gentrified Neigh	0.78** (0.25)
Low SES Neigh	0.51 (0.61)
% Black and Latino	2.38** (0.81)
Change in % Black and Latino	0.65 (0.87)
Change in % Poverty	-1.38 (1.18)
Change in Unemployment	-2.19 (1.54)
Change Violent Crime	-4.11 (2.65)
Change Property Crime	-4.40*** (1.33)
Change Pop.	2.12 (1.25)
R ²	0.06
Adj. R ²	0.06
Num. obs.	2129
RMSE	5.85

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table A3: Multi-unit Properties and Increases in Calls to the Police (2014-2021)

	Increase in Police Calls
Gentrified Neigh	0.60*** (0.16)
Low SES Neigh	0.64* (0.27)
% Black and Latino	-0.20 (0.36)
Change in % Black and Latino	1.02* (0.40)
Change in % Poverty	0.12 (0.55)
Change in Unemployment	-1.26** (0.47)
Change Violent Crime	0.27 (1.05)
Change Property Crime	-2.30*** (0.50)
Change Pop.	0.61 (0.51)
AIC	6682.74
BIC	6750.71
Log Likelihood	-3329.37
Deviance	1426.93
Num. obs.	2129

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

A.4 Austin Census Tracts by Gentrification Status

Table A4: Austin Census Tracts by Gentrification Status

Tract Status	Total Tracts	Percent
Gentrifying	54	21.77%
High SES	154	62.10%
Low SES	38	15.23%
Total	248	100.00%

A.5 Sample Distribution of Observations by Mover Categories

Table A5: Household Types

Category	Observations	% of Sample
gentrifier	4890	0.57%
increase SES	5918	0.69%
no SES change	27680	3.2%
Non-movers	816761	95.5%
Total	855293	100%

A.6 Details on BISG Method

Bayesian Improved Surname Geocoding (BISG) estimation imputes missing voter race information by calculating the joint probability of racial membership given surname and geographic residence. Using individuals' surnames matched to a surname dictionary as the prior, joined to Census geography demographics for the conditional probability, produces more accurate racial estimates relative to other methods (Imai and Khanna 2016). Since the TX voter file data does not contain information on race, I implement BISG to impute missing race data by voter.

To implement, I use wru package and input the surname, census tract, county, state, age, and sex of all the unique voters in my sample. Of the 421,971 unique voters in the sample, 31188 (7.4%) individuals' last names were not matched. The 390,783 observations that were matched returned probabilistic estimates for the likelihood of each racial group membership: white, black, hispanic, asian, and other. From these estimates, I used the highest probability to code each voter into a racial category. The breakdown of the sample by race is located below.

Racial Category	Voters	Percent
White	314554	74.50%
Black	11343	2.69%
Latino	75704	17.90%
Asian	20079	4.76%
Other	291	0.00%
Total	421971	100.00%

A.7 Analysis 1

Likelihood Ratio Tests to Determine Correct GLM Model

First, examine mean and variance of dependent variable in Analysis 1: Total Police Calls

Mean = 0.85

Variance = 4.41

Data appears to be over-dispersed since variance greatly exceeds the mean. To test more thoroughly, conduct likelihood ratio test between poisson model and negative binomial model.

	#Df	LogLik	Df	Chisq	Pr(>Chisq)
1	22	-224981.02			
2	23	-168153.79	1	113654.46	0.0000

Results suggest that the second model (negative binomial) explains the data better and hence is a significantly better fit (as indicated by the p-value).

Regression Tables Analysis 1

Table A6: Regression Table for Analysis 1: Calls to Police in Gentrifying Neighborhoods

	Calls to Police
Gentrifier	0.13 (0.03)***
% Black and Latino	0.87 (0.03)***
Household Asian	−0.23 (0.04)***
Household Black	0.10 (0.04)*
Household Latino	0.29 (0.01)***
Household Age	−0.28 (0.04)***
Household Female	−0.01 (0.02)
Household Mixed Gender	−0.10 (0.01)***
% Homeowner	−0.34 (0.04)***
% Poverty	0.43 (0.04)***
Unemployment Rate	0.02 (0.04)
Population	−0.89 (0.03)***
Violent Crime	0.37 (0.06)***
Property Crime	0.29 (0.07)***
Time: 2014 to 2016	−0.09 (0.02)***
Time: 2015 to 2017	−0.04 (0.02)*
Time: 2017 to 2019	0.05 (0.02)**
Time: 2018 to 2020	−0.07 (0.02)***
Time: 2019 to 2021	−0.09 (0.02)***
AIC	326686.92
BIC	326903.10
Log Likelihood	−163321.46
Deviance	106076.85
Num. obs.	136812

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

A.8 Analysis 2

Likelihood Ratio Tests to Determine Correct GLM Model

First, examine mean and variance of dependent variable in Analysis 2: Increase in Total Police Calls

Mean = 0.32

Variance = 1.54

Data appears to be over-dispersed since variance greatly exceeds the mean. To test more thoroughly, conduct likelihood ratio test between poisson model and negative binomial model.

	#Df	LogLik	Df	Chisq	Pr(>Chisq)
1	22	-701897.22			
2	23	-533256.19	1	337282.07	0.0000

Results suggest that the second model (negative binomial) explains the data better and hence is a significantly better fit (as indicated by the p-value).

Regression Tables Analysis 2

Table A7: Regression Table for Analysis 2: Movement in Gentrifying areas and Increase in Calls to Police

	Increase Police Calls
Mover: Gentrifier	0.80*** (0.04)
Mover: No SES Change	0.24*** (0.02)
Mover: Increase SES	0.11** (0.04)
Household Age	-0.74*** (0.02)
Household Female	-0.01 (0.01)
Household Mixed Gender	-0.09*** (0.01)
Household Asian	-0.49*** (0.02)
Household Black	-0.12*** (0.03)
Household Latino	-0.01 (0.01)
% Black and Latino	1.32*** (0.01)
Change in % Black and Latino	-1.94*** (0.07)
Change % Homeowner	-1.66*** (0.07)
Change in % Poverty	-1.07*** (0.11)
Change in Unemployment	0.03 (0.07)
Change Violent Crime	0.93** (0.33)
Change Property Crime	-1.90*** (0.24)
Change Pop.	0.95*** (0.06)
Time: 2014 to 2016	-0.04*** (0.01)
Time: 2015 to 2017	-0.11*** (0.01)
Time: 2017 to 2019	-0.00 (0.01)
Time: 2018 to 2020	-0.02 (0.01)
Time: 2019 to 2021	-0.06*** (0.01)
AIC	1066443.31
BIC	1066720.44
Log Likelihood	-533197.65
Deviance	372719.83
Num. obs.	764594
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$	

Sensitivity Analysis: Change in Violent Crime

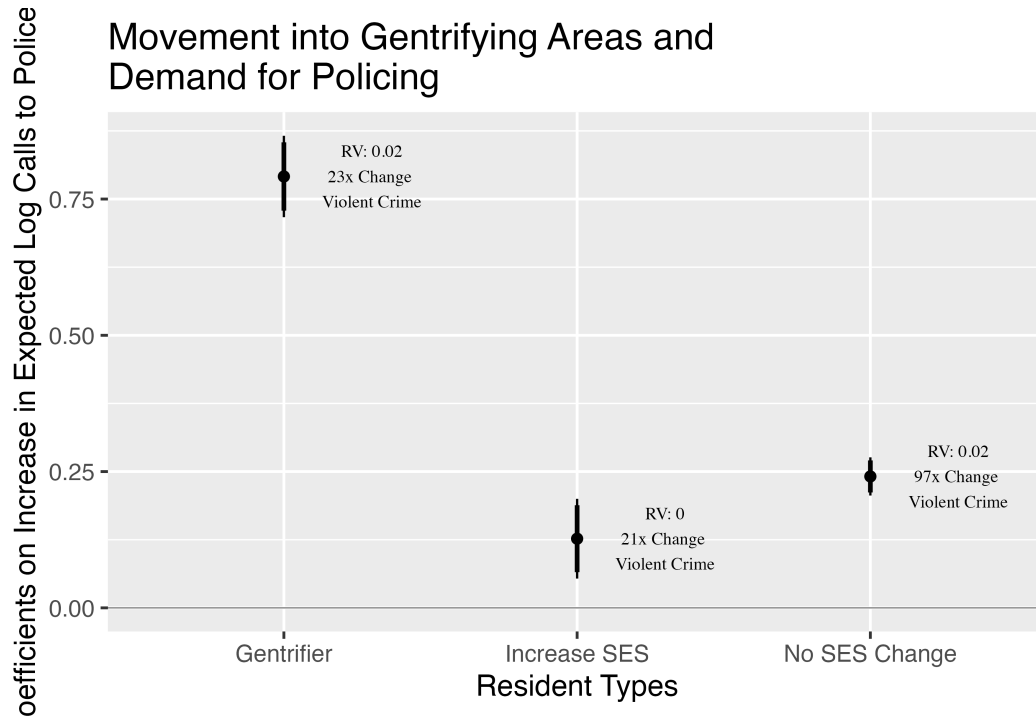


Figure A3: Changes in Demand for Policing Across Types of Urban Movers. X-axis are the different categories of urban movers. Y-axis are the min-max regression coefficient estimates for the increase in expected log count of calls to the police. Annotations denote the robustness value and bounding variable value necessary to attenuate the substantive influence of each mover type to 0. Estimates from fully-specified negative binomial regression models. 95% CIs displayed

Regression Tables by Call Type

Table A8: Regression Table: Increase in 311 and 911 Requests by Type Across Mover Categories.

	Increase 311	Increase 311 OMP	Increase 911	Increase 911 OMP
Mover: Gentrifier	0.65*** (0.04)	0.74*** (0.07)	0.79*** (0.04)	0.76*** (0.06)
Mover: No SES Change	0.07*** (0.02)	0.02 (0.03)	0.28*** (0.02)	0.20*** (0.03)
Mover: Increase SES	-0.01 (0.04)	-0.00 (0.07)	0.15*** (0.04)	0.03 (0.07)
Household Age	-0.21*** (0.02)	-1.38*** (0.04)	-0.59*** (0.03)	-0.78*** (0.05)
Household Female	0.02* (0.01)	-0.10*** (0.02)	0.01 (0.01)	-0.06** (0.02)
Household Mixed Gender	0.02** (0.01)	-0.22*** (0.02)	-0.05*** (0.01)	-0.06*** (0.02)
Household Asian	-0.45*** (0.02)	-0.58*** (0.04)	-0.46*** (0.02)	-0.62*** (0.05)
Household Black	-0.09*** (0.03)	-0.15** (0.05)	-0.11*** (0.03)	-0.19*** (0.05)
Household Latino	-0.01 (0.01)	-0.06*** (0.02)	0.01 (0.01)	-0.01 (0.02)
% Black and Latino	0.52*** (0.02)	1.49*** (0.03)	1.29*** (0.02)	1.46*** (0.03)
Change in % Black and Latino	-1.41*** (0.07)	-2.09*** (0.12)	-2.00*** (0.08)	-2.52*** (0.13)
Change % Homeowner	-0.97*** (0.07)	-1.77*** (0.13)	-1.56*** (0.08)	-2.38*** (0.14)
Change in % Poverty	-1.10*** (0.12)	-2.06*** (0.20)	-0.89*** (0.13)	-1.48*** (0.21)
Change in Unemployment	-0.10 (0.07)	-0.17 (0.12)	0.07 (0.07)	0.15 (0.13)
Change Violent Crime	-0.93** (0.33)	-0.41 (0.57)	3.11*** (0.37)	2.51*** (0.61)
Change Property Crime	-0.52* (0.25)	-2.29*** (0.44)	-1.91*** (0.27)	-3.11*** (0.45)
Change Pop.	1.12*** (0.06)	2.19*** (0.11)	0.59*** (0.06)	0.74*** (0.12)
Time: 2014 to 2016	-0.10*** (0.01)	-0.05* (0.02)	-0.04** (0.01)	-0.03 (0.02)
Time: 2015 to 2017	-0.16*** (0.01)	-0.14*** (0.02)	-0.10*** (0.01)	-0.06** (0.02)
Time: 2017 to 2019	0.10*** (0.01)	0.03 (0.02)	-0.02 (0.01)	-0.02 (0.02)
Time: 2018 to 2020	0.18*** (0.01)	0.24*** (0.02)	-0.08*** (0.01)	-0.18*** (0.02)
Time: 2019 to 2021	0.26*** (0.01)	0.29*** (0.02)	-0.14*** (0.01)	-0.20*** (0.02)
AIC	862462.40	344546.13	917123.85	
BIC	862739.53	344823.26	917400.98	
Log Likelihood	-431207.20	-172249.06	-458537.93	
Deviance	337381.05	132028.03	316706.74	506716.71
Num. obs.	764594	764594	764594	764594

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

A.9 Analysis 3

Likelihood Ratio Tests to Determine Correct GLM Model

First, examine mean and variance of dependent variable in Analysis 3: Among Gentrifiers, Influence of Neighborhood Racial Composition on Demand for Policing

Mean = 0.77

Variance = 6.10

Data appears to be over-dispersed since variance greatly exceeds the mean. To test more thoroughly, conduct likelihood ratio test between poisson model and negative binomial model.

	#Df	LogLik	Df	Chisq	Pr(>Chisq)
1	17	-7599.52			
2	18	-4931.93	1	5335.19	0.0000

Regression Tables Analysis 3

Table A9: Among Gentrifiers: Influence of Neighborhood Racial Composition on Demand for Policing

	Increase Police Calls
% Black and Latino	1.80 (0.22)***
Household Asian	−0.07 (0.25)
Household Black	0.04 (0.29)
Household Latino	−0.05 (0.12)
Household Age	0.67 (0.31)*
Household Female	0.06 (0.10)
Household Mixed Gender	0.22 (0.09)*
Time: 2014 to 2016	−0.15 (0.11)
Time: 2015 to 2017	0.04 (0.14)
Time: 2017 to 2019	0.02 (0.11)
Time: 2018 to 2020	0.02 (0.10)
Time: 2019 to 2021	0.09 (0.12)
AIC	9905.60
BIC	10040.44
Log Likelihood	−4931.80
Deviance	3024.23
Num. obs.	4541

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table A10: Influence of Neighborhood Racial Composition by Resident Type on Demand for Policing

	Full Sample	White Households	Non-white Households
Mover: Gentrifier	0.47 (0.09)***	0.38 (0.11)***	0.72 (0.17)***
Mover: No SES Change	0.13 (0.03)***	0.06 (0.04)	0.38 (0.07)***
Mover: Increase SES	0.43 (0.07)***	0.47 (0.09)***	0.58 (0.13)***
Household Age	−0.75 (0.02)***	−0.50 (0.03)***	−0.80 (0.04)***
Household Female	−0.01 (0.01)	−0.02 (0.01)*	0.02 (0.02)
Household Mixed Gender	−0.08 (0.01)***	−0.23 (0.01)***	0.13 (0.01)***
Household Asian	−0.49 (0.02)***		
Household Black	−0.12 (0.03)***		
Household Latino	−0.01 (0.01)		
% Black and Latino	1.31 (0.01)***	1.31 (0.02)***	0.92 (0.02)***
Change in % Black and Latino	−1.98 (0.07)***	−1.73 (0.09)***	−1.68 (0.11)***
Change % Homeowner	−1.66 (0.07)***	−1.09 (0.09)***	−2.59 (0.12)***
Change in % Poverty	−1.10 (0.11)***	−1.14 (0.14)***	−1.05 (0.18)***
Change in Unemployment	0.03 (0.07)	0.05 (0.08)	0.08 (0.11)
Change Violent Crime	0.90 (0.34)**	1.69 (0.43)***	2.19 (0.39)***
Change Property Crime	−1.88 (0.24)***	−1.14 (0.30)***	−2.44 (0.34)***
Change Pop.	0.96 (0.06)***	0.86 (0.07)***	1.58 (0.10)***
Time: 2014 to 2016	−0.04 (0.01)***	−0.03 (0.01)	−0.06 (0.02)**
Time: 2015 to 2017	−0.11 (0.01)***	−0.11 (0.01)***	−0.10 (0.02)***
Time: 2017 to 2019	−0.00 (0.01)	−0.00 (0.01)	0.01 (0.02)
Time: 2018 to 2020	−0.02 (0.01)	−0.05 (0.01)**	0.03 (0.02)
Time: 2019 to 2021	−0.06 (0.01)***	−0.08 (0.01)***	−0.03 (0.02)
Gentrifier*% Black and Latino	0.68 (0.17)***	0.65 (0.20)**	0.44 (0.29)
No SES Change*% Black and Latino	0.28 (0.07)***	0.38 (0.10)***	−0.05 (0.24)
Increase SES*% Black and Latino	−0.83 (0.16)***	−1.27 (0.22)***	−0.81 (0.13)***
AIC	1066388.59	672222.88	392446.48
BIC	1066700.36	672491.25	392695.17
Log Likelihood	−533167.29	−336087.44	−196199.24
Deviance	372747.51	248263.20	126411.00

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IN PROGRESS Verrilli, Allison, Roman, Marcel, Walker, Hannah, Epp, Derek, Amy Liu and Mike Findley. "Policing Socio-Geographic Boundaries and Inequality."

IN PROGRESS Carlos, Roberto and Vanessa Cruz Nichols, Chris Cassella, Vianney Gomez, Miranda Sullivan, Allison Verrilli, Clinton Willbanks, Ethan Yoo. "Latinx Attitudes on Immigration."

IN PROGRESS Fredriksson, Klara and Allison Verrilli. "Racial Boundaries & Voting."

CONFERENCE PRESENTATIONS

PRIEC PAper: 2023, "New Faces Changing Spaces: How Gentrification Shapes Individual Demand for Policing."

JUSTICE &
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SPSA Paper: 2023, "New Faces Changing Spaces: How Gentrification Shapes Individual Demand for Policing."

PRIEC	Poster: 2022, “New Faces Changing Spaces: How Gentrification Shapes Individual Demand for Policing.”
APSA	Paper: 2022, “Policing Socio-Geographic Boundaries and Inequality.”
PRIEC	Poster: 2018, “Igniting the Fuse: Immigration, Threat, and the Political Activation of White Identity”

FELLOWSHIPS AND AWARDS

2023	Government Department Research Grant Winner with University of Texas Professor: Roberto Carlos and Graduate Students: Chris Cassella, Vianney Gomez, Miranda Sullivan, Clinton Willbanks, Ethan Yoo. <i>The University of Texas at Austin, Department of Government</i> (\$3,500)
2022	Summer Pre-Dissertation Fellowship, <i>The University of Texas at Austin, Department of Government</i> (\$3,500)
2018	John Roos Prize, Best Undergraduate Thesis in the Field of American Politics, <i>The University Notre Dame, Department of Political Science</i>

TEACHING AND DEPARTMENTAL POSITIONS

JANUARY 2022 - Present	Graduate Research Manager, IPD Policing Lab
SPRING 2023	Teaching Assistant, Judicial Processes & Behavior (for J.B. Duck-Mayr)
FALL 2022, 2023	Teaching Assistant, Language, Politics, and Culture (for Amy Liu)
SPRING 2022	Teaching Assistant, Latinx Politics (for Marcel Roman)
FALL 2021	Teaching Assistant, U.S. Congress (for Alison Craig)

PROFESSIONAL EXPERIENCE

2018-2021	Paralegal, <i>Relman Colfax PLLC (Washington, D.C.)</i>
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SKILLS

PROFICIENT	R, L ^A T _E X, ArcGIS
INTERMEDIATE	Mathematica

LANGUAGES

NATIVE	English
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PROFICIENT	Spanish
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MEMBERSHIPS

2022 - PRESENT	American Political Science Association
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2021 - PRESENT	Southern Political Science Association
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