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# Territoriality and the Emergence of Norms During the COVID-19 Pandemic<sup>1</sup>

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ABSTRACT: Although social norms are critical for regulating behavior, the emergence of new norms is rarely studied in consequential real-world settings. Thus, the conditions under which norms arise in certain communities but not in others are not well understood. In this article, we propose *territoriality* as a factor that helps to explain the unequal emergence of norms. When individuals experience a strong sense of territoriality over the physical spaces they inhabit, they feel empowered and justified in regulating others' behavior within those spaces. To the extent that demand for particular norms is widespread, territoriality can facilitate norm emergence. Using daily, geolocated data from the early months of the COVID-19 pandemic in New York City, we find support for this theory; neighborhoods with higher levels of territoriality were more likely to adopt new health-protecting norms. Our territoriality account sheds light on the relationship between norm emergence, physical space, and neighborhood resilience.

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## INTRODUCTION

On January 9, 2020, the first reported death from COVID-19 occurred in Wuhan, China. Within weeks, the virus had spread around the world and incited a global pandemic. In the face of the crisis, health experts determined that successfully mitigating the threat required wholesale changes of behavior, including sheltering in place, social distancing, and mask-wearing. The implementation of such changes required more than top-down mandates or recommendations from local authorities; it required concerted efforts by individuals and communities to modify and regulate their behavior. It required the emergence of new, health-protecting norms to reshape behavior far beyond what formal authorities had the power to influence or enforce.

Yet a demand for new social norms—no matter how urgent—is not generally considered a sufficient condition for their emergence (Coleman 1990; Hechter and Opp 2005; Kitts 2006; Opp 2018; Piskorski and Gorbatâi 2017). Despite the constant and relatively consistent messaging by local government and health officials as to the importance of social distancing and wearing facemasks, and despite the high death toll from COVID-19, not all communities similarly adopted health-protecting norms in response to the pandemic outbreak. Even within the same city, neighborhoods differed in terms of their adoption and enforcement of such behaviors. In this paper, we ask why this was the case; why were some communities better able to enact health-protecting norms while others were not?<sup>2</sup>

This question illustrates a serious issue, not just for COVID-19, but for a variety of community outcomes affected by norms such as discrimination (Choi, Poertner, and Sambanis 2019), disaster responses (Dynes 2005), and delinquency (Becker 2008). Sociologists have long

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<sup>2</sup> Note that our focus is on *reactive* norm emergence, such as happens during disasters, crises, and threats (Kreps 1984). This is in contrast to norm emergence where norms arise gradually when behavioral regularities become increasingly prescriptive over time (Horne 2005; Opp 1982).

argued that the social organization of neighborhoods has significant consequences for differences in social control (Janowitz 1975; Park and Burgess 1925; Sampson and Groves 1989; Shaw and McKay 1942), but they have not studied norm emergence *per se*. The unequal dispersion of health-protecting norms at the onset of the COVID-19 pandemic, despite communities facing similar threats, raises the question of whether and how neighborhood context alters norm emergence. To address this question, we bridge literatures on norm emergence and neighborhood social organization.

In particular, we focus on the concept of territoriality, which Lyman and Scott (1967) described as a “neglected sociological dimension” but which has been used to explain individual behavior such as why people decorate or clean their personal spaces, and erect fences and post “No Trespassing” signs (Brown 2009; Brown and Werner 1985; Caughy, O’Campo, and Patterson 2001; O’Brien 2018; Taylor 1988). We argue that territoriality may also play a role in collective norm emergence. When individuals feel a strong sense of territoriality over the physical spaces they inhabit—meaning that they exert control over, feel familiarity with, and make investments in them (Brown, Lawrence, and Robinson 2005)—they feel empowered and justified in regulating others’ behavior within those spaces. To the extent that demand for a particular norm is widespread—such as due to negative externalities, collective decision-making, or norm entrepreneurs—territoriality can shift individual propensities to conform with and enforce behaviors associated with that demand within a particular space. In the aggregate, these behaviors facilitate the emergence of a new social norm. We suggest that territoriality helps to explain norm emergence in neighborhoods *net of* established neighborhood features such as residential neighborhood disadvantage (Levy, Phillips, and Sampson 2020; Wilson 1996; Wodtke, Harding, and Elwert 2016), social networks (Sampson, Morenoff, and Earls 1999;

Sampson, Raudenbush, and Earls 1997), and physical disorder (Kasarda and Janowitz 1974; O'Brien, Sampson, and Winship 2015; Sampson and Groves 1989). We propose that territoriality facilitates place-based communities' abilities to regulate the behavior of their members.

We evaluate this theory by investigating variation in the emergence of health-protecting norms across New York City neighborhoods in the early weeks of the COVID-19 pandemic. New York City was the epicenter of the virus at a time when health-protecting guidelines—i.e., sheltering in place, social distancing, and wearing a face mask—were first disseminated. With over 500 people dying daily from COVID-19 in the city at its peak, adopting and enforcing such behaviors was a matter of life or death. But not all neighborhoods responded equally; by evaluating normative responses to COVID-19, we demonstrate that those neighborhoods with higher levels of territoriality were better able to adopt and enforce new health-protecting norms. We find that territoriality significantly increased norm compliance and enforcement in this context at a magnitude comparable to well-documented neighborhood effects on crime and social mobility (Sharkey and Faber 2014; Wodtke, Harding, and Elwert 2011). This setting, along with the recent availability of geolocated big data, provides a unique and unprecedented opportunity to study the formation of social norms—a topic that is notoriously challenging to study using observational data—in a consequential real-world setting.

This paper makes several contributions. First, we identify the role of territoriality in facilitating norm emergence. While rational choice and symbolic interactionism theories of norm emergence both highlight the importance of social networks and social interaction (Coleman 1990; Ellickson 1991; Elster 2009; Hechter and Opp 2005; Horne 2005; Lin 2002), we demonstrate how environmental factors—such as territoriality—can also contribute to the

emergence of new norms. Moving the question of norm emergence into physical spaces opens the door for theorizing about connections between social groups and the spaces they inhabit, and how the interplay between them can foster—or impede—the formation of norms. Second, this work offers norm emergence as one source of community resilience in the face of a crisis (Aldrich and Meyer 2015; Rao and Greve 2018; Wildavsky 2017). In line with Klinenberg's (2018) call for attention to the material aspects of resilience in urban spaces, we show that neighborhood territoriality fosters compliance with and enforcement of social norms during a crisis. Low levels of territoriality may in fact help to identify which communities might need more substantial interventions and support during COVID-19 and in future crises due to failures of collective self-regulation (Aldrich and Meyer 2015; Masterson et al. 2014). Finally, our study demonstrates the potential of big data in research on the emergence of social norms and in urban sociology (Cagney et al. 2020; Lazer and Radford 2017; Levy et al. 2020; O'Brien et al. 2015; Phillips et al. 2021). As Hechter and Opp (2005) observe, “Because of the dearth of empirical research on the emergence of social norms, much of the relevant literature is speculative” (xiii). By combining high-resolution GPS data with detailed administrative records, we shed new light on the development of norms.

## THE EMERGENCE OF NORMS

Although a variety of definitions exist, social norms are generally considered to be “behavioral rules that are backed by sanctions” (Bendor and Swistak 2001; Horne 2005). They constitute behavioral regularities—i.e., what others do—in addition to entailing a sense of “ought,” where others believe that a rule ought to be followed (Bicchieri 2017; Coleman 1990;

Hechter and Opp 2005).<sup>3</sup> Behaviorally, a social norm is thought to exist when members of a group tend to act in a particular way—in accordance with the rule—and tend to be punished for not acting in that manner (Blake and Davis 1964; Homans 2013; Horne 2005). The behavioral manifestation of norms within a population therefore has two components: compliance and enforcement. *Compliance* refers to people’s tendency to act in accordance with the behavioral guideline, while *enforcement* refers to the tendency of individuals to sanction those who do not comply. Enforcement can be imposed informally by any member of the community (Ellickson 2005; Elster 2009) and sanctions can include disapproving words, looks, or gestures; negative gossip or ostracism; and signals of contempt (Brauer and Chekroun 2005; Cook and Hardin 2005; Elster 2009; Feinberg, Willer, and Schultz 2014; Guala 2012). Even when mild, such sanctions can arouse shame in norm violators, which may motivate them to better regulate their behavior in the future (Elster 2009).

The above definition raises two important questions regarding norm emergence: where do new behavioral rules come from, and what leads to their adoption as social norms? Although the focus of the paper is on the latter, the former bears addressing as it provides a necessary condition for a new norm’s emergence. From a rational choice perspective, a key foundation of norm emergence is what is variously referred to as the instrumentality proposition (Opp 2001) or consequentialist theory (Horne, Doodoo, and Doodoo 2018). Scholars in this tradition argue that new behavioral rules emerge if they are instrumental in attaining the goals of a group of actors (Coleman 1990; Hechter 1988; Heckathorn 1988, 1989). Particularly relevant is when behaviors create externalities that impose costs or provide benefits to others (Axelrod 1986; Ellickson

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<sup>3</sup> Note that our focus is on injunctive norms, as opposed to descriptive norms. Whereas descriptive norms indicate common patterns of behavior that are not backed by sanctions (what most others do), injunctive norms indicate common behaviors that are backed by sanctions (what most others approve or disapprove) (Cialdini, Reno, and Kallgren 1990).

1991; Fehr and Gintis 2007; Fine 2005; Horne 2009; Opp 2001; Ostrom 2000; Posner 2000; Yamagishi 1988). For example, cigarette smoking does not just affect the smoker; it represents a health hazard to those in the smoker's vicinity. Such externalities generate an incentive for group members to develop norms that encourage or discourage the behavior; in other words, externalities create a demand for particular rules (Coleman 1990).

In contrast, the symbolic interactionism perspective of norm emergence theorizes that new behavioral rules develop through a process of collective interaction and sensemaking. The main tradition within this approach is referred to as Emergent Norm Theory, which views norms as arising out of a precipitating crisis that requires actors to interpret the situation and determine the best course of action (Levine and Hogg 2014; Turner and Killian 1987). In such scenarios, traditional norms are no longer appropriate (Fritz and Williams 1957; Perry 1979) and people look to others to help with the evaluation process (Zeigler et al. 1983). By collectively defining and making sense of an unfamiliar situation, individuals are able to make inferences about what new behavioral rules are most appropriate (Bettenhausen and Murnighan 1985; Prentice 2013; Turner and Killian 1987).

In both traditions, new behavioral rules can be championed by norm entrepreneurs (Ellickson 2001) or "keynoters" (Dynes and Quarantelli 1968; Reicher 2008). These are individuals who support particular rules of behavior and have outsize influence arising from specialized knowledge or abilities such as status, social skills, leadership abilities, or technical expertise. People often look to high-status actors for behavioral guidelines (Paluck, Shepherd, and Aronow 2016; Robalino and Macy 2018), and those actors can help to legitimize particular behaviors in response to a threat (Andrighetto, Grieco, and Tummolini 2015). In particular, the messages disseminated by public officials can influence perceptions of threats and communicate

new standards of behavior, facilitating the demand for new norms (Ellickson 1991; Horne and Mollborn 2020; Opp 2018; Tankard and Paluck 2017). Legal expression serves both a coordinating function and as an informational signal (McAdams 2014). For this reason, “Government has a comparative advantage in changing norms” (Ellickson 2005).

Yet even when strong demand is readily established through negative externalities, collective decision-making, or norm entrepreneurs, demand for a norm is not generally considered sufficient for its emergence (Coleman 1990; Hechter and Opp 2005). If complying with the behavioral rule is individually costly, then individuals may seek to avoid doing so. Individuals may also be reticent to enforce the behavioral rule on others due to the second-order free rider problem (Kitts 2006; Opp 2018; Piskorski and Gorbatâi 2017). Even if there is interest within a group to regulate a particular behavior, there must be individuals willing to sanction violators. Sanctioning, however, is costly; it requires emotional energy and effort, and those who sanction are at risk of retaliation or violence (Molm 1997). For these reasons, individuals are incentivized to be free riders, meaning that they would prefer for someone else to intervene and provide the collective benefits. But if everyone follows the same calculus, sanctioning will not occur and the norm will not emerge.

The opportunity to free-ride raises the question of why individuals are willing to intervene at all, which is widely viewed as necessary for norm emergence. Although some have posited that individual variation may be the cause (Diekmann and Przepiorka 2015; Przepiorka and Diekmann 2013), the most common explanation concerns the density of the group’s network (Coleman 1990; Ellickson 1991; Elster 2009; Horne 2005; Lin 2002). Dense networks facilitate the communication and coordination of sanctioning behavior, which may allow individuals to share costs (Burt 2005; Coleman 1990; Ellickson 1991; Opp 2018). Individuals within dense

networks are also likely to share interdependencies, which may incentivize them to help each other (Opp 2018). Horne (2009) further argues that people sanction not just to prevent deviant behavior, but also because they care about how they look in others' eyes. These tendencies are exacerbated in dense networks, as network density increases conformity pressures (Burt 2005) and the social rewards that sanctioners receive (Horne and Mollborn 2020). Thus, network structure can increase the willingness to sanction others and facilitate norm emergence.

However, research on norm emergence has been constrained by the difficulty of studying social norms in the field as they are in the process of emerging (Hechter and Opp 2005), and as such we know little about the factors beyond social networks that facilitate norm emergence in the presence of widespread demand. We thus turn to a literature that argues that where people live shapes the regulation of their behavior. The following section considers how work on the social organization of neighborhoods provides opportunities for theoretical development, which we utilize by theorizing how territoriality affects norm emergence.

## TERRITORIALITY AND NORM EMERGENCE

Sociologists have long claimed that the “capacity of a society to regulate itself according to desired principles and value” (Janowitz 1975) is influenced by local context. Work in urban sociology in particular has highlighted how features of neighborhoods influence individual behaviors (such as criminal acts) and aggregate community outcomes (such as crime rates) (Sampson 2012; Sampson and Groves 1989; Shaw and McKay 1942). Much of this research focuses on community networks as fundamentally important through such concepts as social capital and collective efficacy. Still, research in this area has recognized the importance of other features that can also shape individual behaviors. We focus on how certain neighborhood

features may undermine or augment the ability of communities to regulate the behaviors of their members.

One feature that has received limited attention is territoriality. Territoriality as a construct originates in the biological sciences, where it is used to describe how animals claim and defend spaces (Ardrey 1966). Later adopted into the social sciences, the term indicates behavior motivated by a concern for physical space (O'Brien 2018).<sup>4</sup> Territoriality manifests in two ways: through caretaking behavior, which involves the maintenance and personalization of space; and through protection, where space is defended against intrusion and violation (Brown 2009; Brown et al. 2005; O'Brien 2018). Territoriality is commonly viewed as manifesting itself at the level of the individual, where individuals establish, maintain, and communicate relations with particular spaces through behaviors such as installing external home decorations, ordering or cleaning spaces, erecting fences, and posting “No Trespassing” signs (Altman 1970; Brown 1987, 2009; Brown and Werner 1985; Caughy et al. 2001; Taylor 1988).

Territoriality is viewed as originating from psychological ownership (Brown et al. 2005). Psychological ownership—which can apply to any object—entails several features: a sense of possession toward a particular target (Wilpert 1991), the target being experienced as having a close connection to the self (Furby 2006), and both cognitive and emotional attachment to the target (Pierce, Kostova, and Dirks 2003). Targets thus become part of an individual’s identity and are perceived as an extension of the self (Carrier and Dittmar 1994). Psychological ownership is related to, but distinct from legal ownership: people can legally own something

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<sup>4</sup> Lyman and Scott (1967) trace the origin of the concept in sociology to Park and Burgess’s *The City*, an important formulation of ecological ideas related to the Chicago School of Urban Sociology (see Park and Burgess 1925). Park and Burgess do talk about territoriality in a broad sense, in the context of ecological, cultural, and political features that characterize geographical units. To our knowledge, however, students of the Chicago School did not theorize territoriality to be an independent source of social control.

without feeling that it is truly theirs (McCracken 1986); they can also feel ownership over something—such as a public space—they do not legally control (Furby 1980).

Three paths have been proposed as leading to psychological ownership, which can act independently or in conjunction with one another (Pierce et al. 2003): the greater the extent to which an individual has control over a target (Furby 2006; Rudmin and Berry 1987), the more an individual becomes intimately familiar with a target, and the more an individual invests in a target—by creating it, caring for it, or improving it—the greater the sense of ownership (Pierce et al. 2003). Thus, over time a gardener will feel that a garden—regardless of property rights—belongs to her (Weil 1952). Together, these mechanisms suggest that psychological ownership can be a gradual process, where individuals slowly develop cognitive and affective attachments to targets around them (Pierce et al. 2003).

Territoriality, therefore, is generally conceived as the behaviors arising from psychological ownership of a particular territory, or physical space (Brown 2009; Brown et al. 2005; Edney 1974).<sup>5</sup> Because territoriality can develop over spaces that are familiar but not owned, an individual's primary territory tends to extend beyond the home and into the space immediately surrounding it (Brown and Altman 1982). In this way, individuals can become territorial over public spaces—e.g., sidewalks, streets, and parks—despite those spaces being available to all (Lyman and Scott 1967). As familiarity decreases the further one moves from the home, the less territorial people tend to feel (Lewicka 2010; Taylor and Brower 1985). This is

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<sup>5</sup> Territoriality is generally considered to be distinct from place attachment. Place attachment is a broad concept that, despite a multitude of definitions and approaches (Hidalgo and Hernández 2001; Scannell and Gifford 2010), generally includes the socio-demographic, social, and physical-environmental factors that contribute to emotional bonds between people and environment (Lewicka 2011). Although the concepts of territoriality and place attachment partially overlap, “attachment to places is an affective, proximity-maintaining bond that can be expressed without an underlying purpose of control” (Scannell and Gifford 2010).

consistent with findings that individuals tend to identify most closely with the area within a block or two of their homes (Coulton et al. 2001; Grannis 2009; Guest and Lee 1984).<sup>6</sup>

One of the consequences of territoriality is that it empowers an individual to regulate the behavior of others within a particular physical space. Consider a rule in many residences that shoes are not permitted to be worn in the house. When new guests arrive, they are informed of the rule and expected to comply; if they do not, they are likely to be confronted or asked to leave. Within one's territory, people feel that they have the legitimate authority to create and enforce rules, and they are willing to defend the space against violations if necessary.

The regulation of behavior within a territory does not only apply to outsiders who enter the space. Because territoriality involves maintaining the space to particular standards—sometimes referred to as custodianship (Brown 2009; O'Brien 2016a)—violations can also come from the person who experiences psychological ownership of the space herself. Consequently, the owner of a space will generally refrain from those same behaviors that are considered violations by others. Keeping the territory protected in a broad sense means preventing certain behaviors from entering the territory, regardless of their origin. Thus, the owner of a territory will tend to manifest both aspects of normative behavior: compliance with a particular standard of behavior, and enforcement of that behavior on others.

For a norm to be established in a community, standards of behavior need to exist beyond a single territory and be enforced more generally; territoriality must go from the individual to the collective. To do so, there first needs to be consensus about the type of rule that is desirable, i.e., there needs to be widespread demand for a particular norm. For our theory, we take consensus as

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<sup>6</sup> Although we discuss the psychological underpinnings of territoriality, it is important to emphasize that territoriality is shaped by policies and institutional conditions such as the built environment, housing markets, and urban development. For example, if housing insecurity is high, then territoriality is likely to be lower, as people spend less time becoming familiar with a particular space and are less likely to invest in it.

a given and are agnostic as to how it comes about, such as through negative externalities, collective decision-making, or norm entrepreneurs. Given consensus in demand for a norm, we expect that people will tend to manifest territoriality in the same manner. When consensus exists and territoriality is high, community members are more easily able to overcome the individual costs associated with compliance and enforcement to implement the same standards of behavior within their personal territories. Not only does this teach violators that non-conforming behavior is unacceptable throughout the community—suggesting to them that it is normative—but it also provides an opportunity for others to witness or hear about these acts of sanctioning, ultimately leading them to infer the presence of a new norm.

This process is important for the socio-cognitive nature of norms; rather than purely being behavioral, many definitions of social norms highlight the importance of beliefs (Bicchieri 2017; Ermakoff 2017; Miller and Prentice 1996). Cognitively, people often generalize from the behavior of a handful of individuals to the whole community (Prentice 2018) and research has found that initial adoption by a minority of a population can be sufficient for initiating group-wide social change (Centola et al. 2018). By facilitating the control of physical spaces, territoriality can help to foster individual compliance and enforcement behaviors within a community that can then be observed, experienced, and shared with other community members. If the individual territorial behaviors are widespread enough and sufficiently well-known, then others are likely to interpret them as evidence that a norm exists (Bettenhausen and Murnighan 1985; Bicchieri 2005; Prentice 2013; Turner and Killian 1987). Ultimately, the inferences people draw from their social environments can produce norms (Frye 2017; Horne and Mollborn 2020).<sup>7</sup>

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<sup>7</sup> This theorization is not meant to imply that territoriality is the only operative factor leading to the emergence of norms. Rather, other factors may additionally function in any given scenario to facilitate norm emergence.

Importantly, the second-order free rider problem—a key concern in rational choice theories of norm emergence—is unlikely to arise through this process. This is because territorial violations are likely not just viewed as normative transgressions, but—because territory is perceived as part of the extended self—as personal offenses as well. Violations of territory threaten a person’s sense of self-efficacy, their ability to express their identity, and their sense of security (Brown et al. 2005). Consequently, territorial violations serve as personal affronts, which likely strengthen emotional responses and spur sanctioning. Indeed, the more psychologically valued the territory, the more individuals are willing to engage in personal sacrifice and the assumption of risk (Pierce et al. 2003), and the more energetically the space is defended (Taylor and Brooks 1980). Whereas an individual who does not enforce a norm *outside* of their territory is subject only to the corresponding externalities of the offending behavior, an individual who does not enforce a norm *inside* of their territory is also in danger of ceding or relinquishing control over that space to others.

This leads to our main hypothesis:

Hypothesis 1 (H1): *Given a shared demand for a norm, greater territoriality among community members is associated with the stronger emergence of that norm.*

From a behavioral perspective, this hypothesis has two components. As described earlier, norms entail *compliance* with a particular code of conduct and decentralized *enforcement* against those who do not comply. We can separate H1 into two sub-hypotheses:

Hypothesis 1a (H1a): *Given a shared demand for a norm, greater territoriality among community members is associated with greater compliance with that behavior.*

Hypothesis 1b (H1b): *Given a shared demand for a norm, greater territoriality among community members is associated with greater enforcement of that behavior when violations are observed.*

These predictions are not perfectly parallel. Whereas territoriality should affect norm compliance whenever demand for a particular norm arises (H1a), its effect on enforcement is conditional on the observation of violations (H1b). Less enforcement does not necessarily mean the behavior is not being enforced; rather, violations may be low despite the willingness to enforce being high. Evaluating how territoriality shapes enforcement therefore requires introducing an interaction term, which we describe in the Methods section after explaining our setting and data.

## COVID-19 AND NEW YORK CITY

To evaluate our hypotheses, we focus on New York City during the early months of the COVID-19 pandemic. The first cases of COVID-19 appeared in the United States in late January of 2020 and New York City quickly emerged as the epicenter of the virus both nationally and across the globe (Stier, Berman, and Bettencourt 2021). After the first documented case on March 1 and the first death on March 14, cases skyrocketed in New York City, with more than 6,000 new cases and over 500 deaths per day at its peak. Figure 1 displays the daily number of cases, hospitalizations and deaths attributed to COVID-19 during this period.

[Insert Figure 1 here]

The pandemic served as a powerful exogenous shock that dramatically changed the consequences of ordinary behaviors. Benign behaviors such as congregating in groups and socializing with others suddenly became risky and unsafe, as they facilitated the spread of the

virus and threatened the health of those nearby (Horne and Johnson 2021). These new externalities led both individuals and communities to have a burgeoning interest in restricting in-person social interaction.

The arrival of COVID-19 in New York City therefore led to a demand for health-protecting norms such as sheltering in place, social distancing, and wearing a face mask. This demand was fostered and strengthened by lawmakers and health experts promoting and encouraging these changes in behavior (Brandtner et al. 2021; Friedson et al. 2021; Wellenius et al. 2021). New York Governor Andrew Cuomo instituted a shelter-in-place order on March 20, 2020, requiring non-essential businesses to shut down and instructing residents to stay home as much as possible.<sup>8</sup> New York City Mayor Bill de Blasio added to these restrictions on March 25 with an executive order banning non-essential gatherings of any size.<sup>9</sup> On April 15, a further state executive order required all individuals to wear masks or face coverings in public.<sup>10</sup> Together, these orders—which were repeated and reinforced at daily press conferences—both communicated the severity of the threat and strengthened demand for particular behaviors to protect public health.

Despite the constant messaging about the importance of engaging in health-protecting behaviors, not all neighborhoods responded as successfully or to the same extent. Norms emerged more powerfully in some places than in others. By distinguishing communities by their degree of territoriality, we can assess whether communities with elevated levels were indeed better able to establish new health-protecting norms in response to the surging pandemic.

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<sup>8</sup> <https://www.governor.ny.gov/news/no-2026-continuing-temporary-suspension-and-modification-laws-relating-disaster-emergency>

<sup>9</sup> <https://www1.nyc.gov/assets/home/downloads/pdf/executive-orders/2020/eo-103.pdf>

<sup>10</sup> <https://www.governor.ny.gov/news/amid-ongoing-covid-19-pandemic-governor-cuomo-issues-executive-order-requiring-all-people-new>

Furthermore, this setting allows us to explore the effects of territoriality on social norms by measuring norm emergence with greater precision than is typically possible. Recall that the behavioral manifestation of norms has two features: compliance and enforcement. One of the main challenges of studying norm emergence is that observing compliance alone may indicate a behavioral regularity but not a norm, and observing enforcement is difficult because enforcement behaviors tend to be rare. New York City during this period lends itself to measuring both. The recent availability of mobility data using cellphones allows us to measure the extent to which people followed guidelines to shelter in place. Sheltering in place was widely publicized as critical to slowing down the spread of the virus, and its prevalence is indicative of the adoption of new health-protecting norms. Further, residents of New York City were directly encouraged by officials to call the city's 311 hotline if they observed others not following the new health guidelines. 311 calls—particularly for “uncivil” behavior—have been found to reflect normative responses of enforcement (O'Brien 2016b, 2018), and the prevalence of COVID-19 related 311 calls reflects a community's willingness to enforce new health-protecting standards of behavior. Not only can we capture both compliance and enforcement using these measures, but we are able to do so on a day-to-day and neighborhood-by-neighborhood basis, allowing us to track their development over time and space through the early period of the COVID-19 pandemic.

Finally, our setting enables us to observe the development of norms in real-time. Typically, norms are observed only after they have been widely adopted, thus missing the key period of emergence. The appearance of COVID-19 therefore provides a rare opportunity to study the emergence of consequential norms as they developed on a daily basis in response to a crisis.

## DATA AND MEASURES

To evaluate norm emergence in New York City in response to the COVID-19 pandemic, we bring together and integrate a variety of data sources. These include comprehensive records from the City of New York, demographic information from the U.S. Census and the American Community Survey (ACS), and detailed mobility data from mobile phones. Together, these data sources offer an opportunity to track daily changes in behavior in unprecedented detail, and they allow us to understand how neighborhoods differ both in terms of exposure and response to the crisis. These data also allow us to create fine-grained “ecometric” measures of neighborhood characteristics (O’Brien et al. 2015; Phillips et al. 2021; Raudenbush and Sampson 1999).

Of the various data sources used in the paper, two are of particular importance. First, New York City maintains and publishes copious amounts of data related to city operations. Of particular interest is the city’s database of 311 calls, which contains details of telephone calls made to the city about incidents—ranging from broken stoplights to noise complaints—that do not rise to the level of an emergency. Our study draws on calls relating to COVID-19, which include reports of social distancing and face mask violations. All such calls are timestamped and linked to GPS coordinates, allowing us to pinpoint the exact time and geographic location that the reported transgression took place.

311 calls in general have previously been connected to norm enforcement (O’Brien et al. 2017; O’Brien, Gordon, and Baldwin 2014), particularly when reporting incivilities by others (O’Brien 2016b). In fact, when asked why they make 311 calls, upholding norms is a commonly given response (O’Brien 2018). Although 311 calls do not capture other forms of enforcement (e.g., disapproving looks or confrontation), filing an official complaint with the city is likely a conservative estimate of other, corollary types of enforcement. Therefore, the prevalence of

COVID-19 related 311 calls should reliably indicate the prevalence of sanctioning behavior within a community when accounting for the local population's propensity to make 311 calls in general.

The second key data source is aggregated GPS data from cellphones compiled by SafeGraph, a company that collects anonymized location data from mobile phones. SafeGraph partners with mobile application services that have opt-in consent from users to collect location data. This allows SafeGraph to maintain a panel of approximately 40 million mobile devices in all of the more than 200,000 census block groups across the United States. This panel is largely unbiased; the data are generally representative of the United States population and the frequency of race, demographic, and income groups closely tracks the same frequency in the Census (Chen et al. 2020). SafeGraph engages in exhaustive data processing to maximize reliability, granularity, anonymity, and accuracy. To protect privacy, data provided by SafeGraph is presented by census block group and block groups with fewer than five devices are excluded from the panel. Using GPS pings to the devices in the panel, SafeGraph is able to track the movement of smartphones.

Mobile location data is increasingly being used in scientific research (Chen and Pope 2020; Couture et al. 2021), and these data specifically have been used in several publications on COVID-19 (e.g., Allcott et al. 2020; Brzezinski et al. 2021; Painter and Qiu 2021). Such data allow us to capture individuals' activity space in "high spatial resolution" and with "temporal continuity" (Cagney et al. 2020). We use Safegraph data that tracks the movement of hundreds of thousands of cellphones in New York City during the early months of the COVID-19 pandemic to observe the extent to which individuals complied with shelter-in-place orders. Using GPS data from mobile phones responds to an emergent concern in urban sociology to consider

mobility among neighborhoods while overcoming the biases of less representative data sources such as location-based social media (Cagney et al. 2020; Levy et al. 2020; Phillips et al. 2021).

We combine these data sources together and aggregate them at the level of the census tract by day. There are 2,168 census tracts in New York City, each with a population of approximately 3,000 to 4,000 people. Following common practice in sociological studies of neighborhoods (e.g., Browning et al. 2017; Hwang and Sampson 2014; Sampson, Mare, and Schachner 2017; Sampson, Morenoff, and Gannon-Rowley 2002; Sharkey 2008; Wodtke et al. 2011), each census tract serves as a neighborhood in our analysis, and evaluating changes by day allows us to observe norm emergence as it occurs.

For our sample, we focus on the period starting on April 1 and ending on May 27, 2020. Despite the fact that cases began to climb in the second half of March, it was only toward the end of March that clear and consistent health guidelines were disseminated by government officials in the form of executive orders. More importantly, on March 30, Mayor Bill de Blasio began encouraging residents to call the city government’s 311 hotline if they observed social distancing violations.<sup>11</sup> Calling 311 became a common way of enforcing compliance with health-protecting behaviors shortly thereafter. As these calls represent our measure of enforcement, starting our sample after the first calls is necessary.

The end of our period of observation is May 27, as the first protests in New York City in response to the death of George Floyd occurred the following day. These protests had a large impact on behavior—including, we expect, on our dependent variables—and we therefore exclude all data once the protests began. Together, the temporal window from April 1 to May 27

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<sup>11</sup> <https://www.ny1.com/nyc/all-boroughs/news/2020/03/30/mayor-slams-trump-after-accusing-workers-of-misusing-masks-during-coronavirus-outbreak->  
<https://patch.com/new-york/new-york-city/cops-days-away-fining-social-distance-violators-mayor-says>

allows us to track behavior before cases peaked and people were just figuring out how to respond to the new threat, until cases declined to a much lower level and COVID-19 had become more familiar. It is exactly in this period that we expect to observe norm emergence as it occurs.

### *Outcome Variables*

As mentioned above, social norms are characterized by two patterns of behavior: compliance with a particular behavior and enforcement of that behavior on others. To capture both compliance and enforcement of health-protecting behaviors during the early months of COVID-19, we include two dependent variables.

*Sheltering in Place (Compliance).* The state-wide shelter-in-place order on March 20 directed all residents to stay home as much as possible, along with requiring social distancing of at least six feet in public. Using SafeGraph data, we measure compliance as the percentage of tracked cellphones that did not leave their place of residence within a particular tract on a particular day. Place of residence is determined by a device's common night-time location over a six-week period delineated by a 153 by 153 meter geo-fence. Thus, devices are considered to be sheltering in place to the extent that they remain within that geo-fence throughout the day.<sup>12</sup>

*COVID-19 311 Complaints (Enforcement).* New York City's database of 311 calls is updated daily and includes historical data going back to 2010. Each call is logged in the database with a variety of identifiers and descriptors. Of particular relevance is the date the issue was reported, the categorization of the incident, and the location where it occurred. The city categorizes incidents by *complaint type* and *descriptor*, the former of which is a broader category than the latter. Across all complaints for the period of interest, there are 145 complaint types and 656

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<sup>12</sup> More information on the data is available here: <https://docs.safegraph.com/docs/social-distancing-metrics>

descriptors. Together, these categorizations are highly specific; for example, there are 38 ways that the city classifies noise complaints. Two types of calls relate to COVID-19: where the descriptor is “social distancing” or “face covering violation” (the complaint type in both cases is “non-emergency police matter”).

The location of each incident includes the address, which the city validates and then generates the associated latitude and longitude coordinates. It is through these coordinates that we assign each incident to a particular tract. Importantly, this address represents the location of the incident, not the place from which the complaint was made. Thus, if someone waited to report until after they left the scene of a violation, they still indicated where the incident took place, as this is what enabled the authorities to respond. Furthermore, the need for a specific address and the timeliness with which it would have to be reported in order to be actionable helps to ensure that these were actual witnesses to the violations, rather than people seeing pictures or videos on social media.

The importance of 311 for reporting COVID-19 violations is clear from the sheer number of complaints filed during this period. Social distancing complaints constitute the single largest category of any *complaint type* and *descriptor* pair with 42,780 complaints, while face mask violations—which did not even begin until about halfway through the period of observation—nevertheless represent the eleventh most common complaint.

To construct our measure, we aggregate data on the two types of normative enforcement behavior at the level of the census tract by day.<sup>13</sup> We then transform this number into a ratio of

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<sup>13</sup> Although we recognize that sheltering in place (compliance) and reporting face mask and social distancing violations to 311 (enforcement) do not capture identical behaviors, we view them as being tightly interconnected. Sheltering in place, social distancing and wearing a face mask were all health-protecting behaviors endorsed by political officials and health experts as necessary for maintaining public health during the COVID-19 pandemic. As norms do not generally exist in isolation, but as sets or systems (Hechter and Opp 2005; Horne and Mollborn 2020), we assume that most people viewed these behaviors as part of an interrelated set of health-protecting norms.

the number of COVID-19 related calls over the total number of 311 calls per tract per day. This method has been used in social media analysis during disasters to measure the relative attention given to those disasters (Guan and Chen 2014; Zou et al. 2018). As we describe below, all results are substantively the same if we instead use counts of COVID-19 complaints.

### *Explanatory Variables*

Based on research on psychological ownership, territoriality comes about in three ways: the greater the extent to which an individual has control over a territory, the more an individual becomes intimately familiar with a territory, and the more an individual invests in a territory. We therefore use different variables to capture each of these processes, along with a combined indicator that captures the underlying construct.

*Territorial Control.* Legal ownership of a territory is associated with control of that space. This variable represents the percentage of owner-occupied housing per tract from the 2018 American Community Survey (ACS), which indicates the extent to which residents have control over the places in which they live.<sup>14</sup> Consistent with this idea of homeownership as an indicator of territorial control, the protection of property tends to be a high priority for homeowners (Lee and Van Zandt 2019; O'Brien 2012) and homeowners have higher levels of place attachment (Brown, Perkins, and Brown 2003; Fischer et al. 1977). To confirm that home ownership is a useful indicator of territorial control, we also considered which homeowners have mortgages on their properties. Those without mortgages have full ownership of their residences, giving them complete equity and greater control over the property. Using an alternative measure based on mortgages leads to similar results.

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<sup>14</sup> All ACS measures use 5-year averages to minimize the standard error of estimates by tract.

*Territorial Familiarity.* Familiarity is enhanced by the length of time in which a person has exposure to or inhabits a space. This variable from the ACS captures the extent to which residents in a tract remain in the same place for an extended period of time, specifically the percentage of tract residents who have not moved in the previous five years. Consistent with this operationalization, long-term residents have been found to have higher levels of place attachment (Brown et al. 2003; Fischer et al. 1977). As a robustness check, we instead used a variable that indicates the percentage of tract residents who have not moved in the previous ten years and the results are the same.<sup>15</sup>

*Territorial Investment.* Using New York City administrative data, we measure the number of residential building permits approved per residence for additions and renovations in the 24 months preceding the onset of COVID-19. We only include individual owners adding to or renovating pre-existing structures, to exclude new construction and construction by development companies. Following O'Brien and Montgomery (2015), this measure captures how invested residents are in improving and maintaining property within their communities. More specifically, we keep all new permits, meaning that we do not include renewals to avoid multiple records for the same property. To ensure that we are capturing owners living at the location, we only include properties where the address of the construction is the same as the address of the owner, as listed on the application. We further only include properties that are indicated as residential and where the permit applicant is an "individual" or "condo unit owner or co-op tenant-shareholder." This excludes permits filed by government agencies, corporations, and partnerships.

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<sup>15</sup> Our measures of territorial control and territorial familiarity—homeownership and residential mobility—have previously been used as part of other constructs. In the robustness checks, we discuss this issue along with providing evidence that territoriality is indeed a distinct construct.

*Territoriality (Combined)*. As control, familiarity, and investment are all pathways that foster psychological ownership and territoriality (Pierce et al. 2003), we view the three aforementioned variables as representing components of the same underlying construct and combine them into a single factor (Cronbach's alpha = 0.67).<sup>16</sup>

### *Treatment Variables*

While publicity and news reports about the COVID-19 pandemic likely saturated New York City uniformly, local variation still existed in the number of cases and deaths in a particular neighborhood. Consistent with our hypotheses, we investigate the relationship between territoriality and the dispersion of norm compliance and norm enforcement separately. Although we expect *compliance* with health protecting norms to largely derive from the global environment in the city, individuals may have also been sensitive to more local conditions. In addition to investigating the main effects of compliance, we therefore introduce an interaction term in subsequent models that indicates the number of new local cases. New local cases represent the immediate local threat and may have increased demand for the norm in specific neighborhoods.

*Enforcement* of health-protecting norms, on the other hand, is always conditional. Norm enforcement is a response to normative violations and therefore only occurs when violations are observed. If no violations are observed, then it is difficult to establish whether or not a norm exists. We therefore require a measure of normative violations to interact with our measures of

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<sup>16</sup> Although researchers often use a cutoff of 0.70 as appropriate for Cronbach's alpha, this has been frequently contested (Taber 2018). Cronbach's alpha is sensitive to both the pairwise covariance between each of the items and the number of items included. For example, a Cronbach's alpha of 0.66 (similar to ours) would be .73 if there was a fourth item with equivalent covariance, or 0.80 if there were six such items. For these reasons, various papers have presented results such as ours as affirming construct validity (Cortina 1993; van Griethuijsen et al. 2015).

territoriality to determine whether territoriality indeed enhances enforcement. However, our compliance outcome—the percentage of people sheltering in place—also affected the ability of those people to observe the compliance of others. In other words, the more people stayed at home, the less ability they had to observe whether others were following social distancing and face mask guidelines.<sup>17</sup> To observe how communities reacted to non-compliance, we therefore need a measure of non-compliance that did not also affect residents’ ability to observe the non-compliant behavior. To do this, we include a treatment variable for the number of non-residents who entered a tract on a given day. Although we cannot know the extent to which these visitors were complying with social distancing or face mask guidelines, it is reasonable to assume that more visitors were associated with a higher absolute number of non-compliers. Every additional person who entered the tract was already not sheltering in place and had a non-zero probability of additional violations. Further, this measure allows us to hold constant the percentage of tract residents sheltering in place (as a control variable), which accounts for the extent to which residents could observe instances of non-compliance and report them. We constructed the two treatment variables as follows.

*New Local Cases (lagged)*. The number of daily COVID-19 cases is maintained by the New York City Department of Health by ZIP code, which we match to each census tract by allocating the proportional number of cases based on the ratio of residences within the ZIP code that are located within a respective tract. This variable reveals variation across geography (tract) and across time (day) of the local severity of the threat. We use the lagged cases as individuals may not have been aware of local case levels on the same day that they occurred.

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<sup>17</sup> This is not to say that individuals sheltering in place were completely unable to observe transgressions. Many people still needed to leave the house on occasion for essential goods, such as groceries or medicine. However, sheltering in place did limit—sometimes dramatically—the opportunities that individuals had to witness violations by others.

*Devices Entering Tract.* We use additional data from SafeGraph to construct a daily weighted network of all devices that traveled between tracts. The data from SafeGraph includes where devices traveled when they left the house, which allows us to aggregate incoming devices for a given tract on a given day, and weight these values by the total number of daily devices tracked.<sup>18</sup> This results in a measure of the number of devices (i.e., people) entering a tract on a particular day from other tracts in the city. As a robustness check, we created an alternative measure that adjusts for the level of compliance—i.e., sheltering in place—in the tracts from which individuals originated. In other words, visitors are weighted by the daily compliance level of the tracts in which they resided, meaning that visitors who arrived from less compliant tracts are weighted more than visitors who arrived from more compliant tracts. This helps to more directly account for the likelihood that visitors violated health-protecting behaviors. Our findings are robust to the use of this alternative measure.

### *Control Variables*

Several other factors may also have an impact on norm emergence; to the extent that they are correlated with our measures of territoriality, it is important to control for them in the models. To account for general features of the neighborhood, we control for population and population density, as larger groups have been associated with having greater difficulty engaging in collective action and norm emergence in response to disasters (Aguirre et al. 2011; Aguirre, Wenger, and Vigo 1998). Both measures are derived from the 2010 Census.

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<sup>18</sup> The data do not include the duration of the visit, as some visitors may have spent brief periods of time in a tract while others may have spent hours. Even though variation undoubtedly existed in how long visits lasted, in aggregate more visits should tend to represent more time spent in the tract.

We also control for *Residential Neighborhood Disadvantage* (RND). RND is a composite measure of disadvantage, and is measured as a principal component of seven neighborhood characteristics: poverty rate, single-headed households, welfare receipt measured as the percentage of households receiving food stamps, percentage of adults with a high school diploma, the percentage of managers and professionals in the workforce (reverse coded), and the rate of adults with a bachelor's or advanced degree (reverse coded) (Cronbach's alpha = .76) (Levy et al. 2020; Wodtke et al. 2016). This captures the extent to which a neighborhood lacks opportunities and resources (Wilson 1996; Wodtke et al. 2016), and serves as a comprehensive measure of neighborhood disadvantage. As such, it may be related to the ability of neighborhoods to develop normative responses to the COVID-19 pandemic, as RND has been found to be associated with weaker informal social control (Sampson et al. 1997) and increased disorder (Brewster, Billy, and Grady 1993; Elliott et al. 1996; Jencks and Mayer 1990). RND is also associated with the ability of residents to enjoy homeownership and housing security, which is another reason to account for its effect.

Similar to RND, the racial or ethnic heterogeneity of a group has also been found to reduce its ability to form strong norms (Chatman 2010). As such, we include a calculation of *Simpson's Diversity Index* using tract race data from the ACS. This indicator is particularly important in our setting, as the ethnic and racial diversity of a community has been found to affect disaster responses in general (Cutter et al. 2008; Cutter, Boruff, and Shirley 2003) and social distancing in response to COVID-19 specifically (Egorov et al. 2021). Further, racial heterogeneity is also associated with residential mobility (Sampson and Groves 1989; Shaw and McKay 1942; Wenger 2019).<sup>19</sup> In addition to racial heterogeneity, we also include an indicator

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<sup>19</sup> If instead of racial diversity, we include race composition indicators in the models, the results are similar.

of the percentage of residents with limited English from the ACS, as those with limited English may be less likely to call 311 due to their language ability, rather than a decreased willingness to enforce health-protecting norms. We further include indicators of the age distribution in each tract, which accounts for the possibility that older residents may be more comfortable using non-confrontational means of enforcement, such as calling 311, whereas younger residents may be more likely to use more direct means, such as confrontation.<sup>20</sup> Older residents may have also been more inclined to shelter in place, due to their greater mortality risk from COVID-19. To account for age, we include indicators of the percentage of residents over the age of 64 and between the ages of 18 and 64, with the reference category being the percentage of residents under the age of 18.

Norm emergence in response to changing conditions requires that individuals share accurate beliefs about the magnitude and direction of the threat (Hechter and Opp 2005; Horne 2005; Opp 2001). We therefore include two variables—indicators of partisanship and trust in government—that likely influenced individuals’ willingness to take the threat and its associated precautions seriously. For the former, wearing a face mask and other COVID-19 precautions took on a partisan meaning beyond its public health significance, as Trump voters and Republicans perceived COVID-19 as less risky than Biden voters and Democrats (Barrios and Hochberg 2020; Bruine de Bruin, Saw, and Goldman 2020). We therefore use the vote share of Democratic candidate Joe Biden in the 2020 Presidential Election to account for each tract’s political leaning. To capture trust in government, we include a variable that represents the percentage of 2020 Census surveys that were returned within a given tract. Responding to the

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<sup>20</sup> Other studies of 311 calls, however, suggest that this is not generally the case. In Boston, a subset of 311 callers were linked to user demographics (O’Brien 2016b). The highest rates of calling were among adults ages 45-54 and 35-44, followed by 55-64 and 25-34. However, it is not clear if any of these differences are statistically significant.

Census is a way of measuring trust in government, as it demonstrates a willingness to cooperate with and respond favorably to government programs (Sullivan 2020; Vigdor 2004; Weakliem and Villemez 2004).

The extent to which a tract consists of commercial versus residential buildings may also impact compliance and enforcement. A greater number of commercial establishments provides reasons to visit the tract for outsiders, along with reasons for leaving the house for residents. On the other hand, tracts with a greater number of residential establishments likely include more parks, which may have been particularly appealing during the onset of the pandemic. Although it is not clear what the effects of the relative prevalence of commercial or residential establishments would have on norm compliance and enforcement—especially considering that all non-essential commercial establishments were shut down during our period of observation—the diversity of tracts in New York City make this an important dimension to account for. We therefore include an indicator of the fraction of business addresses in each tract out of all addresses in the tract. This indicator comes from United States Postal Service data in 2020.

To ensure that we are properly capturing all relevant COVID-19 information, we include a measure of cumulative COVID-19 cases by tract as of April 1, the beginning of our period of observation. This is necessary because our time-varying indicator of local cases only captures the number of new cases on a given day, without consideration of historical patterns.

Finally, we account for the fact that not everyone who wanted to was able to shelter in place. Many frontline workers did not have an option to work from home and continued to go into work throughout the pandemic. In order to control for those constrained in their ability to shelter in place, we include indicators from SafeGraph of the number of devices within each tract that were engaged in full-time work, part-time work, or delivery services outside of the home on

a given day. Essential full-time workers are defined as devices that spent more than six hours at a location other than their home geo-fence between the hours of 8am and 6pm. Essential part-time workers are defined as devices that spent one period of between three and six hours at one location other than their home geo-fence between the hours of 8am and 6pm. Delivery workers are defined as devices that stopped for less than 20 minutes at more than three locations outside of their home geo-fence on a given day.<sup>21</sup>

There are also several control variables that we only include in the compliance or the enforcement models. In the compliance models, we control for lagged enforcement—i.e., the number of COVID-19 related 311 calls in a tract on the previous day—as enforcement behaviors should affect subsequent compliance as part of the process of norm emergence. For similar reasons—and to account for the fact that sheltering in place likely limited residents’ ability to observe violations—we control for sheltering in place in the enforcement models.

In the enforcement models, we control for several additional variables to account for the possibility that certain residents may have differing propensities to use formal channels for complaints. One way of doing so is noted by O’Brien (2018), who suggests that one “...identify [311] case types whose need is likely to be even across the city. For example, one might expect residents of all neighborhoods to have a similar need for sanitation services to pick up bulk items. Another example of an evenly distributed need is for snowplows during a snowstorm, controlling for certain infrastructural characteristics. In these cases, the geographic distribution of reports reflects the likelihood of utilizing the system” (77). We follow O’Brien by including an indicator of the number of requests for bulk pickup in each tract in the 24 months prior to

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<sup>21</sup> Although these measures should reliably capture the percentage of people working away from home per tract-day, we also reran all models with an additional indicator of the percentage of healthcare workers in each tract, as healthcare workers were essential workers who were expected to continue working during the height of the pandemic. The results are substantively the same.

COVID-19 and another indicator of the number of snow-related reports in each tract in the 24 months prior to COVID-19. We also add a third indicator—*Complaints per Permit*—which combines the 311 data with the building permit data to calculate the average number of construction-related 311 complaints (e.g., complaints about construction noise) per building permit within a tract for the 24-month baseline period prior to COVID-19. By including these indicators, while also controlling for previously mentioned covariates such as population and the prevalence of commercial establishments, we are better able to isolate the effects of territoriality on norm enforcement.<sup>22</sup>

We also control for a variety of additional variables in a series of robustness checks to account for alternative explanations relating to social networks, the physical features of neighborhoods, and heterogeneity in the commercial development of different tracts. For example, we use multiple measures to capture social networks within each tract, including a measure developed by Chetty et al. (2022) based on the geo-tagged social networks of 72.2 million users of Facebook, the number of shared activity spaces as measured by the number of local community organizations, and the number of civic events. To examine a neighborhood's housing stock, we use data from the United States Postal Service data in 2020 provided by the U.S. Department of Housing and Urban Development, as well as the estimated share of low-density residential housing (house, detached house, bungalow, etc.) from the Open Street Maps API to account for the particularly defensive sub-culture of certain urban contexts (Kadowaki 2019; Suttles 1972). We also construct measures of private neglect and public denigration, which are two dimensions of physical disorder that may affect the ability of neighborhoods to regulate

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<sup>22</sup> As a further robustness check, we also included an indicator of the average number of 911 calls per arrest during the 24-month period prior to the appearance of COVID-19. This ratio indicates the likelihood of members of each tract to make formal complaints about the substantiated wrongdoing of others. Results remained substantively the same.

their members. Details of how each of these additional variables is constructed are included in the robustness checks.

### *Methods*

Our analysis relies on two different dependent variables, both of which are continuous and time-varying. We therefore evaluate them using OLS regression for panel data. Our unit of analysis in all models is the tract-day and we use both random effects models and fixed effects models to corroborate all results. Whereas random effects models allow for evaluating the relative effect of time-invariant neighborhood features, models with tract fixed effects meet the highest reasonable standard of directly evaluating how territoriality shapes a neighborhood's sensitivity to the treatment variables. All models include day fixed effects to account for temporal trends in the data. We use standard errors clustered at the tract level to address the violation of the assumption that all observations are independently and identically distributed.

## RESULTS

Figure 2 reveals the aggregate trajectory of norm compliance and enforcement across all of New York City throughout the period of interest. The solid line displays the average percentage of individuals sheltering in place per day. As cases increased from March until early April, sheltering in place increased from about 20 percent to over 50 percent of residents. Once cases begin to decline, sheltering in place decreased, but at a much slower rate, declining to about 35 percent by the end of June.

[Insert Figure 2 here]

The dashed line shows the number of COVID-19 311 complaints made per day, meaning complaints about social distancing and face mask violations.<sup>23</sup> Unlike sheltering in place, 311 calls did not begin until the end of March, likely due to Mayor Bill de Blasio beginning to promote the use of the 311 system for policing harmful behaviors around this time. COVID-19 311 complaints gradually increased throughout April until reaching a peak of 2,168 calls on May 2 before decreasing in June. Some of the high variance observed in the graph is due to the cyclical nature of these calls; 311 calls related to COVID-19 tended to spike on weekends.<sup>24</sup>

Because our measure of enforcement did not begin until the very end of March, we begin our period of observation on April 1. Although this omits the period when sheltering-in-place was first increasing, we are still able to capture variation in compliance rates over time and across neighborhoods.<sup>25</sup> The end of our observation period—due to the start of the George Floyd protests—coincides with a drop in COVID-19 related 311 calls. Although we cannot be certain if the protests are the cause of the decline, this reinforces our decision to end the observation window on May 27.

Although Figure 2 provides background context, our geographic unit of analysis is the tract, not the city as a whole. We therefore display the geographic distribution of sheltering in place and COVID-19 related 311 complaints in Figure 3. The left panel indicates the average level of sheltering in place by tract throughout our period of observation, while the right panel

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<sup>23</sup> If we instead plot the number of 311 complaints as a percentage of all 311 calls (the dependent variable), the graph looks similar.

<sup>24</sup> Although we do not have direct evidence as to why calls spike on weekends, we expect that it relates to the fact that more people were outside socializing or visiting public spaces such as parks on weekends. This likely led to more violations, especially if people were less careful around their friends than around professional colleagues. We can corroborate this explanation to some extent by comparing the prevalence of COVID-19 related 311 calls across the entire city by day with calls classified as “Loud Music/Party.” For both types of complaints, the pattern of weekend spikes is almost identical.

<sup>25</sup> If we extend our observation window for sheltering in place back to March 21 for the compliance analysis—the day after sheltering-in-place mandates were put in place—the results are similar.

indicates the location of each 311 complaint related to COVID-19 during the same time period. As Figure 3 demonstrates, the geographic disparities within New York City were substantial.

[Insert Figure 3 here]

Table 1 displays the summary statistics by tract-day for the variables used in the models, while Table 2 displays the associated correlation matrix. The first two rows of Table 1 are the dependent variables, followed by the treatment variables, the key explanatory variables, and the control variables. Approximately 53 percent of individuals within a tract stayed home on a given day in our timeframe, while roughly 16 percent of daily 311 complaints were related to COVID-19. There were on average 1.26 new cases of COVID-19 per tract-day and 0.04 percent of all traveling phones in the city entered a given tract on a given day. Regarding the key indicators of territoriality, there is wide variation in neighborhoods' levels of homeownership, residential stability, and building permit requests.

[Insert Table 1 and Table 2 here]

Important to note is the lower number of observations for *COVID-19 311 Complaints*. On some days, certain tracts did not have any 311 calls, COVID-19 related or otherwise. Because there were no calls, it is not possible to calculate the percentage of calls related to COVID-19, as that would involve dividing by zero. This dependent variable therefore entails the loss of 13 percent of observations. As a robustness check, we replicate all relevant analyses using Poisson regression, where the dependent variable is a count of the number of COVID-19 related 311 calls that took place on a given tract-day. This method does not necessitate dropping any observations and the results (included in Appendix B) are substantively the same.

*Norm Compliance*

*Main Effect on Compliance.* Table 3 displays the results of models examining compliance with sheltering in place. Model 3.1 indicates the effect of territorial control on sheltering in place, Model 3.2 indicates the effect of territorial familiarity on sheltering in place, Model 3.3 indicates the effect of territorial investment on sheltering in place, and Model 3.4 indicates the effect of the combined measure of territoriality on sheltering in place. All models use random effects by tract and include the time invariant controls. All models also include employment controls (the extent to which tracts contained essential full-time, essential part-time, or delivery workers) and fixed effects by date.

[Insert Table 3 here]

We want to first highlight the positive and significant effect of lagged enforcement across all models on compliance. The fact that lagged enforcement affects compliance is important for two reasons. First, it provides face validity for our use of 311 calls as an indicator of norm enforcement. Second, it highlights the fact that norm emergence is a mutually reinforcing process of compliance and enforcement, where increases in one can lead to increases in the other.<sup>26</sup>

Focusing next on the key explanatory variables, all three components of territoriality, along with the combined measure, have a positive and significant effect on sheltering in place ( $p < 0.001$ ). Together this provides support for H1a. Focusing on the combined measure in Model 3.4 specifically, a one standard deviation increase in territoriality within a tract was associated with a 1.62 percent increase in the percentage of people sheltering in place on that particular day. As we discuss below, the effect's magnitude is substantial.

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<sup>26</sup> Although the coefficient of 0.06 is not large, the substantive interpretation is that a single additional 311 call by a lone individual can have a measurable effect on sheltering in place for the *entire census tract*, which on average have 3,905 people in our data. For smaller geographical units than the census tract, we expect this effect to be much larger.

*Interaction Effect on Compliance.* Table 4 extends the analysis in Table 3 by incorporating interaction terms between the territoriality indicators and the lagged number of new local cases. As norms are generally considered to be conditional (Axelrod 1986; Winter, Rauhut, and Helbing 2012), it stands to reason that the severity of the local outbreak—to the extent that residents were aware of it—may have increased the effect of territoriality on sheltering in place.

[Insert Table 4 here]

Models 4.1, 4.3, 4.5, and 4.7 are random effects models replicated from Table 3 with the addition of interactions between the number of lagged local cases and the measures of territoriality. Models 4.2, 4.4, 4.6, and 4.8 use fixed effects to control for unobserved time-invariant factors, which helps to alleviate concerns about omitted variable bias and demonstrates the robustness of the finding. As the measures of territoriality are static characteristics of each tract, they can only enter the models as interactions with a time-varying covariate (i.e., the lagged number of new local cases). Across all models, the interactions are positive and significant ( $p < 0.001$ ), suggesting that a higher number of local cases increased the effect of territoriality on sheltering in place. The number of new local cases is not standardized, so one additional case increased the effect of territoriality on sheltering in place by 0.22 (for Models 4.7 and 4.8). This is consistent with the idea that norms are conditional, as compliance is responsive to both the generalized threat and its local prevalence.

Figure 4 visualizes the interaction of territoriality and the number of new lagged local cases on sheltering in place. When territoriality is a standard deviation below the mean, sheltering in place is largely unchanged as the number of new COVID-19 cases from the previous day increases. For higher levels of territoriality, however, even a single additional

COVID-19 case in a tract markedly increased sheltering in place. In other words, in more territorial communities, small changes in the number of local cases had a rapid and meaningful impact on compliance in a single day. For larger increases in case numbers, sheltering in place rose more substantially.

[Insert Figure 4 here]

*Magnitude of Effects.* The magnitude of the effects of territoriality in the aforementioned models are substantial in several respects. For one, territoriality has one of the largest effects of any of the variables in the model in Model 3.4. Territoriality has a much larger effect on sheltering in place than political orientation, residential neighborhood disadvantage, and racial diversity, even though the latter two variables have previously been associated with the ability of communities to engage in behavioral regulation (Sampson and Groves 1989; Sampson et al. 1997), while political orientation is thought to be a key cleavage in whether people embraced or resisted COVID-19 policies (Painter and Qiu 2021).<sup>27</sup>

These effect sizes should also be interpreted in the specific context in which they take place. A virus such as COVID-19 can spread any time an infected person is in the proximity of non-infected others. By increasing the number of people not in contact with one another, even by a small amount, a large number of possible COVID-19 infections may be prevented. For example, Shenoy et al. (2022) estimate that a one percentage point increase in the number of people leaving home in a given weekend is associated with an additional 14 cases and 1.4 deaths per 100,000 residents. The average number of daily cases in New York City during our period of observation was 2,388 (27 per 100,000), and the average number of deaths was 270 (3.1 per 100,000). Wellenius et al. (2021) similarly attempt to estimate the consequences of changes in

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<sup>27</sup> These effect sizes are comparable, as all of the aforementioned variables are standardized.

mobility on COVID-19 case numbers. They estimate that a five percent decrease in mobility leads to a reduction in cases by 9.2 percent two weeks later, 20.9 percent three weeks later, and 13 percent four weeks later. Together, these studies show that relatively small differences in sheltering in place can substantially alter the odds of a large outbreak, which can have a disproportionate effect on overall case counts and deaths over subsequent weeks. Thus, the impact of territoriality was meaningful, not just on sheltering in place, but because it likely had a much larger impact on subsequent case numbers.

One additional piece of evidence also suggests that our effect sizes are substantial. Our results indicate that one standard deviation increase in territoriality entails a shift of 0.16 standard deviations in the outcome. This is comparable to the effect sizes found in other studies of neighborhood effects. For example, in their review of the neighborhood effects literature, Sharkey and Faber (2014) note common effect sizes of between 0.15 and 0.25 standard deviations, which are characterized by the authors as “strong effects” (p. 565).

### *Norm Enforcement*

Together, the results in Table 3 and Table 4 suggest a consistent story: territoriality increased compliance with new health-protecting behaviors, suggesting the emergence of a new social norm. Further verifying this contention, however, requires examining the other behavioral component of social norms: enforcement. First, however, recall that enforcement is contingent on compliance. If everyone is perfectly compliant, then we would not expect to observe enforcement even in the presence of a new norm. Because enforcement is conditional on

compliance, we therefore focus on the interaction between devices entering the tract and our measures of territoriality, which is the true test of H1b.<sup>28</sup>

*Interaction Effect on Enforcement.* Table 5 displays OLS estimates of how territoriality affected the enforcement of health-protecting behavior through the use of 311 calls. The dependent variable is the proportion of 311 calls on a given tract-day that were complaints about social distancing or face mask violations. Similar to Table 4, Models 5.1, 5.3, 5.5, and 5.7 are random effects models that include all time invariant control variables, along with employment controls and fixed effects by date. Models 5.2, 5.4, 5.6, and 5.8 are fixed effects models which include only time varying covariates.

[Insert Table 5 here]

The effect of *Sheltering in Place* on norm enforcement is negative and significant across all models ( $p < 0.001$ ). This is in line with our expectation that higher levels of sheltering in place reduced the likelihood of observing social distancing and face mask transgressions, leading to a lower percentage of COVID-19 related 311 calls. This finding is also consistent with the idea that tracts with higher rates of compliance also had fewer transgressions to report. The second effect of interest is that of *Devices Entering Tract*. *Devices Entering Tract* is positive and significant ( $p < 0.001$ ), meaning that more individuals visiting a tract was associated with a higher percentage of COVID-19 related 311 calls in that tract. This corresponds with our

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<sup>28</sup> Nevertheless, we include models with only the main effects of territoriality on enforcement in Appendix A. Intriguingly, the main effects of the four measures of territoriality are all negative and significant ( $p < 0.001$ ), indicating that tracts higher in territoriality had less enforcement. This suggests that either tracts with higher levels of territoriality were less likely to enforce health-protecting behaviors when they occurred, or that tracts with higher levels of territoriality had fewer transgressions (and therefore less enforcement). The former interpretation would contradict H1b, while the latter would support it. We find the latter to be more plausible, as the previous analysis indicates that higher levels of territoriality were associated with greater compliance; it seems reasonable that tracts compliant with sheltering in place would be similarly compliant with social distancing and face mask wearing. However, this ambiguity is why we evaluate the hypothesis more directly by looking at the interaction effect.

expectation that visitors to a tract increased the overall number of transgressions, leading to more 311 calls.

What we are particularly interested in, however, is how the effect of territoriality on enforcement varies with rates of transgressions. This requires examining the interactions between the measures of territoriality and outside individuals entering the tract. Across all models, the interactions between the territoriality measures and *Devices Entering Tract* are positive and significant, indicating that higher levels of territoriality were associated with a greater responsiveness to COVID-19 violations. Interestingly, the coefficients between the random effects models and fixed effects models are different, with stronger effects in all fixed effects models. This suggests that the random effects models may be subject to omitted variable bias, which could be depressing the coefficient estimates.<sup>29</sup> Given that the fixed effects models only examine within-tract variation (i.e., they hold all unvarying features constant), their estimates are likely more reliable.

*Magnitude of Effects.* As with compliance, the size of the effect of territoriality on enforcement is also substantively significant. Focusing on the combined measure of territoriality with fixed effects in Model 5.8, the interaction has a coefficient of 1.41. This means that if territoriality was one standard deviation over the mean, then a standard deviation increase in *Devices Entering Tract* increased the percentage of COVID-19 related 311 calls by 1.41 percent (or 2.82 percent if territoriality was two standard deviations above the mean). Such magnitudes are substantively meaningful considering that, on average during our period of observation, only

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<sup>29</sup> Interestingly, one of our robustness checks—replacing the indicator of commercial addresses with an indicator of residential addresses and an indicator of low-density residential addresses—boosted the coefficient of territoriality in Model 5.8 from 0.99 to 1.22, which is more in line with the value in the fixed effects model. This suggests that better accounting for the type of residential housing per tract helps to identify the true effect of territoriality on 311 calls.

16.63 percent of daily 311 calls per tract were about COVID-19 transgressions. With such a low baseline, small changes had relatively large effects.

*Robustness Checks.* One concern from this analysis is the loss of observations due to the dependent variable being a percentage. We therefore used an alternative dependent variable representing the count of all COVID-19 related 311 calls, which does not require dropping any observations. Appendix B shows the results of this analysis using Poisson regression.<sup>30</sup> Results are substantively the same. We also reran all analyses using a third dependent variable to account for the possibility that the population of tracts is influencing our results beyond what we can control for by including *Population* and *Population Density* in the models. To do this, we took the residuals of the count of all COVID-19 311 calls regressed on population and population density. This residual measure indicates the excess calls per tract-day beyond what is predicted by population and population density. We then repeated the analysis using this residual as the outcome variable. Results can be seen in Appendix C and are also substantively the same.

Additionally, our results could potentially be distorted by the presence of so-called “supercallers”, i.e., individuals who call the 311 hotline an extreme number of times (O’Brien et al. 2015; White and Trump 2018). Concerns about supercallers have primarily been raised when using 311 calls to estimate behaviors such as political engagement, as one cannot measure the percentage of individuals who are politically engaged when it is unclear how many times each individual calls. In contrast, our goal is to measure *total* enforcement behaviors, as we fully expect that those high in territoriality will call multiple times to the extent that they observe persistent or multiple violations. Nevertheless, we conduct a series of robustness checks to

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<sup>30</sup> We use Poisson regression rather than negative binomial or zero-inflated negative binomial models because Poisson panel estimators with cluster-robust standard errors are more robust and require weaker distributional assumptions (Cameron and Trivedi 2009; Wooldridge 1999).

prevent any undue influences from supercallers on our findings. These analyses follow approaches used by other scholars, which largely involve eliminating locations or tracts with a disproportionate number of 311 calls (Hong, Kim, and Widener 2020; Ternullo, Zorro-Medina, and Vargas 2024; Wichowsky, Shah, and Heideman 2022).

Various supplementary models presented in Appendix D show that our results are not distorted by the presence of supercallers. In Models 1-4, we use all 311 calls from the previous year and remove all locations (i.e., addresses) that have a volume of calls greater than one standard deviation (Models 1 and 2) or two standard deviations (Models 3 and 4) above the mean number of calls. In other words, locations with a high number of calls—suggesting the possible presence of supercallers—are eliminated from consideration, even if they subsequently had calls related to COVID-19 during our period of observation. We consider this to be a conservative test; by eliminating locations with greater than one (two) standard deviation above the mean number of calls, we are deleting 18 percent (10 percent) of COVID-19 related 311 calls. In comparison, O’Brien et al. (2015) and O’Brien (2018) identified 18 individuals as having made more than 100 reports in a single year (0.1 percent of callers), Hong et al. (2020: 1204) found “less than one percent of repeat noise complaints (>5 times/month) came from the same addresses,” and Wichowsky et al. (2022) identified only one tract out of 209 (0.5 percent) in their study as being subject to supercallers.

It is possible that supercallers are somewhat topic-specific or that the identities of supercallers change over time. To account for this possibility, we calculated the number of COVID-19 related 311 calls per location during our period of observation and deleted COVID-19 calls from any location more than one standard deviation (Models 5 and 6) or two standard deviations (Models 7 and 8) above the mean. Next, we follow Wichowsky et al. (2022), by

removing outliers after aggregating 311 calls by tract, removing tracts more than one standard deviation (Models 9 and 10) or two standard deviations (Models 11 and 12) above the mean. For Models 13 and 14, we focus on noise complaints (Hong et al. 2020) in the year before the COVID-19 pandemic, as noise complaints are likely better proxies for caller location, as callers presumably complain about noises adjacent to their homes. We construct and include variables representing the number of locations with noise complaints greater than one standard deviation (Model 13) and two standard deviations (Model 14) above the mean in each tract. Finally, we replicate the technique used by Ternullo et al. (2024), who exclude all 311 calls from every location that had *any* 311 calls at that location within the previous year (Model 15 and Model 16). We view this as an extreme measure, as supercallers are those who call 311 a disproportionate number of times, while this method removes any location that had a single previous call. This technique causes us to lose 80 percent of our COVID-19 related 311 observations; nevertheless, the key results remain statistically significant ( $p < 0.05$ ) in both random and fixed effects models. Using a number of different analyses with a variety of different assumptions, we find our results to be robust to the exclusion of supercallers.

### *Territoriality Affects Norm Compliance and Enforcement*

Combining the results from Table 3, Table 4, and Table 5 suggest that new health-protecting norms arose in response to the COVID-19 pandemic, but that norm emergence was not uniformly distributed across New York City. Territoriality, as measured independently by three different variables and as a combined construct, was associated with increased compliance with health protecting behavior and with increased enforcement in response to violations.

Together, this demonstrates how territoriality can promote normative responses in the face of an unexpected crisis such as COVID-19.

### *Distinguishing Territoriality from Other Neighborhood Features*

Although the previous analyses support the hypotheses, there remains the task of more carefully distinguishing territoriality from other established concepts. We already addressed a series of potential confounders through the inclusion of control variables. Chief among these concerns is that neighborhoods with greater territoriality are also more privileged, and that race and class may have affected how individuals experienced the pandemic. To account for this possibility, we included measures of residential neighborhood disadvantage, racial diversity, and time-variant measures of travel due to part-time and full-time work. Tract fixed effects also allow us to account for time-invariant confounders.

The three indicators of territoriality—homeownership, residence longevity, and building permits—clearly relate to the three components of psychological ownership (i.e., control, familiarity, and investment); however, the first two of these measures have also been theorized and evaluated as being either a cause of or an indirect measure of social disorganization (Sampson and Groves 1989; Shaw and McKay 1942) or attachment to place or community via social networks and social capital (Harlan et al. 2005; Kasarda and Janowitz 1974; Lewicka 2010). The systemic model of community attachment suggests that length of residence fosters friendship, kinship, and associational networks (Kasarda and Janowitz 1974). Residential stability increases local friendship ties, community attachment, and participation in social and leisure activities, increasing social integration (Sampson 1988). Social disorganization theory further argues that collective characteristics of a neighborhood—including residential instability—weaken social connections among neighbors, leading to the breakdown of social

control and, subsequently, disorder (Sampson and Groves 1989; Shaw and McKay 1942; Steenbeek and Hipp 2011).

As a result, a series of alternative theoretical explanations require special attention. For one, as we explained above, both the rational choice and the symbolic interactionism perspectives on norm emergence highlight interpersonal interactions and relations as critical factors. Relatedly, research on neighborhood effects has established aspects of social disorganization—including proxies of collective efficacy, social networks, and physical disorder—that increase outcomes related to social control, which can be a consequence of norm emergence. We thus offer a variety of robustness checks to account for these issues, along with further exploring the possibility that the level of commercialization within a tract is influencing our results.

*Social networks.* To account for the possibility that our measures of territoriality may also be correlated with social networks, we construct several measures of community networks that we can control for in our models. Doing so helps us to better isolate the effect of territoriality on norm emergence. We begin with a measure of network density, as density is the most common explanation for norm emergence from the rational choice perspective (Coleman 1990; Ellickson 1991; Elster 2009; Horne 2005; Lin 2002). We use a measure developed by Chetty et al. (2022) based on the social networks of 72.2 million users of Facebook.<sup>31</sup> These data, which benchmarking efforts show are close to being representative of the US population (Chetty et al. 2022), were then used to construct a measure of network density. Density is measured on a scale of zero to one, with zero representing all of a person’s friends being disconnected from one

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<sup>31</sup> More specifically, Chetty et al. (2022) constructed their measure using Facebook users aged between 25 and 44 years old, who resided in the United States, who were active on the platform at least once in the past 30 days, and had at least 100 US-based friends. Consistent with other research using Facebook data (Bailey et al. 2018), these data and the resultant measures serve as a proxy for real-world friendships rather than online interactions per se.

another, and one representing all of a person's friends being interconnected with each other. These values were then aggregated at the ZIP code level, which we matched to each census tract by allocating proportionally based on the ratio of residences within the ZIP code that are located within a respective tract. This variable represents “the degree of clustering in a community” (Chetty et al. 2022).

For two additional measures of social networks, we build on work on activity spaces, which are the physical locations in which people go about their daily activities (Browning and Soller 2014; Cagney et al. 2020). Shared spatial contexts—such as workplaces, schools, and shops—are vital for the cultivation of social networks (Cagney et al. 2020; Fischer 1982; Small 2009; Small and Adler 2019), and the places people spend the most time spatially are indicative of their social contacts (Wang et al. 2015). The more that residents share the same activity spaces, the denser their networks (Browning et al. 2017).

The next variable looks at the number of local community organizations per capita present in each tract. Since Putnam (2000), participation in civic organizations has been used to measure social capital, which is an indicator of the resources that individuals can obtain through their social networks, and which is enhanced by a greater number of network connections (Portes 1998). Such organizations contribute to the formation and maintenance of social ties (Small 2009; Small and Adler 2019), providing a spatial basis for interaction (Blau and Schwartz 1997; Oldenburg 2013; Small 2009). These organizations can range from schools to churches to volunteer organizations, all of which provide local social foci (Feld 1981, 1982) that foster the growth of relationships within the community. A greater density of civic organizations is also associated with higher levels of collective efficacy, which is partially based on the density of networks within communities (Ohmer 2007; Sampson et al. 2005, 2002). Our measure captures

the extent to which a community has these organizational contexts in which to associate and interact with one another (Sharkey, Torrats-Espinosa, and Takyar 2017). Civic organization density was calculated based on the number of non-profit organizations headquartered in the same Census tract. To create this measure, we aggregated the number of unique IRS form 990 filings of tax-exempt 501(c)(3) organizations in 2017, the most recent year where comprehensive filings are available from the National Center for Charitable Statistics.

The final indicator of social networks is the number of events held within the neighborhood, including recreational events such as art events, block parties, play streets, fairs, and sidewalk sales. Civic events—defined as “collective, non-violent events oriented towards community civic engagement” (Sampson et al. 2005)—reflect local differences in civil society and thus the ability of the neighborhood to engage in collective action. Similar to local organizations, neighborhood events create activity spaces in which residents can broaden and deepen ties, enhancing the density of the local network (Sampson et al. 2005). The data for this indicator come from a database representing all permitted events reported to the NYC Office of Citywide Event Coordination and Management. Events were excluded that were likely to have been organized by individuals external to the community, such as concerts and athletic events. What remains are events likely to have been organized by local residents and organizations for members of the community, such as block parties, clean-ups, and play streets. These events encompass the period from 2010 to 2017, when 30,400 such events took place.<sup>32</sup>

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<sup>32</sup> We also tried two additional measures intended to capture social relationships within neighborhoods. For the first, we leveraged the SafeGraph data to reveal patterns of movement within and outside of communities. When an individual left their place of residence, their destination was either a location within that neighborhood or a location outside of it. Using a baseline period of the month before COVID-19 appeared, we measured the extent to which trips outside of the home led to destinations within the tract or outside of the tract. A greater percentage of trips within the tract indicates that residents were more frequently sharing space and interacting with other residents, fostering the growth of intra-neighborhood network ties. The second measure was developed by Fraser, Page-Tan,

Table 6 replicates the analysis from Table 3 and Table 5 but includes the three new measures of social networks as controls. As these new measures are time-invariant, we only include the results of the random effects models. The first four models examine compliance, where the dependent variable is sheltering in place; while the last four models evaluate enforcement, where the dependent variable is the percentage of COVID-19 related 311 complaints.

[Insert Table 6 here]

As the table shows, the inclusion of the three network variables does little to change the key results from the earlier tables. The four territoriality main effects for sheltering in place are all significant ( $p < 0.001$ ), as are the four territoriality interactions for COVID-19 related 311 complaints ( $p < 0.001$  for three of the coefficients,  $p < 0.05$  for the fourth). Compared to the previous tables, the effect of the combined measure of territoriality on sheltering in place decreased slightly from 1.62 to 1.33, suggesting that our measures of territoriality in the random effects models were perhaps picking up some variation due to social networks. However, the interaction of the combined territoriality measure for 311 complaints is 0.95 (Model 6.8), which is similar to the coefficient of 0.97 in the previous table (Model 5.8). Together, these findings show that territoriality had an effect independent of common measures of neighborhood social organization.<sup>33</sup>

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and Aldrich (2022), and combines nine indicators from the U.S. census that represent similarity among members of the same census tract, indicated by race, age, gender, language, and communication capacity. As homophily can lead to both the development of group identification and stronger networks (McPherson, Smith-Lovin, and Cook 2001)—both of which may affect norm emergence—this measure helps us to better isolate the effects of territoriality. Including these measures in the analysis does not change the results.

<sup>33</sup> Note that the purpose of this analysis is not to argue that other neighborhood characteristics, such as social networks, did not play a role in the emergence of norms. Rather, our objective is simply to isolate the effect of territoriality to identify its particular impact on norm emergence. Most likely, a variety of different factors beyond territoriality played a role in the emergence of health-protecting norms during the early days of the COVID-19 pandemic.

*Physical Features of Neighborhoods*. Another commonly cited mechanism by which neighborhood characteristics influence social control, and presumably could affect norm emergence, is through physical disorder. Physical disorder “undermines neighborhood regulatory capacity and creates a perception of disinterest and non-intervention by local actors” (Keizer, Lindenberg, and Steg 2008; Levy et al. 2020; O’Brien, Farrell, and Welsh 2019; Wilson and Kelling 1982) and has been found to be negatively correlated with territoriality (Sampson et al. 2002). According to O’Brien (2018), physical disorder can take two forms: private, which includes housing issues and uncivil use of space; and public, which includes graffiti and litter (see Marwell and Morrissey 2020). Although lower rates of physical disorder could be why territoriality affects norm enforcement in the context of COVID-19, we expect that the construct has an ambiguous relationship to both territoriality and norm emergence. To test this expectation, we used 311 call data to replicate “ecometric” measures of private neglect and public denigration pioneered by O’Brien (2018) to directly test whether physical disorder overlaps with territoriality.

Specifically, we followed O’Brien’s (2018) strategy to construct measures of physical disorder by sorting the stated reasons for each 311 call into five broad categories using all 311 calls in the 24 months prior to the advent of COVID-19. We then analyzed the distinctive dimensions underlying these categories using a principal component analysis. The public categories were trash and graffiti; the private ones were housing issues and uncivil use of space.<sup>34</sup> We were able to replicate O’Brien’s (2018) construction of two distinct factors indicating public denigration and private neglect, respectively.

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<sup>34</sup> Since the categories reported by New York City differ from those reported in Boston—where the measure was originally constructed—we could not include a category for complaints related to big buildings; results were consistent when we included the natural environment as well as public infrastructure as additional public categories.

Our regression findings are robust to the inclusion of controls for physical disorder both in the private and public sphere, as all of our results remain statistically significant and are substantively similar. Together, this suggests that territoriality had an independent effect on norm emergence even when accounting for levels of physical disorder.

To confirm that territoriality really captures a neighborhood characteristic that operates independent of social networks and forms of physical disorder, we also conducted an exploratory factor analysis of these concepts. The results reported in Appendix E show that the analysis generated three factors with eigenvalues greater than one. Furthermore, the different items loaded onto the factors as expected, indicating distinct constructs for territoriality, social networks, and physical disorder. We conclude that territoriality is conceptually distinct from other channels of neighborhood effects.<sup>35</sup>

*Commercial Development.* An additional concern is that our results are influenced by the level of commercial development in different tracts within New York City, as the city has a great deal of variation in how residential or commercial a particular area is. It is possible that norm emergence is more challenging in highly commercialized areas that have many transitory office workers or shoppers. Alternatively, norms may still develop within large apartment buildings where residents observe and model the behavior of other residents. Furthermore, all commercial establishments with the exception of essential businesses were shut down during our period of observation; thus, there were unlikely to have been tracts dominated by commercial activity.<sup>36</sup> Regardless, to account for any such effects, tract-level commercialization is included in all

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<sup>35</sup> We conducted an additional robustness check on our results by including a measure of the tract-level dog population in New York City, which is available from city records. It is possible that some individuals were unable to fully shelter in place due to the need to take their dogs for walks. If the prevalence of dog ownership varies by tract, then not accounting for dog-owning households could bias our results. Including an indicator of dog ownership in the random effects models does not substantively affect our findings.

<sup>36</sup> Indeed, the correlation between the fraction of business addresses in a tract and the percentage of devices entering that tract is 0.17, which means that the relation between the two variables is weak.

models. As an alternative, we controlled for the number of total residential addresses and the number of low-density residential addresses in all models, and the results are the same.

To explore this issue further and ensure that commercialization is not influencing our results, we reran the analysis using data subsets that exclude the most commercialized tracts. We used four different measures of commercialization for added robustness: the ratio of business addresses to all addresses, the absolute number of business addresses, the ratio of residential addresses to all addresses, and the absolute number of business establishments. The first three measures come from United States Postal Service data in 2020 provided by the U.S. Department of Housing and Urban Development, while the last one comes from the 2019 Economic Census. We conducted the analysis separately for each of these four indicators, each time removing all tracts more than a standard deviation above the mean level of commercialization (or more than a standard deviation below the mean level of residential addresses for the third indicator). A visualization of this analysis can be seen in Appendix F.

The left panel in Appendix F displays the coefficient of *Territoriality* from Model 3.4 of Table 3 when we subset the data based on the different indicators of commercialization. The top indicator shows the coefficient from the baseline model with a 95 percent confidence interval, while the following four values show the same coefficient under the different subsetting rules based on each of the four commercialization variables. The middle panel displays the coefficient of *Territoriality* from Model 5.7 (the random effects model), while the right panel displays the coefficient of *Territoriality* from Model 5.8 (the fixed effects model). Across all three panels, the results demonstrate that the effects are not driven by highly commercialized tracts and are robust to their exclusion. These results are not particularly sensitive to the cutoff we select for excluding commercialized tracts. For example, the results hold if we instead exclude the top 25 percent

most commercialized tracts rather than a standard deviation above the mean. In sum, we have high confidence that the effect of territoriality on norm emergence is both statistically and substantively significant controlling for a slew of alternative considerations.

## DISCUSSION

Our analysis of health-protecting behavior during the early months of the COVID-19 pandemic demonstrates how territoriality enhanced the emergence of new norms. Neighborhoods with higher levels of territoriality engaged in more compliance and more enforcement of behaviors intended to mitigate the spread of the virus. These findings support our proposition that when individuals experience a sense of ownership over a physical space, they feel empowered to make rules regarding the use of that space and to maintain and defend the space against violations. In other words, territoriality shifts individual motivations to follow and enforce rules due to an interest in caring for a particular space. When multiple community members implement the same rules, this can lead to the emergence of new norms as others hear about and observe these compliance and enforcement behaviors and ultimately infer the existence of community-wide norms.

### *Implications for the Study of Social Norms*

Building on previous research on norm emergence, we reveal how features of neighborhoods can contribute to the development of new norms. This opens the door for further theorizing about the connections between the physical environment and the people living in it, and how the interplay between them can foster—or impede—the formation of new norms. We

view this work as a first step towards integrating norm emergence with urban sociology, two literatures that have only peripherally been in conversation with one another.<sup>37</sup>

In addition to identifying territoriality as a factor in norm emergence, this work contributes to the norm emergence literature in two important ways. For one, we reveal a previously unrecognized means by which the second-order free rider problem—where individuals hesitate to take on costly enforcement actions in support of a norm—can be overcome. Given the internalization of one’s territory as part of the extended self, violations of that territory threaten a person’s sense of self-efficacy, their ability to express their identity, and their sense of security (Brown et al. 2005). As such, violations serve as personal affronts, which likely strengthen emotional responses and spur sanctioning. In this sense, sanctioning becomes less of a rational decision and more of an emotional reaction to a personally offending behavior, as individuals are increasingly willing to engage in personal sacrifice (Pierce et al. 2003) and more energetically defend space (Taylor and Brooks 1980) when a territory is more valued.

Second, our study reveals an intriguing connection between social norms and physical space. Although norms are typically thought of as applying to a social group, also considering them in relation to physical space provides fodder for theoretical development. For example, this connection is relevant for considering *norm targets*—those who are expected to follow a norm and are likely to be sanctioned for deviating—and *norm beneficiaries*—those who benefit from the norm and serve as potential sanctioners when witnessing violations (Coleman 1990). In our case, norm targets are determined by individuals’ presence in a particular spatial location, while norm beneficiaries are those who make use of and inhabit that particular space. Tying norms to physical space reveals a class of disjoint norms (Horne and Mollborn 2020) where targets

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<sup>37</sup> Of course, urban sociology has long been interested in neighborhood capacities for social control (Sampson, Raudenbush, and Earls 1997), but that work has not focused on norm emergence specifically.

represent a more expansive group than beneficiaries depending on the movement of people through space.

The connection between norms and physical space also provides insights into the nature of dependence between group members and how this may facilitate the emergence of norms and social control more broadly within a community. Our work reveals that the dependence between group members that gives rise to norms—such as when their actions cause negative externalities—does not just mean dependence on people outside of the physical context. Given that territories tend to be overlapping, individuals in a community are dependent on others for help in maintaining and defending that space. This likely leads those with high levels of territoriality to place social pressure on neighbors to align in their behavior vis-à-vis the shared territorial space; thus, the nature of overlapping territories may foster alignment and subsequent norm formation within the group.

This spatially determined sense of dependence is likely augmented by the fact that the more that individuals depend on a group—due to a lack of desirable alternatives, moving costs, and strong personal ties—the more they are willing to accept normative obligations (Hechter 1988). Territoriality likely decreases the appeal of alternative spaces, as people become attached to and value a particular place, leading to dependence on their neighborhoods and by extension their neighbors for the maintenance of that space. This territorial-induced dependence should similarly lead to an increased willingness to accept normative obligations within the neighborhood, facilitating the emergence of new norms. In sum, not only might members of more territorial communities be willing to set and enforce individual standards of behavior within their territories, but they might also be more willing to accept normative obligations from their neighbors.

Given the above discussion of the theoretical relation between social groups and physical spaces, we do not view the role of territoriality in norm emergence as being constrained by or particular to places of residence. There are a variety of non-residential settings where individuals may feel territorial over a space: e.g., the office where a person works, a bar that a person has frequented for years, the public transportation that an individual consistently uses for her commute. In all three cases, territoriality may arise from control of or familiarity with a space. Indeed, territoriality has been found to exist in workplaces, where its manifestations include decorating personal workspaces, setting boundary markers, and defending ownership (Brown et al. 2005). Such processes may help to provide insight into an established finding from the whistleblowing literature, that longer tenured workers are more likely to blow the whistle (Mesmer-Magnus and Viswesvaran 2005). Similar to our finding that communities with longer-termed residents engage more in normative control, office workers with longer tenures may feel similarly empowered to control behavior within the workplace. Further, territoriality can potentially help to explain the puzzle of why individuals enforce standards of behavior in transitory settings such as in trains (Przepiorka and Berger 2016), subway stations (Balafoutas and Nikiforakis 2012), and streets (Berger and Hevenstone 2016); it may be due to “regulars” greater familiarity with those spaces.

However, the above discussion is not meant to argue that *all* emergent norms are equally affected by territoriality. We expect territoriality to be relevant for norm emergence primarily when associated behaviors are apparent and easy to discern. This visibility allows an individual to determine whether or not others in their territory are engaging in a particular behavior or violating a nascent norm. If the offending behavior is more difficult to observe, then actors do

not know when to sanction others through observation alone. In this case, social networks and communication channels may become relatively more important as drivers of norm emergence.

The norms we evaluate in this study are cooperation norms, meaning standards of behavior that are in the interest of the group but impose a cost on the individual. However, other norms exist that are not cooperation norms: coordination norms occur when “individuals’ interests are (partly) aligned, but the multiple ways of best pursuing these interests make it difficult for these individuals to tacitly coordinate” (Przepiorka and Diekmann 2021, p. 2), whereas signaling norms exist to solve trust problems and demonstrate commitment to a particular group (Posner 2002). Consistent with our findings, we expect territoriality to often be relevant for cooperation norms. Although territoriality is likely less relevant for coordination norms, as territoriality is less useful for determining which among a set of behavioral rules to embrace, we expect it to shape signaling norms in situations where a physical location and a social group are closely linked, such as a gang claiming ownership over a particular turf, fraternity members living together in a frat house, or motorcyclists feeling territorial over a particular bar.

Although our work builds on both rational choice and symbolic interactionism theories of norm emergence, we view it as having more kinship with the former. Although actions stemming from territoriality are not necessarily “rational” in nature, territoriality helps to resolve the key rational choice problem of second-order free riders by revealing how a shift in individual self-interested behavior due to a desire to protect and defend spaces can have important implications for group-level—i.e., normative—behaviors. In this respect, territoriality is perhaps just one example of a class of individual-level motivational factors that can function as a value or

resource to the group without explicitly being group-oriented, thus facilitating the emergence of collective norms.

In addition to its theoretical implications, this study serves as a rare evaluation of norm emergence in a real-world, meaningful context, demonstrating the potential for using big data to study norms and norm emergence. Due to challenges in observing compliance and enforcement over time, norm emergence is difficult to study. Common methods include surveys and vignettes (Horne, Dodoo, and Dodoo 2013), ethnographic studies (Fine 2005), agent-based models (e.g., Centola et al. 2005), and textual analysis of documents such as etiquette manuals (Abrutyn and Carter 2015). Yet more and more cities are making large-scale data available to the public, opening the door for new techniques to study the emergence and persistence of norms. Both 311 hotlines and cellphone mobility data are increasingly available, and our work provides new methods for studying norm emergence at large scales. By making use of neighborhood-level data and leveraging exogenous shocks such as the COVID-19 pandemic, it is possible to observe and better understand shifting norms in real-time.

### *Implications for Urban and Community Sociology*

Beyond its contributions to norm emergence, this work also contributes to the sociology of cities. Our analyses are among the first to connect community resilience to the well-established literature on the social organization of neighborhoods. Neighborhood effects studies have historically focused on crime, social mobility, and public health, but only alluded to neighborhoods' ability to rebound from crises (Klinenberg 2018; Sampson et al. 2002). By studying fine-grained variation within cities using big data, we show that neighborhood characteristics affect community resilience (O'Brien et al. 2015). Further, we move beyond the

key factors thought to determine neighborhood social organization—namely socio-economic hardship, physical disorder, social isolation, and the lack of institutional resources (Levy et al. 2020; Wodtke et al. 2016)—and identify territoriality as a means by which neighborhoods are able to impose informal social control, the latter of which is a key mechanism of neighborhood studies (Sampson et al. 1997).

Furthermore, social disorganization theory argues that the key mechanisms or mediators by which structural conditions affect neighborhood outcomes are social ties and social control (Kubrin 2009; Kubrin and Weitzer 2003). This work stresses the importance of moving beyond a focus on resources or capacities (e.g., social networks and social capital) into purposive action, which is typically captured by and included in the concept of collective efficacy (Sampson et al. 1999, 1997). Yet “it is not always clear how social ties differ from informal control” (Kubrin and Mioduszewski 2019), as social control is often referred to as “the process of activating or converting social ties to achieve desired outcomes” (Sampson et al. 1999). Our work identifies territoriality as an unexplored determinant of social control that may impact collective efficacy—and potentially crime rates or other outcomes—beyond the social networks and social capital that are typically theorized.

In addition to these theoretical contributions, our paper speaks to recent calls to consider how mobility processes affect urban social life (Cagney et al. 2020; Levy et al. 2020). Combining high-resolution GPS data with detailed administrative records sheds new light on the determinants of social integration in a major U.S. city. Prior research has shown that inter-neighborhood mobility differs among cities; connectedness is greater in less populous, more cosmopolitan, and less racially segregated cities (Phillips et al. 2021). Although our measure of visits by residents from other neighborhoods serves as an indicator of norm violations, it also

suggests how inter-neighborhood mobility and its consequences relate to features of the neighborhoods themselves, including peoples' relations to territory.

### *Limitations and Future Work*

This paper has several limitations. For one, we are unable to measure beliefs about the emergent social norms, which is a key component of certain definitions (e.g., Bicchieri 2017). Instead, we measure the daily behavioral manifestation of norms, by evaluating compliance and enforcement behaviors within each community. Similarly, we are unable to measure the psychological experience of territoriality, but infer it by operationalizing each of its three components. In both of these cases, we make a trade-off in our use of big data; although our data has the benefit of being able to track day-by-day changes in behavior over a large geographical area, we lack direct insight into individuals' perceptions and beliefs. We view this as an acceptable trade-off, as the behavioral manifestations we study are carefully rooted in their associated concepts. However, future research would helpfully measure norm emergence and territoriality both behaviorally and cognitively.

Another limitation is the fact that we do not have records of all forms of sanctions (such as nonverbal disapproval or confrontation). However, we view this as a necessary trade-off between the breadth and scope of our data and its comprehensiveness. To evaluate the emergence of norms across a city on a day-by-day basis, we were unable to distribute city-wide surveys or other surveillance mechanisms that would allow for the collection of other forms of sanctions. However, as long as our measure of 311 calls represents a reasonable proxy for capturing the tendencies of certain tracts to enforce norms—and prior research linking 311 calls

with survey data find that this is indeed a primary motivation (O'Brien et al. 2017; O'Brien, Gordon, and Baldwin 2014; O'Brien 2016; O'Brien 2018)—our results are valid.

These limitations raise the question as to what extent we observe an emergent, group-level phenomenon versus an aggregation of individual territorially motivated behaviors. In either case, the observed behavior would be similar, as certain communities would evince more compliance and enforcement behavior in accordance with social distance and facemask mandates. And perhaps initially, perceptions of the existence of the norm would differ, as those in the latter scenario might simply perceive their neighbors to be acting at a purely individual level. If that is the case, by some definitions (e.g., Bicchieri 2017) one could argue that the social norm remains nascent but not fully formed. Ultimately, however, we expect this distinction to dissolve over time. Even if members of communities initially follow and enforce new standards of behavior purely at the individual level, we expect that, as the same behaviors are repeated by different members within a community, individuals will begin to perceive that these behaviors represent *community* norms. We therefore expect beliefs about the existence of emergent norms to increase in tandem with their behavioral manifestations, even if the proximate cause of compliance and enforcement begins with individual territoriality.

## CONCLUSION

By explaining responses to the COVID-19 pandemic, this paper contributes to research on norm emergence and the social organization of cities. Our work opens up new opportunities for future scholarship, such as evaluating the role of territoriality in other settings and for other kinds of social norms. More generally, we highlight the potential of new neighborhood factors to

inform theories of norm emergence and provide novel methods for testing them in real-world settings.

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FIGURES

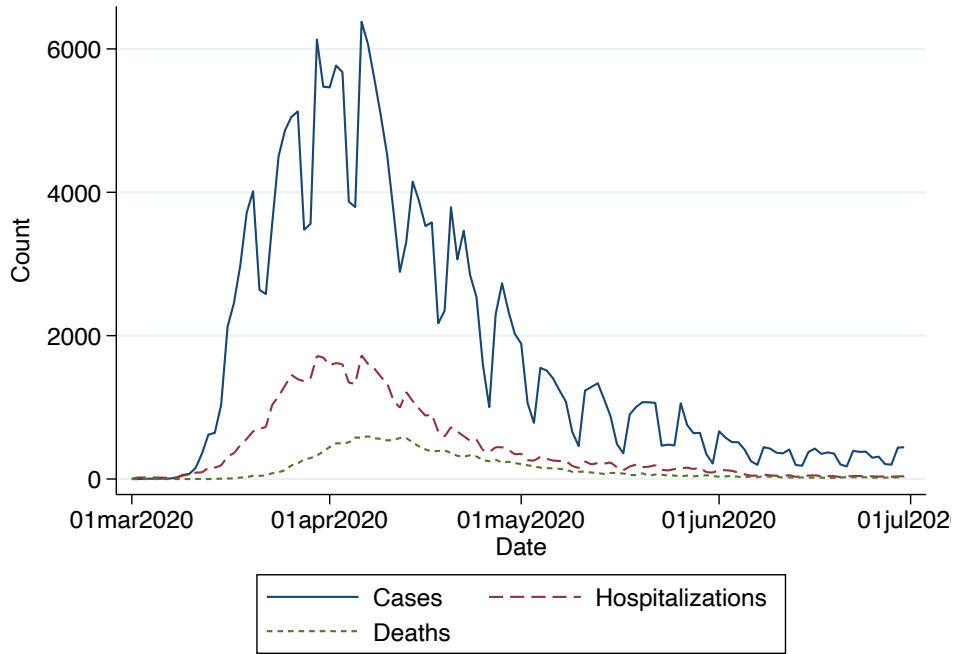


Figure 1. COVID-19 Cases, Hospitalizations and Deaths in New York City

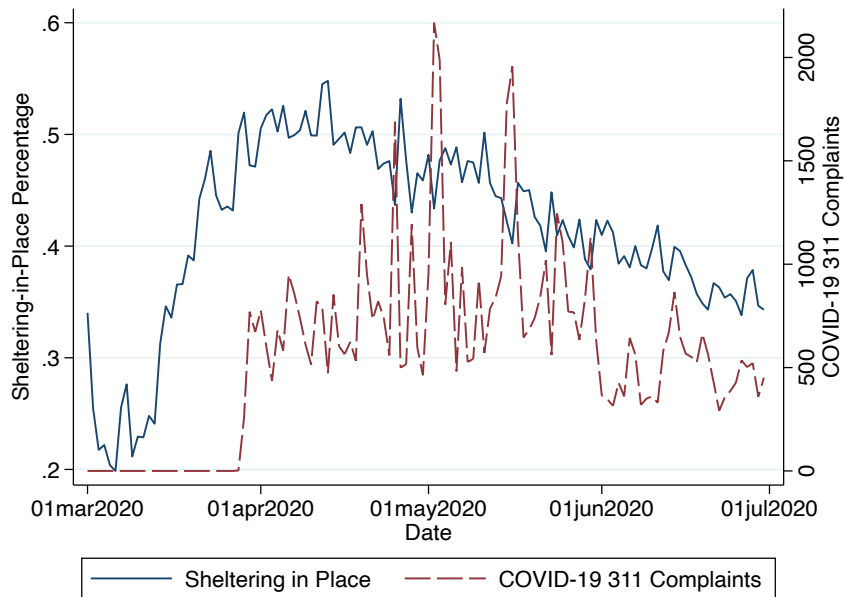


Figure 2. Sheltering-in-place and COVID-19 311 Complaints in New York City

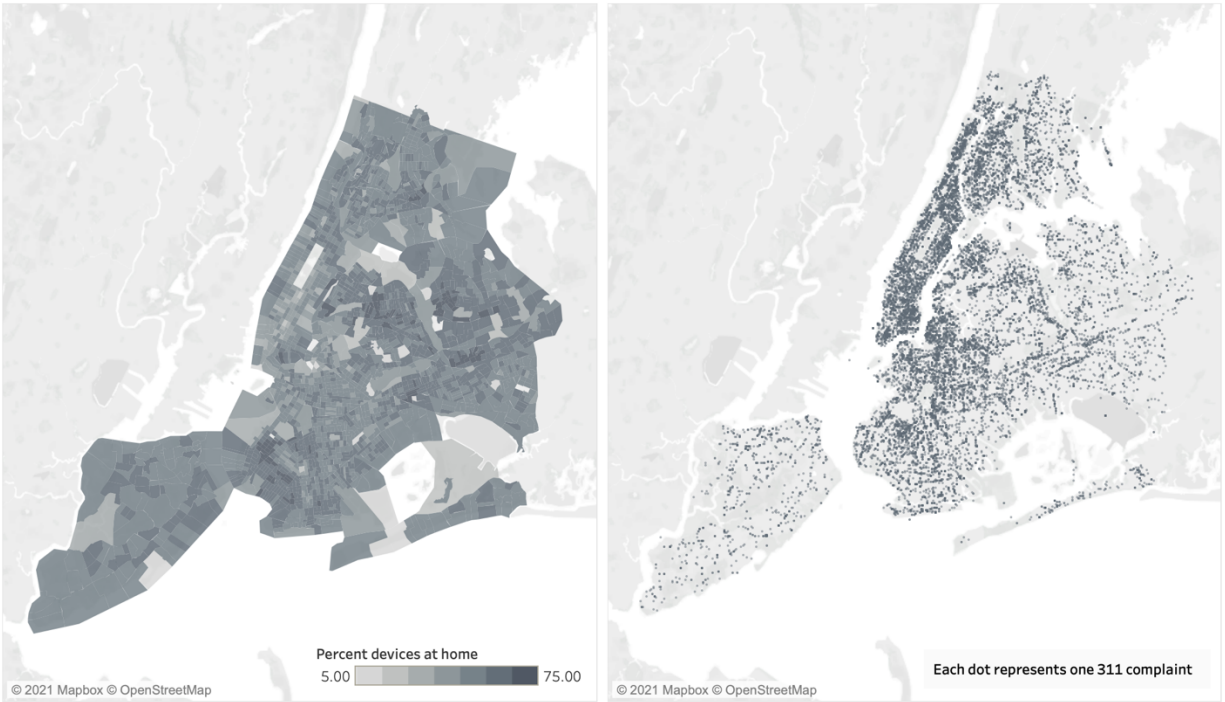


Figure 3. Spatial Distribution of Sheltering-in-Place and COVID-19 311 Complaints in New York City

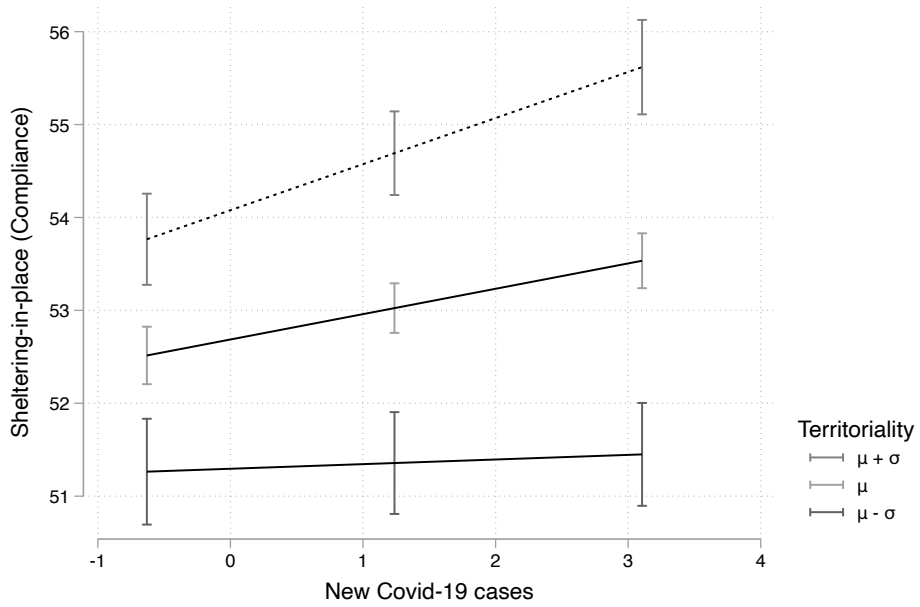


Figure 4. Effects of New COVID-19 Cases on Sheltering in Place at Different Levels of Territoriality

TABLES

	Mean	SD	Min	Max	Count
<i>Dependent Variables</i>					
Sheltering-in-place (Compliance)	53.08	9.25	2.86	88.24	101757
COVID-19 311 Complaints (Enforcement)	16.63	28.59	0.00	100.00	88761
<i>Treatment Variables</i>					
New cases	1.25	1.64	0.00	48.11	101757
Devices Entering Tract	0.04	0.04	0.00	1.05	101757
<i>Explanatory Variables</i>					
Territorial Control	38.65	24.84	0.00	98.90	101757
Territorial Familiarity	89.58	6.21	46.50	100.00	101757
Territorial Investment	0.87	0.83	0.00	7.51	101757
Territoriality (Combined)	0.06	0.97	-2.21	5.48	101757
<i>Control Variables</i>					
Population	3920.13	1906.97	258.00	16231.00	101757
Population Density	51966.89	34389.74	789.48	241752.30	101757
Residential Neighborhood Disadvantage	-0.04	0.93	-2.13	2.78	101757
Racial Diversity	47.11	18.91	0.00	80.14	101757
Percent Age 18-64	65.83	7.39	35.70	93.96	101757
Percent Age 65 or older	12.88	5.81	0.00	51.07	101757
Percent with Limited English	17.68	13.39	0.00	71.70	101757
2020 Vote share Biden	71.74	22.56	2.07	98.32	101757
Census Response Rate	52.23	8.18	15.30	74.80	101757
Commercial Address Share	6.87	6.92	0.00	87.33	101757
Total positive cases by April 1	17.91	11.42	0.51	118.63	101757
Bulk Pickup Requests	127.03	113.10	0.00	966.00	101757
Snow Related Reports	1.28	1.91	0.00	18.00	101757
Complaints per Permit	9.86	17.64	0.13	246.33	101757
Essential Workers (Full-Time)	3.37	1.96	0.29	33.33	101757
Essential Workers (Part-Time)	3.81	2.11	0.30	33.33	101757
Delivery Workers	3.17	1.89	0.06	37.50	101757

Table 1. Summary Statistics of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Sheltering-in-place												
(2) Covid-19 311 Complaints	-0.08											
(3) New Cases (lagged)	0.20	-0.01										
(4) Devices Entering Tract	-0.12	0.07	0.16									
(5) Territorial Control	0.01	-0.02	-0.10	-0.14								
(6) Territorial Familiarity	0.17	-0.06	0.04	-0.14	0.31							
(7) Territorial Investment	0.05	-0.04	-0.09	-0.12	0.71	0.24						
(8) Territoriality	0.07	-0.04	-0.08	-0.16	0.90	0.54	0.86					
(9) Population	0.11	-0.02	0.36	0.30	-0.28	-0.07	-0.26	-0.29				
(10) Population Density	0.09	-0.01	0.14	-0.03	-0.54	-0.15	-0.48	-0.54	0.59			
(11) Residential Neighborhood Disadvantage	0.16	-0.08	0.14	0.07	-0.49	0.22	-0.23	-0.30	0.07	0.19		
(12) Diversity	0.22	-0.05	0.09	0.07	-0.37	-0.13	-0.22	-0.33	0.13	0.18	0.36	
(13) Percent Age 18-64	-0.09	0.03	-0.08	0.06	-0.19	-0.43	-0.13	-0.28	0.00	0.10	-0.34	0.13
(14) Percent Age 65 or older	0.02	0.01	0.01	-0.03	0.36	0.14	0.12	0.29	0.01	-0.12	-0.29	-0.26
(15) Percent with Limited English	0.36	-0.02	0.07	0.02	-0.21	0.13	-0.16	-0.15	0.08	0.16	0.36	0.34
(16) 2020 Vote share Biden	-0.07	-0.06	0.03	-0.01	-0.37	-0.22	-0.15	-0.33	0.10	0.27	0.21	0.25
(17) Census Response Rate	0.08	0.00	0.11	0.03	0.03	0.06	-0.12	-0.04	0.27	0.19	-0.17	0.05
(18) Bulk Pickup Requests	0.03	0.01	0.00	0.03	0.31	0.01	0.32	0.31	0.20	-0.14	-0.36	-0.15
(19) Snow Related Reports	-0.01	0.01	0.06	0.15	0.12	0.00	0.10	0.12	0.14	-0.10	-0.17	-0.07
(20) Complaints per Permit	-0.12	0.05	0.01	0.17	-0.36	-0.31	-0.35	-0.43	0.09	0.18	0.00	0.12
(21) Total positive cases by April 1	0.11	-0.02	0.46	0.28	-0.17	-0.01	-0.20	-0.19	0.74	0.36	0.06	0.10
(22) Devices Working Full-Time	-0.16	0.05	-0.10	-0.15	-0.01	-0.05	-0.03	-0.02	-0.08	0.03	-0.17	-0.15
(23) Devices Working Part-Time	-0.20	0.05	-0.11	-0.10	-0.02	-0.06	-0.04	-0.04	-0.07	0.02	-0.14	-0.15
(24) Devices Working on Deliveries	-0.17	0.06	-0.11	-0.17	-0.04	-0.05	-0.04	-0.04	-0.08	0.04	-0.13	-0.16

Table 2. Correlation Matrix of Variables

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(14) Percent Age 65 or older	-0.49										
(15) Percent with Limited English	-0.16	0.03									
(16) 2020 Vote share Biden	0.34	-0.28	-0.34								
(17) Census Response Rate	0.01	0.25	-0.03	0.00							
(18) Bulk Pickup Requests	0.11	0.06	-0.17	-0.18	0.02						
(19) Snow Related Reports	0.01	0.06	-0.13	-0.15	0.16	0.29					
(20) Complaints per Permit	0.27	-0.14	-0.04	0.14	0.06	-0.17	-0.02				
(21) Total positive cases by April 1	-0.05	0.04	0.10	0.00	0.22	0.09	0.12	0.07			
(22) Devices Working Full-Time	0.03	-0.02	-0.17	0.02	-0.05	0.06	0.01	-0.02	-0.09		
(23) Devices Working Part-Time	0.02	-0.02	-0.17	0.01	-0.05	0.04	0.01	0.01	-0.08	0.77	
(24) Devices Working on Deliveries	0.03	-0.05	-0.19	0.06	-0.05	0.04	-0.01	-0.02	-0.09	0.83	0.79

Table 2. Correlation Matrix of Variables (*continued*)

Outcome: Sheltering in Place	Model 3.1 (RE)	Model 3.2 (RE)	Model 3.3 (RE)	Model 3.4 (RE)
Constant	48.57*** (1.10)	49.67*** (1.08)	48.05*** (1.12)	48.29*** (1.10)
Population	-0.41 (0.24)	-0.27 (0.25)	-0.45 (0.24)	-0.41 (0.24)
Population Density	-0.61** (0.21)	-1.02*** (0.19)	-0.89*** (0.20)	-0.55** (0.21)
Residential Neighborhood Disadvantage	0.65* (0.28)	-0.48 (0.26)	0.13 (0.27)	0.38 (0.27)
Racial Diversity	1.24*** (0.19)	1.37*** (0.18)	1.22*** (0.19)	1.29*** (0.19)
Percent Age 18-64	0.46 (0.32)	0.47 (0.32)	0.26 (0.32)	0.52 (0.32)
Percent Age 65 or older	-0.61* (0.31)	-0.56 (0.31)	-0.48 (0.33)	-0.50 (0.31)
Percent with Limited English	3.87*** (0.20)	3.71*** (0.20)	3.81*** (0.20)	3.81*** (0.20)
2020 Vote share Biden	0.66** (0.22)	0.68** (0.22)	0.46* (0.22)	0.59** (0.22)
Census Response Rate	0.07*** (0.02)	0.05** (0.02)	0.08*** (0.02)	0.08*** (0.02)
Commercial Address Share	-2.83*** (0.35)	-2.76*** (0.36)	-2.98*** (0.34)	-2.74*** (0.35)
Total positive cases by April 1	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)	0.02 (0.01)
New cases (lagged)	0.23*** (0.03)	0.23*** (0.03)	0.23*** (0.03)	0.23*** (0.03)
Covid-19 311 Complaints (lagged)	0.06* (0.03)	0.06* (0.03)	0.06* (0.03)	0.06* (0.03)
Devices Entering Tract	0.14 (0.15)	0.14 (0.15)	0.14 (0.15)	0.15 (0.15)
Territorial Control	1.68*** (0.24)			
Territorial Familiarity		1.83*** (0.22)		
Territorial Investment			0.94*** (0.16)	
Territoriality (Combined)				1.62*** (0.22)
Employment Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	106461	106461	106461	106461

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Table 3. OLS Estimates of Sheltering in Place (Compliance)

Outcome: Sheltering in Place	Model 4.1 (RE)	Model 4.2 (FE)	Model 4.3 (RE)	Model 4.4 (FE)	Model 4.5 (RE)	Model 4.6 (FE)	Model 4.7 (RE)	Model 4.8 (FE)
New cases (lagged)	0.26*** (0.03)	0.18*** (0.04)	0.21*** (0.05)	0.15** (0.05)	0.28*** (0.04)	0.25*** (0.03)	0.27*** (0.04)	0.21*** (0.04)
Covid-19 311 Complaints (lagged)	0.06* (0.03)	0.07** (0.02)	0.05* (0.03)	0.05* (0.02)	0.06* (0.03)	0.06* (0.02)	0.06* (0.03)	0.06** (0.02)
Devices Entering Tract	0.15 (0.14)	0.23 (0.14)	0.13 (0.15)	0.34* (0.14)	0.15 (0.14)	0.24 (0.14)	0.16 (0.14)	0.23 (0.14)
Territorial control	1.50*** (0.24)							
New cases (lagged) x Territorial Control	0.17*** (0.02)	0.15*** (0.02)						
Territorial Familiarity			1.45*** (0.22)					
New cases (lagged) x Territorial Familiarity			0.35*** (0.06)	0.36*** (0.06)				
Territorial Investment					0.72*** (0.16)			
New cases (lagged) x Territorial Investment					0.21*** (0.03)	0.22*** (0.02)		
Territoriality (Combined)							1.39*** (0.22)	
New cases (lagged) x Territoriality (Combined)							0.22*** (0.03)	0.22*** (0.023)
Time Invariant Controls	Yes	No	Yes	No	Yes	No	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106461	117908	106461	119606	106461	118183	106461	117852

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Table 4. OLS Estimates of Sheltering-in-Place (Compliance) with Interactions

Outcome: 311 Complaints	Model 5.1 (RE)	Model 5.2 (FE)	Model 5.3 (RE)	Model 5.4 (FE)	Model 5.5 (RE)	Model 5.6 (FE)	Model 5.7 (RE)	Model 5.8 (FE)
Sheltering in place	-0.09*** (0.02)	-0.07*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)	-0.09*** (0.02)	-0.07*** (0.02)
New cases (lagged)	-0.18* (0.09)	-0.03 (0.07)	-0.18* (0.09)	-0.04 (0.07)	-0.18* (0.09)	-0.02 (0.08)	-0.18* (0.09)	-0.02 (0.07)
Devices Entering Tract	1.62*** (0.24)	1.63*** (0.35)	1.52*** (0.33)	1.17*** (0.34)	1.65*** (0.26)	1.50*** (0.34)	1.70*** (0.25)	1.79*** (0.35)
Territorial control	-2.60*** (0.34)							
Devices Entering Tract x Territorial Control	0.97*** (0.20)	1.30*** (0.29)						
Territorial Familiarity			-0.57 (0.32)					
Devices Entering Tract x Territorial Familiarity			0.43* (0.21)	0.45*** (0.10)				
Territorial Investment					-1.31*** (0.28)			
Devices Entering Tract x Territorial Investment					0.92*** (0.24)	1.17** (0.37)		
Territoriality (Combined)							-1.99*** (0.31)	
Devices Entering Tract x Territoriality (Combined)							0.97*** (0.19)	1.41*** (0.28)
Time Invariant Controls	Yes	No	Yes	No	Yes	No	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74693	86340	74693	87070	74693	86482	74693	86330

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Table 5. OLS Estimates of COVID-19 311 Complaints (Enforcement)

	Shelter-in-place (compliance)				311 complaints (enforcement)			
	Model 6.1 (RE)	Model 6.2 (RE)	Model 6.3 (RE)	Model 6.4 (RE)	Model 6.5 (RE)	Model 6.6 (RE)	Model 6.7 (RE)	Model 6.8 (RE)
New cases (lagged)	0.23*** (0.03)	0.23*** (0.03)	0.23*** (0.03)	0.23*** (0.03)	-0.18* (0.09)	-0.18* (0.09)	-0.18* (0.09)	-0.18* (0.09)
Devices Entering Tract	0.12 (0.14)	0.12 (0.15)	0.12 (0.15)	0.13 (0.14)	1.58*** (0.24)	1.62*** (0.26)	1.50*** (0.33)	1.66*** (0.25)
Sheltering in place					-0.09*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)	-0.09*** (0.02)
Covid-19 311 Complaints (lagged)	0.06* (0.03)	0.06* (0.03)	0.05* (0.03)	0.06* (0.03)				
Territorial control	1.38*** (0.24)				-2.59*** (0.34)			
Territorial Investment		0.76*** (0.16)				-1.27*** (0.28)		
Territorial Familiarity			1.57*** (0.22)				-0.66* (0.32)	
Territoriality (Combined)				1.33*** (0.22)				-2.00*** (0.32)
Devices Entering Tract x Territorial Control					0.94*** (0.20)			
Devices Entering Tract x Territorial Familiarity						0.91*** (0.24)		
Devices Entering Tract x Territorial Investment							0.44* (0.20)	
Devices Entering Tract x Territoriality (Combined)								0.95*** (0.19)
Social Network Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Invariant Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106060	106060	106060	106060	74428	74428	74428	74428

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Table 6. OLS Estimates of Sheltering-in-Place and COVID-19 311 Reports with Social Network Controls (Compliance and Enforcement)

APPENDIX A

Outcome: 311 Complaints	Model A1.1 (RE)	Model A1.2 (RE)	Model A1.3 (RE)	Model A1.4 (RE)
Constant	16.19*** (2.04)	16.62*** (2.08)	17.50*** (2.06)	16.62*** (2.06)
Population	-0.32 (0.43)	-0.43 (0.45)	-0.38 (0.44)	-0.45 (0.43)
Population Density	0.71* (0.36)	1.77*** (0.34)	1.19*** (0.35)	0.91* (0.36)
Residential Neighborhood Disadvantage	-2.95*** (0.39)	-1.77*** (0.38)	-2.14*** (0.38)	-2.34*** (0.38)
Racial Diversity	-0.48 (0.25)	-0.44 (0.25)	-0.44 (0.25)	-0.51* (0.25)
Percent Age 18-64	-1.73*** (0.37)	-1.35*** (0.38)	-1.50*** (0.37)	-1.72*** (0.38)
Percent Age 65 or older	-0.88* (0.40)	-1.04* (0.41)	-1.13** (0.41)	-1.03* (0.40)
Percent with Limited English	-0.34 (0.30)	-0.12 (0.30)	-0.15 (0.30)	-0.22 (0.30)
2020 Vote share Biden	-2.03*** (0.32)	-1.83*** (0.33)	-1.64*** (0.32)	-1.86*** (0.32)
Census Response Rate	0.06* (0.03)	0.05 (0.03)	0.04 (0.03)	0.05 (0.03)
Bulk Pickup Requests	0.25 (0.23)	0.13 (0.24)	0.40 (0.24)	0.36 (0.23)
Snow Related Reports	-0.26 (0.21)	-0.09 (0.22)	-0.14 (0.22)	-0.16 (0.22)
Complaints per Permit	0.31 (0.20)	0.76** (0.23)	0.50* (0.21)	0.33 (0.21)
Commercial Address Share	3.12*** (0.52)	3.32*** (0.55)	3.31*** (0.54)	3.12*** (0.53)
Total positive cases by April 1	-0.02 (0.03)	-0.01 (0.03)	-0.02 (0.02)	-0.02 (0.02)
Sheltering in place	-0.09*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)	-0.09*** (0.02)
New cases (lagged)	-0.18 (0.09)	-0.18* (0.09)	-0.18 (0.09)	-0.18 (0.09)
Devices Entering Tract	1.30*** (0.33)	1.39*** (0.35)	1.31*** (0.34)	1.29*** (0.34)
Territorial Control	-2.73*** (0.34)			
Territorial Familiarity		-0.50 (0.31)		
Territorial Investment			-1.58*** (0.26)	
Territoriality (Combined)				-2.17*** (0.31)
Employment Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	74693	74693	74693	74693

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Appendix Table A. OLS Estimates of 311 Complaints (Enforcement) Main Effects

APPENDIX B

Outcome:	Model	Model	Model	Model	Model	Model	Model	Model
311 Complaints	B.1 (RE)	B.2 (FE)	B.3 (RE)	B.4 (FE)	B.5 (RE)	B.6 (FE)	B.7 (RE)	B.8 (FE)
Sheltering in Place	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
New cases (lagged)	0.01* (0.01)	0.01*** (0.00)	0.01* (0.01)	0.01*** (0.00)	0.01* (0.01)	0.01*** (0.00)	0.01* (0.01)	0.01*** (0.00)
Devices Entering Tract	0.18*** (0.02)	0.14*** (0.02)	0.14** (0.05)	0.11*** (0.02)	0.18*** (0.02)	0.13*** (0.02)	0.19*** (0.02)	0.15*** (0.02)
Territorial Control	-0.44*** (0.03)							
Devices Entering Tract x Territorial Control	0.11*** (0.03)	0.07** (0.02)						
Territorial Familiarity			-0.11* (0.04)					
Devices Entering Tract x Territorial Familiarity			0.05** (0.02)	0.01** (0.00)				
Territorial Investment					-0.22** (0.07)			
Devices Entering Tract x Territorial Investment					0.12** (0.04)	0.05* (0.02)		
Territoriality (Combined)							-0.34*** (0.03)	
Devices Entering Tract x Territoriality (Combined)							0.12*** (0.03)	0.07*** (0.02)
Time Invariant Controls	Yes	No	Yes	No	Yes	No	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101757	116225	101757	117776	101757	116493	101757	116169

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Appendix Table B. Poisson Estimates of the Count of COVID-19 311 Complaints (Enforcement)

APPENDIX C

Outcome: Residualized 311 Complaints	Model C.1 (RE)	Model C.2 (FE)	Model C.3 (RE)	Model C.4 (FE)	Model C.5 (RE)	Model C.6 (FE)	Model C.7 (RE)	Model C.8 (FE)
Sheltering in Place	-0.10*** (0.02)	-0.07*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)
New cases (lagged)	-0.19* (0.09)	-0.03 (0.07)	-0.20* (0.09)	-0.04 (0.07)	-0.19* (0.09)	-0.02 (0.08)	-0.19* (0.09)	-0.02 (0.07)
Devices Entering Tract	1.55*** (0.23)	1.63*** (0.35)	1.42*** (0.31)	1.17*** (0.34)	1.54*** (0.24)	1.50*** (0.34)	1.59*** (0.24)	1.79*** (0.35)
Territorial Control	-3.10*** (0.29)							
Devices Entering Tract x Territorial Control	0.97*** (0.20)	1.30*** (0.29)						
Territorial Familiarity			-1.06*** (0.30)					
Devices Entering Tract x Territorial Familiarity			0.45* (0.22)	0.45*** (0.10)				
Territorial Investment					-1.84*** (0.26)			
Devices Entering Tract x Territorial Investment					0.88*** (0.24)	1.17** (0.37)		
Territoriality (Combined)							-2.54*** (0.28)	
Devices Entering Tract x Territoriality (Combined)							0.95*** (0.19)	1.41*** (0.28)
Time Invariant Controls	Yes	No	Yes	No	Yes	No	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74693	86340	74693	87070	74693	86482	74693	86330

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Appendix Table C. Alternative Enforcement Dependent Variable using Residuals

APPENDIX D

Outcome: 311 Complaints	Model D.1 (RE)	Model D.2 (FE)	Model D.3 (RE)	Model D.4 (FE)	Model D.5 (RE)	Model D.6 (FE)	Model D.7 (RE)	Model D.8 (FE)
Sheltering in place	-0.08*** (0.02)	-0.06** (0.02)	-0.09*** (0.02)	-0.07*** (0.02)	-0.09*** (0.02)	-0.07*** (0.02)	-0.09*** (0.02)	-0.07*** (0.02)
New cases (lagged)	-0.14 (0.09)	-0.01 (0.07)	-0.18 (0.09)	-0.03 (0.07)	-0.21** (0.08)	-0.04 (0.07)	-0.21* (0.08)	-0.03 (0.07)
Devices Entering Tract	1.63*** (0.23)	1.81*** (0.34)	1.64*** (0.24)	1.79*** (0.34)	0.98*** (0.22)	1.28*** (0.32)	1.15*** (0.23)	1.47*** (0.33)
Territoriality (Combined)	-1.57*** (0.31)		-1.79*** (0.31)		-1.43*** (0.26)		-1.67*** (0.28)	
Devices Entering Tract x Territoriality (Combined)	0.96*** (0.18)	1.41*** (0.28)	0.96*** (0.18)	1.41*** (0.28)	0.53** (0.16)	1.04*** (0.27)	0.70*** (0.17)	1.13*** (0.27)
Time Invariant Controls	Yes	No	Yes	No	Yes	No	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Noise Control (> 1 SD)	No	No	No	No	No	No	No	No
Noise Control (> 2 SD)	No	No	No	No	No	No	No	No
Observations	74303	85819	74489	86053	74010	85511	74338	85908

Appendix Table D. Accounting for the Presence of Supercallers in 311 Models (Enforcement)

Outcome: 311 Complaints	Model D.9 (RE)	Model D.10 (FE)	Model D.11 (RE)	Model D.12 (FE)	Model D.13 (RE)	Model D.14 (RE)	Model D.15 (RE)	Model D.16 (FE)
Sheltering in place	-0.10*** (0.02)	-0.07** (0.02)	-0.10*** (0.02)	-0.08*** (0.02)	-0.10*** (0.02)	-0.10*** (0.02)	-0.04** (0.01)	-0.02 (0.01)
New cases (lagged)	-0.21* (0.10)	-0.12 (0.08)	-0.19* (0.09)	-0.04 (0.08)	-0.18* (0.09)	-0.18* (0.09)	-0.08 (0.05)	0.01 (0.04)
Devices Entering Tract	1.81*** (0.27)	2.22*** (0.41)	1.66*** (0.25)	1.95*** (0.39)	1.69*** (0.25)	1.69*** (0.25)	0.29* (0.12)	0.81*** (0.20)
Territoriality (Combined)	-1.36*** (0.31)		-1.62*** (0.31)		-1.99*** (0.31)	-1.98*** (0.31)	0.20 (0.17)	
Devices Entering Tract x Territoriality (Combined)	1.22*** (0.20)	1.85*** (0.33)	0.97*** (0.19)	1.52*** (0.32)	0.96*** (0.19)	0.96*** (0.19)	0.24* (0.10)	0.66*** (0.18)
Time Invariant Controls	Yes	No	Yes	No	Yes	Yes	Yes	No
Employment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Noise Control (> 1 SD)	No	No	No	No	Yes	No	No	No
Noise Control (> 2 SD)	No	No	No	No	No	Yes	No	No
Observations	63763	73349	70215	80594	74693	74693	71411	82465

\*  $p \leq .05$ ; \*\*  $p \leq .01$ ; \*\*\*  $p \leq .001$  (two-tailed tests).

Note: Models 1-4 eliminate all locations with 311 calls in the previous year that are more than one standard deviation (Models 1 and 2) or two standard deviations (Models 3 and 4) above the mean number of calls. Models 5-8 eliminate all locations with COVID-19 related 311 calls in the period of observation that are more than one standard deviation (Models 5 and 6) or two standard deviations (Models 7 and 8) above the mean number of calls. Models 9-12 eliminate all tracts with COVID-19 related 311 calls in the period of observation that are more than one standard deviation (Models 9 and 10) or two standard deviations (Models 11 and 12) above the mean number of calls. Models 13-14 include control variables indicating the number of locations in the previous year with noise complaints more than one standard deviation (Model 13) or two standard deviations (Model 14) above the mean. Models 15-16 eliminate all locations with *any* 311 calls in the previous year.

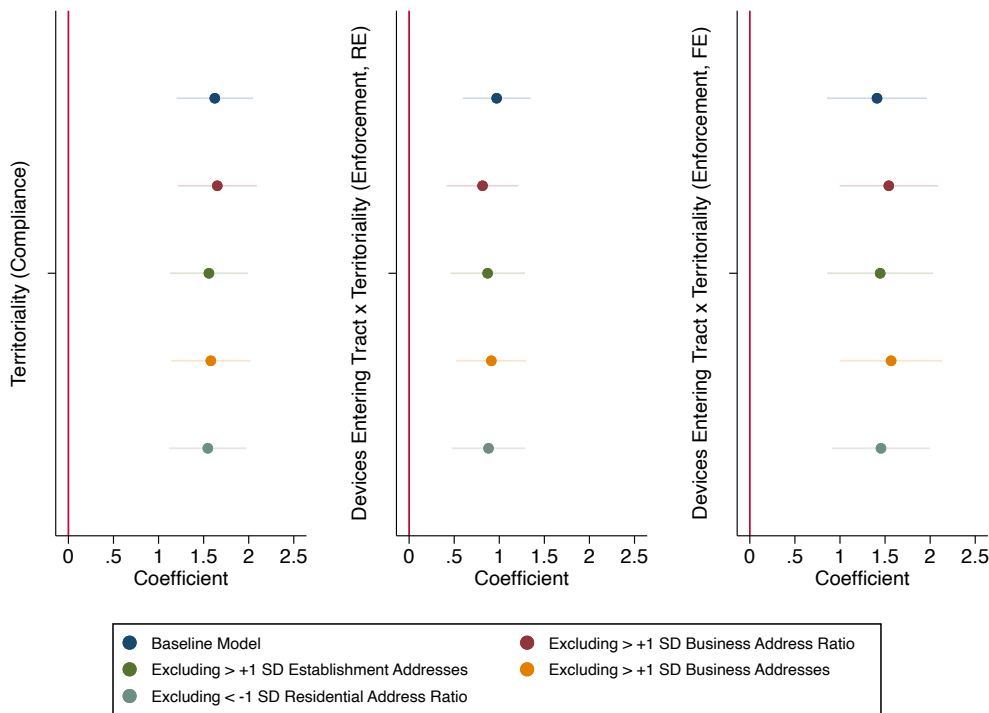
Appendix Table D. Accounting for the Presence of Supercallers in 311 Models (Enforcement) (*continued*)

APPENDIX E

	Territoriality	Network density	Physical disorder
Territorial investment	<b>0.77</b>	0.13	0.30
Territorial control	<b>0.87</b>	0.21	0.16
Territorial familiarity	<b>0.54</b>	-0.43	0.00
Private neglect	-0.71	-0.02	<b>0.47</b>
Public denigration	-0.14	0.03	<b>0.90</b>
Friendship density	0.36	<b>0.50</b>	0.18
Civic events density	-0.06	<b>0.57</b>	-0.21
Civic organizations density	-0.24	<b>0.81</b>	-0.08
Eigenvalue	2.34	1.48	1.23
Proportion of variance	0.29	0.19	0.15

Appendix Table E. Exploratory Factor Analysis of Measures of Territoriality, Network Density, and Physical Disorder

APPENDIX F



Appendix Figure F. Key Coefficient Values for Subsets of Data Based on Level of Commercial Development