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DOCTORAL THESIS

Essays on Local Violence

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Declaration of Authorship

I, Carlo CAPORALI, declare that this thesis titled, "Essays on Local Violence" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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"You don't need to wear a patch on your arm to have honor"

A Few Good Men (1992), and Dad.

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Abstract

Doctor of Philosophy

Essays on Local Violence

by Carlo CAPORALI

As in the case of other place-specific social phenomena, violence makes no exceptions when it comes to the investigation of common patterns, including both its origins and outcomes. One immediate consequence of this fundamental premise is that finding unanimous consensus within the academic literature can be a challenging task, with only a few exceptions when it comes to overarching theoretical frameworks. This thesis represents a dedicated effort to enhance our understanding of violence through the adoption of a localized and specific perspective. From a geographical standpoint, this thesis delves into the intricacies of violence and recognizes that the causes, manifestations, and consequences of violence are often deeply rooted in the unique historical, cultural, and social contexts of a given region. By zooming in on these local nuances, we can gain a richer and more comprehensive understanding of the complex tapestry of violence. Moreover, the thesis acknowledges the inherent diversity within violence itself. It is not a monolithic phenomenon but rather a multifaceted one, encompassing various forms such as interpersonal violence, structural violence, political violence, and more. Each of these forms carries distinct characteristics, motives, and implications. They affect individuals differently, depending on their socioeconomic status, gender, ethnicity, and other factors. Moreover, these forms of violence can have varying impacts on different communities and societies, perpetuating cycles of inequality and conflict in unique ways. This effort is built upon two key theoretical pillars.

The first pillar posits that different stimuli produce different outcomes, influenced by personal and environmental characteristics, necessitating the discrimination of various stimuli. The second pillar highlights the significance of understanding violence as a place-based and place-specific phenomenon. From this perspective, while connected to larger processes of material transformation and power relations, urges the need to interpret violence and its spatiality as a site-specific phenomenon rooted in local histories and societies. The thesis consists of a collection of three papers. In the first one, I explore the causal link between police-perpetrated homicides and migration during the Venezuelan crisis (2017-2018), revealing heterogeneous effects across age, gender, and education levels of migrants. The second paper delves into the relationship between terrorism and electoral participation, dissecting the *Anni di Piombo* era in Italy by analyzing provincial-level exposure to terrorism and its influence on voting behavior at national elections spanning from 1972 to 1992. We weigh the mediated effects of terrorist violence, considering casualties and physical damage, by applying the Causal Mediation Analysis framework. Lastly, leveraging exclusive data on intimate partner femicides in Italian metropolitan areas from 2012 to 2020 geo-located at a street-level granularity, in the third paper I map their distribution, highlighting ecological factors correlated with an increased probability of observing femicides. Together with a theoretical introduction aimed at disentangling the multifaceted nature of *violence*, these papers provide comprehensive insights into migration dynamics, political violence, and gender-based violence, contributing valuable knowledge to the understanding of these nuanced social issues.

Acknowledgements

English Version

These four years have not just been about studying, working, exams, and research. Rather, they have been primarily about people—good people, less good people. Some are destined to remain in my present, while others, already, belong to the past. Individuals who, for better or worse, have shaped this journey as it was, intense and unique—the most beautiful so far. On one side, I would like to express my gratitude to those who stood by my side, supporting, aiding, and enduring my choice to embark on this path. My family, a constant stronghold. Claudia, my little sister. Mom and Dad, whose advice and unwavering support have shaped my journey. Without them, I don't hesitate to say, I don't know if I would have ever reached the point where I am now. Thanks to lifelong friends, those of Bar "Mai Dire," different-blooded siblings with whom I have always shared the most crucial and meaningful moments of my life. And to Francesco, Nazareno, Riccardo, and Erica, steadfast companions since university days. On the other side, the people I've encountered along the way. I would start with my professor, Alessandra, because she is the person who insisted that all of this could begin. The person who chose me and who, through highs, lows, and a myriad of challenges, granted me the freedom to transform work into passion. To Claudio, the figure most akin to a mentor I have ever had, a heartfelt thank you for the time and, let's be honest, the patience you have consistently devoted to me. I would also like to express my gratitude to the entire faculty of the Social Science area. Each of them, albeit in completely different ways, has contributed to my professional growth. And what can I say to the invaluable Gor and Biswa, my roommates Giulia and Cecilia, and to Samu, Davide, Federico, Thea, Mattia, Giorgio, and Fabio? To all of you, what can I say but "thank you for everything." For the evenings, the arguments, the escapes, the meals, the drinks, the farewells, and the reunions. Lastly, thanks to the person who encapsulates the essence of everything I have written so far. The person who keeps me standing tall, who urges me to always take the next step, even when my legs seem too heavy. The person who has been with me for six years, sharing the weight of my decisions, my bets, and my mistakes. The person with whom I have decided to share every moment of my life. Thanks to Anna, my wife, to whom this work is dedicated.

Italian Version

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Chapter 1

Conceptualization of Violence

So in the nature of man, we find three principal causes of quarrel. First, competition; secondly, diffidence; thirdly, glory. The first makes men invade for gain; the second, for safety; and the third, for reputation. The first use violence to make themselves masters of other men's persons, wives, children, and cattle; the second, to defend them; the third, for trifles, as a word, a smile, a different opinion, and any other sign of undervalue, either direct in their persons or by reflection in their kindred, their friends, their nation, their profession, or their name.

T. Hobbes, *The Leviathan*, XIII, 1651.

1.1 What is *Violence*?

In the conceptual framework articulated by Sen (2000), development can be seen as a process of expanding the real freedoms enjoyed by human beings. This suggests that the trajectory of societal progress should be perceived as interconnected with the opportunities for individuals to (fully) realize their own *potential*, living lives of meaningful fulfillment. Well-being, as Sen puts it, isn't just about material wealth indeed (Sen, 2000; Pressman and Summerfield, 2000).

With this (broad) perspective in mind, it appears fair to say that how we feel (inside, from a psychological standpoint) is a key element, which is also strictly connected to the security and safety (actual or perceived) we experience in our daily lives. This feeling not only shapes our own well-being but also impacts the overall health and happiness of the communities we're part of. As people move through their daily lives, feeling safe is essential for them to live freely and fully, and, arguably, personal safety can be considered a key part of our well-being. Crime (and violence in general) poses to victims both immediate and long-term costs, in terms of financial loss, physical harm, and mental stress, and one of the deepest effects of such events is the lasting feeling of vulnerability. The specter of potential victimization hangs over individuals' thoughts, influencing their choices, behaviors, and overall outlook (Schütz, 1944, Bauman, 2013, Becker, Rubinstein, et al., 2004).

The fear of crime (Pain, 2000) can greatly impact personal freedoms, individual quality of life, and even community development. This constant worry can lead some to avoid public spaces, limit their daily personal activities, and hold back from contributing to society. Hence, ensuring security becomes vital for enabling individual and community growth. Security isn't just about protection from threats; it's also about giving people the confidence to reach their potential and seize opportunities. It connects personal aspirations with community goals. In this context, security becomes a foundation for human progress. Henceforth, it's important to understand how different factors like culture, politics, economy, and social practices (might) influence these aspects.

Understanding the broader concept of violence is a complex task, both theoretically and practically, because understanding violence implies accounting for how it intertwines with feeling safe, which is a multifaceted issue. As pointed out by Springer and Le Billon (2016), this understanding requires analyzing various factors influenced by culture, politics, economics, and social practices. To this end, it is important to note that violence defies a singular definition. The understanding of violence is continually evolving, contextualized by space and time. As noted by Scheper-Hughes, Bourgois, et al. (2004), it represents a slippery concept, that can be at the same time nonlinear, productive, destructive, and reproductive. Also in light of this, violence has been defined by Featherstone et al. (2006) and Kilby (2013a) as a *meta-concept*, which gains meaning and power through its social and cultural dimensions. According to Briceño-León (2006), it is possible to consider violence as a form of communication in which the main message is a relation of power[1] between two or more actors (either individuals or groups).

Building a consistent and exhaustive taxonomy of violence able to be/remain valid through space and time, is almost impossible. However, it is worth mentioning some of the most important attempts. Some categorizations are based on the aim of violence, some on its origins, and others on the modality. This variety has generated an intricate galaxy of attempts, in which violence has been classified as *direct*, *indirect*, *repressive*, *alienating* (Salmi, 1993); *insidious*, *structural*, *impending* (Copans, 1998); *organized*, *disorganized* (Pécaut, 1997) and *epistemological* (Schrijvers, 1993)[2]. One of the

[1] It is interesting to notice how violence, which encompasses specific power dynamics in terms of its recognition and manifestation, does not equate to power itself. While various power relations can exist without violence, imagining violence devoid of power proves challenging. The complex interplay between violence and power, which lies outside the specific scope of this introduction, underscores the need for rigorous examination and critical analysis in comprehending the intricate nature of violence.

[2] See McIlwaine (1999) for a more comprehensive review and analysis.

most used and renowned taxonomy, which appears more comprehensive and 'manageable' is the one provided by Moser and Shrader (1999) and Moser and McIlwaine (2000). According to the authors, violence should be subdivided into three main categories. i) The *political* violence: the commission of violent acts aimed at gaining, or maintaining political power. ii) the *economic* violence, as the commission of violent acts driven by economic gain (including obtaining economic power). iii) The *social* violence, that is the commission of violent acts necessary to obtain social power.

Scholars such as Briceño-León (2007), argue that violence gains specificity when viewed through historical, social, and geographical lenses, and that violent phenomena require singular and unique explanations since science can only offer conjectures about particulars that will never become universal(Briceño-León, 2006)[3]. However, there are alternative perspectives. For instance, proponents of the rational choice theory, including figures like Gary Becker, suggest that individuals commit violent acts based on a calculation of potential benefits versus risks. This viewpoint emphasizes the strategic nature of violence, rather than its historical or socio-cultural context. Therefore, while it may be challenging to draw direct comparisons between the violence in ancient Greece, the atrocities of the Second World War, and the actions of serial killersBriceño-León (2007), some theories propose that underlying rational motivations can be identified across different instances of violence.

As researchers have sought to deepen our understanding of the complex factors contributing to the emergence of violence, models have been progressively refined and expanded (Álvarez-Garavito and Acosta González,

[3]Most of his work is centered on the promotion of the need for a new (or different) understanding of violence in order to understand the endemic violent dynamics affecting societies across Latin America. To support his claim on the specificity of violence, the author focuses his theoretical reflections on two pivotal aspects of social life. The first pillar is the situational sphere, which encompasses both the general conditions of society and specific circumstances that inevitably influence individual decision-making processes. The second pillar is the cultural sphere, which encompasses the ways individuals interpret, perceive, and interact with real or potential situations.

2021). These evolving frameworks aim to provide the adoption of a more nuanced view by identifying at least three key explanatory dimensions: *structural*, *meso-social*, and *micro-social*. This multidimensional approach, which can be found declined in slightly different ways adapted by researchers to better fit their exploratory and explanatory needs (see for instance Heise, 1998; Voith, 2019; and WHO, 2023), provides a huge advantage with respect to the process of operationalization of concepts for applied analysis, allowing for a more comprehensive analysis of violence, capturing its origins from societal structures to community influences and individual behaviors.

The *structural dimension* serves as a lens through which we can explore the macro-social processes that contribute to the emergence of violence. Although these processes may not explicitly or directly instigate violent acts, they play a pivotal role in shaping the foundational conditions that might increase the likelihood of observing violent phenomena. These systemic factors can encompass a range of social, economic, and political elements, such as institutional (ine)quality, governance deficiencies, or entrenched discrimination. Importantly, the structural dimension doesn't necessarily imply intentional harm; rather, it highlights how larger societal frameworks can inadvertently create an environment that fosters violence. By understanding these underlying structures, researchers can better dissect the complex tapestry of factors that lead to violent behaviors and events.

The *meso-social* level occupies a critical space between societal structures and individual actions, serving as the realm where cultural norms and situational variables exert a considerable influence on the occurrence of violence (an example being urban inequalities[4]. In this dimension, individuals are not merely passive recipients of structural forces but have a greater degree of agency in how they respond to (potentially violent) stimuli. Factors such as community norms, localized social networks, and immediate environmental conditions come into play, shaping the choices available to individuals. This level is particularly important for understanding the nuances of violence because it allows for the consideration of context-specific variables that can either mitigate or exacerbate violent behaviors. By examining the meso-social level, researchers can gain insights into how culture and situation act as intermediaries, influencing individuals' responses to the broader structural conditions they find themselves in.

The *micro-social* level delves into the individual dimension, focusing on personal characteristics that may serve as facilitators — rather than direct causes — of violent actions. At this granular level, the individual's propensity towards violence is influenced by a multitude of factors that operate within broader cultural and situational spheres. Specifically, five key factors emerge as instrumental in shaping this propensity. i) *Educational and Employment Levels*: the levels of education and employment opportunities available to an individual can either provide alternatives to violence or exacerbate feelings of frustration and marginalization. iii) *Religious influence*: in the cultural sphere, the waning influence of institutional religion, such as Catholicism, can have significant implications. Traditionally, religion has acted as a social behavior moderator, and its diminishing role can affect societal norms related to violence. iv) *Aspirations alignment*: pertaining both

[4]The disparities often found in urban settings can act as catalysts, influencing individual choices and behaviors related to violence. For example, *Collective efficacy*, which will be specifically addressed in Chapter 4, is one of the key concepts within urban (and neighborhood) studies (Sampson et al., 1997), which deal with the degree of the propensity to 'care' about the common goods. The socio-criminological often deals with these kinds of operationalization processes. Even if delving into this kind of literature is out of the scope of this thesis, it is worth mentioning one of the most important and recognized examples, the *Broken Windows Theory*, by Kelling, Wilson, et al. (1982).)

to the cultural and psychological dimensions, the (mis)alignment between an individual's aspirations and the opportunities for fulfilling them can be a powerful motivator for behavior, including violent actions. v) *Family/-household environment*: Changes or disruptions in the family structure or dynamics have the power to influence an individual's psychological well-being and, consequently, their propensity for violent behavior. By examining these factors at the micro-social level, researchers can gain a more ordered, if not complete, understanding of the complex interplay between individual characteristics and broader societal influences, thereby enriching our comprehension of the multiple dimensions that contribute to the emergence of violence. In conclusion, the multidimensional (and nuanced) nature of violence is reflected in the equally complex set of possible typologies and classifications related to its analysis.

These types of classification and/or taxonomies gain particular importance with respect to their role in providing methodological tools to deepen the analysis of the relationships between personal and local factors by applying a narrow geographical lens, precisely to minimize the potential for biases in quantitatively assessing the relationship between individual characteristics and local factors. tying the presence of certain individuals or groups of people to a specific space poses one of the most intricate challenges for this kind of literature. The dilemma of whether the individual influences the space; the space influences the individual and, in turn, continues to influence the space; or whether it depends, remains complex. Is there a concrete possibility of providing an answer to this socio-historical-geographical question? Arguably, this is a challenge that has been (overall, successfully I would say) collected by the economic geography, broadly speaking, through concepts such as path-dependence, or lock-in mechanisms. However, there probably is a seemingly nuanced aspect of this relationship, which lays even more in the background, which gives multifaceted specificities to space. The meaning. As we have discussed and acknowledged, space can become a place when interpreted in terms of the meaning it holds for a particular individual or group of individuals. A consequence of this dynamic, which I believe underlies the conflicts we are witnessing in the weeks as the author writes these words, is that the discrepancy among individuals or groups of individuals in assigning meaning to a space generates friction and conflicts. It's a battle of interpretation, or better, a struggle to seize the meaning of space, more than its actual physical and geographical availability. This premise, which may seem lofty or detached from the reasoning developed here, nonetheless represents one of the fundamental reasons supporting the need to implement the intersection between personal and local factors at the smallest possible level. Furthermore, this is necessary to partially overcome the significant limitation of this type of economic-applied analysis—the inherent difficulty of considering psychological factors, whether individual or social. For this reason, the elements we use as 'proxies' must be particularly accurate and disaggregated. Another aspect that underscores the importance of the interaction between personal and local factors is the ability to capture the nuances of the relationship itself. In other words, the same type of people can exhibit different behavioral patterns depending on the locality they are in. Conversely, the same (or the same type of) locality can have different effects depending on the type of individual. Closing the circle, the ability to grasp these idiosyncrasies is one possible step toward a quantitative analysis of the concept of place.

Besides its multidimensionality, violence is also characterized by the way it manifests. The first (and among the most relevant) step in this intellectual journey is to (try to) clearly define the specific type of violence under investigation (Kilby, 2013b). Within the broader intuition of Galtung (1969), according to which violence identifies the constraints on human potential[5], in this study we tend to a definition of violence close to the description provided by Ruiz-Perez et al. (2010), which characterizes it as an act involving

[5]In concluding our theoretical discussion on violence, it's crucial to underscore the profound yet straightforward definition put forth by Galtung. While it might not be as easily operationalized, it is far superior to definitions such as the one proposed by the World Health Organization. The WHO defines violence as "the intentional use of physical force

the use of physical, moral, or psychological power that inflicts (direct or indirect) harm, with the involvement of individuals, groups, institutions, or the State.

1.2 The Economics of Violence

Talking about the *economics of violence* does not necessarily imply that we refer only to economic factors and/or economic effects. Among notable contributions to this discourse, it is significant to highlight the work of Morrison (1993). Trying to grasp the effect of violence on migration in Guatemala, the author proposed a novel perspective diverging from the traditional Harris-Todaro-type models. Instead of solely focusing on income maximization, the proposed model emphasizes the concept of *utility* maximization, overcoming a purely rational economic perspective and trying to grasp the weight of 'non-economic' factors in the individual decision-making process.

From this perspective, the economics of violence refers to a conceptual paradigm related to the multifaceted and complex nature of violence, underscoring its 'economic' aspect, with profound potential impacts on individuals, groups, and community behaviors. Violence, in its various forms and manifestations, is indeed pivotal for comprehending human interactions and the development of societies (Humphreys, 2003; Besouw et al., 2016; Verwimp et al., 2019; North et al., 2009). The society's ability to manage and mitigate violence plays a crucial role in its overall stability and capacity to sustain high levels of well-being. The 'economic' dimension of violence becomes even more clear when we consider its far-reaching consequences. Violence can have a tremendous physical and psychological impact on individuals, often resulting in long-term trauma, medical

or power, threatened or actual, against oneself, another person, or against a group or community, that either result in or has a high likelihood of resulting in injury, death, psychological harm, maldevelopment, or deprivation" (WHO, 2023). Relying solely on this definition could inadvertently overlook the nuances of unintentionality, especially those rooted in societal or macro-structural characteristics expenses, and lost productivity. It disrupts the social fabric of communities, erodes trust, and hampers social cohesion, ultimately impeding the pursuit of common goals and prosperity. Moreover, violence can have severe economic implications for society at large. It diverts resources away from productive endeavors, such as education and healthcare, towards law enforcement, security measures, and the rehabilitation of victims (Besouw et al., 2016). Indeed, a lack of control over violence can significantly erode the social contract that forms the foundation of any stable and functioning society (Verwimp et al., 2019). The social contract is an implicit agreement among individuals within a society to abide by certain rules, norms, and laws in exchange for protection, security, and the promotion of their collective well-being. This perspective has deep historical roots, stretching back at least as far as the understanding of the modern state in the political philosophy of thinkers like Thomas Hobbes. Within this framework, the state's principal role, as codified in the social contract, lies in ensuring the security and protection of its citizens. Failing to effectively control violence directly undermines this foundational responsibility, leaving individuals exposed to harm and eroding their confidence in the government's capacity to fulfill its part of the societal pact. Moreover, the social contract leans heavily on the principle of the rule of law, which necessitates adherence to a structured system of laws and regulations designed to maintain order and justice (North et al., 2009). As North put it, when violence persists without consequence, it corrodes the very essence of this legal framework, cultivating an atmosphere of lawlessness and impunity. Consequently, the legitimacy of the legal system itself is compromised, diminishing the willingness of citizens to abide by its decrees (North et al., 2009). Further complicating matters, violence fractures the social bonds and trust among members of a community. When people feel unsafe in their neighborhoods or when violence becomes pervasive, it disrupts the intricate social fabric, leading to isolation and the disintegration of communal ties (Durkheim, 1893). This fractures the sense of shared purpose and collective responsibility that is indispensable for a well-functioning society. In addition, it can deter foreign investments, stifle economic growth, and increase the cost of doing business in affected regions (among others, Greenbaum et al., 2007; Dell, 2015). A lack of control over violence might act indeed as a deterrent to economic growth and development. Investors and businesses exhibit reluctance to operate in regions plagued by violence, thereby limiting job opportunities and economic prospects for the local population. This economic stagnation, in turn, handicaps the government's ability to provide essential services and public goods to its citizens. Finally, the social contract's viability is intrinsically tied to the consent and trust of the governed. In instances where violence is pervasive and the government appears inept or unwilling to address it effectively, citizens may begin to lose faith in the government's legitimacy. Such disenchantment can foster civil unrest, and protests, or even lead to political instability, further undermining the social contract that binds society together. A vast literature has been dealing with the analysis of the direct and indirect costs of crime or of the fear of being victimized. Such estimations can help in understanding the relevance of this issue (Anderson, 2021).

Social order, as defined by North et al., 2009, can be maintained through the interaction of competition, institutions, and beliefs. A compelling example in this context is the military. The control of the military must be administered by the government, and government control should be subject to both political and economic competition as well as institutional constraints. Even a single failure within this seemingly simple yet extraordinarily complex nested socio-institutional structure can lead to the breakdown of the social contract. This is exemplified by Venezuela's recent history, for instance, at least with respect to the analysis of the country's political and economic crisis we propose in Chapter 2. It is not a country at war (Verwimp et al., 2019) nor a region embroiled in civil conflict. Still, it is a state incapable of ensuring equal enforcement of the contract, thus rendering it unable to uphold social order. Notwithstanding the role of the form of the (natural) state in dealing with violence (Besouw et al., 2016), it permeates societies worldwide, impacting individuals and communities on various levels. Among the ways violence can threaten social order, terrorism appears particularly interesting for the combination of direct and indirect socioeconomic effects. As highlighted by Sanso-Navarro et al., 2019, the indirect consequences can be even more significant since they are linked to an atmosphere of uncertainty, stress, and risk, which ultimately shapes the behavior of individuals (Becker, Rubinstein, et al., 2004). The victimization process, in particular, can shape and reshape individuals' behavioral patterns, emphasizing the intricate interplay between violence and its social context (Vezzadini, 2012; Pazzona, 2020; Vargas et al., 2023). This underscores the compelling need to differentiate between various forms of violent stimuli and assess them based on their consequences, particularly in the context of violent phenomena such as *domestic* terrorism, as we endeavor to do in Chapter 3.

Another important area of inquiry in the economics of violence centers around the relationship between violence and *social-space*. Extensive research has revealed that violence displays geographical patterns, with observed heterogeneity across places and communities. Factors such as poverty, unemployment, and inequality have been consistently identified as strong correlates of violence, as well as the characteristics of the built environment (Glaeser and Sacerdote, 2000). Furthermore, the social and economic environment in which individuals reside plays an important role in influencing their propensity to engage in violent behaviors, whether as victims or perpetrators. To fully recognize the societal nature of violence and its concentration in specific contexts, it is imperative to transcend the notion of space as a mere empty container, passive backdrop, or vacant grid (Massey, 2005). Rather, space should be recognized as a fundamental element in the formation of violence. Equally important is the understanding that violence itself plays a constitutive role in shaping space[6]. By moving beyond conventional spatial interpretations, we can grasp the intricate relationship between violence and space. This perspective acknowledges that space is not a neutral entity but an active participant in the dynamics of violence. As Springer puts it, space, in its physical and social dimensions, influences the occurrence and manifestation of violence, while violence, in turn, leaves its imprint on the spatial order (Springer and Le Billon, 2016). However, particularly within the context of Italy, and even more so concerning gender violence, this aspect remains understudied. This is the gap we aim to bridge in Chapter 4.

1.2.1 Why Local?

As clearly outlined by Justino and Verwimp (2013), the majority of research on the causes and consequences of violent conflict has been concentrated at the country scale. Similarly, programs of conflict resolution have been mainly dealing with the state(s) capacity. However, this perspective might prevent from adopting sufficient consideration for individuals, households, and communities directly or indirectly affected by violence (Kalyvas et al., 2008; Autesserre, 2011 in Justino and Verwimp, 2013). In 2019, Verwimp and co-authors drafted a critical reflection on the recently born (or recently

[6] A clear illustration of the interplay between society and spatial structures is evident in housing models (see for instance Landman and Schönteich, 2002; Coy, 2006). Particularly in the rapidly expanding urban regions of the Global South, residents often confront various forms of violence, including gang activities. These represent challenges not only difficult to navigate but also basically unpredictable. As who is writing experienced in the first person during field-work research, a significant response to these challenges is the emergence of specific housing designs, coupled with enhanced security measures for businesses. These initiatives primarily aim to offer an added layer of private protection. The *gated community* housing model exemplifies this trend. By establishing distinct spatial boundaries, these communities (inadvertently or intentionally) lead to diminished social connections over time, as physical boundaries overlap with social ones. This, in turn, contributes to a more fragmented society, which is frequently associated with a rise in violence. Even if deepening the analysis of what just described is beyond the scope of this Chapter, it seems worth highlighting how such examples underscore the intricate and cyclical relationship between societal dynamics and their spatial manifestations.

recognized) sub-field of the *micro-economics of violent conflict* (Verwimp et al., 2019). They underline how the development and growth of this area of research have been made possible thanks to the collaboration of more disciplines, ranging from political science to conflict and security studies, from (development) economics to sociology and psychology.

Arguably, the emphasis on the micro-economics of violent conflict represents one of the most recent manifestations of the pressing push towards the need of *going local* with the study of violence in both theoretical and applied economics. By doing so, researchers (and practitioners) might not just broaden their horizons but also showcase a readiness to tackle the challenges of incomplete or elusive data[7]. This shift highlights a proactive approach, hopefully prioritizing a deeper understanding of localized contexts over the convenience of readily available but potentially oversimplified data. If we reframe our understanding of violent conflict, not merely as a synonym of 'war' (or concerning countries at war), but as an underpinning force that has the potential to threaten the upholding of the social contract even at a smaller scale[8], we might be able to grasp (and manage) its broader implications. This deeper perspective can be a relevant shift, particularly for fields like Regional Science. By recognizing the multifaceted nature of conflict and its community level (and regional level), regional sciences could more comprehensively address and engage with the challenges it presents.

In conclusion, it appears worth highlighting that eminent scholars have warned that, while grappling with these conceptual complexities (Beck, 2011; Springer and Le Billon, 2016; Bauman, 2013, among others) researchers should always acknowledge the diverse and interconnected aspects of violent phenomena. These dimensions are deeply interconnected with the

[7]One of the greatest challenges in this kind of research, as will be extensively outlined in the following chapters, is the one related to access to a (reliable) complete set of data at the sub-national level (Clemens and Mendola, 2020). An issue which becomes even more compelling in the attempt of grasping *feelings*, or the perception-related dynamics, from a quantitative perspective.

[8]In this sense, the reader might also refer to Matias et al. (2020).

human experience, influencing how we perceive and interpret a wide array of events. In other words, violence includes not only extraordinary and shocking incidents that grab public attention but also the everyday, commonplace actions that define our daily lives (Springer and Le Billon, 2016). Both shocking events and routine acts of violence contribute to shaping human identity and our shared understanding of who we are.

Chapter 2

Violence and Migration

In this chapter, we unveil the causal effect of authoritative violence on individuals' likelihood to migrate. Specifically, we examine the migration patterns of Venezuelans during the 2017-2018 political and economic crisis. We draw insights from regional-level data on civilian casualties caused by security forces, along with information extracted from the ENCOVI-2018 survey data that captures migration flows. The estimates rely on the travel time from the capital city as an instrumental variable and are robust to the inclusion of several households and socio-economic regional-level characteristics. The findings strongly suggest that authoritative violence is a significant non-economic push factor for international migration. Moreover, additional evidence indicates that this type of violence influences the skill composition of migrants, especially in the context of South-to-South migration flows.

DISCLAIMER:

This paper, co-authored with Federico Maggio (PhD Candidate at the Free University of Bozen), is currently accepted for publication by the *Journal of Population Economics*.

2.1 Introduction

Networks and wage differentials are among the most analyzed migration determinants, together with distance, unemployment rates, educational characteristics, and level of human capital in origin and destination countries. However, especially in a context like Latin America, non-economic factors could play an important role in shaping the cost-benefit analysis of potential migrants. In particular, the decision to migrate might also depend on the risks individuals are exposed to (Rodriguez and Villa, 2012; Massey et al., 2010). As clearly noted by Rodriguez and Villa, 2012, households in developing countries confront a variety of threats. Although some of them can be countered by formal and informal mechanisms, some others imply a higher level of risk (actual or perceived) for which the above-mentioned mechanisms might not be enough. In light of this, there is good reason to suspect that a particular non-economic component, such as the fear of death from political violence, plays a crucial role in many people's migration decisions (see Morrison, 1993).

With this paper, we examine whether *authoritative violence*[1] represents a significant push factor for Venezuelan international migration. Interestingly, despite a consistent number of works that have addressed the impact of Venezuelan migrants on the society and the economy of the neighboring countries (Anatol and Kangalee, 2021; Knight and Tribin, 2020), we still know very little about the determinants of their choice to abandon their country of origin. The role of violence as an independent push factor, in particular, has not been investigated yet (Niedomysl, 2011). Focusing on the regional level, to account for the possible variation across the different Venezuelan federal entities (hereafter, regions), we aim at proving that, as the percentage of homicides committed by police forces with respect to the

[1] We use the definition of *authoritative violence* following the one provided by Morrison and May, 1994. According to the authors, *authoritative violence* includes also the actions of *state-sponsored* actors, such as the so-called death-squad activity, which is often "authorized" by the state, even when the perpetrators are not wearing police or military uniforms or are officially off-duty.

overall number of homicides rises, the likelihood for an individual to migrate increases significantly. To investigate this relationship, we first look for trends or relevant patterns in our data using a Linear Regression Model. In addition to the specific individual and household characteristics, our approach relies on ad hoc regional controls to account for the local economic opportunities and demographic, political, and geographical characteristics of the Venezuelan regions. Our results suggest that *authoritative violence* is a significant non-economic push factor for international migration. We also find evidence that this type of violence plays a role in shaping the migrants' skill composition. In fact, the effect is significant only among males and people with a lower level of education.

To overcome the endogeneity issues, we adopt an IV strategy using the *travel time* from the Capital City to each region's most populated city to instrument the *authoritative violence*. The Capital District and its neighboring regions have experienced a higher level of President Maduro's loyal armed body's interventions with respect to the furthest ones. We, therefore, adopt the travel time from Caracas to account for the quality, ease, and security of the movements across the Country. Our assumption is consistent with the literature, according to which state-sponsored violence spreads faster in areas with greater state capacity (defined as a shorter distance from the capital). Pieces of evidence also suggest that, in general, political or state-sponsored violence is significantly higher close to the capital city because rebellions can be more effective when they take place closer to the capital itself. Therefore, the state has the incentive to violently control the political discontent in the areas closest to the political seat of the country.

Although prior empirical research on the impacts of violence on migration has not been conclusive, it does highlight some crucial factors. The claim that violence in some places encourages emigration is supported by numerous international studies (Schultz, 1971; Morrison, 1993; Ibáñez Londoño, Vélez, et al., 2005; Ibáñez and Vélez, 2008; Bohra-Mishra and Massey, 2011; Contreras, 2014; Fernandez-Dominguez, 2020). While the majority of them found violence to be significantly related to the intra-national migration or displacement only (Schultz, 1971; Morrison, 1993; Morrison and May, 1994; Engel and Ibáñez, 2007; Ibáñez and Vélez, 2008), Moore and Shellman, 2006 found that state violence targeting civilians tend to produce international refugees. Similarly, Bohra-Mishra and Massey, 2011 studied how armed violence during a period of civil conflict in Nepal influenced intra-national and inter-national migration[2]. They found that people migrated only under conditions of extreme violence in which the threats to safety are perceived to exceed the risks of traveling. When it comes to developing countries, the risk related to state violence is one of the most difficult to insure against. When the insurance costs are perceived to be too high as noted by Rodriguez and Villa, 2012, even life-threatening, households may choose to migrate to escape them. As highlighted by Fernandez-Dominguez, 2020, the sensibility of the effect of violence on migration may depend, indeed, on the level of violence. According to Bohra-Mishra and Massey, 2011 and Morrison, 1993, this relationship is not linear; that is, when societal violence levels are low, they have a negative impact on emigration. On the other hand, when societal violence levels rise above a certain threshold, the impact turns positive. In addition, as highlighted by Ibáñez Londoño, Vélez, et al., 2005, particular violent environments might modify the net effect of many key migration determinants (i.e. education and location-specific assets).

However, the lack of a clear uniform understanding and of strong quantitative evidence is mainly given by the great variety of the type of violence at the sub-national level, as so as to the difficulties in identifying the sub-national place of origin of both violent stimuli and migrants (Clemens, 2017). In this sense, the migration literature is also missing a consistent understanding of the impact of violence on the migrants' skills composition and, therefore, the self-selection processes, particularly regarding the

[2]As put by Chiquiar and Hanson, 2005, 'intra-state' and 'inter-state' migration are two different phenomena, which need to be analyzed separately (see also Fernandez-Dominguez, 2020)

so-called South-to-South migration flows (Clemens and Mendola, 2020). In addition, the difficulties related to the analysis of violence are related to the role of perception, a process of mediation driven by personal characteristics, which is not always easy to account for (Becker, Rubinstein, et al., 2004). Depending on an individual's socioeconomic (Arceo-Gómez, 2012) or psychological (Becker, 2011) circumstances, violence may have an impact on migration decisions. Regarding this, Becker, 2011 argued that fear influences emotions, which in turn influences beliefs and behaviors.

This paper is organized as follows. In section 2.2, we provide a detailed explanation of the process of militarization adopted by President Maduro, and of its role in strengthening the unstable position of the ruling party during the last 10 years.
In section 2.3, we present the different sources of data and the variables analyzed, differentiating data and variables used for analyzing migration choice, violence, and regional and household controls. We then present the empirical approach and discuss the main econometric challenges such as the potential omitted variable bias related to the analysis of violence impact.
Section 2.4, is dedicated to the outline of the results, by presenting the main estimates regarding the coefficients of the variable of interest.
In conclusion, we provide, in section 2.5, a discussion about the most relevant findings, along with their potential implications.

2.2 The Militarization Process in Venezuela

During the 2010s, Venezuela underwent the worst and deepest economic and demographic crisis of any *non-war-ridden* country in modern history (Bull and Rosales, 2020). Migration rates have been growing exponentially since 2016, becoming the largest human mobilization in South America's recent history. Contextually the level of violence[3] has been constantly increasing. Venezuela has been showing one of the highest rates in Latin America of civilians killed by officials. In 2016, according to the Public Prosecutor Office (Galavís, 2020), public security officers were responsible for 22 percent of the total number of homicides. Between 2015 and June 2017 there were 8,292 alleged extrajudicial executions. Between 2018 and May 2019, the government reported 6,856 killings by officials during security operations that were classified as "resistance to authority", which may constitute extrajudicial executions (OHCHR 2019 in Galavís, 2020). Such a dramatic soar in officials' brutality is mainly due to a change in citizens' securitization policies. The militarization of police is, indeed, one of the key instruments for the transition of the Venezuelan system from a democratic to an authoritarian regime (Marsteintredet, 2020; Corrales, 2020; Pareja, 2020; Legler, 2020). As explained by the Inter-American Commission on Human Rights (Goldman, 2009; Cerna, 2019), the police and the military have different purposes, as well as training, equipment, and skills. As Osse, 2006 put it, while the military is trained to use force to kill, the police are only to shoot to kill as a last resort. Therefore, the police militarization process[4] occurred in Venezuela, based on the transformation of the civil police into a military body, as well as on the engagement of the military in domestic security operations, represents a critical factor in the developing of the relationship between Government and citizens (Mummolo, 2018).

In 2015, Maduro's government started resorting to manipulation of laws,

[3]We proxy the level of violence through the homicide rate also drawing on UN recommendations. See for more: https://www.unodc.org/unodc/en/data-and-analysis/global-study-on-homicide.html

[4]There are different types of militarization (Flores-Macías and Zarkin, 2021; Galavís, 2020). The first is the one in which the militarized police rely on military tactics and equipment, maintaining civilian jurisdiction as well as a low-hierarchy structure. The second one is the paramilitary police, operating under military deployment tactics and units, maintaining civilian jurisdiction and a police rationale. The third one is represented by the *constabularized* militaries, assuming citizen security tasks such as "crime prevention, crime contention, and prison security while reporting to the Ministry of Defence" Galavís, 2020:71).

as well as the use of the National Bolivarian Armed Forces to repress the opponents, and to assure their ability to govern in such a difficult environment (Maya, 2014). The National Government approved the Homeland Security Plan, through which President Maduro implemented the militarization of public safety police forces, placing the national police under the control of the Army. In the same year, the Ministry of the Interior headed by Néstor Reverol created a new instrument for the systematic repression of the government opponents: Operation Liberation and Protection of the People (Operacion de Liberacion del Pueblo, hereafter OLP). According to the United Nations High Commissioner for Human Rights (Galavís, 2020), Venezuelan authorities used these operations as a tool to demonstrate their alleged success in crime reduction. In reality, according to OHCHR and the media (García Marco, 2016), OLP actions have been showing patterns of disproportionate and unnecessary (ab)use of force and violence, producing a relevant number of extrajudicial victims, as reported above. In 2017, under pressure from the NGOs and international bodies, President Maduro was forced to cease the OLP. However, to maintain its purposes, he created an elite body within the new Bolivarian National Police, the Special Action Forces (hereafter, FAES). FAES became the new form of OLP, whose work was not focused on reducing crime rates, but rather on constituting a mechanism of social and territorial control, to face civil unrest, the loss of consensus, and the political discontent due to the severe humanitarian crises. They have been massively employed in the surroundings of the Capital City, in the attempt to secure the central government headquarters and the centers of power of the Federal Administration (Ades and Glaeser, 1995; McDoom, 2014). The worst-affected areas were the *barrios* of Caracas, and the regions of Carabobo, Miranda, Aragua, Zulia, Merida, and Anzoategui, low-income communities which have experienced a higher level of anti-government protests.

2.3 Data and Empirical Approach

2.3.1 Migration Data

We use the Encuesta Nacional de Condiciones de Vida (hereafter, ENCOVI) to examine Venezuelan citizens' decision to migrate out of their country of origin. The survey was carried out by the Universidad Catolica Andres Bello de Caracas between July and September 2018. It is representative by design of the Venezuelan population and provides information about 21.382 individuals, divided into 5,950 households across 22 regions (the sample does not include Amazonas and Dependencias Federales[5]).

Our dependent variable is binary and takes value 1 if an individual has left the Country between 2017 and September 2018. Individual information on migrants' characteristics and their destinations is reported by the interview respondents, who are the household heads. We report here the questionnaire question translated from Spanish to English: "*During the last few years, since June 2013, has anyone who lived with you in this household moved to another country? In what year and month did they migrate?*". We restrict the sample of migrants to those who moved between 2017 and September 2018. We decided to keep the observations of 2018 in the estimation mainly to grasp the potential time-lagged effect of the *authoritative violence* 'outbreak' of 2017[6]. Moreover, we use ENCOVI to draw information regarding individual and household characteristics. At the individual level, we account for age, education, and gender. We then consider the number of the members of the

[5] As shown in Figure 2.1 and Figure 2.2, we dropped the migration data regarding Portuguesa, because we do not have data on violence for that region.

[6] ENCOVI only accounts for those migrants who have at least a household member left behind. This could imply a loss of representativity of the sample, limiting the validity of our analysis. To overcome such a limitation, we use the Encuesta Dirigida a la Poblaciòn Venezolana que reside en el Pais (see section 2.4.1). The survey, performed at the end of 2018, collects information about 9.847 Venezuelan migrants residing in Peru, which is the second-largest receiving country.

family, and the level of education of the household head[7].

Figure 2.2 maps the percentage of migrants in relation to the population in August 2018. It shows that the majority of migrants are from regions near the Capital District and the northwest part of the country. Consistently with IOM estimates[8], we observe that Colombia and Peru are the main receiving countries worldwide. The other main destinations are Chile, Ecuador, and the US. Migrants are on average younger and more educated[9] compared to the population remaining in the Country.

2.3.2 Homicide data

To proxy the level of violence we use data on homicides estimated and made public by the Observatorio Venezolano de Violencia (OVV)[10]. Since 2016, the OVV has been collecting data on violent deaths by discriminating among their causes: common crime, resistance to authorities, and others (see Figure 2.3).

[7] The variable regarding the education level is a binary one, and takes value 1 if the household head has at least attained a high school diploma.

[8] So far it has been estimated that 5.2 million Venezuelans have moved beyond the border. The most common destination (1.8 million migrants) is Colombia; Peru welcomed 830,000 migrants, Chile 455,000, Ecuador 360,000, and the USA 352,000.

[9] The average age of the migrants in the sample is 29 years old with respect to 41 of the population remaining in Venezuela. 32 percent of the migrants have at least a bachelor's degree, whereas only 13 percent of those who have remained at home are college graduates.

[10] It is an institution capillary distributed across the country, which analyzes data on homicides matching governmental sources, journalistic investigation, and international organizations inquiries. In early 2005, the Laboratory of Social Sciences (LACSO) of Venezuela set out to build a Violence Observatory in order to obtain accurate information on the phenomenon of victimization and the perception of insecurity in Venezuela, given the restrictions that at the time existed for journalists and academics in accessing official statistics on "known cases" of violence registered by the police (https://observatoriodeviolencia.org.ve/sobre-nosotros/; Uribe et al., 2016). If until 2010 OVV's work was mainly relying on statistical predictions, starting from 2016/2017 the observatory has begun applying a more complex methodology of collecting information by media, via victimization surveys, by organizing focus groups and in-depth interviews, and by collecting extra-official information from different institutions (OVV, 2017 in Ávila, 2018).

We use the total number of violent deaths classified as homicides[11] as a proxy for the level of Total Violence. The level of *authoritative violence* is proxied by the number of violent deaths of civilians killed by security forces, while the number of fatalities caused by 'common' criminal activity represents the level of *common violence*[12]. We designed these indicators following the suggestions by the World Health Organization and by the literature analyzing violence in the South American region (Neumayer, 2003; Rivera, 2016). Indeed, homicide is the most extreme form of physical violence, and the crime affects the most fear and perception of insecurity in Latin America (Ávila, 2018). As described by Uribe et al. in Martínez Herrera, 2020, homicide is the best representation of the type of violence affecting Venezuela, and at the same time the evidence of an extraordinarily complex scenario generated by more than one factor. Furthermore, homicide is a more reliable indicator with respect to other forms of criminal activity such as robbery, theft, and assault. Indeed, while theoretically relevant, these types of crime are less reliable and are missing for many country-year observations (Rivera, 2016).

Table 2.1 presents the descriptive statistics of our key variables of interest along with the control variables. We report clustered means and standard deviation at the regional level. Figure 2.4 shows the distribution across space of our main variable of interest, *authoritative violence*. It shows a large variance across regions, ranging from 13 percent to 47 percent. It is also interesting to notice how the average level of repression is highest in the northern regions close to the Capital District.

[11] A death is classified as an intentional homicide following the International Statistical Classification of Diseases and Related Health Problems published by the World Health Organization.

[12] All the violence-related variables are weighted, per 100,000 inhabitants. Data regarding violent deaths refer to the year 2017 and are aggregated at the regional level.

2.3.3 Estimation Strategy

As discussed in section 2.2, the years 2017 and 2018 provide a unique context for studying the effect of repressive violence by the Venezuelan government. Given the lack of institutional data in the years prior to 2017 and the consequent impossibility to address variation in the level of violence across time, we exploit the (high) heterogeneity across Venezuelan regions. In particular, as shown in Eq. 3.1, we want to estimate the impact of an increase in the share of *authoritative violence* on the probability of an individual leaving the Country. Given i, h, and j indicating respectively the individual, the household, and the regional level,

$$Mig_{i,h,j} = \alpha_0 + \alpha_1 AV_j + \alpha_2 H_j + \alpha_3 X_i + \alpha_4 V_h + \alpha_5 W_j + \epsilon_{i,h,j} \tag{2.1}$$

where $Mig_{i,h,j}$ is a dummy variable that has value 1 if the individual has migrated between January 2017 and September 2018, and is currently leaving outside the Venezuelan border[13]. AV_j is the percentage of homicides as a consequence of opposition to security forces (2017). H_j is the logarithm of the homicide rate at the regional level (2017). Vector X_i represents individual characteristics, such as age, gender, and education. Vector V_h represents household characteristics, such as household head education and household size. W_j is a vector that includes regional-level covariates.

To account for those characteristics that vary widely over the years, such as regional education level, employment rate[14] and income per capita, we rely on ENCOVI, which represents the most recent source of information at our availability.
We then draw demographic variables from the 2011 National Census[15]. We

[13]The details of the construction of the dependent variable are outlined in section 2.3.1

[14]In particular, the regional employment rate is calculated using the percentage of employed people aged 19 to 54, and the education level is based on the average number of years of education.

[15]By considering data from 2011, we aim at excluding the heterogeneous effect of the political and economic crisis across regions.

include the population density, the percentage of the urban population, the average availability of essential services in the region[16], and the share of the indigenous population. The presence of indigenous communities is indeed an important element in understanding the uniqueness of state violence at the regional level. They often become the object of repression by the central government (Briceño-León and Perdomo, 2019), which acts violently to expropriate their lands. By including the distance to the nearest national border, we are also able to take into account the cost of moving out of the country, such as transportation fees, network, and information availability. To proxy the access to healthcare, the vector also includes an index of the average availability of medicine for each region using the information made available by Encuesta Nacional de Hospitales (ENH)[17]. By including the number of mines and the Gross National Income (US Dollars, reference year 2011), we account for the local industrial structure. Finally, we weigh the political situation including a dummy variable equal to 1 if the governor of a region is an exponent of the political party opposed to President Maduro's (Ingram and Costa, 2019).

Although Eq. 3.1 is based on a complete set of standardized and operationalized variables, as well as on the complete display of households and geographical controls, we set up an IV Linear Regression Model to strengthen our estimations as much as possible, countering potential source of endogeneity that would prevent us from inferring a causal relationship among our main variables of interest. We also put in place a falsification test to deal with exclusion restrictions.

[16]The average access to running water is represented by the percentage of households with at least weekly access to it.

[17]The Encuesta Nacional de Hospitales showed that in November 2018, 33 percent of the beds in the country's hospitals were inoperative. Given the inoperability of laboratories, 43 percent of hospitals in Venezuela do not have the capacity to examine medical tests. In addition, about 70 percent of hospitals reported experiencing a lack of electrical service and water shortages. Hospitals also experience a shortage of emergency medicines (50 percent shortage). The ENH is conducted by the "Médicos por la Salud" Observatory and data were collected in the major hospitals in Venezuelan regions during the second week of November 2018.

Instrumental Variable: Travel Time from Caracas

To complete our empirical approach, and to address in the best possible way the potential endogeneity issue, we use the logarithm of the *travel time* (expressed in minutes) required to reach every region's most populated city from the Capital District as an instrument for the share of *authoritative violence*. As we know especially from the media, and as already explained in section 2.2, we observe a higher concentration of the actions of FAES in the Capital District and immediate bordering regions, with respect to the furthest ones. Starting from such evidence, we consider the potential difficulties for Maduro's loyal armed bodies to travel across the country in battle array. Figure 2.4 and Figure 2.5 seem to confirm this pattern, showing more intense state repression in regions closer to Caracas, and along the main traffic routes. We adopt the travel time from Caracas to account for the quality, ease, and security of the movements across the Country.

Evidence suggests that political or state-sponsored violence is significantly higher close to the capital city, headquarters of the government, and the national police bodies. From a potential insurgent group perspective, rebellions are more effective when they take place closer to the capital city, based on the principle that "spatial proximity to power increases political influence" (Ades and Glaeser, 1995), and especially when this influence is mediated by the threat of violence. In other words, the variable that influences the extent to which an individual or group poses a danger to an incumbent elite is its distance from the seat of political power. This intuitively leads to the conclusion that the state has the incentive to repress the political discontent in areas closest to the political seat of the country.

Our assumptions are also consistent with the work of McDoom, 2014. Analyzing the evolution of Rwanda's civil conflict, the author found that state violence spread faster in areas with greater state capacity (defined as a shorter distance from the capital). Similar evidence is supported by the literature on the logistics of violence. Physical distance is among the most significant drivers of costs (Boulding and Singh, 1962; Sprout and Sprout, 2015; Starr, 1978; Schutte and Donnay, 2014). As the distance between central logistical bases of the army and conflict zones increases, armies divert more resources to non-combat tasks such as escort and supply chain management (Cederman et al., 2009), and more investment becomes necessary to maintain control. Moreover, Anderton and Brauer, 2016, through a district-level analysis of the African context, found that violence against civilians is more intense where logistical costs are low. The authors capture logistical costs with two covariates: the road density, or the kilometers of paved primary and secondary roads per square kilometer of area, and the physical distance from the center of each district to the center of political and military power in the country.

Although we do not use a road quality index, and the location of the Capital City in Venezuela should be considered completely exogenous, we are aware that the *travel time* might display potentially endogenous dimensions. For instance, it might be related to the characteristics of the region in which the road has been built such as its wealth, its geographical characteristics, and its economic interests. However, we account for these relationships by including control variables such as the GNI per capita, the regional education level, the access to services, the shortage of medicines, the distance from the national borders, the presence of mines, the share of the rural population and the population density. Furthermore, the development of the main road network is not exclusively driven by socio-economic dynamics but rather influenced by exogenous geographic and territorial characteristics. To further increase the credibility of our instrument, we also perform the analysis using the distance from the Capital expressed in *kilometers*, as shown in Table A2, and Table A3. Although the estimations are confirmed and present higher coefficients, we decided to maintain the *travel time* as the main instrument because we consider it more correct and complete from the theoretical perspective.

Regarding the exclusion restrictions related to our identification strategy,

we argue that being close to the Capital is not a relevant factor in shaping the probability of migrating. First of all, being aware of the literature demonstrating that the economic development of similar countries is positively related to the proximity to the Capital City and that such proximity would make easier access to the network and information about possible countries of destination (Sassen, 2013), we account for these factors through the aforementioned control variables in the model.
Second, even if the area of Caracas is on the coast and shows a higher concentration of airports in the country, only a negligible part of the migrants[18] we analyze left Venezuela by air and by sea. Finally, there is no evidence of historical migratory patterns concentrated in the regions closest to the Capital. On the contrary, as shown in Figure 2.1 and Figure 2.2, regional-level migration rates between 2013 and 2016 are consistently different from those registered between 2017 and 2018. To corroborate our assumption, we perform a falsification test through which we estimate the effect of the distance from the capital on the individual probability to migrate before the sudden increase in police violence[19].

2.4 Results

Table 2.2 presents the results of the OLS estimation[20]. As shown, the coefficient of *authoritative violence* is positive and significant, while the one related to Total Violence is very small and non-significant. This is in line

[18] According to our estimations performed thanks to the data provided by the Encuesta Dirigida a la Poblaciòn Venezolana que reside en el Pais (see section 2.4.1), only the 0,09% of the migrants abandon Venezuela are by sea, the 3,85% by air, and the 1,47% by foot. The high majority of them (94,59%), leave the Country by bus.

[19] The dependent variable used in the test is a dummy variable that takes value 1 if the individual migrated during the period of 2014-2016. Conversely, it takes value 0 if the individual continued to reside in Venezuela until 2016. For individuals who migrated during 2017-2018, the migration variable was set to 0. As a result, these individuals were designated as non-migrants in this particular sample.

[20] Table A4, in the Appendix, reports the coefficients of the Logistic estimation and the related marginal values, performed as a robustness check to support the stability and the consistency of the main linear empirical assumptions.

with our theoretical hypothesis regarding the need to differentiate between the different forms of violence when addressing the existence of potential patterns of socioeconomic impact. A relevant concern is that the estimation of the impact of *authoritative violence* on the probability of migration might be driven by omitted variable bias. A commonly recognized approach to tackle this type of endogeneity is the sensitivity analysis proposed by Oster, 2019, which is based on the earlier work of Altonji et al., 2005. Table 2.2 shows how the coefficients maintain their stability and consistency and how the R-square constantly increases with the gradual inclusion of the control variables (Columns 2 to 5)[21]. In addition, we report the estimates of δ[22], which is a measure of the correlation between the stability of the coefficient and the R-square. The value of δ ranges from 1.544 to 1.997. Since both Oster, 2019 and Altonji et al., 2005 suggest value 1 as a reasonable upper-bound for δ, our values indicate that a very strong unobservable selection might be needed for our non-zero estimates to represent a spurious correlation.

Table 2.3 summarizes the statistical tests we adopted in the first-stage estimation to assess the appropriateness of our identification strategy. It includes a set of statistics for the under-identification and weak identification tests. The first is intended to ensure that the excluded instrument is relevant, i.e., that it is correlated with the endogenous variable. The aim of the second is to test the strength of the correlation between the instrument and the endogenous regressor, i.e., whether the IV estimator performs poorly. Since our model includes regional-level standard errors, the i.i.d. hypothesis is no longer valid and, consequently, we report the appropriate statistics (Ascani et al., 2020) for these cases: the LM and Wald versions of Kleibergen and Paap, 2006. The 5 percent statistical significance of the Kleibergen-Paap LM statistic suggests that we can largely reject the null hypothesis that the

[21] The R-squared greatly increases from 0.001 to 0.074, while the coefficient of *authoritative violence* ranges from 0.054 to 0.056, also considering the inclusion of the ENPOVE sample as a robustness check.

[22] As suggested by Oster, 2019, we choose a Rmax = 1.3R cutoff and we report the values of δ for which $\beta = 0$.

equation is under-identified thus corroborating the relevance of our instrument (Table 2.3). For the identification of weak instruments, we adopt the dimension method (Stock and Yogo, 2005). The Kleibergen-Paap rk statistic F exceeds the critical values for the maximum desired bias of 10 percent in all three specifications, thus allowing us to reject the null hypothesis that our instrument is weak[23]. Table 2.3 also reports the estimated coefficients for the first-stage regressions. It shows a statistically strong and negative correlation between our instrument and the percentage of *authoritative violence*. In line with our previous discussion, this means that regions closer to the Capital City experience a higher percentage of homicides committed by authorities, i.e., a more repressive response by the state.

Table 2.4 presents the second-stage estimates for the IV specification[24]. In Column 2 we consider only migration towards other Latin American countries, excluding those households whose members have migrated outside South America. In Column 3, we report the specification without considering households residing in the Capital District. The coefficient of the main variable of interest does not change significantly, showing robustness to both sample restrictions. All our estimations are performed with standard errors clustered at the regional level. Such evidence supports our main hypothesis regarding the effect of *authoritative violence* on migration. The estimates show that, for a 10 percent increase in the share of *authoritative violence*, the probability of migration increases by approximately 0.5 percent. The magnitude of this result should be interpreted considering that the mean of the dependent variable *Migration* is 0.023[25]. Considering that, as shown in Figure 2.3, the deaths caused by resistance to authorities show

[23]Since heteroscedasticity, serial correlation, and data clustering can affect instrument strength we also compute F-statistic of Montiel Olea-Pflueger and we report the TSLS critical values (Olea and Pflueger, 2013). Again, the F statistic exceeds the critical TSLS value at 5 percent, thus confirming the result of the Stock and Yogo under-identification test.

[24]We performed a Durbin-Wu-Hausman test to prove the consistency of both OLS and instrumental variable approach (Baum et al., 2003). The non-significant chi-square statistic (0.60853) suggests that both the estimators are consistent, although the OLS is the more efficient. Despite such evidence, we perform them both to see if their results are comparable.

[25]The coefficient does not change consistently across different specifications.

an increase of almost 50 percent, which has potentially led up to 2,5 percent of the Venezuelan population to leave their own country.

Table 2.4 also reports the coefficients related to individual and household characteristics. In particular, at both levels, we observe a positive and significant effect on the level of education. This confirms that, in the decision-making process, economic and non-economic factors may coexist. Furthermore, it is interesting to notice that coefficients related to the level of education are lower when we consider only migrants who move to neighboring countries.
According to the literature, one would expect to find a negative relationship between employment and the regional-level out-migration rate. However, as also shown by the OLS estimates in Table 2.2, the employment rate is positively related to the probability of migration (Table 2.4). Moreover, while education at the individual level has a positive effect on migration, the coefficient of the regional average education level is negative. Such peculiar evidence may be due to a misalignment in the local labor market between low-skill demand and high-skill supply. This would imply that, especially in regions where a prevalence of labor-intensive employment and low average education is observed, the higher educated individuals are driven to leave in search of better opportunities (Brown et al., 1989; Brown and Goetz, 1987). Having said that, even if the results are robust to the inclusion or exclusion of the other control variables (Table 2.2), the interpretation of such controls should be taken with caution, as some may suffer from endogeneity issues, and addressing all of them simultaneously is beyond the scope of this paper.

Table A5 shows the results of the falsification test introduced in section 2.3.3. The coefficients suggest that, before the militarization process, the distance from the Capital district[26] did not have any effect on the individual probability of migration. Therefore, based on these results, and despite

[26] We perform the falsification test by using both the logarithmic functional forms of travel time and kilometers from the Capital.

the structural limitations associated with the lack of panel data, we have a high level of confidence in affirming the existence of a causal relationship between *authoritative violence* and the likelihood of an individual migrating from the Country.

We also explore the effect of *authoritative violence* on migrants' gender and skills composition. Columns 1 and 2 of Table 2.5 show that our variable of interest has a positive and significant effect on males' decision to migrate[27], while the migration of females appears to be driven by educational attainment. Columns 4 to 6 show that *authoritative violence* is a push factor only for low-educated Venezuelans, suggesting that the highly educated decide to migrate for factors other than state violence. Taking a look at the sample's skills composition, as already mentioned in section 2.3.1, we observe a relevant number of low-educated migrants[28]. Column 3 and Column 7 report the coefficients of the 'means equality test', respectively across gender (statistically significant) and skill level (statistically not significant). Our hypothesis is that this kind of violence has reshaped the selection process, towards a higher representativeness of the less educated ones. In the absence of violence, therefore, we would expect an even higher presence of highly educated migrants[29].

2.4.1 Robustness Check to Whole Household Migration

ENCOVI only accounts for those migrants who have at least a household member left behind. This could imply a loss of representativity of the sample, limiting the validity of our estimations. To overcome such a limitation, we use the Encuesta Dirigida a la Poblaciòn Venezolana que reside en el

[27]The Venezuelan Observatory Monitor de Victimas shows that in the Capital District and in the governorate of Miranda between 2017 and 2018, 92 percent of victims of police violence were male

[28]In Table 2.1 we report the descriptive statistics of our migrants' sample. 44 percent of migrants have a high-school diploma, and 24 percent do not have formal education at all.

[29]An in-depth discussion related to these findings is presented in section 2.5.

Pais (hereafter, ENPOVE). The survey, performed at the end of 2018, collects information about 9.847 Venezuelan migrants residing in Peru, which is the second-largest receiving country[30]. In particular, unlike other surveys on Venezuelan migrants residing in foreign countries, ENPOVE provides their city of origin. This allows us to assess the effect of exposure to pre-migration violence on their decision-making process[31]. Column 4 of Table 2.4 shows the coefficients regarding the new sample, in which we merged the weighted samples from ENCOVI and ENPOVE[32]. The stability of the estimations, confirms the robustness of our results to the inclusion of households that entirely migrated.

2.5 Discussion and Conclusions

This paper investigates the significance of police violence as one of the push factors behind international migration and considers how it might help to explain migration patterns and the distribution of skills among migrants. We address these issues by analyzing the Venezuelan exodus taking place between 2017 and 2018. Relying on the distance from the Capital to each region's most populated city as an instrumental variable, we find evidence that the rise of homicides committed by security forces causes an increase in the likelihood that an individual will migrate outside the Country. This finding is robust to the gradual inclusion of several socio-economic controls at the individual, household, and regional levels. This represents a

[30]ENPOVE was carried out by the Peruvian National Institute for Statistics (INEI) between November and December 2018. It is 'representative by design' of the Venezuelan population residing in Peru. In particular, it was conducted in the five largest cities in the country, where 85 percent of Venezuelans reside. According to IOM estimates, Peru is the second-largest receiving country for Venezuelan migrants; currently about 1 million out of 5.2 million of them live there. Therefore the ENPOVE sample can be largely representative of Venezuelan households that have entirely migrated.

[31]While ENCOVI is representative of the whole Venezuelan population (25 to 28 million people estimated), ENPOVE is representative of approximately 550,000 Venezuelan migrants. The merge has been performed by applying the appropriate sample weights.

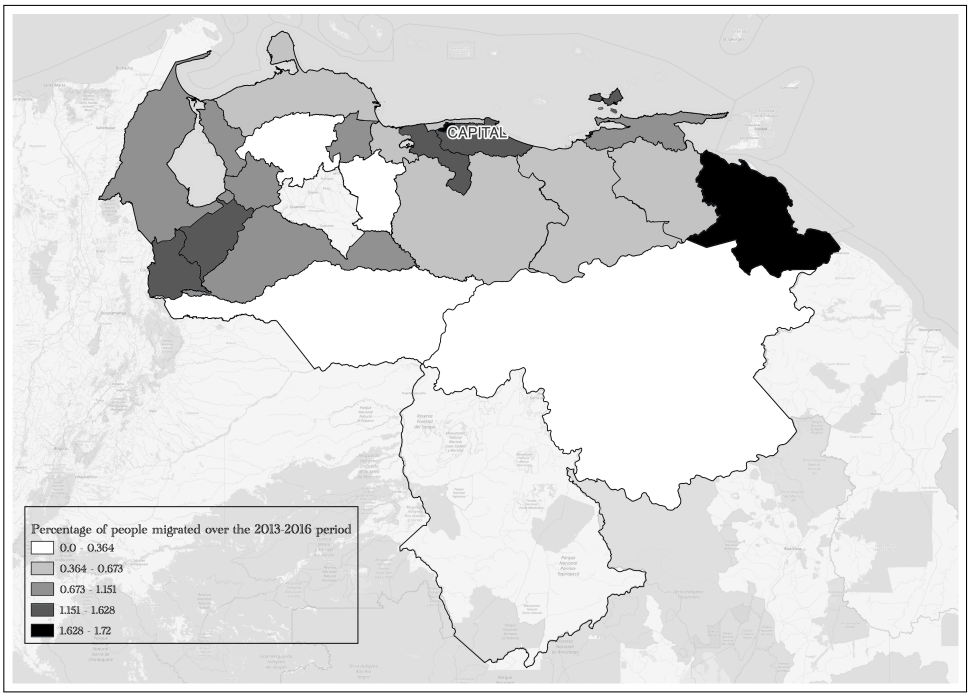
[32]We considered only those Venezuelans who declared not to have any left-behind member of their family.

step forward with respect to the literature finding that political violence alone is not a push factor for international migration, but rather for internal displacement. In this regard, it's interesting to notice how, as shown by the estimations performed excluding individuals who migrated outside Latin America, the coefficient of *authoritative violence* is higher. As presented in section 2.4, we also find interesting heterogeneous effects across gender and education. In particular, our estimations seem to suggest that the impact of *authoritative violence* is significant only among people with a lower level of education (Table 2.5, Column 4). The high *p-value* confirms the role of *authoritative violence* as a clean push factor for less educated individuals. Although the coefficient for high-skilled migrants remains positive, it is no longer statistically significant. Nonetheless, the 'means equality test' indicates that the coefficients for different education levels are not statistically different, suggesting that the estimation of the coefficient for high-skilled migrants may lack precision. This implies that other socio-economic or migration policy-related factors, both in the country of origin and destination, may be interacting with the impact of *authoritative violence*. This finding implies that our results make a valuable contribution to the ongoing debate surrounding the self-selection of migrants, particularly in inter-developing and underdeveloped countries (see Clemens and Mendola, 2020). Whereas previous literature has focused mainly on observable migrant characteristics and attractive elements, ignoring the role of 'domestic' non-economic circumstances as push factors, our study confirms and emphasizes the significance of non-economic factors in shaping the skill composition of migrants, particularly in the Latin American context.

In conclusion, with respect to the analysis of violence and its role in individual decision-making, the aim of this paper is to stress the importance of discriminating between different possible violent stimuli. The total level of violence, as well as the level of common violence, might fail to explain the mechanisms related to perception and fear with an acceptable level of approximation, as represented by the non-significance of its effect on the probability of migration. This discrepancy might indeed represent the disruptive effect of the sharp change in the *production of violence*, where a (relative or actual) higher share passes to another actor. As written by Galavís, 2020, "[v]iolence in Venezuela is a multifaceted phenomenon that authorities have not only been unable to reduce but have also aggravated". The militarization of citizens' security represents the failure of a policy whose main outcome is to deprive the Country of a whole generation of the young male labor force, and this represents a severe long-term cost. Furthermore, especially in the case of South-to-South migration, it is worth considering how such an intense low-skilled migration wave in such a small time window could strain both the local labor market and the socio-cultural dynamics of the receiving country (Anatol and Kangalee, 2021; Bahar et al., 2021). This is especially true when considering the relatively short time window in which the diaspora of Venezuelans took place. This outflow, coupled with economic crises and uncertainty, may contribute to a shift in the demographic pyramid of the country. Such changes can have significant long-term implications for socio-economic development.

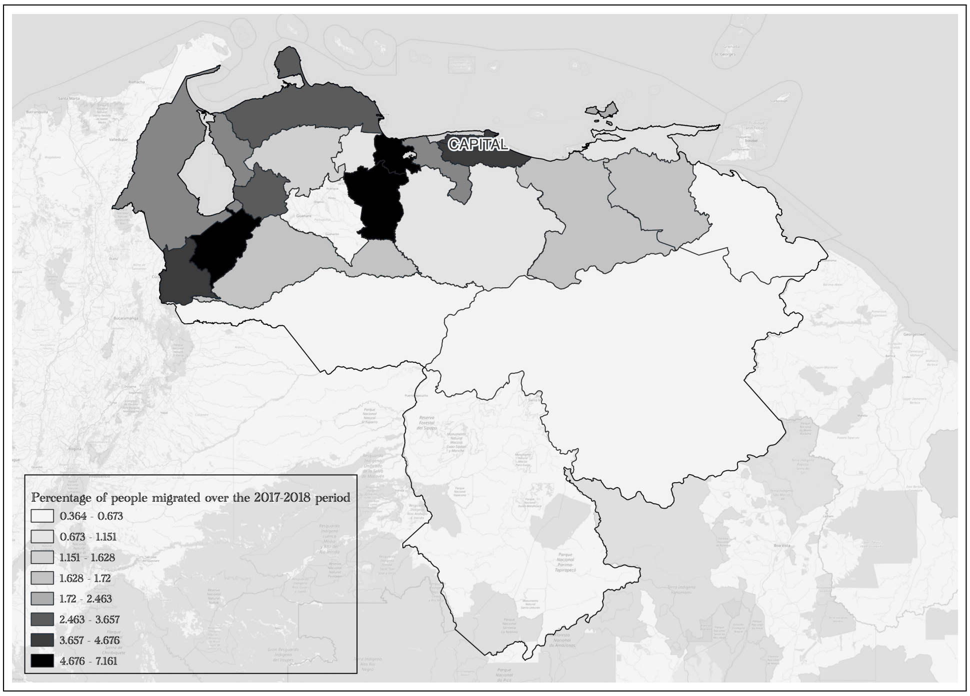
2.6 Figures and Tables

FIGURE 2.1: *Average regional level migration rates (2013-2016)*



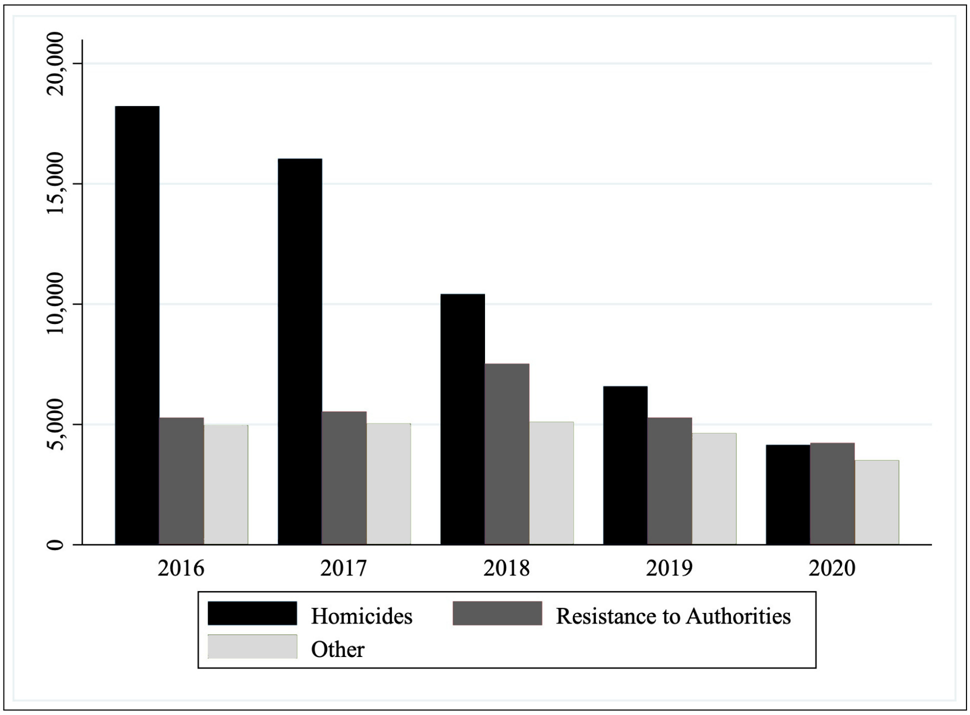
Note: The map shows the average out-migration rate at the regional level, in the period between 2013 and 2016.

FIGURE 2.2: *Average regional level migration rates (2017-2018)*



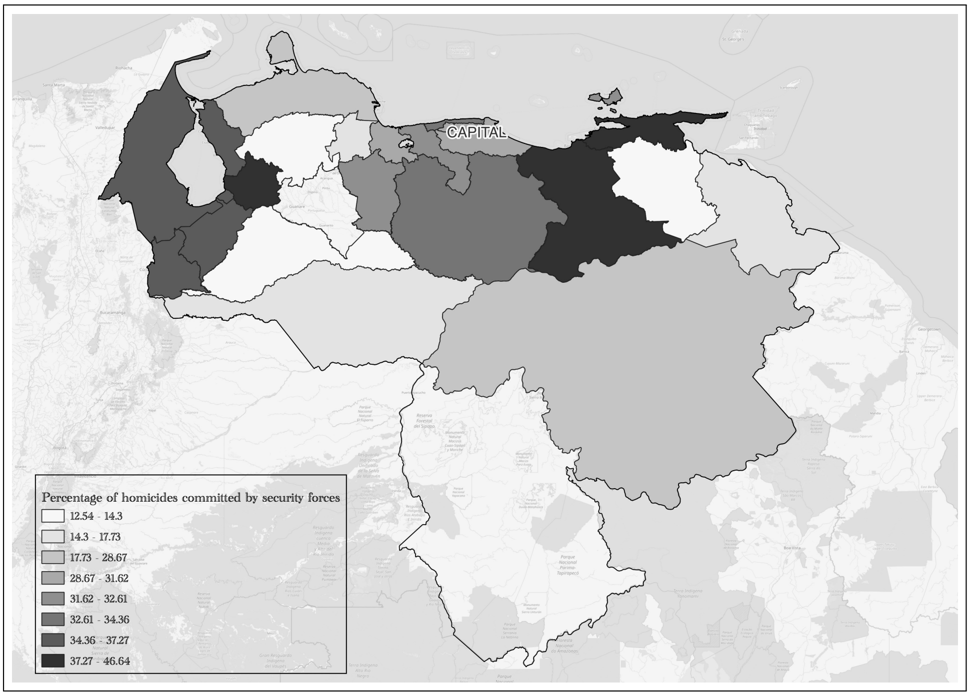
Note: The map shows the average out-migration rate at the regional level, in the period between 2017 and 2018.

FIGURE 2.3: *Violent deaths trend (2016-2020)*



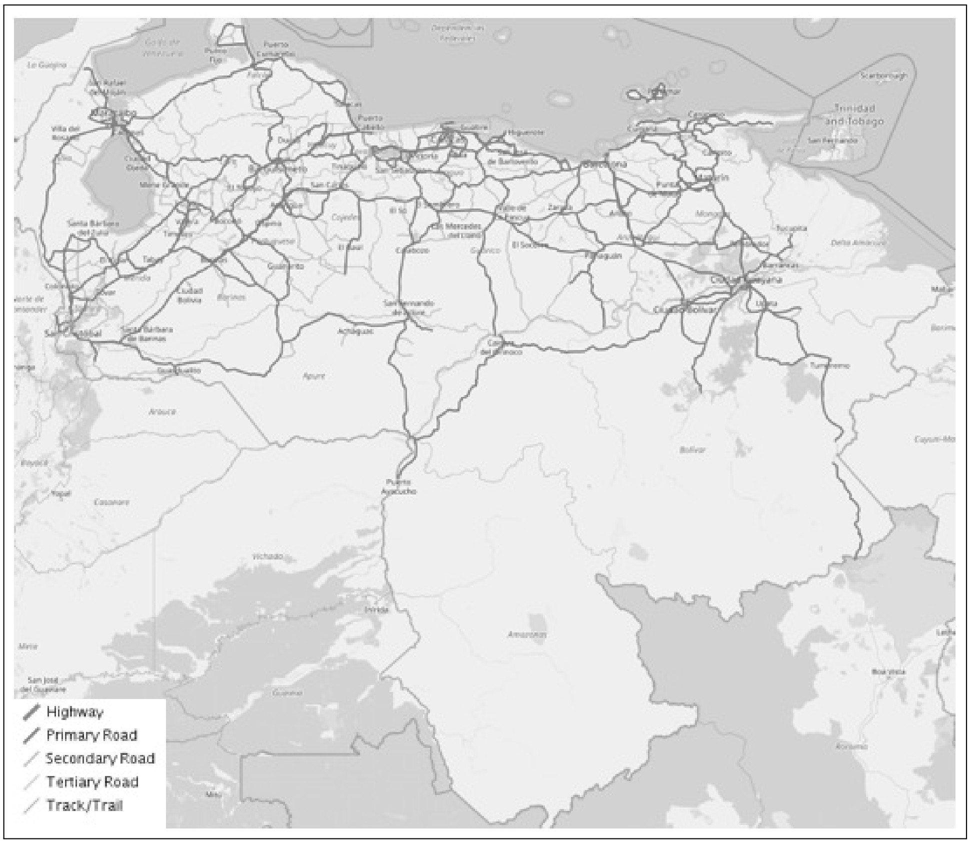
Note: The histogram displays the trend of violent deaths in Venezuela, from 2016 to 2020. The deaths are divided into three main categories: *homicides* reflecting violent death caused by common or organized criminal activities; the deaths as a consequence of *resistance to authorities*; and *other*, including all the violent deaths with different causes from the previous ones. Authors' elaboration on data provided by the Observatorio Venezolano de Violencia - OVV.

FIGURE 2.4: *Authoritative violence (2017)*



Note: The map shows the distribution of the homicides committed by security forces in each region, during the year 2017.

FIGURE 2.5: *Main roads distribution*



Note: The map shows the distribution of the main roads across the entire country.

TABLE 2.1: Descriptive statistics

	Migrants		Non Migrants	
Individual Level	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Less than High School Diploma	0.24	0.42	0.63	0.48
High School Diploma	0.44	0.50	0.24	0.43
College Graduated	0.32	0.47	0.13	0.34
Age	29.45	9.62	41.70	12.87
Female	0.45	0.50	0.56	0.50

	Full Sample	
Household Level	**Mean**	**Std. Dev.**
Education of the household head	0.42	0.49
Household size	3.29	2.12
Regional Level		
Homicide rate (2017)	61.52	25.62
Percentage of homicide committed by authorities (2017)	0.28	0.10
Education Level (2017)	10.45	1.24
Employment rate (2017)	0.64	0.05
Average Income per capita (monthly/BS) (2017)	755.65	485.83
Population density (2011)	316.35	942.29
Percentage of indigenous (2011)	0.02	0.05
Travel time from Caracas	359.00	183.00
Percentage of Rural Population (2011)	0.32	0.28
Shortage medicine in the main hospitals (2017)	0.41	0.21
Households with access to running water (2011)	0.60	0.17
Distance from national borders	358.45	183.66
Governor opponent of Maduro	0.18	0.39
Presence of Mines (2011)	24.773	92.01
Gross National Income (1,000 US Dollars, 2011)	9.77	0.23

Source: Author's elaboration on ENCOVI 2018.
Notes: Distance from Caracas is represented by the Minutes of travel time under normal traffic conditions from the Capital District; Household size is measured pre-migration.

TABLE 2.2: The effect of *authoritative violence* on the probability to migrate (OLS)

	(1)	(2)	(3)	(4)	(5)
	Probability to Migrate				
Variable of interest					
Authoritative violence (%)	0.054*	0.047**	0.055***	0.053***	0.056***
	(0.0311)	(0.0185)	(0.0162)	(0.0172)	(0.0167)
Individual characteristics					
High School				0.028***	0.010**
				(0.0055)	(0.0035)
College graduated				0.046***	0.022***
				(0.0056)	(0.0041)
Age				-0.009***	-0.009***
				(0.0014)	(0.0014)
Age Squared				0.000***	0.000***
				(0.0000)	(0.0000)
Female				-0.015**	-0.016***
				(0.0054)	(0.0053)
Household characteristics					
Education of the household head					0.046***
					(0.0068)
Household size (Log)					0.017***
					(0.0039)
Regional controls					
Total violence (Log)	-0.001	-0.002	-0.012	-0.010	-0.010
	(0.0103)	(0.0092)	(0.0089)	(0.0085)	(0.0082)
Governor is an opponent of Maduro		0.000	-0.005	-0.006*	-0.008**
		(0.0059)	(0.0041)	(0.0036)	(0.0034)
Education level (Log)		-0.052***	-0.031	-0.047**	-0.056**
		(0.0173)	(0.0234)	(0.0218)	(0.0217)
Employment		0.323***	0.273**	0.299**	0.321***
		(0.0615)	(0.1046)	(0.1105)	(0.1072)
Average income *per capita* (Log)		0.002	-0.001	-0.002	0.002
		(0.0029)	(0.0055)	(0.0057)	(0.0053)
Population density (Log)			-0.004**	-0.005***	-0.005***
			(0.0014)	(0.0013)	(0.0013)
Access to running water		0.027*	0.052**	0.049***	0.046**
		(0.0140)	(0.0187)	(0.0166)	(0.0165)
Shortage of medicines		0.042***	0.029**	0.033**	0.037***
		(0.0074)	(0.0137)	(0.0139)	(0.0128)
Indigeneous			-0.019	-0.019	-0.024
			(0.0728)	(0.0664)	(0.0636)
Rural Population			-0.010	-0.011	-0.012
			(0.0130)	(0.0125)	(0.0124)
Distance from national borders (Log)			-0.001	0.000	0.001
			(0.0024)	(0.0023)	(0.0022)
Number of mines (Log)			-0.001	-0.001	-0.001
			(0.0011)	(0.0012)	(0.0011)
GNI		0.012	0.023**	0.022*	0.023**
		(0.0104)	(0.0105)	(0.0117)	(0.0104)
δ		1.544	1.357	1.800	1.997
R-square	0.001	0.007	0.008	0.055	0.074
Observations	21,382	21,382	21,382	19,776	19,776
Capital District observations	Yes	Yes	Yes	Yes	Yes
Migration outside LAC	Yes	Yes	Yes	Yes	Yes
Households migrated	No	No	No	No	No

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The mean of Dependent Variable *migration* is 0.023. *Authoritative violence (%)* is represented by the percentage of violent deaths due to resistance to authority out of total homicides (per 100.000 inhabitants). We report the value of δ for which $\beta = 0$ with $R_{max} = 1.3R$ and it exceeds 1. It suggests that the results are not driven by unobservables (Oster, 2019).

TABLE 2.3: First-stage: estimates of the *authoritative violence*

	(1)	(2)	(2)
	Authoritative violence (%)		
Instrumental variable			
Travel time from Caracas (Log)	-0.199***	-0.199***	-0.212***
	(0.0316)	(0.0316)	(0.0283)
Regional controls			
Total violence (Log)	0.133***	0.133***	0.107***
	(0.0445)	(0.0445)	(0.0411)
Governor is an opponent of Maduro	0.325***	0.325***	0.329***
	(0.0394)	(0.0394)	(0.0388)
Education level (Log)	0.345***	0.345***	0.428***
	(0.1327)	(0.1327)	(0.1238)
Employment	3.326***	3.325***	3.231***
	(0.8122)	(0.8121)	(0.7151)
Average income *per capita* (Log)	-0.080***	-0.080***	-0.092***
	(0.0205)	(0.0205)	(0.0192)
Population density (Log)	-0.215***	-0.215***	-0.039
	(0.0376)	(0.0376)	(0.1007)
Access to water	-0.326***	-0.326***	-0.292***
	(0.1025)	(0.1025)	(0.0974)
Shortage of medicines	0.426***	0.426***	0.416***
	(0.0918)	(0.0917)	(0.0829)
Indigenous	0.088	0.087	0.094
	(0.4128)	(0.4125)	(0.4132)
Rural Population	0.199***	0.199***	0.235***
	(0.0707)	(0.0707)	(0.0726)
Distance from national borders (Log)	-0.059***	-0.059***	-0.070***
	(0.0122)	(0.0122)	(0.0143)
Number of mines (Log)	0.015	0.015	0.017*
	(0.0104)	(0.0104)	(0.0090)
GNI	-0.252***	-0.252***	-0.300***
	(0.0794)	(0.0794)	(0.0828)
Under-indentification	5.28**	5.28**	5.61**
Weak-identification:			
Kleibergen-Paap Wald F-stat	39.56	39.57	56.44
Stock-Yogo 10%	16.38	16.38	16.38
Stock-Yogo 15%	8.96	8.96	8.96
Montiel Olea-Pflueger F-stat	39.56	39.57	56.44
TSLS 5%	37.42	37.42	37.42
TSLS 10%	23.11	23.11	23.11
Observations	19,776	19,716	18,607
Capital District observations	Yes	Yes	No
Migration outside LAC	Yes	No	Yes
Households migrated	No	No	No

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance:***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. We report the Kleibergen-Paap LM statistic to test whether the model suffers from Under-Identification. It suggests that we can largely reject the null hypothesis that the equation is under-identified thus corroborating the relevance of our instrument. For the identification of weak instruments, we report The Kleibergen-Paap rk statistic F, which exceeds the critical values for the maximum desired bias of 10 percent in all three specifications. We also compute the F-statistic of Montiel Olea-Pflueger. Again, the F statistic exceeds the critical TSLS value at 5 percent, thus confirming the result of the Stock and Yogo under-identification test.

TABLE 2.4: IV-REG second stage: the effect of *authoritative violence* on the probability to migrate

	(1)	(2)	(3)	(4)
		Probability to Migrate		
Variable of interest				
Authoritative violence (%)	0.045**	0.048**	0.046**	0.068*
	(0.0215)	(0.0202)	(0.0214)	(0.0349)
Individual characteristics				
High School	0.010***	0.008***	0.010***	0.012***
	(0.0034)	(0.0028)	(0.0036)	(0.0033)
College graduated	0.022***	0.014***	0.021***	0.033***
	(0.0040)	(0.0038)	(0.0042)	(0.0039)
Age	-0.009***	-0.008***	-0.009***	-0.011***
	(0.0014)	(0.0013)	(0.0015)	(0.0012)
Age Squared	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female	-0.016***	-0.016***	-0.016***	-0.027***
	(0.0052)	(0.0049)	(0.0055)	(0.0051)
Household characteristics				
Education household of the head	0.046***	0.042***	0.045***	0.055***
	(0.0066)	(0.0062)	(0.0070)	(0.0070)
Household size (Log)	0.017***	0.014***	0.016***	0.149***
	(0.0038)	(0.0035)	(0.0042)	(0.0021)
Regional controls				
Total violence (Log)	-0.008	-0.006	-0.008	-0.023
	(0.0084)	(0.0069)	(0.0091)	(0.0140)
Governors is an opponent of Maduro	-0.006	-0.003	-0.006	-0.018**
	(0.0037)	(0.0031)	(0.0039)	(0.0089)
Education level (Log)	-0.055**	-0.045**	-0.054**	-0.076**
	(0.0215)	(0.0183)	(0.0233)	(0.0384)
Employment	0.321***	0.359***	0.317***	0.448***
	(0.1102)	(0.1078)	(0.1146)	(0.1298)
Average income *per capita* (Log)	0.001	0.001	0.001	0.024***
	(0.0049)	(0.0046)	(0.0050)	(0.0080)
Population density (Log)	-0.005***	-0.005***	-0.003	-0.003
	(0.0012)	(0.0010)	(0.0159)	(0.0025)
Access to water	0.040**	0.035**	0.041**	0.060*
	(0.0174)	(0.0145)	(0.0181)	(0.0335)
Shortage of medicines	0.038***	0.042***	0.038***	0.042**
	(0.0137)	(0.0128)	(0.0140)	(0.0167)
Indigenous	-0.032	-0.026	-0.031	-0.035
	(0.0640)	(0.0632)	(0.0642)	(0.1441)
Rural Population	-0.012	-0.006	-0.011	-0.001
	(0.0128)	(0.0121)	(0.0130)	(0.0183)
Distance from national borders (Log)	0.001	-0.000	0.000	0.007
	(0.0022)	(0.0022)	(0.0024)	(0.0044)
Number of mines (Log)	-0.001	-0.002	-0.001	0.004**
	(0.0011)	(0.0011)	(0.0012)	(0.0015)
GNI	0.022**	0.016*	0.021**	0.030**
	(0.0094)	(0.0093)	(0.0093)	(0.0150)
Observations	19,776	19,716	18,607	20,868
Capital District observations	Yes	Yes	No	Yes
Migration outside LAC	Yes	No	Yes	Yes
Households migrated	No	No	No	Yes

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance:*** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. The mean of Dependent Variable *migration* is 0.023. *Authoritative violence (%)* is represented by the percentage of violent deaths due to resistance to authority out of total homicides (per 100.000 inhabitants). *Total violence (Log)* is the logarithm of the total homicides (per 100.000 inhabitants). We also perform a Durbin-Wu-Hausman test. The chi2 statistic shows a value of 0.60853, which suggests that we cannot reject the null hypothesis that both the OLS and IV estimators are consistent, and therefore the OLS estimator is preferred because it is more efficient.

TABLE 2.5: Heterogeneous effects

	(1) Female	(2) Male	(3) t-test (p-value)	(4) Low-skilled	(5) Medium-skilled (Diploma)	(6) High-skilled (College)	(7) t-test (p-value)
Variable of interest							
Authoritative violence (%)	0.014	0.119**	0.0285	0.056***	0.016	0.089	0.5405
	(0.0140)	(0.0533)		(0.0124)	(0.0449)	(0.0601)	
Individual characteristics							
High School	0.018***	-0.002					
	(0.0048)	(0.0039)					
College graduated	0.028***	0.014**					
	(0.0040)	(0.0064)					
Age	-0.009***	-0.010***		-0.004***	-0.016***	-0.015***	
	(0.0014)	(0.0023)		(0.0009)	(0.0033)	(0.0032)	
Age Squared	0.000***	0.000***		0.000***	0.000***	0.000***	
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Female				-0.015***	-0.013*	-0.022*	
				(0.0036)	(0.0072)	(0.0118)	
Household characteristics							
Educ of household head	0.033***	0.060***		0.037***	0.062***	0.076***	
	(0.0052)	(0.0097)		(0.0063)	(0.0096)	(0.0091)	
Household size (Log)	0.014***	0.019***		0.002	0.048***	0.054***	
	(0.0039)	(0.0057)		(0.0018)	(0.0102)	(0.0133)	
Regional controls							
Total violence (Log)	-0.001	-0.028		-0.016***	0.014	-0.030	
	(0.0057)	(0.0251)		(0.0051)	(0.0163)	(0.0245)	
Opponent of Maduro	-0.001	-0.018		-0.010***	0.015	-0.026	
	(0.0030)	(0.0111)		(0.0020)	(0.0102)	(0.0183)	
Education level (Log)	-0.018	-0.156**		-0.025*	-0.088**	-0.175***	
	(0.0136)	(0.0683)		(0.0150)	(0.0450)	(0.0430)	
Employment	0.164***	0.611**		0.147**	0.485**	0.758***	
	(0.0580)	(0.2423)		(0.0604)	(0.2278)	(0.2205)	
Average income *pc* (Log)	-0.001	-0.002		0.000	0.011	0.014	
	(0.0036)	(0.0101)		(0.0026)	(0.0106)	(0.0101)	
Population density (Log)	-0.005***	-0.005		-0.004***	-0.007***	-0.005	
	(0.0011)	(0.0040)		(0.0008)	(0.0023)	(0.0039)	
Access to water	0.046***	0.048		0.045***	0.037	0.057	
	(0.0124)	(0.0549)		(0.0109)	(0.0371)	(0.0601)	
Shortage of medicines	0.006	0.085**		0.010	0.080***	0.089***	
	(0.0072)	(0.0337)		(0.0083)	(0.0304)	(0.0232)	
Indigenous	-0.007	-0.032		0.013	-0.014	0.085	
	(0.0356)	(0.1375)		(0.0276)	(0.1456)	(0.0905)	
Rural Population	-0.011*	-0.007		-0.011	-0.018	-0.020	
	(0.0060)	(0.0338)		(0.0084)	(0.0260)	(0.0256)	
Distance from borders (Log)	-0.002*	0.005		0.000	0.002	0.014***	
	(0.0012)	(0.0049)		(0.0011)	(0.0048)	(0.0043)	
Number of mines (Log)	-0.002***	0.000		-0.001	-0.000	0.003	
	(0.0007)	(0.0025)		(0.0007)	(0.0021)	(0.0025)	
GNI	0.030***	0.020		0.015***	0.039*	0.014	
	(0.0086)	(0.0196)		(0.0050)	(0.0212)	(0.0194)	
Observations	10,973	8,803		12,020	5,095	2,661	
Regional Controls	Yes	Yes		Yes	Yes	Yes	
Capital District obs	Yes	Yes		Yes	Yes	Yes	
Migration outside LAC	Yes	Yes		Yes	Yes	Yes	
Households migrated	No	No		No	No	No	

Notes: Robust standard errors in parentheses and they allow for Education Level clustering. Asterisks denote statistical significance:***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. Column 3 presents the 'means equality t-test' across samples by gender, and Column 7 presents the 'means equality t-test' across samples by class of education.

Appendix

TABLE A1: The effect of *authoritative violence* on the probability to migrate

	(1)	(2)	(3)	(4)	(5)
Variable of interest					
Authoritative violence (Log)	0.010**	0.008***	0.007**	0.008**	0.008**
	(0.0043)	(0.0029)	(0.0033)	(0.0033)	(0.0032)
Individual characteristics.					
High School				0.028***	0.010**
				(0.0055)	(0.0035)
College graduated				0.046***	0.022***
				(0.0056)	(0.0041)
Age				-0.009***	-0.009***
				(0.0014)	(0.0014)
Age Squared				0.000***	0.000***
				(0.0000)	(0.0000)
Female				-0.015**	-0.016***
				(0.0054)	(0.0053)
Household characteristics					
Education of the household head					0.046***
					(0.0068)
Household size (Log)					0.017***
					(0.0039)
Regional controls					
Common violence (Log)	-0.012	-0.011	-0.019**	-0.017**	-0.018**
	(0.0117)	(0.0091)	(0.0078)	(0.0076)	(0.0075)
Governor is an opponent of Maduro		0.001	-0.005	-0.006	-0.008**
		(0.0060)	(0.0043)	(0.0038)	(0.0035)
Education level (Log)		-0.050***	-0.032	-0.048**	-0.057**
		(0.0164)	(0.0229)	(0.0214)	(0.0212)
Employment		0.325***	0.285**	0.312***	0.333***
		(0.0609)	(0.1041)	(0.1091)	(0.1056)
Average income \textit{per capita} (Log)		0.002	-0.001	-0.001	0.002
		(0.0029)	(0.0055)	(0.0057)	(0.0053)
Population density (Log)			-0.004**	-0.005***	-0.005***
			(0.0014)	(0.0013)	(0.0013)
Access to running water		0.027*	0.051**	0.048***	0.044**
		(0.0140)	(0.0185)	(0.0162)	(0.0161)
Shortage of medicines		0.042***	0.031**	0.035**	0.038***
		(0.0073)	(0.0136)	(0.0137)	(0.0126)
Indigeneous			-0.018	-0.017	-0.022
			(0.0719)	(0.0652)	(0.0624)
Rural Population			-0.008	-0.009	-0.010
			(0.0129)	(0.0122)	(0.0121)
Distance from national borders (Log)			-0.001	0.000	0.001
			(0.0024)	(0.0022)	(0.0021)
Number of mines (Log)			-0.001	-0.002	-0.002
			(0.0011)	(0.0012)	(0.0011)
GNI		0.011	0.022*	0.021*	0.022*
		(0.0104)	(0.0107)	(0.0119)	(0.0105)
R-square	0.001	0.007	0.008	0.055	0.075
Observations	21,382	21,382	21,382	19,776	19,776
Capital District observations	Yes	Yes	Yes	Yes	Yes
Migration outside LAC	Yes	Yes	Yes	Yes	Yes
Households migrated	No	No	No	No	No

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Authoritative violence (Log)* is represented by the logarithm of the total violent deaths due to resistance to authority (per 100.000 inhabitants). *Common violence (Log)* is the number of fatalities (per 100.000 inhabitants) caused by 'common' criminal activity.

TABLE A2: First stage: estimates of the *authoritative violence* (robustness check)

	(1)	(2)	(3)
	Authoritative Violence (%)		
Instruments			
Kilometers from Caracas	-0.196***	-0.196***	-0.196***
	(0.0281)	(0.0281)	(0.0283)
Regional controls			
Total violence (Log)	0.182***	0.182***	0.185***
	(0.0409)	(0.0409)	(0.0412)
Governor is an opponent of Maduro	0.375***	0.375***	0.375***
	(0.0319)	(0.0318)	(0.0324)
Education level (Log)	0.389***	0.389***	0.380***
	(0.1373)	(0.1373)	(0.1405)
Employment	3.723***	3.722***	3.771***
	(0.9019)	(0.9025)	(0.9677)
Average income *per capita* (Log)	-0.191***	-0.191***	-0.189***
	(0.0299)	(0.0299)	(0.0295)
Population density (Log)	-0.187***	-0.187***	-0.216***
	(0.0303)	(0.0303)	(0.0723)
Access to water	-0.593***	-0.593***	-0.597***
	(0.1172)	(0.1171)	(0.1193)
Shortage of medicines	0.418***	0.418***	0.423***
	(0.0774)	(0.0774)	(0.0794)
Indigenous	-0.438**	-0.438**	-0.431**
	(0.2063)	(0.2061)	(0.2032)
Rural Population	0.145	0.145	0.141
	(0.0909)	(0.0909)	(0.0889)
Distance from national borders (Log)	-0.104***	-0.104***	-0.102***
	(0.0137)	(0.0137)	(0.0134)
Number of mines (Log)	0.010	0.010	0.010
	(0.0064)	(0.0064)	(0.0065)
GNI	-0.534***	-0.534***	-0.529***
	(0.0938)	(0.0937)	(0.0912)
Under-indentification	5.65**	5.66**	5.68**
Weak-identification:			
Kleibergen-Paap Wald F-stat	48.54	48.49	47.95
Stock-Yogo 10%	16.38	16.38	16.38
Stock-Yogo 15%	8.96	8.96	8.96
Montiel Olea-Pflueger F-stat	48.54	48.49	47.95
TSLS 5%	37.42	37.42	37.42
TSLS 10%	23.11	23.11	23.11
Observations	19,776	19,716	18,607
Capital District observations	Yes	Yes	No
Migration outside LAC	Yes	No	Yes
Households migrated	No	No	No

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance:***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. We report the Kleibergen-Paap LM statistic to test whether the model suffers from Under-Identification. It suggests that we can largely reject the null hypothesis that the equation is under-identified thus corroborating the relevance of our instrument. For the identification of weak instruments, we report The Kleibergen-Paap rk statistic F, which exceeds the critical values for the maximum desired bias of 10 percent in all three specifications. We also compute the F-statistic of Montiel Olea-Pflueger. Again, the F statistic exceeds the critical TSLS value at 5 percent, thus confirming the result of the Stock and Yogo under-identification test.

TABLE A3: The effect of *authoritative violence* on the probability to migrate

	(1)	(2)	(3)
	IV Kilometers from Caracas		
Variable of interest			
Authoritative violence (%)	0.060***	0.061***	0.060***
	(0.0197)	(0.0201)	(0.0197)
Individual characteristics			
High School	0.010***	0.008***	0.010***
	(0.0034)	(0.0028)	(0.0036)
College graduated	0.022***	0.014***	0.021***
	(0.0040)	(0.0038)	(0.0041)
Age	-0.009***	-0.008***	-0.009***
	(0.0014)	(0.0013)	(0.0015)
Age Squared	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)
Female	-0.016***	-0.016***	-0.016***
	(0.0052)	(0.0049)	(0.0055)
Household characteristics			
Education of the household head	0.046***	0.042***	0.045***
	(0.0066)	(0.0062)	(0.0070)
Household size (Log)	0.017***	0.014***	0.016***
	(0.0038)	(0.0035)	(0.0042)
Regional controls			
Total violence (Log)	-0.011	-0.009	-0.011
	(0.0089)	(0.0081)	(0.0096)
Governor is an opponent of Maduro	-0.009*	-0.006	-0.009*
	(0.0046)	(0.0046)	(0.0047)
Education level (Log)	-0.056***	-0.045***	-0.055**
	(0.0208)	(0.0176)	(0.0227)
Employment	0.321***	0.359***	0.316***
	(0.1031)	(0.1026)	(0.1082)
Average income *per capita* (Log)	0.002	0.001	0.002
	(0.0053)	(0.0050)	(0.0053)
Population density (Log)	-0.005***	-0.005***	-0.003
	(0.0013)	(0.0011)	(0.0164)
Access to water	0.047***	0.041**	0.048***
	(0.0173)	(0.0161)	(0.0182)
Shortage of medicines	0.036***	0.040***	0.036***
	(0.0126)	(0.0119)	(0.0130)
Indigenous	-0.021	-0.018	-0.022
	(0.0614)	(0.0619)	(0.0614)
Rural Population	-0.012	-0.006	-0.011
	(0.0119)	(0.0114)	(0.0122)
Distance from national borders (Log)	0.001	0.000	0.001
	(0.0022)	(0.0021)	(0.0023)
Number of mines (Log)	-0.001	-0.002	-0.001
	(0.0011)	(0.0011)	(0.0011)
GNI	0.023**	0.018	0.022**
	(0.0108)	(0.0107)	(0.0105)
Observations	19,776	19,716	18,607
Capital District observations	Yes	Yes	No
Migration outside LAC	Yes	No	Yes
Households migrated	No	No	No

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance:*** $p < 0.01$,** $p < 0.05$,* $p < 0.1$.

TABLE A4: The effect of *authoritative violence* on the probability to migrate (logistic specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable of interest	Coeff.	DY/DX	Coeff.	DY/DX	Coeff.	DY/DX	Coeff.	DY/DX	Coeff.	DY/DX
Authoritative violence (%)	2.494*	0.057	1.613*	0.036	2.013***	0.045	1.838***	0.037	1.459**	0.063
	(1.3471)	(0.034)*	(0.9177)	(0.020)*	(0.6510)	(0.015)***	(0.6652)	(0.013)***	(0.7197)	(0.030)**
Individual characteristics										
High School							1.415***	0.028	0.588***	0.025
							(0.1532)	(0.004)***	(0.1584)	(0.007)***
College graduated							1.954***	0.039	1.010***	0.043
							(0.1120)	(0.003)***	(0.1515)	(0.007)***
Age							-0.163***	-0.003	-0.172***	-0.007
							(0.0511)	(0.001)***	(0.0507)	(0.002)***
Age Squared							0.001	0	0.001	0
							(0.0007)	0	(0.0007)	0
Female							-0.683***	-0.014	-0.710***	-0.03
							(0.2350)	(0.005)***	(0.2235)	(0.010)***
Household characteristics										
Educ of household head									-	0
										0
Household size (Log)									1.345***	0.058
									(0.1719)	(0.008)***
Regional controls										
Total violence (Log)	-0.032	-0.001	0.207	0.005	-0.389	-0.009	-0.222	-0.004	-0.029	-0.001
	(0.4522)	-0.01	(0.3999)	-0.009	(0.3936)	-0.009	(0.3696)	-0.007	(0.4245)	-0.018
Opponent of Maduro			0.166	0.004	-0.254	-0.006	-0.278	-0.006	-0.312*	-0.013
			(0.2549)	-0.006	(0.2188)	-0.005	(0.1889)	-0.004	(0.1705)	(0.007)*
Education level (Log)			-1.710**	-0.039	0.238	0.005	-0.919	-0.018	-1.819*	-0.078
			(0.7065)	(0.016)**	(0.9189)	-0.021	(0.7354)	-0.015	(1.0305)	(0.044)*
Employment			16.547***	0.373	13.107***	0.295	16.886***	0.339	15.623***	0.67
			(2.7407)	(0.068)***	(3.8825)	(0.089)***	(3.7077)	(0.075)***	(4.6310)	(0.198)***
Average income *pc* (Log)			0.201**	0.005	-0.359*	-0.008	-0.269	-0.005	-0.170	-0.007
			(0.0889)	(0.002)**	(0.2008)	(0.005)*	(0.1962)	-0.004	(0.2567)	-0.011
Population density (Log)					-0.208***	-0.005	-0.240***	-0.005	-0.219***	-0.009
					(0.0673)	(0.002)***	(0.0602)	(0.001)***	(0.0735)	(0.003)***
Access to running water			0.370	0.008	1.339	0.03	1.112	0.022	0.179	0.008
			(0.6282)	-0.014	(0.8422)	-0.019	(0.7407)	-0.015	(0.9208)	-0.039
Shortage of medicines			2.598***	0.059	1.639***	0.037	2.207***	0.044	2.119***	0.091
			(0.4018)	(0.009)***	(0.4686)	(0.010)***	(0.4840)	(0.009)***	(0.4671)	(0.020)***
Indigeneous					-7.922***	-0.178	-8.610***	-0.173	-11.781***	-0.505
					(2.8998)	(0.065)***	(2.9783)	(0.061)***	(3.8579)	(0.169)***
Rural Population					-0.549	-0.012	-0.342	-0.007	-0.355	-0.015
					(0.4822)	-0.011	(0.3955)	-0.008	(0.5310)	-0.023
Distance from borders (Log)					-0.256***	-0.006	-0.212**	-0.004	-0.261**	-0.011
					(0.0885)	(0.002)***	(0.0837)	(0.002)**	(0.1085)	(0.005)**
Number of mines (Log)					-0.136**	-0.003	-0.135**	-0.003	-0.118**	-0.005
					(0.0565)	(0.001)**	(0.0562)	(0.001)**	(0.0570)	(0.002)**
GNI			0.730*	0.016	1.430***	0.032	1.604***	0.032	1.591***	0.068
			(0.4295)	(0.010)*	(0.4236)	(0.010)***	(0.4515)	(0.009)***	(0.4226)	(0.019)***
R-square	0.001		0.007		0.008		0.055		0.074	
Obs	21,382		21,382		21,382		19,776		19,776	
Capital District obs	Yes		Yes		Yes		Yes		Yes	
Migration outside LAC	Yes		Yes		Yes		Yes		Yes	
Households migrated	No		No		No		No		No	

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The odd-numbered columns show the coefficients of the Logit estimate, while the even-numbered columns show the marginal effects.

TABLE A5: Falsification test: correlation between pre-militarization individual probability to migrate and distance from Caracas

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-Militarization Probability to Migrate					
Travel Time from Caracas (Log)	-0.002	-0.002	-0.002			
	(0.0019)	(0.0015)	(0.0021)			
Kilometers from Caracas (Log)				0.003	0.002	0.003
				(0.0021)	(0.0016)	(0.0021)
Age	-0.005***	-0.003***	-0.005***	-0.005***	-0.003***	-0.005***
	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)
Age Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
High School	0.013***	0.008***	0.012***	0.013***	0.008***	0.012***
	(0.0031)	(0.0018)	(0.0032)	(0.0031)	(0.0018)	(0.0032)
College Graduated	0.022***	0.010***	0.020***	0.022***	0.010***	0.020***
	(0.0043)	(0.0030)	(0.0042)	(0.0043)	(0.0030)	(0.0041)
Female	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.0014)	(0.0010)	(0.0015)	(0.0014)	(0.0009)	(0.0015)
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Capital District	Yes	Yes	No	Yes	Yes	No
Internation migration	Yes	No	Yes	Yes	No	Yes
Observations	19,959	19,818	18,770	19,959	19,818	18,770
R-squared	0.030	0.018	0.028	0.030	0.018	0.028

Notes: Robust standard errors in parentheses and they allow for Regional Level clustering. Asterisks denote statistical significance:*** $p < 0.01$,** $p < 0.05$,* $p < 0.1$. The regional controls include employment rate, educational level, Gross National Income, Shortage of Medicine, Access to water Index, dummy variable opposition to Maduro, Population density, percentage of rural population, percentage of indigenous, distance to the border, and number of mines.

Chapter 3

Violence and Electoral Outcomes

This chapter presents a study aimed at unraveling the causal relationship between terrorist violence during the so-called 'Anni di Piombo' and the declining voter turnout in Italian political elections. The analysis, which covers electoral participation at the provincial level from 1972 to 1992, relies on data from the Global Terrorism Dataset for information regarding terrorist attacks, the number of casualties, victims, and a proxy for material damages. To assess the causal effect, we adopt a methodological framework that is still relatively uncommon in regional and applied economics: the Causal Mediation Analysis (CMA). Thanks to the Front Door Criterion (FDC), we can identify the unbiased (although indirect) effect of terrorism on electoral participation as mediated by the size of the terrorist attack, proxied by the presence of deaths, wounded, and damages. The analysis considers a wide range of time-lagged terrorism-related variables, ranging from 1 to 12 quarters before each election day. The results, supported by naive estimations performed using a regression model à la Barro (1991), reveal that while terrorism, in general, has a time-decreasing effect leading up to election day, this effect is primarily driven by physical damages. In contrast with our original hypothesis, victims do not play a relevant and significant role, while the effect of terrorism mediated by the wounded shows a positive and significant effect on voter turnout in the medium-long run. Moreover, our analysis confirms the literature in terms of political party dynamics, with particular reference to the loss of consensus for the incumbent party.

3.1 Introduction

During the twenty years following the end of the Second World War, a large number of countries across the continents experienced, directly or indirectly, episodes or seasons of political violence and, more precisely, domestic and organized terrorism. From the United States to Germany, from Puerto Rico to Corsica, Spain, Ireland, and South Tyrol, such a universal phenomenon strongly impacted people's daily lives. Between the 1970s and 1980s, Italy, in particular, was plagued by a wave of political violence, commonly known as the "Years of Lead" (Anni di Piombo, in Italian), which was characterized by bombings, assassinations, and kidnappings carried out by both left-wing and right-wing extremist groups (see Figure 3.4 for a glimpse of the geographical distribution across Italian provinces). This period of political violence had a profound impact on the social, political, and economic landscape of Italy (Greenbaum et al., 2007). According to the Italian newspaper *La Repubblica*, in 1984, the majority of Italians involved in a national-level survey selected the recent wave of political terrorism as the event within the last 50 years of the country's collective experience that would have received the most attention from future historians. In the same period, Italy witnessed the first drop in voter turnout in its republican history, as shown in Figure 3.6.

European domestic terrorism has some specific characteristics, such as the rejection of negotiation, the secretive nature of the organization, selective recruitment but always among the youth, ideological justification, and theoretical and cultural background, common across the different countries. However, as noted by Galleni and Andreotti, 1981, Italian terrorism has some peculiar and distinctive characteristics. The main aim of the Red Brigades and the other - less known - terrorist groups was to hit the heart of the State: a project as ambitious as vague (Galleni and Andreotti, 1981). Italian terrorism does not seem to have a purpose outside itself. It stands at the same time as a mean and an end. For most of the period under consideration, the action of terrorist groups was mainly oriented toward spreading terror following three directions. The first was to strike random targets (human and non-human), democratizing the threat and sowing terror. The second was to strike at the uniforms and symbols of the "regime," including schools, universities, and the media. The last one was leading upward to the top of the state, to show that no one can actually claim to be safe (Galleni and Andreotti, 1981).

This paper aims to analyze, in the context of the general decline of electoral participation, the relationship between citizens' exposure to terrorist violence and their electoral behaviors across Italian provinces, considering the turnout at the political elections of 1972, 1976, 1979, 1983, and 1992[1].

The connection between political terrorism and voting participation in Italy is intricate and multifaceted. For this reason, we tackle the identification issues by drawing on the Causal Mediation Analysis framework (hereafter, CMA. See Celli, 2022; VanderWeele, 2016; VanderWeele, 2015; Powell, 2008; Pearl, 2009). Specifically, to isolate our causal effect of interest, we apply the so-called Front Door Criterion (hereafter, FDC) technique (Fulcher et al., 2020; Bellemare et al., 2019) to estimate the impact of terrorist incidents on voter turnout through the effect of the deaths, the wounded and the damages of the terrorism itself, here considered as the mediators. Our premise is that, while terrorism can in general increase concern with the political environment and increase the salience of upcoming elections (Robbins et al., 2013), the local exposure to different *consequences* of violence, can re-shape this relationship. In line with this, our preliminary results suggest that, while terrorist violence has a time-decreasing positive effect on voter turnout, this effect seems to be led mainly by physical damages.

[1]Between 1976 and 1979 Italy experienced the first substantial drop in the electoral participation of its republican history. despite the modesty of the aggregated loss of voters, the change of pattern has been considered noteworthy and permanent (Cerruto, 2012). See Figure 3.6 for trend comparison.

The presence of causalities shows mostly a negative sign, while the presence of wounded tends to show significant and positive coefficients in the medium-long term

Our main theoretical assumption is that a given terrorist incident *per se* has no meaning if one does not consider its objective, timing, and magnitude. Especially when it comes to analyzing individuals' behaviors, perception plays a key role[2]. As found by Frey et al., 2007, terrorism generates both a direct and an indirect negative influence on the utility of individuals. While the direct effects of terrorist attacks refer to the destruction of physical and human capital, the indirect ones are more subtle and challenging to evaluate. However, as pointed out by Sanso-Navarro et al., 2019, those indirect consequences are more relevant as they are related to the atmosphere of uncertainty, stress, and risk which, in the end, modifies the behavior of the agent [3]. It is important to note from the beginning that CMA can only establish that there is a causal link between a mediator and the outcome, not that the mediator is the only cause of the outcome. Our hypothesis is then two-fold. On the one hand, we believe that terrorism has discouraged electoral participation through fear. At the same time, the outbreak of this phenomenon intersected with a context of political polarization, whereby if one was disappointed with one's own party, one would give up voting, or vote for an extremist party, rather than vote for the opponent. Indeed, the political situation in Italy during this period was marked by deep divisions and polarization, both within society and among the political parties. The main political parties during this period were the Christian Democracy (DC) and

[2]Here, perception is understood as the process of *socio-psycho-biological* mediation through which each individual 'reads', or decodes the stimuli around him/her.

[3]In this line, Becker, Rubinstein, et al., 2004 introduced the *fear hypothesis* according to which the intense and prolonged exposition to more or less imaginary fright changes the psychology of individuals and, therefore, might substantially modify their choices. These authors developed a theoretical framework where economic agents have incentives to invest in controlling their fears until they reach an optimal level, which is different for each person and depends on their cognitive abilities. Moreover, the model establishes that the tendency to overreact to terror is inversely related to the educational level of the agents and directly correlated to the strength of media coverage of terrorism (see Sanso-Navarro et al., 2019)

the Italian Communist Party (PCI). The DC, which had dominated Italian politics since the end of World War II, was a center-right party that represented the interests of the Catholic Church and the business elite. The PCI, on the other hand, was a left-wing party that represented the interests of the working class. The polarization of the electorate during this period was also reflected in the rise of new political parties and movements, such as - respectively - the right-wing Movimento Sociale Italiano (MSI) and the left-wing movement *Lotta Continua*. These new movements and parties attracted a growing number of supporters, particularly among the younger generation, and contributed to the polarization of the political landscape[4].

The chapter is organized as follows. After a review of the literature (3.1.1), we will present our main set of data and the *naive* estimation model. Section 3.2.3 includes a detailed presentation of the identification strategy based on the implementation of the Causal Mediation Analysis framework in Section 3.2. Finally, in Section 3.3, will be presented the main results divided according to the different estimation processes and discussed final considerations.

3.1.1 Background Literature

As noted by Robbins et al., 2013, work on voter turnout has focused on a myriad of causal mechanisms including political culture, economics, and political institutions (Almond and Verba, 1963; Jackman, 1987; Jackman and Miller, 1995; Pacek et al., 2009; Pacek and Radcliff, 1995; Powell, 1986).

[4]At the local level, the electoral preferences were heavily influenced by regional and cultural factors. For example, in the North of Italy, particularly in the industrial cities, the PCI had a strong support base, while in the South, the support for the Christian Democracy was strong. Additionally, in the rural areas, the support for Christian Democracy was strong due to the party's traditional roots in these areas. In general, our understanding is that the terrorist violence led to a decrease in support for the traditional political parties, particularly the Christian Democracy and the Italian Communist Party, as the voters may have been disillusioned with the traditional political system and the inability of the traditional parties to address the problem of political violence.

However, while empirical evidence for these claims remains quite convincing, violence still remains an unexplored contextual variable for understanding the various forms and aspects of political behavior, and studies on turnout have generally overlooked terrorism despite the increased attention terrorism research has received lately. This is even more surprising because, from the perspective of political sciences, there is a wealth of evidence suggesting that violent political conflict can have a significant impact on public opinion (such as rally-around-the-flag effects Robbins et al., 2013. On the other hand, from a more applied perspective, even less attention is given to the impact of violence (particularly regarding the victimization process) on participation (see, among others, Bateson, 2012 and Pazzona, 2020).

However, the literature is still inconclusive in identifying the impact of fear and exceptional events on people's electoral choices[5]. While the theoretical framework linking fear and terrorism to voting behavior is relatively straightforward, empirical results are contradictory. There are two broad sources of disagreement in the current literature. First, there is evidence that incumbents lose electoral support following attacks and casualties (Gassebner et al., 2008; Aldrich et al., 2006; Karol and Miguel, 2007). However, Berrebi and Klor, 2008 and Koch and Tkach, 2012 find that in Israel incumbents do not seem to be blamed and, consequently, punished at the ballot box as a consequence of suicide attacks. Second, while there is some evidence that right-wing parties increase their vote shares after terrorist events (Berrebi and Klor, 2008; Kibris, 2011; Koch and Tkach, 2012; Abramson et al., 2007), other studies show that terrorism may also shift the entire political spectrum to the left, as was the case of the 2004 train bombings in Madrid (Montalvo, 2011; Gould and Klor, 2010; Bali, 2007). In addition, while Bellows and Miguel, 2009 found that being exposed to war increases the willingness to vote, through the analysis of the civil conflict

[5]This applies also for the research investigating the impact of natural disaster (Gasper and Reeves, 2011; Heersink et al., 2017; Ramos and Sanz, 2020; Masiero and Santarossa, 2021) or pandemic (Fernandez-Navia et al., 2021; Beall et al., 2016; Campante et al., 2020; Bisbee and Honig, 2020) and electoral behaviors.

in Sierra Leone (1991-2002), Kibris, 2011 finds that exposure to PKK terrorism in Turkey increases turnout and the vote share for right-wing parties (tougher against the PKK cause), Gardeazabal, 2010, Montalvo, 2011, and Gassebner et al., 2008, focusing on the case of Spain, found a significant role of terrorist violence on vote shares and that terrorism increases the turnout; Gallego, 2018 finds that *guerrilla* violence in Colombia reduces turnout. According to their analysis, paramilitary violence does not affect participation, while benefits non-traditional third parties at the ballot box.

These conflicting findings, as noted by Baccini et al., 2021, are possibly (also) a product of the difficulties in assessing the effect of terrorism on electoral outcomes due to selection bias[6]. Arguably, terrorists are likely to choose the targets and the timing of their attacks strategically targeting populations that are more likely to respond in the desired manner, either by voting for right-wing parties (if the terrorists' goal is to 'spoil' talks or facilitate recruitment) or for left-wing parties (if the goal is to extract concessions). In short, there is a concrete risk of overestimating the impact of terrorism on voting behavior. Furthermore, in light of this, it is also difficult to find an appropriate empirical strategy for the identification.

However, the analysis of the adverse effects of terrorist violence on political trust and attitudes as well as on individual behavior (Birkelund et al., 2019; Bove et al., 2021) may represent a renovated stimulus amidst the recent partial stagnation of the field of study and research on terrorism in general (see Schuurman, 2020 for a comprehensive review). Furthermore, besides the not-unanimous findings offered by the related literature and the different empirical approaches, what emerges from the review of the related literature is the absence of a direct-specific focus on the phenomenon of electoral participation.

[6]Indeed, while terrorist attacks may not adhere to a pattern of complete randomness, certain research efforts, such as the work of Abadie (Abadie and Gardeazabal, 2003), skillfully utilize a donor pool of similar regions to construct a counterfactual, offering a nuanced approach to understanding the economic impact of these events.

3.2 Empirical Approach

3.2.1 Main Data

We base our analysis on a panel of provinces. This panel includes provinces that both experienced and did not experience terrorist attacks (see Table B1 for the list of provinces), spanning the years 1970 to 1992. Our dependent variable is the variation in electoral participation at the NUTS-3 level. Following the methodology of Greenbaum et al., 2007, we calculate the percentage change in the share of voters (defined as the percentage of actual voters out of the eligible ones) from one election to the following one. By using percentage change, we achieve two main objectives: firstly, we mitigate any disproportionate influence from more populous provinces; and secondly, we more accurately capture variations within the broader declining trend of electoral participation in Italy. The data regarding electoral outcomes are derived from Openpolis' analysis of information supplied by the Italian Ministry of Interior. We focus solely on the lower chamber, *Camera dei Deputati*. This emphasis might seem unbalanced given that both the Chamber of Deputies and the Senate have equivalent powers within a bicameral system. However, a reason for our approach lies in the distinction between their respective electoral bases. The Chamber of Deputies draws its mandate from a broader segment of the population, specifically those aged 18 and above. This is in contrast to the Senate, which has a different age threshold for its electorate. Consequently, the wider representational scope of the Chamber of Deputies could make it a more pertinent subject of focus, as it encapsulates a larger portion of the citizenry. Second, the electoral districts related to the Senate elections, are different and broader (Faggian et al., 2021). The elections under consideration took place in 1972, 1976, 1979, 1983, 1987, and 1992.

The primary variable of interest in our study, the level of terrorist violence, is derived from the open-source Global Terrorism Database (GTD). For our study's objectives, we adopt the terrorism definition underpinning the database:

> *"The threatened or actual use of illegal force or violence to attain a political, economic, religious, or social goal through fear, coercion, or intimidation."* (LaFree and Dugan, 2002)

The majority of the data in the GTD was initially gathered by the Pinkerton Global Intelligence Service (PGIS) using comprehensive reports of both international and domestic terrorist events spanning 1970 to 1997[7].Compared to other open-source terrorist incident databases, the GTD covers a wider range of incidents over an extended time frame. Notably, while many publicly accessible terrorism databases primarily focus on international attacks, domestic terrorism significantly surpasses international terrorism incidents (Greenbaum et al., 2007)[8].

Another advantage of the GTD is related to its very origin. Being collated by a private company, it encountered fewer political pressures than those databases overseen by political entities[9].

[7]During this period, PGIS-trained researchers logged all identifiable terrorism incidents sourced from wire services (such as Reuters and the Foreign Broadcast Information Service), US State Department reports, other US and foreign government reports, and US and foreign newspapers (including outlets like the New York Times, The Financial Times, the Christian Science Monitor, the Washington Post, the Washington Times, and the Wall Street Journal). PGIS offices globally supplied the information, occasionally supplemented by inputs from organized political opposition groups, PGIS clients, and other individuals both in official and private roles (LaFree and Dugan, 2002).

[8]Schmid, Jongman, et al. (1988) contend that the omission of domestic terrorism data in many open-source databases has severely hindered terrorism research. Falkenrath (2001) suggests that the primary reason for excluding domestic terrorism from these databases is the bureaucratic distinction governments traditionally make between domestic and international responsibilities (e.g., the US Justice Department versus the US State Department). This artificial separation between domestic and international terrorist events hampers a comprehensive understanding of terrorism and the continuity of terrorist activities. Unlike many databases, the GTD encompasses both international and domestic incidents, making it approximately seven times larger than any other existing open-source database.

[9]As pointed out by Greenbaum et al., 2007, the US State Department often overlooked terrorist attacks by the right-wing *Contras* in Nicaragua during the 1980s. Conversely, following the 1972 Munich Olympics massacre, in which 11 Israeli athletes were killed, representatives from a coalition of Arab, African, and Asian nations successfully thwarted the United Nations' actions by arguing that "*People who struggle to liberate themselves from foreign oppression and exploitation have the right to use all methods at their disposal, including force*"

While the GTD is a valuable resource, it's not without its limitations, many of which are inherent to other open-source terrorism databases and, more broadly, to data derived from secondary media sources. The GTD data collection aligns with the military definition of terrorism, which is among the broadest definitions employed in open-source database creation. Several challenges with the GTD are also prevalent in other media-sourced databases. These encompass potential media inaccuracies, misinformation, contradictory claims, instances with either multiple or no claims of responsibility for incidents, governmental censorship or disinformation campaigns, and 'false flag' events (where a group either wrongly claims or doesn't claim responsibility for an act). However, it's crucial to highlight that many of these overarching issues, such as conflicting claims and false flags, are less likely to skew our analysis. Our focus is on the frequency of incidents in each province without delving into the specifics of which group claimed responsibility[10]. In a broader sense, despite its constraints, the GTD employs one of the most comprehensive definitions of terrorism among available open-source databases and is frequently referenced in academic literature (see, among the others, Greenbaum et al., 2007; Peri et al., 2020).

3.2.2 Control Variables and *Naive* Estimation

Aware of the limitations due to the lack of data, we compute a *naive* estimation adopting a regression model drawing on Barro (1991) represented[11]. The model, in its general form, is represented by Equation 3.1.

(Hoffman 1998, p. 31). These political considerations partially explain why the United Nations has yet to establish a universally accepted terrorism definition.

[10] To provide context, during the peak of the Italian terrorist activity, discerning the actual group or faction responsible for an attack was often challenging (Galleni and Andreotti, 1981). This ambiguity arose primarily from two factors: the limited and often inadequate investigative resources available, and the occasional strategic intent of the attack's orchestrators to mislead the public into believing that the perpetrator was from an opposing political faction.

[11] In this sense, we acknowledge that we are not able, in particular, due to the historical nature of our inquiry, to provide the full set of covariates needed to perform a standard - and identified - estimation.

$$\Delta P_{jt} = \alpha_i + \beta_t + \gamma_1 \, Ter_{j(t;t-k)} + \gamma_2 \, P_{j(t-1)} + \gamma_3' \, W_{jt} + V_{jt} \tag{3.1}$$

As briefly mentioned before, P_{jt} represented the electoral participation, and it is calculated by the percentage of all the votes including the non-valid and the blank ballots over the number of eligible voters. $\Delta P_{jt} = P_{jt} - P_{jt-1}$, where 1 indicates one electoral round, represents the variation of the electoral participation in province j at time t. P_{jt-1} is the term included to control for convergences. α_j and β_t represent respectively province and year-fixed effects to account for differences across provinces and over time. Being k the number of quarters before the election day, $Ter_{j(t;t-k)}$ represents the number of terrorist incidents per 100,000 inhabitants in province j during the time frame from t to $t-k$. The value of k ranges from 1 to 12, because 12 quarters is the minimum distance between the considered electoral rounds. $W_{j(t-1)}$ is a vector including the largest set of provincial-level confounding factors we have been able to put in place. In particular, we account for the total population, the gross added value per capita, and the rate of enrollment in universities. In addition, we include the rate of *property crime*, which refers to a category of crimes that involve the theft or damage to someone's personal property. This includes offenses such as theft, aggravated theft, robbery, extortion, and the like[12]. Finally, in order to take into account the Italian political and party landscape, we include in the estimation the *Pluralism Index*[13]. As highlighted in Section 3.1, it is essential to recognize that the political landscape in Italy during the period under consideration was characterized by profound societal divisions and intense polarization, not only within the broader society but also among the various political parties. In light of this complex and dynamic environment, we developed the PI, crafting it to address the crucial aspect of voter elasticity

[12]These data have been collected, harmonized, and digitized through archival research at the ISTAT Central Library in Rome (IT). This novel dataset also includes violent crimes, which are excluded from this analysis to avoid potential clashes with the measure of terrorism.

[13]This index, is calculated to an adaptation of the Herfindahl-Hirschman index (see Rhoades, 1993), and account for the 'dispersion' of votes among the political parties.

and its role in explaining the fluctuations in electoral participation. Specifically, the PI serves as a measurement tool capable of capturing the dispersion of votes among the diverse political parties vying for support during this tumultuous period. A higher PI value indicates a greater level of pluralism, meaning that the votes are more evenly distributed among multiple parties. Conversely, a lower pluralism index value suggests a lower level of pluralism, with votes concentrated among fewer parties. Figures 3.22 - 3.28 show the evolution of PI with respect to the voter turnout across the period considered[14]. In the estimation, which results are summarized in Tables 3.1, all these variables have been lagged by one year to address potential endogeneity concerns.

In consistency with the literature, and with our assumptions related to the importance of the political parties, we analyze the dynamics related to the trend related to the consensus for the main ones. In particular, as shown in Eq. 3.2, we run our regression model to assess the relationship between terrorism and the votes gathered by *Democrazia Cristiana* (DC), *Partito Comunista Italiano* (PCI), and *Movimento Sociale Italiano* (MSI). As already mentioned, these parties represent respectively the party of government, the main (left-wing) opposition, and the largest right-wing parties. Results are summarized in Tables 3.2 -3.4.

$$\Delta P_{jt} \in \{\Delta\, DC_{jt}, \Delta\, PCI_{jt}, \Delta\, MSI_{jt}\} \tag{3.2}$$

Notwithstanding the aforementioned set of controls included in our model, we are not able to exclude the bias coming from the presence of other (observable and non-observable) confounding factors, affecting both the distribution of terrorism and the trend of electoral participation.

According to our hypothesis, a terrorist attack does not have meaning *per se* in terms of perception if one does not consider its timing and the magnitude of its consequences. Therefore, to discern the distinct impact of the attacks,

[14]In Figures 3.15 - 3.21, is represented the PI against the terrorist attacks.

we separate out the number of casualties, wounded individuals, and physical damages. Also in this case, we adapted the variables to capture their time-varying effects, organizing them into quarters (3-month periods, see Figure 3.7) leading up to election day. Arguably, these three elements represent the most immediate and *direct* consequences of terrorism and might play a key role in explaining the real dynamics in terms of impact assessment, as already mentioned in some related research such as, among the others, Gassebner et al. (2008), Brownlow (2012), and Besley and Mueller (2012). The transition from theory to practice hinges on the accessibility of data concerning fatalities, injuries, and physical damages. This data is crucial for implementing the Front Door Criterion as an identification strategy, as elaborated in the following section.

3.2.3 Identification Strategy

The main aim of our empirical approach is to infer the causal relationship between the *treatment* variable (i.e. terrorism) and the *outcome* variable (i.e. electoral participation). However, standard methods for inference about direct and indirect effects require stringent no-unmeasured-confounding assumptions which often fail to hold in practice, particularly in observational studies (Fulcher et al., 2020). Over the last couple of decades, social scientists have given greater attention to methodological issues related to causation. As Imai et al. (2013) pointed out, this trend has led to a growing number of laboratory, field, and survey experiments, as well as increased use of natural experiments, instrumental variables, and quasi-randomized studies. However, many of these empirical studies focus on merely establishing whether one variable affects another and fail to explain how such a causal relationship arises. Following Imai et al. (2013), if we define a causal mechanism as a process in which a causal variable of interest, i.e., a treatment variable, influences an outcome, the identification of a causal mechanism requires the specification of an intermediate variable or a mediator that lies on the causal pathway between the treatment and outcome variables. This approach is known as Causal Mediation Analysis. The traditional approach to CMA has been to use structural equation models - SEMs (e.g., Fairchild and MacKinnon, 2009; MacKinnon and Luecken, 2008). Such traditional approaches rely upon non-testable assumptions and are often inappropriate even under those assumptions (Imai et al., 2013). In particular, contrary to the commonly held belief, conventional exogeneity assumptions alone are insufficient for the identification of causal mechanisms[15].

CMA is an approach that focuses on the study of causal mechanisms and seeks to disentangle a total treatment effect into an indirect effect operating through one or several mediators; as well as the direct effect. As explained by Celli (2022), the main fields in which mediation has been developed are psychology and sociology. For instance, Brader et al. (2008) go beyond the standard causal analysis in estimating the framing effects of ethnicity-based media cues on immigration preferences. Instead of simply asking whether media cues influence opinion, they explore the mechanisms through which this effect operates. Consistent with the earlier work that suggests the emotional power of group-based politics (Kinder and Sanders, 1996), the authors find that the influence of group-based media cues arises through changing individual levels of anxiety. Another example can be borrowed from the literature on electoral politics. Gelman and King (1990) found the existence of a positive incumbency advantage in elections. A few years later, in 1996, Cox and Katz (1996) led the incumbency advantage literature in a new direction by considering possible causal mechanisms that explain why incumbents have an electoral advantage. They decomposed the incumbency advantage into a “scare off/quality effect” and effects due to other causal mechanisms such as name recognition and resource advantage (Celli, 2022).

In order to design our CMA setting, we build our theoretical framework

[15]The reader can refer to the work of Imai et al., 2013, and to the several pieces of research on causal inference, such as Imai et al., 2013, Pearl, 2001, Petersen et al., 2006, Robins et al., 2003, Bullock et al., 2010, Glynn and Quinn, 2011.

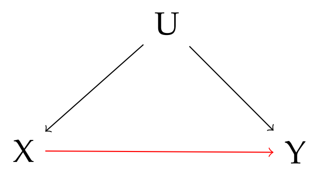


FIGURE 3.1: Basic DAG

Note to Figure 3.1: the DAG represents the causal direct effect of the independent variable X on the dependent variable Y, and the confounding effects of unobservable variables U affecting both X and Y.

by the use of Directed Acyclic Graphs (DAG)[16]. DAGs are a subgroup of graphs with directed edges, and without cyclic paths, depicting the data-generating process, neatly capturing researchers' assumptions in a path diagram[17]. DAGs can be considered as the graphical representations of *structural causal models* (SCMs): each node in the graph corresponds to a variable in the SCM (Pearl, 2009), with the edges between the nodes representing the relationship between the variables. As Pearl (2009) clearly explained, DAGs are fully derivable from SEMs: deleting an equation from SEM corresponds to deleting an arrow from a DAG.

We can now consider the DAG represented in Figure 3.1 as a basic causal setting and a simplified version of the one just mentioned above, outlying the relationship between a *treatment* and *outcome* variables, and the role of the confounding factors affecting both of them.

In the impossibility of controlling for the whole set of variables that may induce a confounding effect, the mediation analysis framework offers the possibility of identifying an alternative *path*, or way of estimation. As Baron

[16]The use of DAGs has become popular in the social and health sciences, to explain and resolve complicated problems of causal inference in a rigorous, yet accessible manner. For more, see Cinelli et al., 2020.

[17]As Scott Cunningham put it, "DAG is supposed to be a theoretical representation of the state-of-the-art knowledge about the phenomena you're studying. It's what an expert would say is the thing itself, and that expertise comes from a variety of sources. Examples include economic theory, other scientific models, conversations with experts, your own observations and experiences, literature reviews, as well as your own intuition and hypotheses" (Cunningham, 2021).

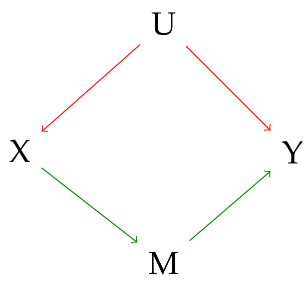


FIGURE 3.2: Mediation DAG

Note to Figure 3.2: the DAG represents the direct effect of X on Y as the sum of two indirect ones: the effect of X on M and the effect of M on Y.

and Kenny, 1986 put it, mediation represents the generative mechanism through which the focal independent variable (treatment) is able to influence the dependent variable of interest (outcome). Mediators, as explained by Cinelli et al., 2020, are patterns of the form $X \rightarrow M \rightarrow Y$. This means that X causally affects Y through the mediator M. Figure 3.2, which represents the theoretical (basic) framework of our analysis, represents the existence of a mediated effect of the treatment on the outcome. This DAG can be described by the following equations.

$$Y = \lambda + \delta M + \tau U + V_Y \tag{3.3}$$

$$M = \kappa + \gamma X + V_M \tag{3.4}$$

$$X = \omega + \theta U + V_X \tag{3.5}$$

To demonstrate the issues related to the full estimation of the system, we M in Equation 3.3 with the expression given in Equation 3.4. We obtain Equation 6, which represents the estimation of the total effect of X on Y.

$$\begin{aligned} Y &= \lambda + \delta(\kappa + \gamma X + V_M) + \tau U + V_Y & (3.6)\\ &= (\lambda + \delta\kappa) + \delta\gamma X + (\delta V_M + \tau U + V_Y) & (3.7)\\ &= \alpha + \beta X + \epsilon & (3.8) \end{aligned}$$

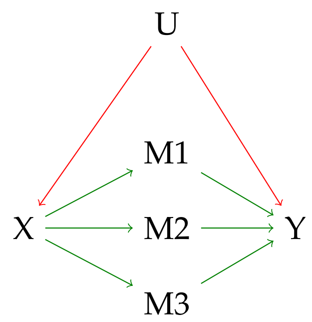


FIGURE 3.3: Mediation DAG with Multiple Mediators

Note to Figure 3.3: The DAG represents the direct effect of X on Y as the sum of multiple indirect paths through $M1$, $M2$, and $M3$.

As already briefly mentioned, however, it is not possible to estimate the direct effect of X on Y. In fact, X and ϵ are correlated because they both linearly depend on U. To partially solve the issue, we then applied the Front Door Criterion (Fulcher et al., 2020; Bellemare et al., 2019) technique. The FDC procedure allows us to overcome this limitation by simultaneously estimating two partial effects: the effect of X on M, and the effect of M on Y after controlling for X. In this case, both effects can be consistently estimated because nothing confounds the effect of X on M, and X blocks the only back-door path between M and Y. The indirect effect (i.e. the effect of X on Y through M) is the result of the multiplication of the coefficients δ and γ, respectively in Equation 3.3 and Equation 3.4 (see Pearl, 2009).

As already briefly mentioned, the key assumption behind applying the FDC is that the mediators, just block all the pathways between the treatment and the outcome. For this reason, our empirical setting is based on the use of three mediators: the victims, the wounded, and the physical damages caused by terrorism. The general DAG representing such a setting is shown in Figure 3.3. The analysis has been performed drawing on

Preacher and Hayes (2008) [18]. Following the same strategy, we run the analysis considering the share of votes for the main political parties instead of the total voter turnout. The results are presented in Section 3.3.

3.3 Results and Discussion

3.3.1 *Naive* Estimation Results

In Table 3.1 are summarized the results of the regression model. As anticipated, the variable *terrorism* is lagged over twelve quarters. The coefficient is always positive. However, it is significant until the 5th quarter before the election day, suggesting a time-decreasing pattern. It is also interesting to notice the behavior of the control variables, overall aligned with the literature on electoral participation. In particular, the added value is positive and significant. It seems also worth analyzing the negative and significant value of the Pluralism Index. Slightly different results emerge from the analysis of the share of votes for the main parties. Tables 3.2, 3.3, and 3.4 show the estimates regarding the DC, PCI, and MSI respectively. Consistent with the literature highlighting the mechanisms of the electorate punishing the incumbent party, *terrorism* shows a negative relationship with the preferences for the DC. Also, in this case, the effect is time decreasing. Similarly, with respect to the PCI, the coefficient is significant only in the short term, but in this case, is positive. It seems also interesting to notice how, regarding the votes for PCI, the Pluralism Index is not significant. Finally, with respect to MSI, there is no significant correlation with exposure to terrorism violence. However, it seems to benefit from increased pluralism.

[18] We use STATA *sureg* command (sureg — Zellner's seemingly unrelated regression | https://www.stata.com/manuals/rsureg.pdf), adapting it to the inclusion of three mediators, starting from what is shown by *UCLA: Statistical Consulting Group* (2023)

3.3.2 CMA Results

Figures 3.9a, 3.9b, 3.9c, and 3.9d present the results of the FDC. The time span examined ranges from one quarter up to 12 quarters prior to the election day. These estimates reveal varying patterns of impact on voter turnout. Specifically, it appears that the ATE of terrorist attacks, which diminishes over time, is predominantly influenced by the presence of physical damages. Conversely, as observed in Figures 3.9a and 3.9b, while the presence of casualties primarily exhibits a negative and statistically non-significant effect, the coefficients pertaining to the number of wounded demonstrate a significant positive impact in the medium to long term. The confidence intervals shown in the plots reflect the bias-corrected and accelerated confidence intervals which are reported in Table B2.

As already mentioned, given the characteristics of the Italian political landscape in the period considered, we run the same analysis to check the impact of violence on the change in the share of votes collected by the main political, with the aim of providing a clearer understanding of the electoral dynamics. Figures 3.10a, 3.10b, 3.10c, and 3.10d include the coefficients and their significance levels concerning the influence of various factors on the variation in vote shares for the incumbent party, *Democrazia Cristiana*. Echoing findings from key contributions in the literature (as explained in Section 3.1.1, the incumbent party appears to face electoral backlash. Notably, the primary driver of this effect seems to be the presence of physical damage. In Table B2 are presented the coefficients of the estimation. Conversely, the dynamics appear different for the primary opposition party, the *Partito Comunista Italiano* (PCI). As indicated in Figures 3.11a, 3.11b, 3.11c, and 3.11d, the vote share for PCI seems to rise, likely capitalizing on the situation. In Table B2 are presented the coefficients of the estimation. In every instance, physical damages emerge as the predominant mediating variable influencing the impact of terrorism. Moreover, the effect is more pronounced closer to the election day and diminishes as we move further away from it, considering the trimesters leading up to the election. It's also worth noticing that, overall, no significant trends or patterns emerge concerning the vote share of the extreme right party, *Movimento Sociale Italiano*. As depicted in Figures 3.12a, 3.12b, 3.12c, and 3.12d, the party's vote share appears not to be influenced by terrorist wave, and in general remain consistent throughout the entire period under study (refer to Figure 3.6 for detailed trends). In Table B2 are presented the coefficients of the estimation.

Despite the consistency of the results and the correct implementation of the FDC, however, this approach still presents some limitations. In particular, our analysis might suffer from what in the literature is called post-treatment bias, or post-treatment confounders issue (Celli, 2022). This basically can be originated by the impossibility of measure/control for potential confounding factors that might affect the second part of the mediated relationship $X \rightarrow M_n \rightarrow Y$. In our case, this bias might be related to the impossibility of distinguishing between the type of deaths (nor claiming that, in terms of perception, all deaths 'equals'), the severity of the injuries or accounting for non-physical damages, the specific type of structure, or whether it has been affected a public/private asset.

3.3.3 Robustness Checks

In our analysis, we consider the terrorist events recorded within three years of each election day. However, not all the elections were held every three years; sometimes they occurred every four years, and sometimes every five years. To address the irregularities in the election schedule, we conduct FDC estimations using electoral participation as the dependent variable, weighted by the number of years between consecutive electoral rounds. The results are summarized in Figures 3.14a, 3.14b, 3.14c, and 3.14d. The magnitude and the direction of the results are perfectly comparable with the ones obtained from the main estimation.

Another relevant concern pertains to the potential *spillover* effect of terrorism. Given that our geographical unit of analysis is the province (NUTS-3 level), especially within the Italian context, it's challenging to assume that events in one province remain contained within its borders. To partially address this, we constructed a new set of variables for terrorism, deaths, wounded, and damages. Each of these variables accounts for events in province i as well as events in neighboring provinces. We then conducted our estimations to examine the impact of this new set of explanatory variables on voter turnout in province i. Figures 3.13a, 3.13b, 3.13c, and 3.13d display the respective coefficients (with precise coefficients and confidence intervals detailed in Table B4). Even including spatial spillover, the trends and the magnitude of the effects align closely with our earlier estimations (see Table B5 for the results of the naive estimation).

3.4 Conclusions

In this paper, we have attempted to disentangle the nuanced causal relationship between terrorist violence during the 'Anni di Piombo' and the contextual decline in voter turnout in Italian political elections. Utilizing the FDC, we have identified the unbiased, albeit indirect, effect of terrorism on electoral participation, which is mediated by the magnitude of the terrorist attack, approximated by the occurrence of deaths, injuries, and damages. We have considered a broad spectrum of time-lagged terrorism-related variables, spanning from 1 to 12 quarters preceding each election day, to account for the time-varying effect.

Our analysis suggests that in a context of declining electoral participation and growing public disaffection with political dynamics (Cerruto, 2012), higher levels of terrorism increase the salience of the upcoming electoral round (Peri et al., 2020). Simultaneously, our estimates indicate that the incumbent party is negatively impacted by terrorist violence. These findings, while specific to a particular phenomenon and context, align with the conclusions of the work by Gardeazabal (2010) and Montalvo (2011), which focused on the analysis of post-regime electoral dynamics in Spain, as well as with the findings of Kibris (2011) in his analysis of the Turkish context.

In general, we observe that the ATE is mainly driven by the presence of physical damages, while the presence of casualties does not seem to have any effect on voter turnout, nor on political party dynamics. On the other hand, it is worth highlighting the trends of the coefficients associated with the effect of terrorism mediated through the presence of *wounded* (i.e. survived, victims), which tends to gain positive significance in the medium-long run. Such evidence would align with the well-established sociological and criminological literature on victimization and the post-victimization dynamics, as well as a more recent and more applied line of research according to which *victims* tend to be - overall - more civically engaged and to participate more (Bateson, 2012; Pazzona, 2020; Vargas et al., 2023).

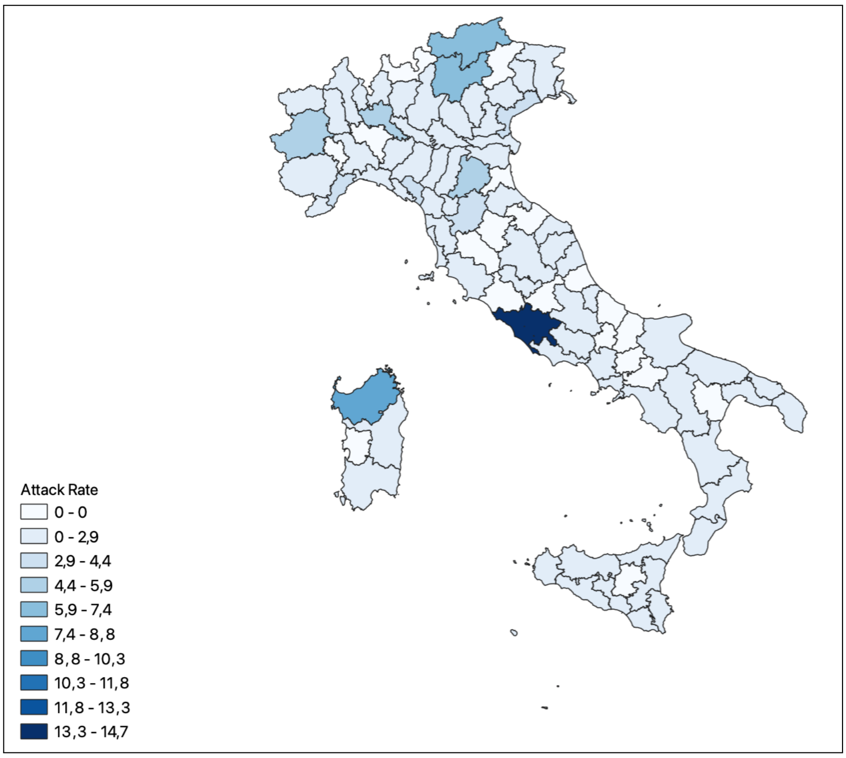
Another circumstance that might be worth discussing, in conclusion, is that as shown in Figure 3.7, the picks of terrorist violence are further from the day of the election. At first, this might seem puzzling. Nevertheless, it aligns with the prevailing theoretical framework characterizing Italian terrorism, which has been generally attributed to having limited strategic capabilities (Galleni and Andreotti, 1981). Within this context, it is conceivable that the primary objectives of the terrorist groups active during the period we examine may not have been focused on influencing the electoral outcome. As previously noted, the political landscape of the time was primarily characterized by a bipolar party system, with Christian Democracy in a dominant position. Furthermore, in the case where a majority of these attacks were attributed to leftist groups like the Red Brigades (*Brigate Rosse*, in Italian), it becomes challenging to argue that their intentions were geared towards propelling the communist party to power. This is because the communist party itself was actively opposed to terrorism and consistently condemned their actions.

In conclusion, our paper makes a significant contribution to two key areas of inquiry. Firstly, it enriches the discourse on the intricate interplay between violence, particularly violent shocks, and electoral behavior. This exploration sheds light on the ways in which external factors, such as acts of terrorism, can influence the political choices made by individuals, thereby broadening our understanding of the dynamics that underpin democratic processes. By digging into the relationship between terrorist violence and electoral participation, we are also contributing to the scarce academic production on the history of electoral dynamics in Italy. On the other hand, our study addresses a notable gap in the existing literature, one that has yet to comprehensively cover various facets of a complex and multifaceted period in Italian history. This gap, especially from a quantitative perspective, has left several aspects unexplored. Our research endeavors to bridge this void by providing a detailed analysis that not only adds to the empirical body of knowledge but also offers fresh insights into the historical context. By examining this period quantitatively, we aim to offer a more comprehensive understanding of the historical and political landscape of Italy during this time, setting the stage for further research and discussion on this fascinating and pivotal period.

We acknowledge that the method we apply is still little used within the fields of applied economics and regional sciences. In fact, apart from isolated methodological discussions, few empirical applications, and the occasional treatment in textbooks, there has been virtually no reception of the rich DAG literature in economics. As noted by Barop, 2022, this is likely at the same time one of the main reasons inhibiting a more widespread application of DAGs. According to Imbens, indeed, "credible applications are what drives the adoption of new methodologies on economics" (Imbens, 2020, p.1172). Quoting again Johanna Barop, when we reject "new approaches in favor of old ones because we feel that the old ones 'fit better' we need to be careful to not simply reject the new approach because it differs from the old one" (Barop, 2022, p.38).

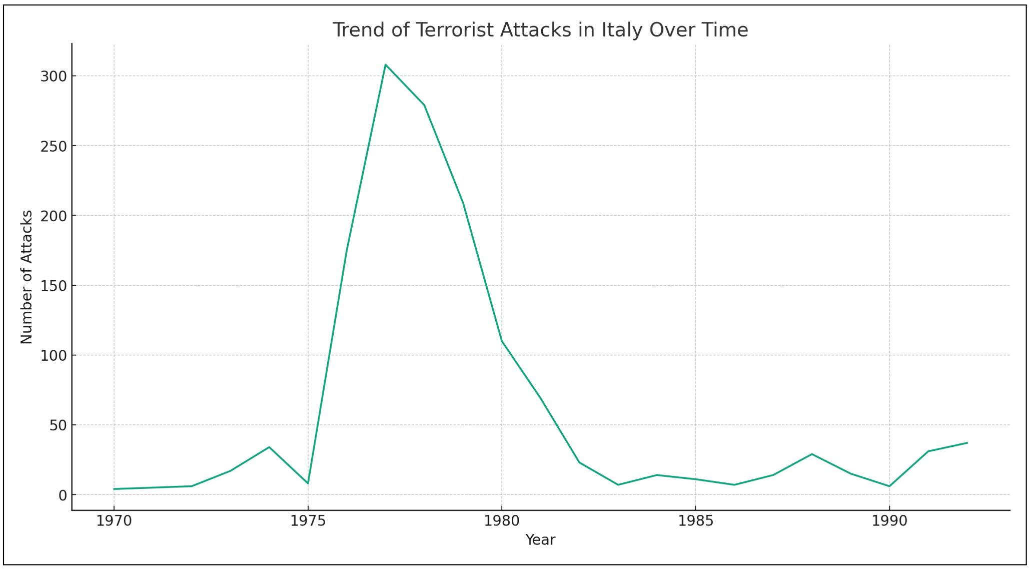
3.5 Figures and Tables

FIGURE 3.4: *Terrorist Attacks Across Italian Provinces (1970-1992)*



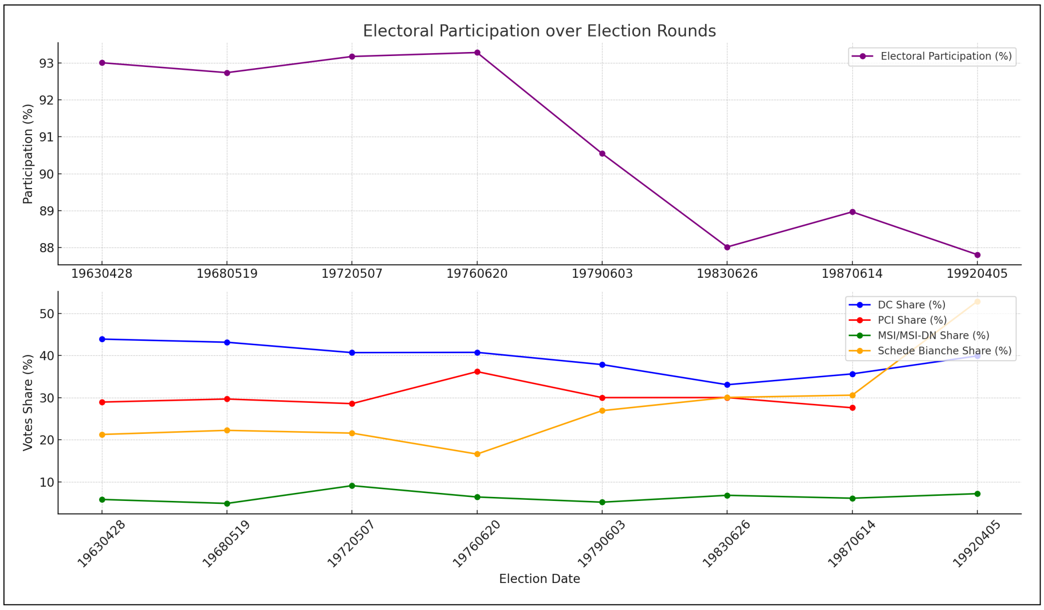
Note: The map shows the aggregate concentration of terrorist attacks from 1970 to 1992 across the Italian Provinces. The attack rate represents the number of attacks per 100,000 inhabitants.

FIGURE 3.5: *Terrorist Attacks Over Time (1970-1992)*



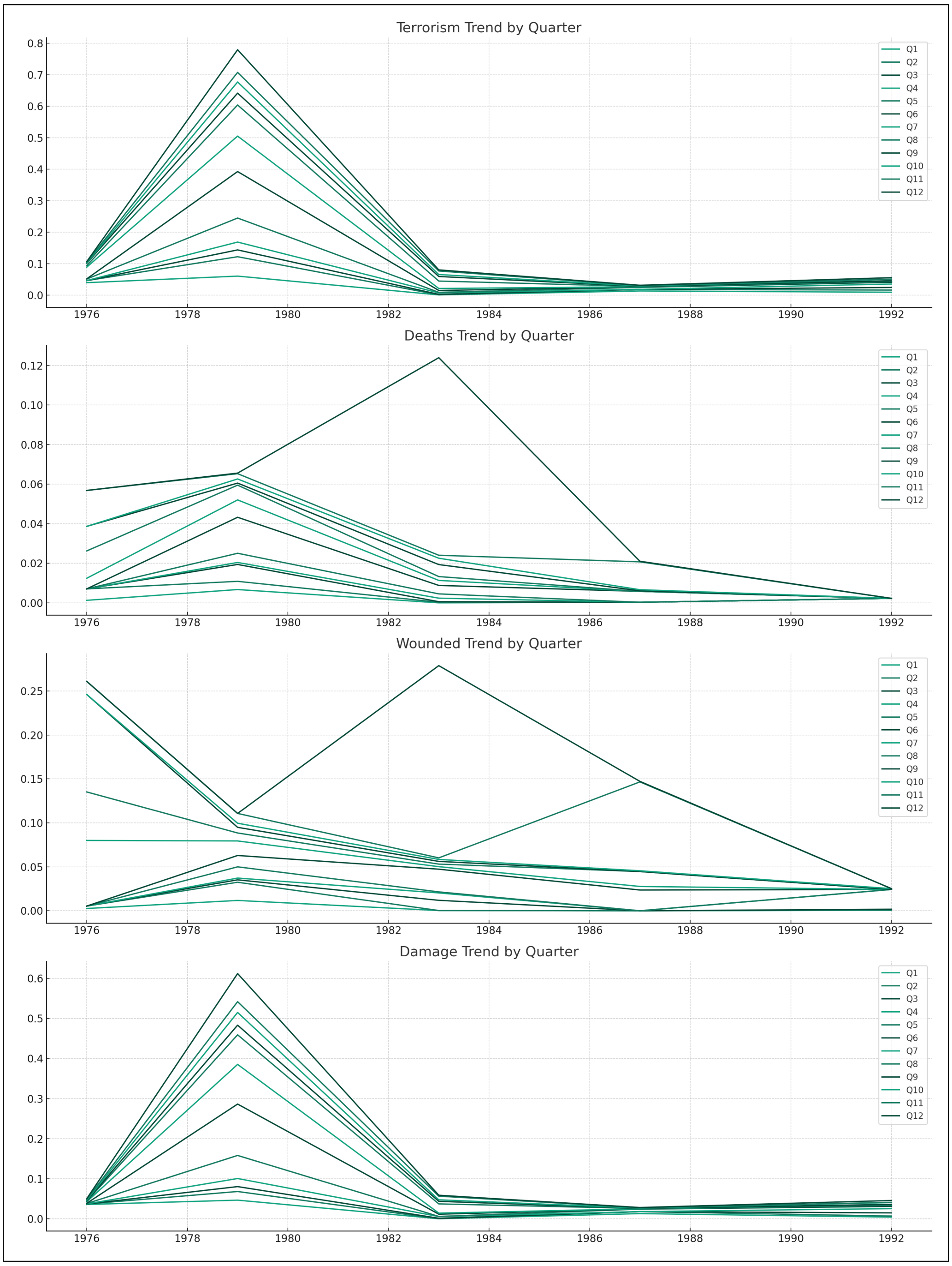
Note: The figure displays the overall trend in terrorist attacks recorded in Italy by the Global Terrorism Dataset, from 1970 to 1992.

FIGURE 3.6: *Trends in Electoral Participation and Votes for the Main Parties*



Note: The figure delineates aggregate trends, expressed as a percentage, depicting electoral participation in the upper part of the graph. This percentage is calculated based on all votes expressed during the election relative to the total number of eligible voters. In the lower section of the graph, the data illustrates the distribution of votes among the main parties and the percentage of spoiled ballots.

FIGURE 3.7: *Distribution of Terrorism, Killings, Wounded, and Damages Over 12 Quarters*



Note: The figure delineates a dis-aggregated trend with respect to the variables related to terrorism (number of attacks, number of killings, number of wounded, and physical damages. In each subsection of the graph, the lines represent the distribution of the variables in each quarter prior to the election day.

FIGURE 3.8: *Terrorist Attacks Distribution Across Provinces*

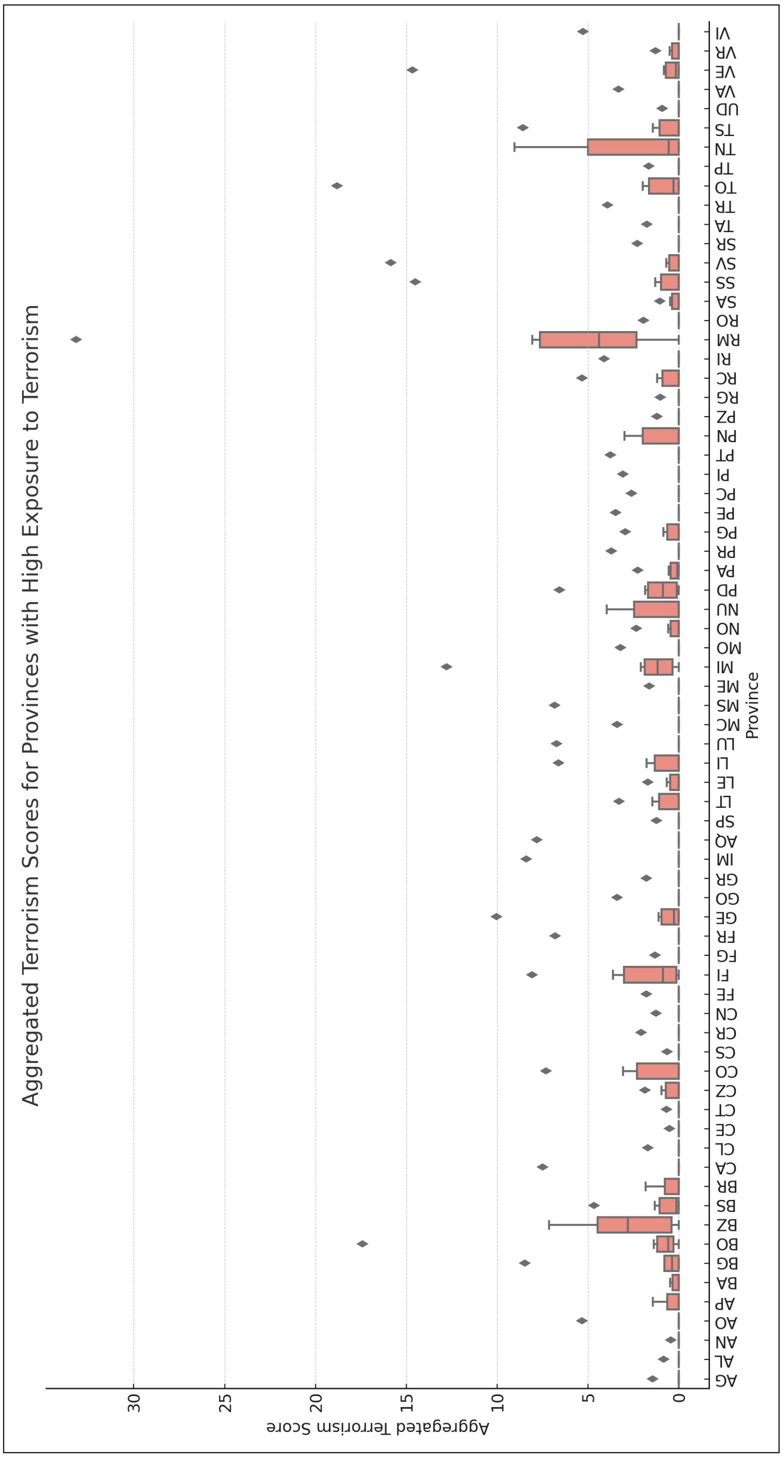
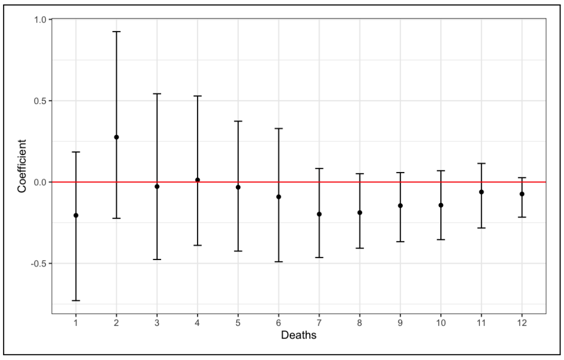
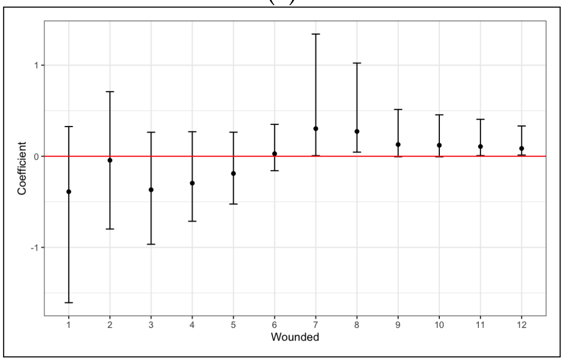


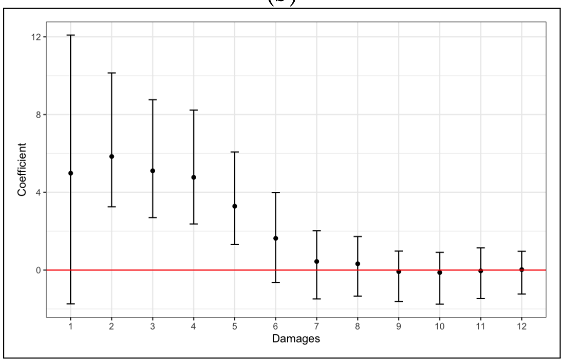
FIGURE 3.9: *FDC Results - Effect on Voter Turnout*



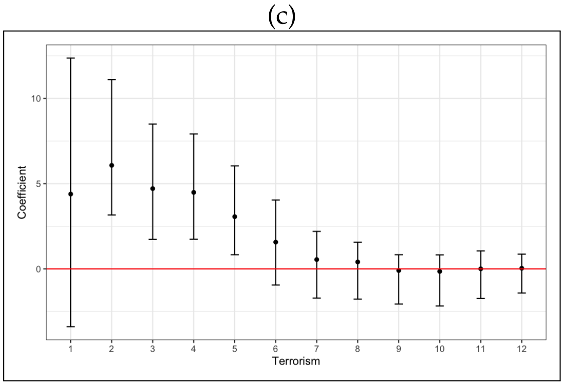
(a)



(b)



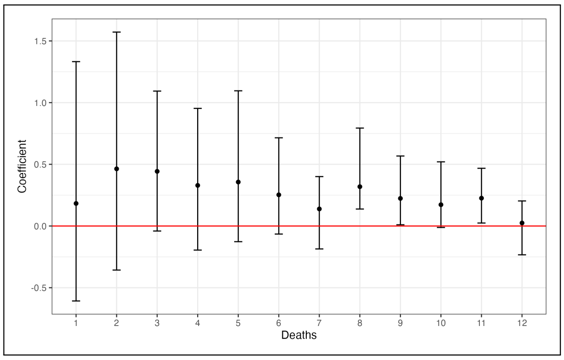
(c)



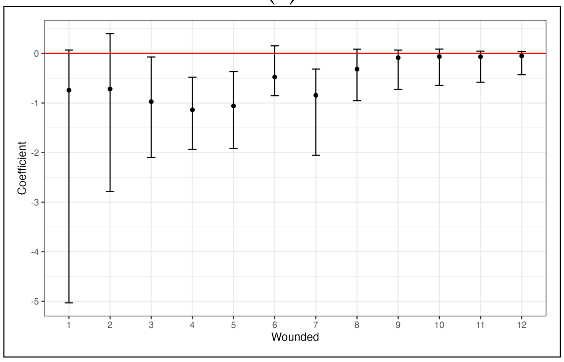
(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B2. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

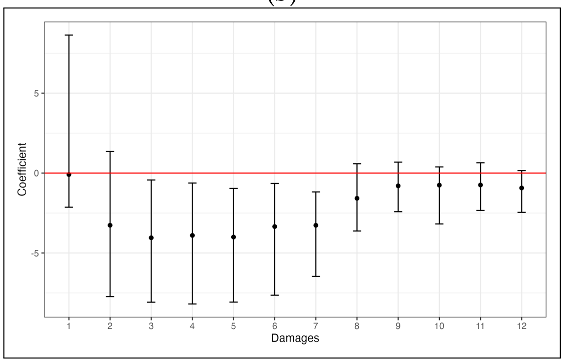
FIGURE 3.10: *FDC Results - Effect on Votes for the Incumbent Party*



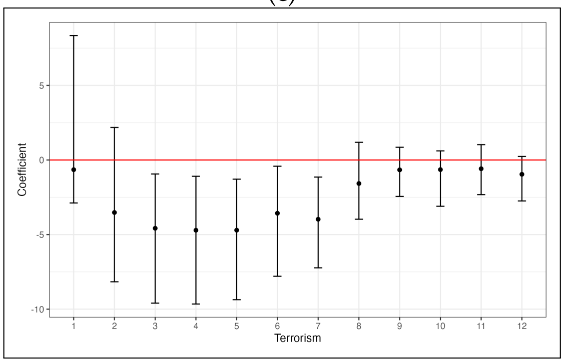
(a)



(b)



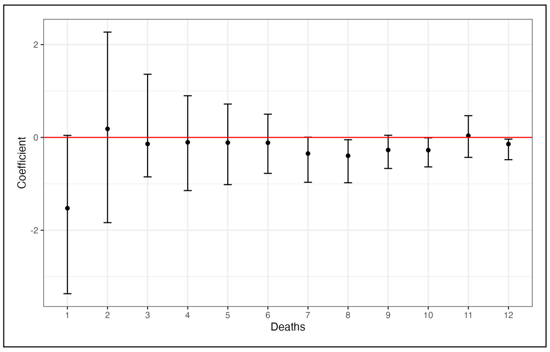
(c)



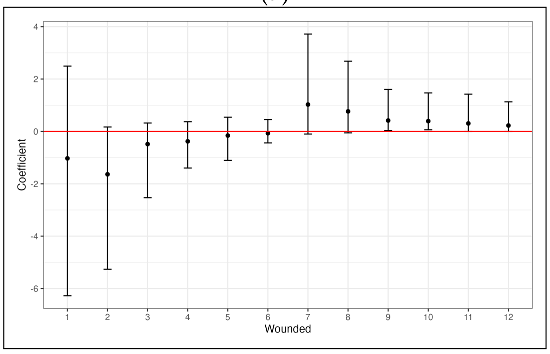
(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B2. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

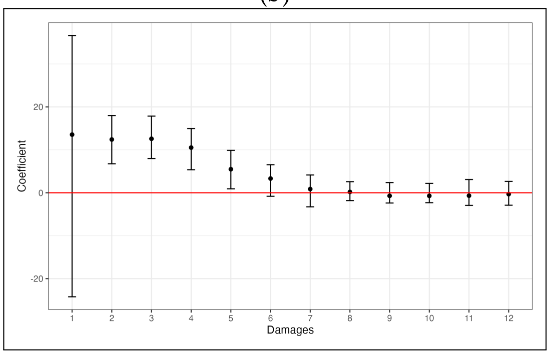
FIGURE 3.11: *FDC Results - Effect on Votes for the Main Opposition Party*



(a)



(b)



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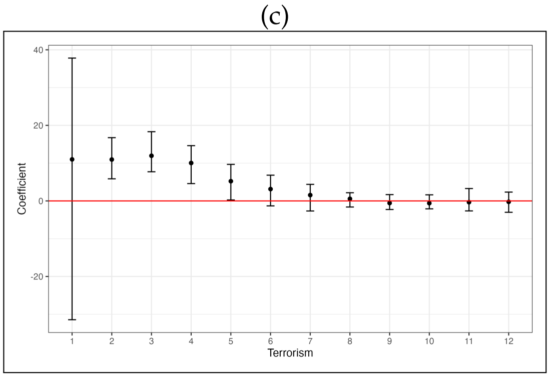
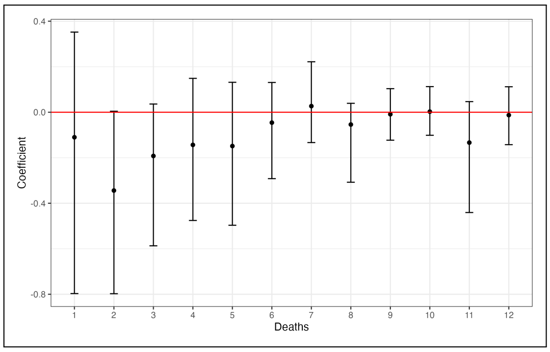


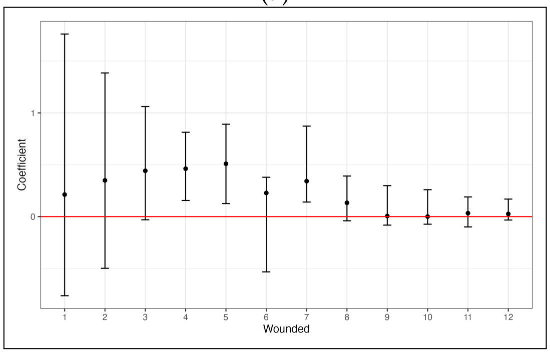
(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B2. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

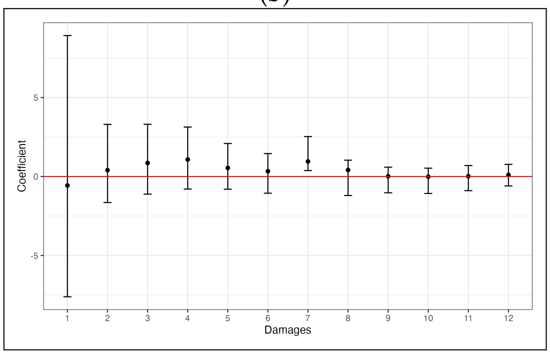
FIGURE 3.12: *FDC Results - Effect on Votes for the Extreme Right Party*



(a)



(b)



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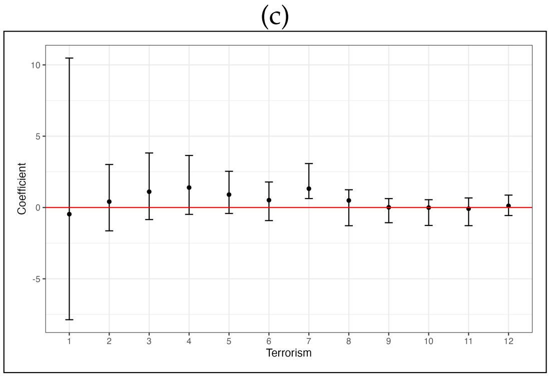
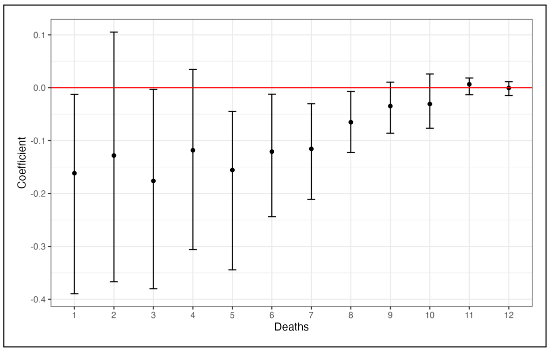


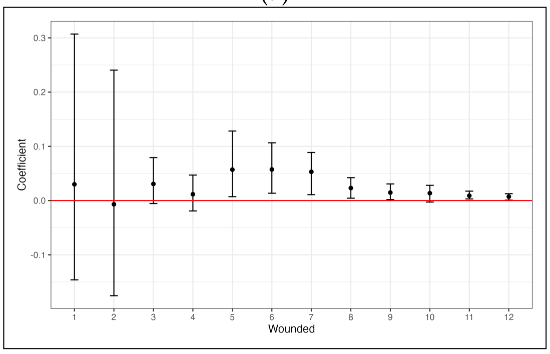
(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B2. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

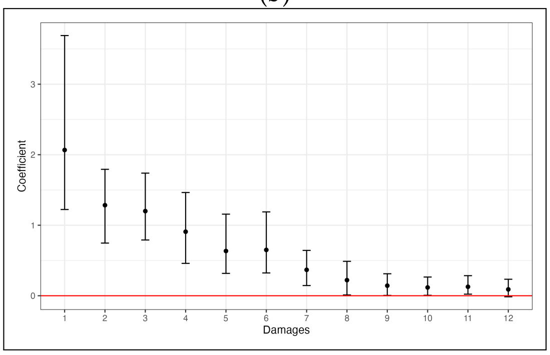
FIGURE 3.13: *FDC Results - Effect on Voter Turnout (Early Check for Potential Spatial Spillovers)*



(a)



(b)



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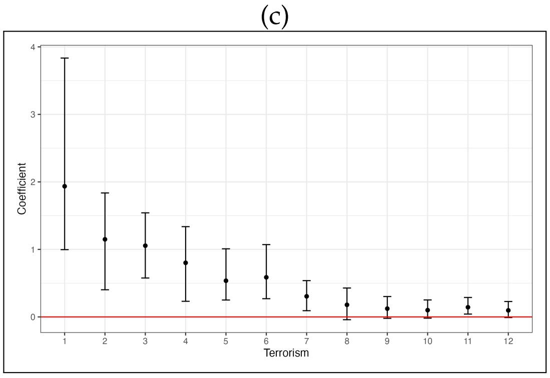
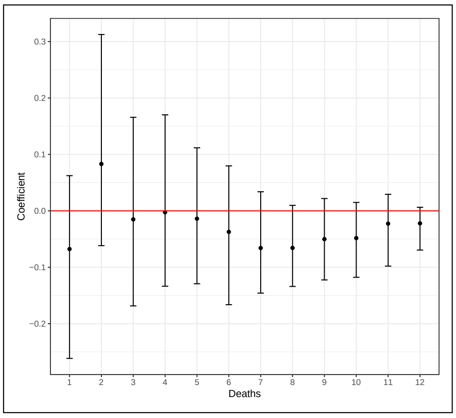


(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B4. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

FIGURE 3.14: *FDC Results - Effects on Average Voter Turnout*



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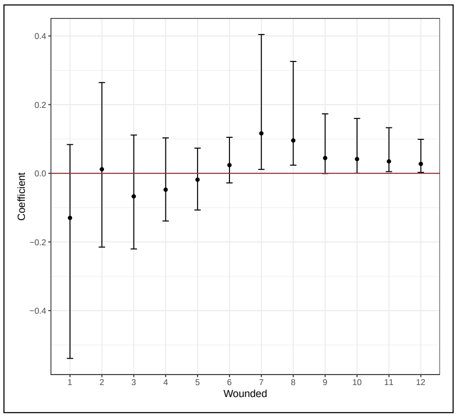
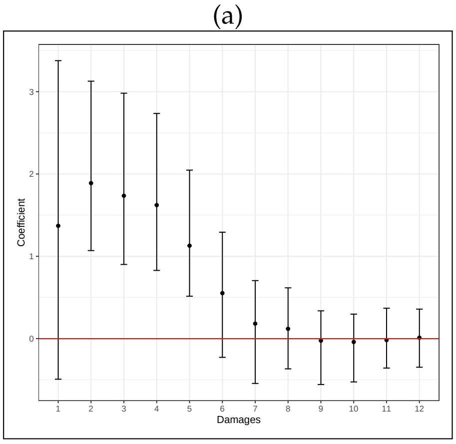


(b)



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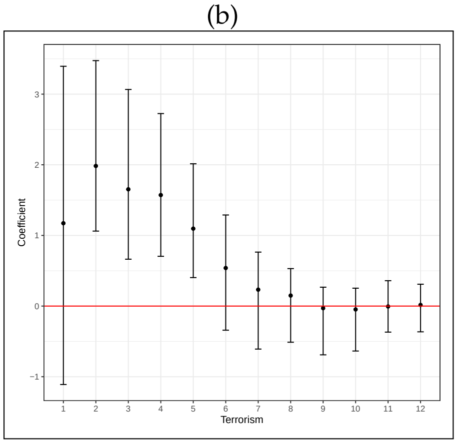


(d)

Note: The confidence interval represented by the plots reflects the bias-corrected and accelerated c.i., 5,000 bootstrap replications. The full numerical values are presented in Table B3. Plot *a)* represents the mediated effect of terrorism through the presence of deaths. Plot *b)* represents the mediated effect of terrorism through the presence of the wounded. Plot *c)* represents the mediated effect of terrorism through the presence of physical damages. Plot *d)* represents the Average Treatment Effect of terrorism.

TABLE 3.1: Effect of Terrorism on Voters Turnout - Naive Regression Model

	1	2	3	4	5	6	7	8	9	10	11	12
VARIABLES	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$
Electoral Participation$_{(t-1)}$	-0.163***	-0.164***	-0.164***	-0.163***	-0.163***	-0.167***	-0.168***	-0.168***	-0.168***	-0.168***	-0.168***	-0.168***
	(0.0327)	(0.0329)	(0.0330)	(0.0328)	(0.0328)	(0.0335)	(0.0334)	(0.0335)	(0.0334)	(0.0334)	(0.0334)	(0.0333)
Attack Rate$_{(t-k)}$	1.424***	0.930**	0.777**	0.799**	0.726***	0.172	0.126	0.081	0.091	0.084	0.073	0.030
	(0.5000)	(0.3783)	(0.3588)	(0.3523)	(0.2748)	(0.2618)	(0.2115)	(0.1787)	(0.1604)	(0.1514)	(0.1406)	(0.1190)
Property Crime (log)	0.151	0.156	0.154	0.153	0.142	0.169	0.170	0.172	0.170	0.171	0.172	0.179
	(0.1559)	(0.1544)	(0.1548)	(0.1545)	(0.1533)	(0.1654)	(0.1682)	(0.1686)	(0.1679)	(0.1671)	(0.1667)	(0.1642)
Pluralism Index (log)	-1.426***	-1.441***	-1.430***	-1.446***	-1.416***	-1.462***	-1.463***	-1.461***	-1.462***	-1.461***	-1.461***	-1.466***
	(0.5188)	(0.5209)	(0.5227)	(0.5229)	(0.5199)	(0.5293)	(0.5308)	(0.5335)	(0.5319)	(0.5321)	(0.5322)	(0.5316)
Population (log)	-0.170	-0.162	-0.162	-0.168	-0.182*	-0.128	-0.127	-0.122	-0.124	-0.124	-0.123	-0.115
	(0.1067)	(0.1070)	(0.1079)	(0.1086)	(0.1080)	(0.1088)	(0.1068)	(0.1070)	(0.1068)	(0.1070)	(0.1074)	(0.1071)
Added Value (log)	2.806***	2.815***	2.824***	2.768***	2.761***	2.849***	2.852***	2.863***	2.862***	2.859***	2.861***	2.871***
	(0.7669)	(0.7679)	(0.7701)	(0.7712)	(0.7757)	(0.7666)	(0.7602)	(0.7624)	(0.7647)	(0.7638)	(0.7645)	(0.7615)
Univ. Enrollment (log)	3.442	3.435	3.128	3.282	2.725	2.845	2.854	2.892	2.734	2.743	2.735	2.848
	(6.0489)	(6.0912)	(6.1614)	(6.1929)	(6.2751)	(6.1980)	(6.2010)	(6.1867)	(6.2143)	(6.2117)	(6.2096)	(6.1681)
Constant	-20.633***	-20.868***	-20.826***	-20.432***	-19.930***	-21.560***	-21.580***	-21.716***	-21.682***	-21.656***	-21.680***	-21.917***
	(7.2624)	(7.2941)	(7.3389)	(7.3158)	(7.3317)	(7.2739)	(7.2492)	(7.3036)	(7.3019)	(7.2971)	(7.3078)	(7.2754)
Observations	465	465	465	465	465	465	465	465	465	465	465	465
R-squared	0.587	0.586	0.586	0.587	0.588	0.584	0.584	0.584	0.584	0.584	0.584	0.584

Robust standard errors in parentheses

Notes: *Notes*: The table presents the results of the linear convergence estimation following the Barro approach, serving as a benchmark estimation. The control variables reflect values recorded one year before the election, as detailed in Section 3.2.2. The values of k represent the quarters before the day of elections. Robust Standard Errors in parenthesis. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 3.2: Effect of Terrorism on Votes for DC - Naive Regression Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$
Electoral Participation$_{(t-1)}$	-0.531***	-0.522***	-0.517***	-0.518***	-0.520***	-0.512***	-0.507***	-0.513***	-0.511***	-0.508***	-0.510***	-0.505***
	(0.1773)	(0.1772)	(0.1765)	(0.1761)	(0.1758)	(0.1761)	(0.1761)	(0.1758)	(0.1759)	(0.1758)	(0.1757)	(0.1758)
Attack Rate$_{(t-k)}$	-4.603**	-1.871	-0.920	-0.907	-0.924	-0.127	0.333	-0.138	0.005	0.165	0.033	0.306
	(1.7944)	(1.4525)	(1.4368)	(1.3783)	(0.8818)	(0.6292)	(0.4527)	(0.3684)	(0.3508)	(0.3494)	(0.3218)	(0.2891)
Property Crime (log)	-1.157	-1.219	-1.247	-1.241	-1.221	-1.275	-1.334	-1.264	-1.290	-1.321	-1.295	-1.345
	(0.8307)	(0.8401)	(0.8383)	(0.8353)	(0.8350)	(0.8439)	(0.8567)	(0.8408)	(0.8394)	(0.8412)	(0.8376)	(0.8430)
Pluralism Index (log)	-14.635**	-14.624**	-14.622**	-14.609**	-14.652**	-14.592**	-14.584**	-14.602**	-14.589**	-14.579**	-14.587**	-14.555**
	(6.8079)	(6.7981)	(6.7841)	(6.7944)	(6.7837)	(6.7795)	(6.7658)	(6.7776)	(6.7769)	(6.7747)	(6.7774)	(6.7745)
Population (log)	0.348	0.246	0.192	0.200	0.229	0.135	0.059	0.144	0.116	0.081	0.110	0.040
	(0.7996)	(0.7752)	(0.7735)	(0.7745)	(0.7860)	(0.7816)	(0.7710)	(0.7806)	(0.7823)	(0.7803)	(0.7864)	(0.7782)
Added Value (log)	-2.505	-2.634	-2.758	-2.729	-2.693	-2.840	-2.990	-2.820	-2.875	-2.941	-2.888	-3.075
	(3.7481)	(3.7610)	(3.7781)	(3.7985)	(3.7771)	(3.7832)	(3.7714)	(3.7630)	(3.7663)	(3.7709)	(3.7704)	(3.7674)
Univ. Enrollment (log)	-104.195	-103.390	-102.778	-102.867	-102.047	-102.354	-102.663	-102.347	-102.450	-102.861	-102.539	-103.498
	(65.7846)	(65.5906)	(65.4284)	(65.4605)	(65.4201)	(65.3336)	(65.2880)	(65.3053)	(65.2366)	(65.3007)	(65.2870)	(65.4364)
Constant	3.775	5.864	7.423	7.224	6.186	8.857	11.119	8.470	9.392	10.500	9.613	12.334
	(68.2831)	(68.2596)	(68.7938)	(68.9431)	(68.9811)	(69.3276)	(69.6936)	(69.2011)	(69.3436)	(69.5533)	(69.4651)	(69.9116)
Observations	465	465	465	465	465	465	465	465	465	465	465	465
R-squared	0.679	0.678	0.677	0.677	0.677	0.677	0.677	0.677	0.677	0.677	0.677	0.677

Notes: *Notes*: The table presents the results of the linear convergence estimation following the Barro approach, serving as a benchmark estimation. The control variables reflect values recorded one year before the election, as detailed in Section 3.2.2. The values of k represent the quarters before the day of elections. Robust Standard Errors in parenthesis. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 3.3: Effect of Terrorism on Votes for PCI - Naive Regression Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$	$k = 7$	$k = 8$	$k = 9$	$k = 10$	$k = 11$	$k = 12$
Electoral Participation$_{(t-1)}$	0.607***	0.598***	0.594***	0.588***	0.594***	0.589***	0.587***	0.588***	0.585***	0.584***	0.585***	0.582***
	(0.2190)	(0.2192)	(0.2190)	(0.2187)	(0.2181)	(0.2189)	(0.2190)	(0.2190)	(0.2192)	(0.2192)	(0.2190)	(0.2193)
Attack Rate$_{(t-k)}$	5.197**	2.169	1.337	0.327	0.903	0.334	0.162	0.184	0.029	-0.065	0.012	-0.159
	(2.0786)	(1.6544)	(1.6161)	(1.7308)	(1.0836)	(0.7882)	(0.5128)	(0.4798)	(0.4716)	(0.4612)	(0.4303)	(0.3622)
Property Crime(log)	0.200	0.268	0.289	0.332	0.283	0.314	0.327	0.316	0.343	0.362	0.347	0.378
	(1.1480)	(1.1398)	(1.1377)	(1.1324)	(1.1439)	(1.1395)	(1.1362)	(1.1422)	(1.1375)	(1.1311)	(1.1336)	(1.1175)
Pluralism Index (log)	-1.298	-1.309	-1.302	-1.342	-1.288	-1.342	-1.346	-1.333	-1.348	-1.353	-1.348	-1.367
	(6.0765)	(6.1043)	(6.1081)	(6.0977)	(6.1130)	(6.0987)	(6.0936)	(6.0999)	(6.0977)	(6.0984)	(6.1022)	(6.1011)
Population (log)	-0.608	-0.496	-0.456	-0.377	-0.456	-0.393	-0.376	-0.382	-0.353	-0.333	-0.350	-0.307
	(1.0900)	(1.0641)	(1.0619)	(1.0591)	(1.0692)	(1.0763)	(1.0681)	(1.0653)	(1.0684)	(1.0687)	(1.0725)	(1.0711)
Added Value (log)	3.642	3.780	3.890	4.005	3.881	3.970	4.001	3.987	4.048	4.084	4.052	4.163
	(4.4907)	(4.5136)	(4.5366)	(4.5611)	(4.5365)	(4.5445)	(4.5339)	(4.5330)	(4.5417)	(4.5474)	(4.5465)	(4.5516)
Univ. Enrollment (log)	18.095	17.216	16.607	16.267	15.730	15.893	16.002	15.991	16.042	16.279	16.075	16.663
	(72.9520)	(73.1557)	(73.2431)	(73.2496)	(73.4542)	(73.4655)	(73.3909)	(73.3663)	(73.2976)	(73.3225)	(73.3522)	(73.3630)
Constant	-63.411	-65.662	-66.899	-68.944	-66.612	-68.392	-68.861	-68.527	-69.540	-70.165	-69.624	-71.262
	(72.6082)	(72.7030)	(73.2903)	(73.5899)	(73.7793)	(73.6564)	(73.4267)	(73.5025)	(73.7266)	(73.8823)	(73.9534)	(74.0696)
Observations	465	465	465	465	465	465	465	465	465	465	465	465
R-squared	0.735	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733

Notes: *Notes*: The table presents the results of the linear convergence estimation following the Barro approach, serving as a benchmark estimation. The control variables reflect values recorded one year before the election, as detailed in Section 3.2.2. The values of k represent the quarters before the day of elections. Robust Standard Errors in parenthesis. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 3.4: Effect of Terrorism on Votes for MSI - Naive Regression Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$
Electoral Participation$_{(t-1)}$	0.121**	0.124**	0.124**	0.123**	0.123**	0.124**	0.122**	0.122**	0.121**	0.121**	0.121**	0.122**
	(0.0509)	(0.0513)	(0.0512)	(0.0510)	(0.0509)	(0.0509)	(0.0507)	(0.0507)	(0.0506)	(0.0506)	(0.0505)	(0.0508)
Attack Rate$_{(t-k)}$	-0.553	0.169	0.057	-0.077	-0.064	0.037	-0.148	-0.131	-0.146	-0.128	-0.134	-0.077
	(0.7218)	(0.4978)	(0.4243)	(0.3690)	(0.2532)	(0.2156)	(0.1705)	(0.1513)	(0.1395)	(0.1334)	(0.1242)	(0.1104)
Property Crime (log)	0.452**	0.430**	0.433**	0.440**	0.441**	0.432*	0.456**	0.460**	0.465**	0.461**	0.463**	0.450**
	(0.2146)	(0.2093)	(0.2110)	(0.2125)	(0.2162)	(0.2201)	(0.2199)	(0.2211)	(0.2221)	(0.2212)	(0.2215)	(0.2169)
Pluralism Index (log)	5.608***	5.616***	5.615***	5.612***	5.609***	5.614***	5.611***	5.602***	5.607***	5.605***	5.602***	5.605***
	(0.8435)	(0.8524)	(0.8525)	(0.8505)	(0.8521)	(0.8511)	(0.8470)	(0.8508)	(0.8492)	(0.8494)	(0.8497)	(0.8492)
Population (log)	0.072	0.032	0.039	0.051	0.051	0.039	0.070	0.069	0.074	0.072	0.077	0.063
	(0.1995)	(0.2032)	(0.2039)	(0.2037)	(0.2007)	(0.1968)	(0.1974)	(0.1981)	(0.1982)	(0.1984)	(0.1991)	(0.1972)
Added Value (log)	3.596***	3.530***	3.544***	3.564***	3.564***	3.542***	3.603***	3.602***	3.601***	3.604***	3.613***	3.602***
	(1.2122)	(1.2152)	(1.2129)	(1.2102)	(1.2053)	(1.1970)	(1.2007)	(1.2019)	(1.2029)	(1.2023)	(1.2007)	(1.2019)
Univ. Enrollment (log)	-9.758	-9.461	-9.526	-9.584	-9.520	-9.572	-9.447	-9.461	-9.198	-9.218	-9.131	-9.281
	(12.3369)	(12.3041)	(12.3355)	(12.3267)	(12.4054)	(12.4545)	(12.3734)	(12.4088)	(12.3600)	(12.3730)	(12.3634)	(12.3932)
Constant	6.508	7.495	7.298	6.997	6.960	7.327	6.398	6.331	6.296	6.295	6.139	6.433
	(10.3101)	(10.4999)	(10.4591)	(10.4217)	(10.3647)	(10.2950)	(10.2617)	(10.3000)	(10.2500)	(10.2682)	(10.2679)	(10.2957)
Observations	465	465	465	465	465	465	465	465	465	465	465	465
R-squared	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828

Notes: *Notes*: The table presents the results of the linear convergence estimation following the Barro approach, serving as a benchmark estimation. The control variables reflect values recorded one year before the election, as detailed in Section 3.2.2. The values of k represent the quarters before the day of elections. Robust Standard Errors in parenthesis. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

FIGURE 3.15: *Pluralism Index and Terrorist Attacks - 1968 Political Elections*

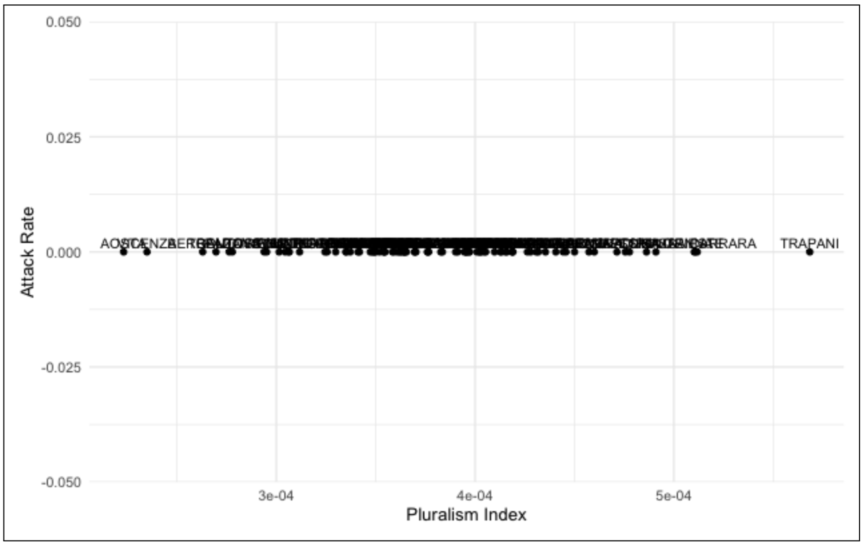


FIGURE 3.16: *Pluralism Index and Terrorist Attacks - 1972 Political Elections*

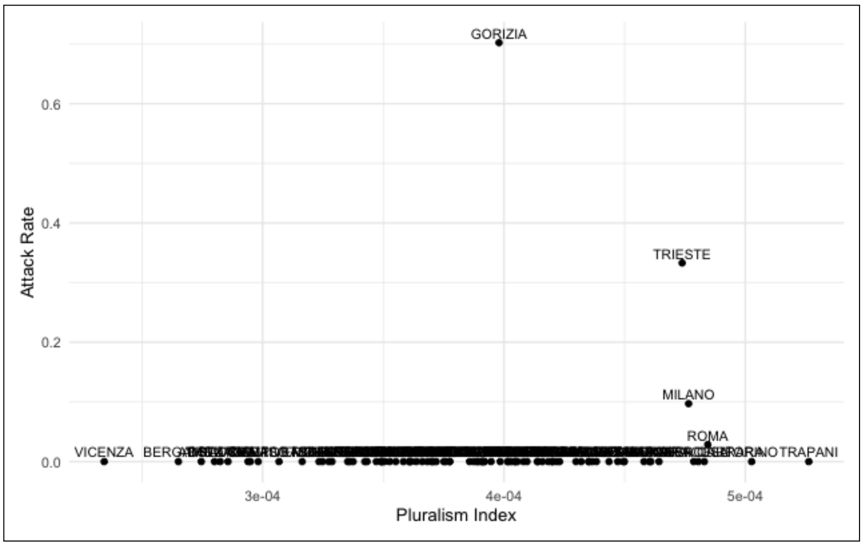


FIGURE 3.17: *Pluralism Index and Terrorist Attacks - 1976 Political Elections*

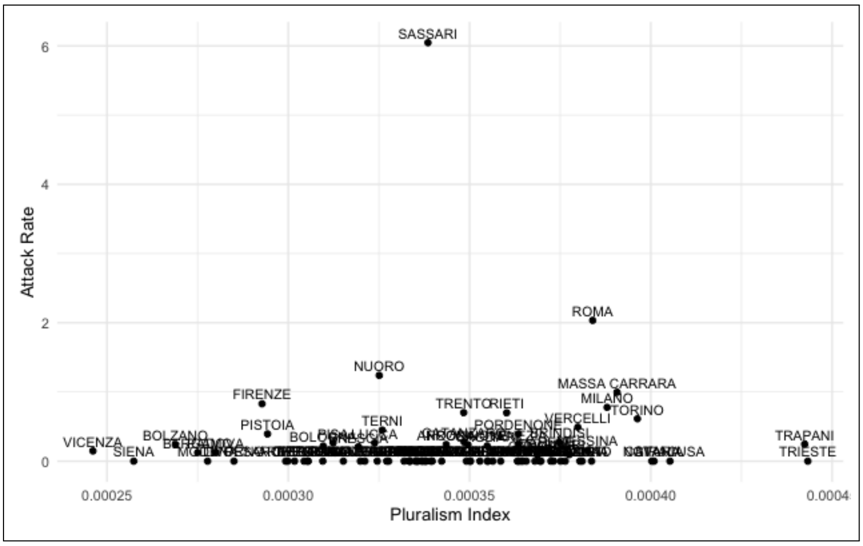


FIGURE 3.18: *Pluralism Index and Terrorist Attacks - 1979 Political Elections*

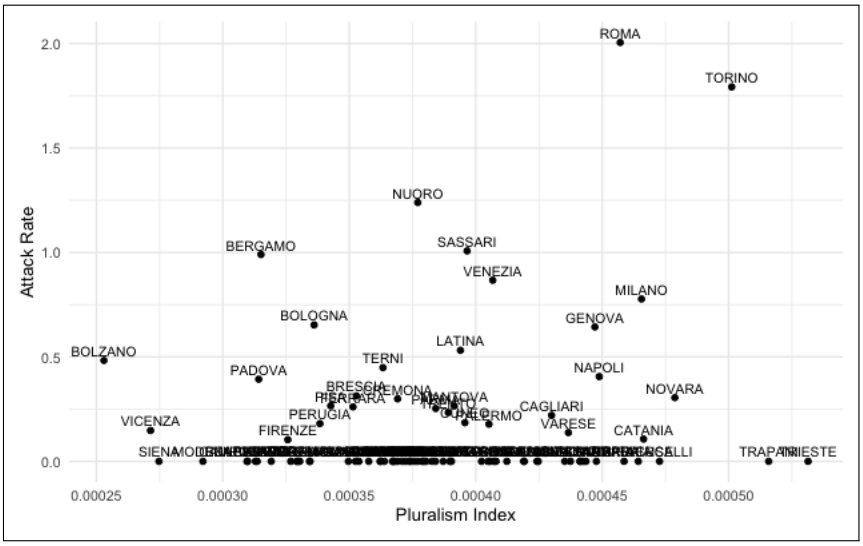


FIGURE 3.19: *Pluralism Index and Terrorist Attacks - 1983 Political Elections*

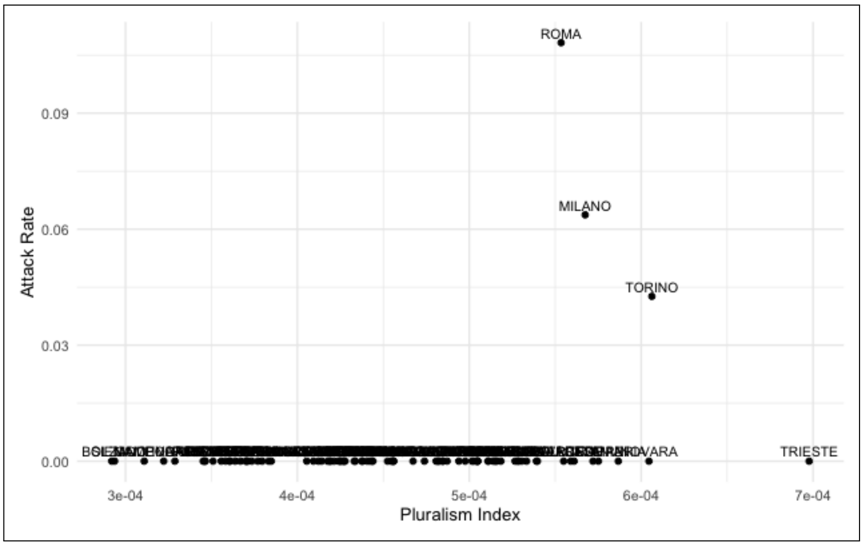


FIGURE 3.20: *Pluralism Index and Terrorist Attacks - 1987 Political Elections*

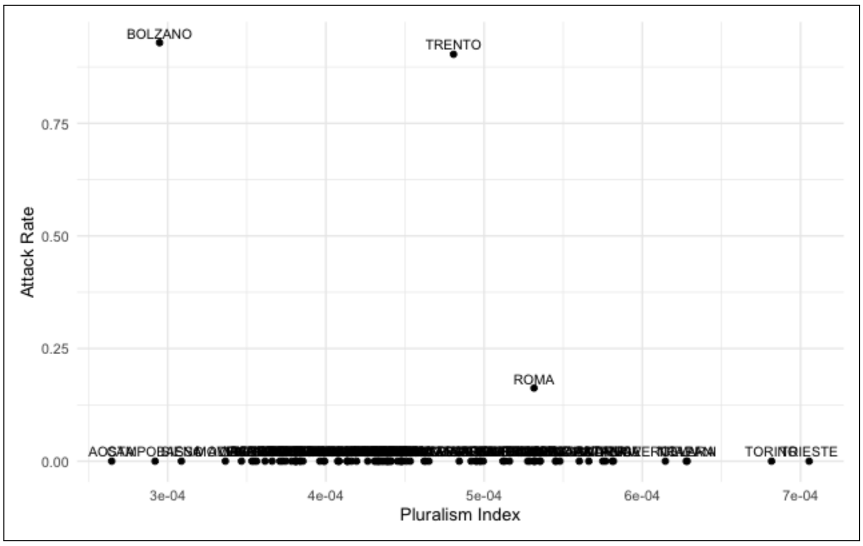


FIGURE 3.21: *Pluralism Index and Terrorist Attacks - 1992 Political Elections*

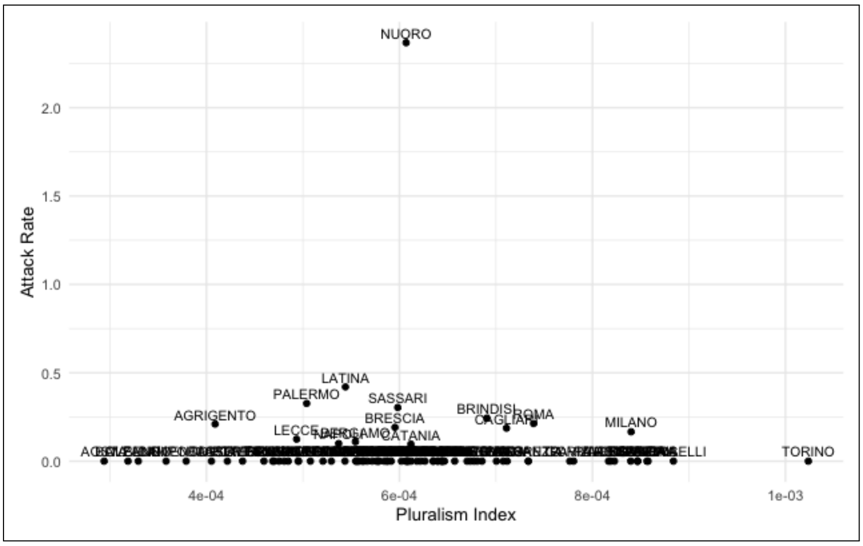


FIGURE 3.22: *Pluralism Index and Electoral Participation - 1968 Political Elections*

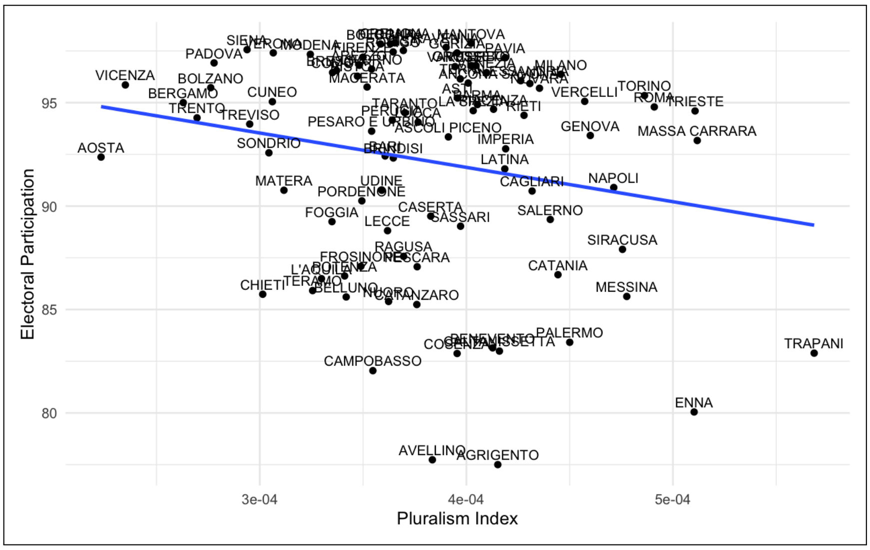


FIGURE 3.23: *Pluralism Index and Electoral Participation - 1972 Political Elections*

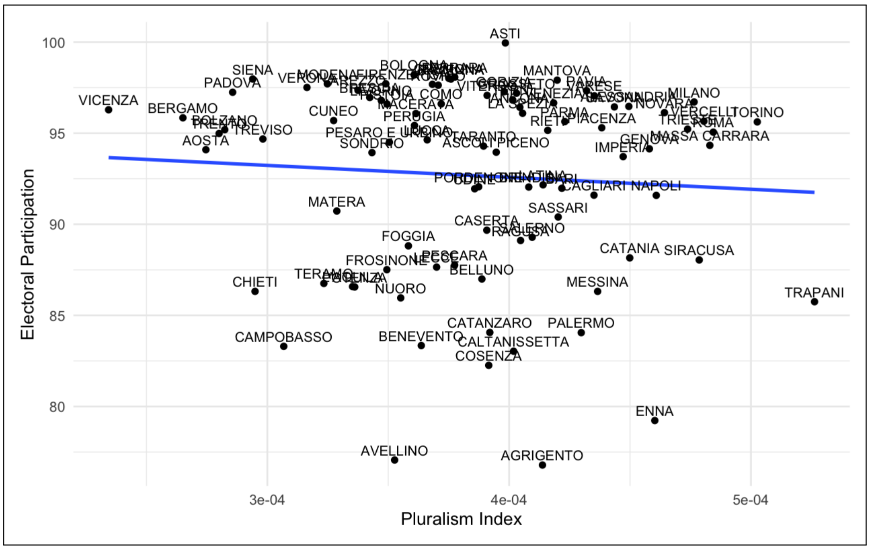


FIGURE 3.24: *Pluralism Index and Electoral Participation - 1976 Political Elections*

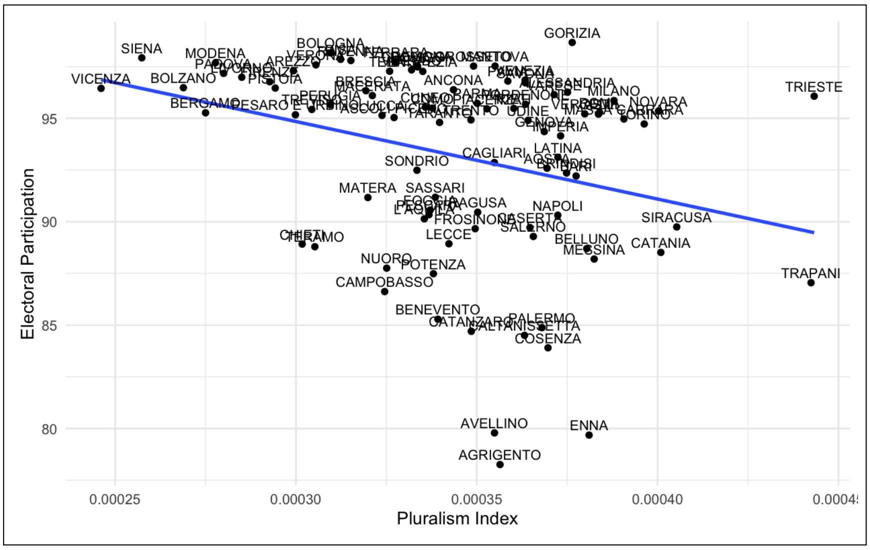


FIGURE 3.25: *Pluralism Index and Electoral Participation - 1979 Political Elections*

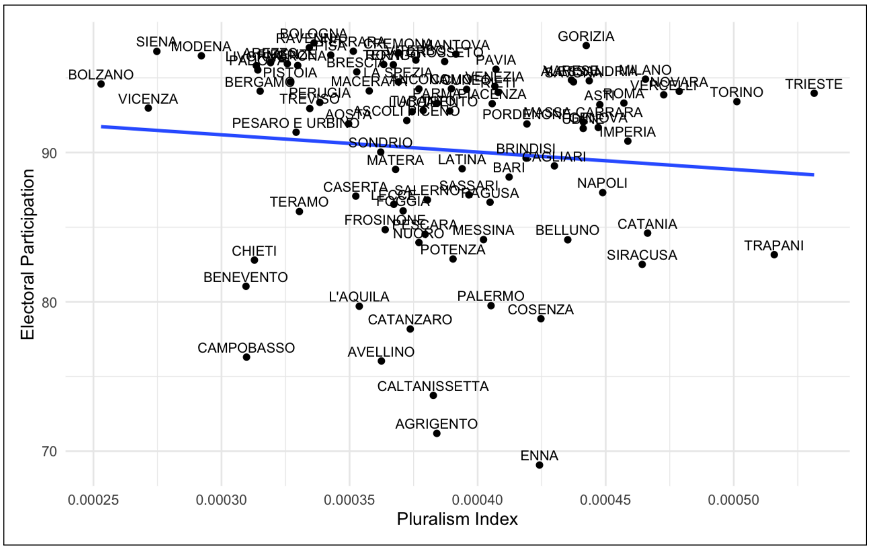


FIGURE 3.26: *Pluralism Index. and Electoral Participation - 1983 Political Elections*

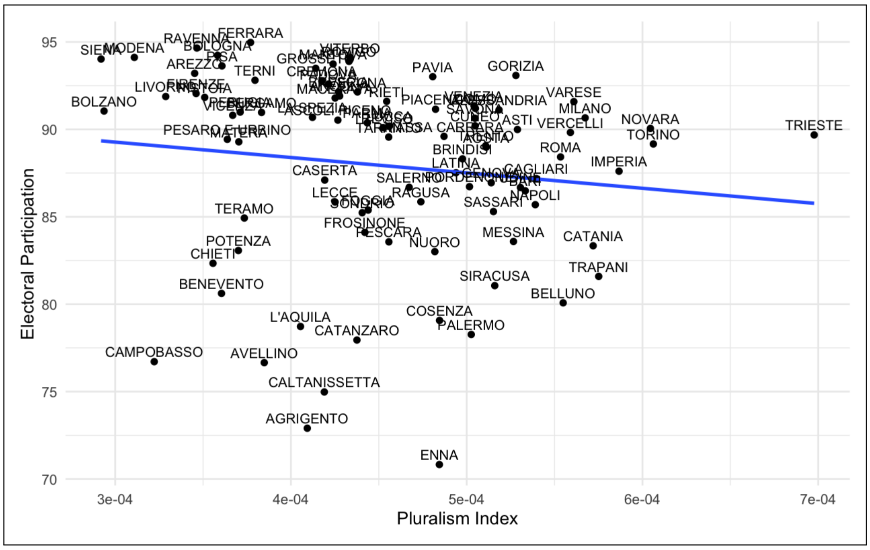


FIGURE 3.27: *Pluralism Index and Electoral Participation - 1987 Political Elections*

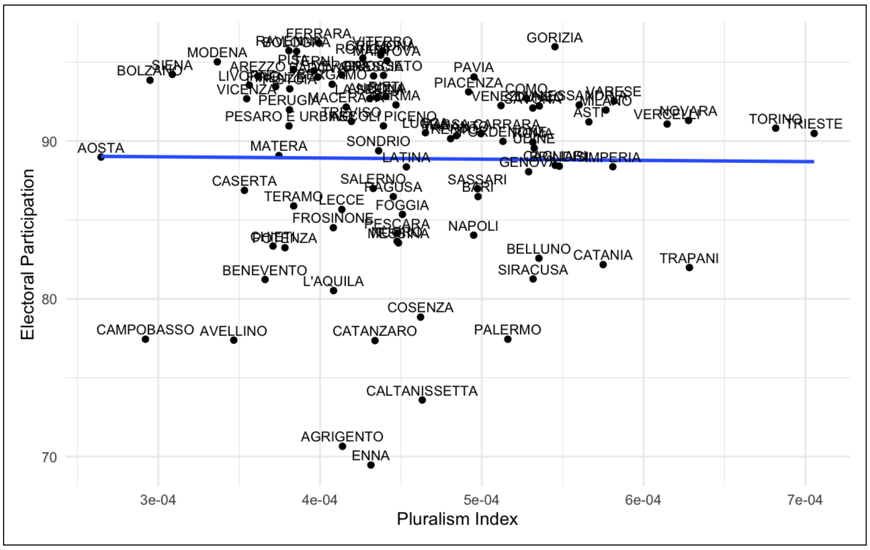


FIGURE 3.28: *Pluralism Index and Electoral Participation - 1992 Political Elections*

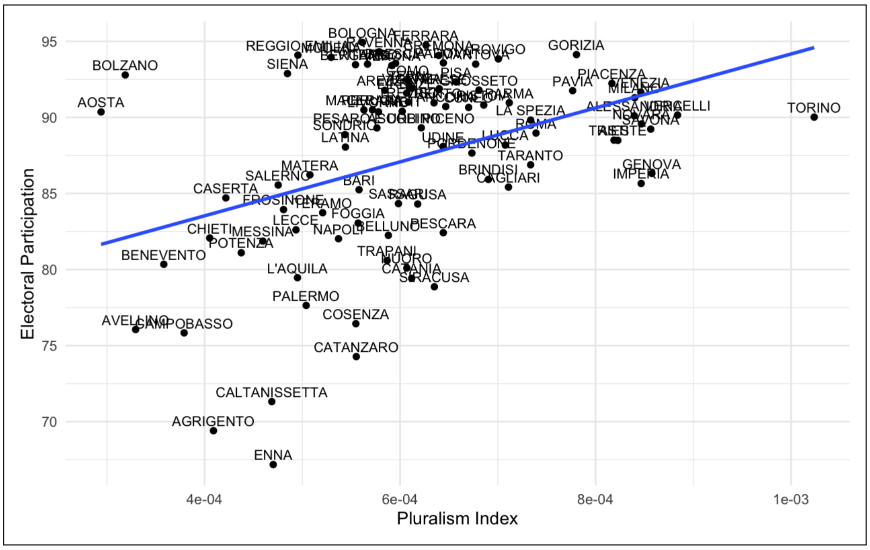


TABLE B1: Provinces and Terrorist Attacks

Provinces in which there has been at least one attack		
Agrigento (AG)	Alessandria (AL)	Ancona (AN)
Aosta (AO)	Ascoli Piceno (AP)	L'Aquila (AQ)
Bari (BA)	Bergamo (BG)	Bologna (BO)
Brindisi (BR)	Brescia (BS)	Bolzano (BZ)
Cagliari (CA)	Caserta (CE)	Caltanissetta (CL)
Cuneo (CN)	Como (CO)	Cremona (CR)
Cosenza (CS)	Catania (CT)	Catanzaro (CZ)
Ferrara (FE)	Foggia (FG)	Firenze (FI)
Frosinone (FR)	Genova (GE)	Gorizia (GO)
Grosseto (GR)	Imperia (IM)	Lecce (LE)
Livorno (LI)	Latina (LT)	Lucca (LU)
Macerata (MC)	Messina (ME)	Milano (MI)
Modena (MO)	Massa-Carrara (MS)	Novara (NO)
Nuoro (NU)	Palermo (PA)	Piacenza (PC)
Padova (PD)	Pescara (PE)	Perugia (PG)
Pisa (PI)	Pordenone (PN)	Parma (PR)
Pistoia (PT)	Potenza (PZ)	Reggio Calabria (RC)
Ragusa (RG)	Rieti (RI)	Roma (RM)
Rovigo (RO)	Salerno (SA)	La Spezia (SP)
Siracusa (SR)	Sassari (SS)	Savona (SV)
Taranto (TA)	Trento (TN)	Torino (TO)
Trapani (TP)	Terni (TR)	Trieste (TS)
Udine (UD)	Varese (VA)	Venezia (VE)
Vicenza (VI)	Verona (VR)	
Provinces in which there has never been an attack		
Arezzo (AR)	Asti (AT)	Avellino (AV)
Belluno (BL)	Benevento (BN)	Campobasso (CB)
Chieti (CH)	Enna (EN)	Forlì (FO)
Mantova (MN)	Matera (MT)	Pesaro e Urbino (PU)
Pavia (PV)	Ravenna (RA)	Reggio Emilia (RE)
Siena (SI)	Sondrio (SO)	Teramo (TE)
Treviso (TV)	Vercelli (VC)	Viterbo (VT)

TABLE B2: ATE and Mediated Effect of Terrorism on Voter Turnout and Parties Preferences

	Voter Turnout			Democrazia Cristiana			Partito Comunista Italiano			Movimento Sociale Italiano		
Variables	Coefficient	Bca		Coefficient	Bca		Coefficient	Bca		Coefficient	Bca	
						1 Quarter						
M1	-0.205	-0.729	0.185	0.183	-0.608	1.332	-1.525	-3.366	0.044	-0.110	-0.797	0.352
M2	-0.389	-1.607	0.326	-0.742	-5.032	0.069	-1.029	-6.273	2.493	0.213	-0.762	1.760
M3	4.982	-1.739	12.087	-0.090	-21.364	8.637	13.545	-24.222	36.614	-0.569	-7.615	8.926
ATE	4.389	-3.393	12.368	-0.649	-28.812	8.341	10.991	-31.447	37.811	-0.467	-7.868	10.478
						2 Quarter						
M1	0.276	-0.223	0.925	0.463	-0.357	1.572	0.184	-1.836	2.269	-0.344	-0.798	0.004
M2	-0.044	-0.799	0.709	-0.719	-2.788	0.399	-1.637	-5.264	0.169	0.349	-0.498	1.385
M3	5.842	3.255	10.140	-3.265	-7.728	1.354	12.407	6.757	17.982	0.403	-1.647	3.300
ATE	6.074	3.162	11.104	-3.520	-8.164	2.179	10.954	5.852	16.743	0.408	-1.636	3.016
						3 Quarter						
M1	-0.027	-0.476	0.543	0.443	-0.0406	1.093	-0.139	-0.850	1.361	-0.192	-0.587	0.0361
M2	-0.368	-0.966	0.264	-0.972	-2.099	-0.072	-0.484	-2.530	0.321	0.442	-0.030	1.062
M3	5.105	2.696	8.764	-4.048	-8.081	-0.432	12.573	7.976	17.849	0.856	-1.116	3.307
ATE	4.710	1.733	8.496	-4.577	-9.597	-0.939	11.949	7.719	18.323	1.106	-0.845	3.823
						4 Quarter						
M1	0.013	-0.389	0.529	0.329	-0.195	0.953	-0.105	-1.145	0.898	-0.144	-0.476	0.149
M2	-0.295	-0.714	0.269	-1.138	-1.933	-0.479	-0.379	-1.398	0.371	0.462	0.156	0.813
M3	4.769	2.368	8.229	-3.899	-8.191	-0.623	10.522	5.368	14.958	1.078	-0.795	3.132
ATE	4.487	1.739	7.917	-4.709	-9.656	-1.092	10.038	4.587	14.628	1.396	-0.482	3.649
						5 Quarter						
M1	-0.032	-0.424	0.374	0.356	-0.127	1.096	-0.112	-1.017	0.719	-0.149	-0.497	0.131
M2	-0.189	-0.524	0.264	-1.059	-1.916	-0.367	-0.1578	-1.107	0.542	0.509	0.126	0.891
M3	3.284	1.317	6.073	-4.002	-8.075	-0.960	5.489	0.925	9.869	0.543	-0.804	2.089
ATE	3.063	0.829	6.043	-4.705	-9.364	-1.286	5.219	0.252	9.671	0.904	-0.418	2.539
						6 Quarter						
M1	-0.091	-0.490	0.329	0.253	-0.065	0.715	-0.114	-0.775	0.501	-0.046	-0.292	0.131
M2	0.028	-0.158	0.350	-0.477	-0.853	0.154	-0.069	-0.438	0.454	0.228	-0.532	0.380
M3	1.633	-0.642	3.987	-3.346	-7.644	-0.648	3.318	-0.821	6.536	0.333	-1.057	1.452
ATE	1.570	-0.946	4.039	-3.569	-7.795	-0.418	3.135	-1.313	6.811	0.515	-0.918	1.789
						7 Quarter						
M1	-0.197	-0.464	0.083	0.138	-0.186	0.401	-0.347	-0.967	0.006	0.027	-0.133	0.222
M2	0.303	0.007	1.342	-0.844	-2.054	-0.315	1.027	-0.101	3.717	0.342	0.141	0.872
M3	0.440	-1.484	2.023	-3.268	-6.467	-1.178	0.865	-3.269	4.148	0.953	0.376	2.529
ATE	0.546	-1.716	2.199	-3.973	-7.228	-1.145	1.544	-2.668	4.381	1.321	0.627	3.081
						8 Quarter						
M1	-0.188	-0.407	0.051	0.319	0.138	0.794	-0.395	-0.976	-0.050	-0.054	-0.308	0.0391
M2	0.273	0.045	1.023	-0.317	-0.954	0.085	0.765	-0.055	2.680	0.133	-0.040	0.392
M3	0.321	-1.343	1.724	-1.578	-3.623	0.588	0.190	-1.824	2.584	0.415	-1.201	1.033
ATE	0.406	-1.776	1.562	-1.577	-3.971	1.185	0.561	-1.609	2.166	0.494	-1.277	1.244
						9 Quarter						
M1	-0.145	-0.367	0.058	0.224	0.0105	0.567	-0.271	-0.669	0.047	-0.009	-0.123	0.104
M2	0.129	-0.005	0.514	-0.086	-0.727	0.067	0.416	0.033	1.604	0.009	-0.082	0.299
M3	-0.079	-1.619	0.977	-0.799	-2.414	0.685	-0.712	-2.382	2.372	0.015	-1.031	0.591
ATE	-0.095	-2.062	0.829	-0.662	-2.442	0.852	-0.567	-2.275	1.669	0.012	-1.066	0.624
						10 Quarter						
M1	-0.142	-0.354	0.070	0.173	-0.012	0.520	-0.275	-0.635	-0.009	0.003	-0.101	0.112
M2	0.121	-0.006	0.455	-0.063	-0.647	0.087	0.394	0.064	1.470	0.001	-0.073	0.259
M3	-0.127	-1.753	0.910	-0.754	-3.181	0.387	-0.719	-2.310	2.179	-0.012	-1.075	0.528
ATE	-0.149	-2.176	0.820	-0.645	-3.102	0.611	-0.601	-2.096	1.613	-0.008	-1.258	0.547
						11 Quarter						
M1	-0.061	-0.282	0.114	0.226	0.024	0.468	0.038	-0.430	0.468	-0.133	-0.441	0.0467
M2	0.107	0.007	0.406	-0.067	-0.581	0.046	0.306	-0.002	1.422	0.034	-0.099	0.190
M3	-0.043	-1.463	1.143	-0.744	-2.338	0.648	-0.678	-2.944	3.079	0.017	-0.895	0.694
ATE	0.003	-1.732	1.054	-0.586	-2.322	1.029	-0.335	-2.645	3.279	-0.082	-1.273	0.670
						12 Quarter						
M1	-0.073	-0.216	0.027	0.024	-0.233	0.203	-0.143	-0.480	-0.037	-0.012	-0.143	0.112
M2	0.086	0.013	0.333	-0.052	-0.429	0.038	0.225	-0.002	1.131	0.026	-0.033	0.169
M3	0.023	-1.234	0.965	-0.932	-2.457	0.158	-0.322	-2.900	2.641	0.099	-0.597	0.769
ATE	0.036	-1.417	0.865	-0.959	-2.746	0.238	-0.239	-3.012	2.336	0.113	-0.563	0.869

Notes: *M1* represents the coefficients of the mediated effect through the deaths. *M2* represents the coefficients of the mediated effect through the wounded. *M3* represents the coefficients of the mediated effect through the damages. *ATE* represents the coefficients of the mediated total effect of terrorism. The confidence interval of reference is the bias-corrected and accelerated confidence interval (5000 bootstrap replications), whose lower and upper bounds are shown respectively in columns c7 and c8. If the confidence interval does not contain zero, then the indirect effect is considered statistically significant.

TABLE B3: ATE and Mediated Effect of Terrorism on Average Voter Turnout - Robustness Check

Variable	Coefficient	BCa		Variable	Coefficient	BCa	
	1 Quarter				*7 Quarter*		
M1	-0,068	-0,262	0,062	M1	-0,066	-0,146	0,034
M2	-0,130	-0,539	0,084	M2	0,116	0,011	0,404
M3	1,370	-0,493	3,377	M3	0,182	-0,545	0,705
ATE	1,173	-1,111	3,395	ATE	0,232	-0,609	0,764
	2 Quarter				*8 Quarter*		
M1	0,083	-0,062	0,313	M1	-0,066	-0,134	0,010
M2	0,012	-0,215	0,264	M2	0,096	0,024	0,326
M3	1,889	1,070	3,127	M3	0,119	-0,368	0,617
ATE	1,983	1,061	3,475	ATE	0,149	-0,512	0,530
	3 Quarter				*9 Quarter*		
M1	-0,015	-0,168	0,166	M1	-0,050	-0,122	0,022
M2	-0,067	-0,220	0,111	M2	0,045	-0,001	0,173
M3	1,735	0,901	2,981	M3	-0,024	-0,558	0,338
ATE	1,653	0,664	3,066	ATE	-0,030	-0,690	0,267
	4 Quarter				*10 Quarter*		
M1	-0,003	-0,134	0,170	M1	-0,048	-0,118	0,015
M2	-0,048	-0,139	0,103	M2	0,041	0,000	0,160
M3	1,622	0,828	2,735	M3	-0,041	-0,526	0,298
ATE	1,572	0,705	2,725	ATE	-0,048	-0,636	0,253
	5 Quarter				*11 Quarter*		
M1	-0,014	-0,129	0,112	M1	-0,023	-0,098	0,029
M2	-0,019	-0,107	0,073	M2	0,035	0,005	0,133
M3	1,129	0,515	2,047	M3	-0,018	-0,358	0,369
ATE	1,096	0,403	2,014	ATE	-0,006	-0,369	0,359
	6 Quarter				*12 Quarter*		
M1	-0,037	-0,166	0,080	M1	-0,022	-0,070	0,006
M2	0,024	-0,028	0,105	M2	0,027	0,003	0,099
M3	0,552	-0,228	1,293	M3	0,011	-0,347	0,358
ATE	0,539	-0,342	1,289	ATE	0,016	-0,364	0,309

Notes: *M1* represents the coefficients of the mediated effect through the deaths. *M2* represents the coefficients of the mediated effect through the wounded. *M3* represents the coefficients of the mediated effect through the damages. *ATE* represents the coefficients of the mediated total effect of terrorism. The confidence interval of reference is the bias-corrected and accelerated confidence interval (5000 bootstrap replications), whose lower and upper bounds are shown respectively in columns c7 and c8. If the confidence interval does not contain zero, then the indirect effect is considered statistically significant.

TABLE B4: ATE and Mediated Effect of Terrorism on Voter Turnout - Early Check for Spatial Spillover

Variable	Coefficient	BCa		Variable	Coefficient	BCa	
	1 Quarter				*7 Quarter*		
M1	-0.162	-0.389	-0.013	M1	-0.116	-0.211	-0.030
M2	0.029	-0.146	0.307	M2	0.053	0.011	0.089
M3	2.067	1.223	3.690	M3	0.367	0.145	0.643
ATE	1.935	0.997	3.834	ATE	0.305	0.092	0.538
	2 Quarter				*8 Quarter*		
M1	-0.128	-0.367	0.105	M1	-0.065	-0.122	-0.007
M2	-0.007	-0.175	0.241	M2	0.023	0.004	0.042
M3	1.284	0.747	1.793	M3	0.221	0.011	0.488
ATE	1.149	0.402	1.836	ATE	0.179	-0.041	0.428
	3 Quarter				*9 Quarter*		
M1	-0.176	-0.380	-0.003	M1	-0.035	-0.086	0.011
M2	0.031	-0.005	0.079	M2	0.0148	0.002	0.031
M3	1.200	0.791	1.739	M3	0.143	0.005	0.312
ATE	1.055	0.576	1.542	ATE	0.123	-0.021	0.302
	4 Quarter				*10 Quarter*		
M1	-0.118	-0.306	0.0345	M1	-0.031	-0.077	0.026
M2	0.012	-0.019	0.047	M2	0.014	-0.003	0.028
M3	0.908	0.459	1.464	M3	0.117	0.006	0.265
ATE	0.801	0.231	1.337	ATE	0.100	-0.019	0.252
	5 Quarter				*11 Quarter*		
M1	-0.156	-0.344	-0.045	M1	0.006	-0.013	0.018
M2	0.057	0.007	0.128	M2	0.009	0.003	0.017
M3	0.635	0.317	1.157	M3	0.127	0.022	0.285
ATE	0.536	0.250	1.009	ATE	0.143	0.042	0.288
	6 Quarter				*12 Quarter*		
M1	-0.121	-0.244	-0.012	M1	-0.000	-0.015	0.011
M2	0.057	0.014	0.107	M2	0.007	0.001	0.013
M3	0.650	0.323	1.189	M3	0.090	-0.015	0.234
ATE	0.587	0.270	1.071	ATE	0.097	-0.010	0.228

Notes: *M1* represents the coefficients of the mediated effect through the deaths. *M2* represents the coefficients of the mediated effect through the wounded. *M3* represents the coefficients of the mediated effect through the damages. *ATE* represents the coefficients of the mediated total effect of terrorism. The confidence interval of reference is the bias-corrected and accelerated confidence interval (5000 bootstrap replications), whose lower and upper bounds are shown respectively in columns c7 and c8. If the confidence interval does not contain zero, then the indirect effect is considered statistically significant.

TABLE B5: Spatial Naive on terrorism

	1	2	3	4	5	6	7	8	9	10	11	12
VARIABLES	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$
Electoral Participation$_{(t-1)}$	-0.163***	-0.162***	-0.163***	-0.164***	-0.164***	-0.164***	-0.164***	-0.164***	-0.164***	-0.164***	-0.165***	-0.164***
	(0.0405)	(0.0405)	(0.0407)	(0.0408)	(0.0408)	(0.0408)	(0.0407)	(0.0407)	(0.0408)	(0.0408)	(0.0408)	(0.0408)
(W) *Attack Rate*$_{(t-k)}$	0.149***	0.095***	0.077***	0.077***	0.050***	0.031***	0.025***	0.023***	0.024***	0.023***	0.020***	0.019***
	(0.0461)	(0.0305)	(0.0251)	(0.0252)	(0.0170)	(0.0106)	(0.0081)	(0.0076)	(0.0076)	(0.0073)	(0.0066)	(0.0062)
Property Crime (log)	0.212	0.214	0.215	0.219	0.218	0.217	0.214	0.213	0.213	0.213	0.213	0.214
	(0.2066)	(0.2065)	(0.2068)	(0.2073)	(0.2069)	(0.2068)	(0.2067)	(0.2067)	(0.2067)	(0.2068)	(0.2069)	(0.2068)
Pluralism Index (log)	-1.632**	-1.638**	-1.646**	-1.638**	-1.638**	-1.657**	-1.652**	-1.644**	-1.643**	-1.642**	-1.645**	-1.648**
	(0.6552)	(0.6570)	(0.6584)	(0.6579)	(0.6583)	(0.6603)	(0.6602)	(0.6594)	(0.6593)	(0.6593)	(0.6600)	(0.6601)
Population (log)	-0.016	-0.017	-0.013	-0.002	-0.008	-0.020	-0.016	-0.013	-0.007	-0.005	-0.006	-0.007
	(0.1152)	(0.1153)	(0.1156)	(0.1164)	(0.1154)	(0.1147)	(0.1156)	(0.1157)	(0.1161)	(0.1162)	(0.1161)	(0.1160)
Added Value (log)	2.932***	2.948***	2.952***	2.952***	2.971***	2.944***	2.963***	2.974***	2.998***	3.000***	2.997***	2.989***
	(0.9485)	(0.9518)	(0.9558)	(0.9581)	(0.9606)	(0.9570)	(0.9601)	(0.9608)	(0.9625)	(0.9630)	(0.9639)	(0.9638)
Univ. Enrollment (log)	-0.269	-0.258	-0.248	-0.067	-0.215	-0.277	-0.311	-0.308	-0.319	-0.303	-0.260	-0.238
	(7.9408)	(7.9904)	(7.9348)	(7.8546)	(7.8272)	(7.8383)	(7.8544)	(7.8478)	(7.8462)	(7.8380)	(7.8198)	(7.8135)
Constant	-27.787***	-27.995***	-28.083***	-28.118***	-28.143***	-27.944***	-28.099***	-28.169***	-28.405***	-28.426***	-28.415***	-28.373***
	(9.4986)	(9.5294)	(9.5778)	(9.5974)	(9.6178)	(9.6037)	(9.6190)	(9.6157)	(9.6314)	(9.6371)	(9.6452)	(9.6519)
Observations	465	465	465	465	465	465	465	465	465	465	465	465
R-squared	0.577	0.577	0.577	0.578	0.579	0.577	0.577	0.577	0.578	0.578	0.578	0.578

Notes: *Notes*: The table presents the results of the linear convergence estimation following the Barro approach, serving as a benchmark estimation. The control variables reflect values recorded one year before the election, as detailed in Section 3.2.2. (W) *Attack Rate*$_{(t-k)}$ represents the sum of terrorist events in province i and the events recorded in the neighboring provinces. The values of k represent the quarters before the day of elections. Robust Standard Errors in parenthesis. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 4

Local Determinants of Violence

In this Chapter, we present the effort to map the distribution of Intimate Partner Femicide (IPF) across and within the fourteen Italian Metropolitan Areas. Leveraging exclusive data on IPF incidents recorded between 2012 and 2020, we have constructed a unique dataset of geo-coded events. We then integrate this dataset with census-level data from national censuses to delve into the set of correlations between the socio-economic and demographic characteristics and the presence of this specific manifestation of violence. Our main estimation strategy relies on the implementation of a hurdle-like model, which is complemented with estimations from alternative model specifications. Our main results highlight the role of collective efficacy as one of the factors more correlated with a lower incidence of femicides, as well as the relevance of population in influencing the non-occurrence of IPF. While we cannot establish causal effects, we diligently strive to account for a broad set of observable influences and factors, as our primary goal is to offer a comprehensive exploration of contextual features that relate to IPF in largely populated urban contexts, to emphasize the critical importance of conducting such studies.

4.1 Introduction

Several countries, spanning diverse homicide rates across regions like Europe, Oceania, and the Americas, have witnessed a decline in their homicide rates since 1990, even when compared to specific racial or ethnic groups. This reversal comes after a preceding period of escalation that began in the early 1960s. A multitude of criminological theories have sought to illuminate these shifting patterns, encompassing concepts like modernization, conflict perspectives, and a theoretical model referred to as "elite convergence," which posits a hybrid amalgamation of modernization and conflict viewpoints (LaFree, 2005). Eisner (2013), taking a broader viewpoint, proposed that this phenomenon should be examined within a wider context, potentially stemming from a long-term fluctuation in the likelihood of male-on-male conflicts in public spaces.

However, as highlighted by Terranova and Zen (2018), amidst the myriad of factors influencing these downward trajectories, it's crucial to underline that a significant proportion of total homicide victims, accounting for 21%, are female. Notably, a substantial portion of female homicides can be attributed to acts committed by their intimate partners or family members. As of 2012, this distressingly held true for 47% of all female homicide victims, a stark contrast to the fewer than 6% of male homicide victims facing the same fate Terranova and Zen (2018).

Drawing attention to the gender-specific dynamics of homicides, it's noteworthy that the ratio of female victims within intimate partner and family-related homicides has remained relatively higher and stable on a global scale in recent times, as per data from the United Nations Office on Drugs and Crime. During the last few decades, violence against women has been increasingly recognized as a critical health problem worldwide (WHO, 2021; WHO, 2005), and as a critical component of the development agenda (WHO, 2014; Michau et al., 2015; UN-Women, 2015) has gained increasing public attention. This phenomenon persists despite discernible variations across regions. In this intricate mosaic of shifting homicide rates, the distinct patterns and vulnerabilities experienced by different genders highlight the nuanced complexities underpinning these tragic events. From an academic perspective, the understanding of homicide as a gender-neutral phenomenon has been overcome (Corradi et al., 2016). As put by Campbell et al. (2003), scholars must examine more carefully the distinctive characteristics associated with the killing of women versus men, not least for the fact that the majority of women who are victims of murder are killed by their intimate partners, or in a family setting; while the majority of male victims are killed in a non-intimate or domestic setting.

The analysis of Intimate Partner Violence (IPV) and Intimate Partner Femicide (IPF) has been mainly driven by theories focusing on individual and dyadic levels: from the study of personality development and learned behaviors in childhood and/or adolescence (Ainsworth, 1979; Bartholomew and Horowitz, 1991; Shaver and Mikulincer, 2009) to the inter-generational transmission of domestic violence Kalmuss (1984); under the theoretical framework of social cognitive theory, the change of cultural norms (Straus et al., 1976;Straus, 2008) or the feminist approach (Buss and Malamuth, 1996; Huppin et al., 2019; Qureshi et al., 2021)[1]. While individual-level theories play an important role in IPV research, and despite their hypothesis of ecological effects on IPV, they are too broad - from the social perspective - and too specific - from the psychological one - to translate into measurement models able to disentangle the role of environmental factors.

The aim of this paper is to contribute to the research on gendered violence in Italy from a geographical and contextual perspective, mapping potential relevant patterns behind the concentration of IPF across Italian Metropolitan Areas. The main reason behind the choice to focus only on the killings of women as a proxy for this specific type of violence, and not to account for other indicators such as *non-lethal* form of violence, is that femicide is

[1]Intimate Partner Femicide is the specific term adopted to better identify the killing of a woman in an intimate/family setting and to overcome the indiscriminate usage of the gender-neutral Intimate Partner Homicide (IPH).

an indicator that does not suffer from under-reporting issues. According to the United Nations Office on Drugs and Crime (UNODC, 2019), the study of intentional homicide is relevant because it is one of the most measurable and comparable indicators for monitoring (and/or estimating) the level of direct violence. At the same time, the homicide rate represents one of the best and globally recognized indicators of the level of social violence (see Rivera, 2016; Kubrin and Herting, 2003)[2]. In section 4.1.2 we explain the reasons behind the choice of focusing on the Italian urban environment.

As in the case of other place-specific social phenomena, violence makes no exceptions when it comes to the investigation of common patterns, both regarding its causes and consequences. One direct implication of this premise is that it is not always simple to find general agreement in the literature, with some exceptions for broad theoretical frameworks. To deal with such specificities, particularly during the 1990s, after some decades of evolution of the academic debate originated during the 1940s about the role of the *environment* in shaping individual behavior (e.g. the School of Chicago), some scholars have begun framing what has been called the *ecological perspective*, which may be understood as a comprehensive theoretical and practical framework within the social sciences, placing profound emphasis on the intricate interplay between an individual and their surrounding environment[3]. This perspective delves into the dynamic relationships and

[2]With *rate* is here intended the standardized form of the variable, weighted respect to the population (i.e. homicide *per 10.000 inhabitants*)

[3]The urban social ecology school of Chicago, especially during the 1920s and 1930s, emerged as a pioneering force in sociological analysis, devoting significant attention to the issues linked to urban transformation and its structural shifts. This encompassed a focus on distinguishing between living patterns in downtown areas and suburban regions, urban versus rural quality of life, the diverse city types, and the interactive organizational modes between individuals within urban spaces. The School's exploration delved into factors contributing to disorganization and social fragmentation within modern cities, spanning from deviance to the repercussions of processes of individualization in urban life, and culminating in the pivotal matters of immigrant social integration and ethnic relations. This emphasis on these themes represents a clear manifesto of an analytical agenda that continues to resonate through its effective relevance in contemporary times. In fact, they laid the groundwork for a comprehensive examination of urban dynamics, paving

reciprocal influences that transpire between human beings and the ever-changing ecological systems they inhabit. It recognizes that an individual's development, behavior, and experiences are profoundly shaped not only by their internal characteristics but also by the multifaceted interactions with the broader ecological context they are immersed in. This approach highlights the crucial role played by the environment in shaping human lives and underscores the need to comprehend and address the intricate web of connections that exists between individuals and their surroundings for a holistic understanding of human behavior and social dynamics. In other words, as put by Satchell et al. (2021), an ecological approach is about the understanding of an individual's perceived behavioral opportunities and gives important focus on what the environment might offer an individual in a given place.

Especially during the last fifteen years, numerous variables, ranging from educational attainment and employment rates to divorce statistics and accessibility to domestic violence prevention services, have been meticulously examined within the context of the decline in interpersonal homicide rates - particularly by research focusing on Northern America (Voith, 2019). However, the outcomes of these analyses haven't consistently aligned to unequivocally uphold either of the two competing theories (Terranova and Zen, 2018; Dawson et al., 2009; Dugan et al., 1999). This underscores the intricate and multifaceted nature of the factors at play and the challenge of attributing these trends to a singular explanatory framework. The intersection of social, cultural, economic, and psychological factors contributes to the complexity of this landscape, yielding outcomes that often defy simple categorization. Results of studying the relationship between neighborhood disadvantage and individual risk of IPV have been mixed. Several

the way for subsequent urban sociological studies and reflecting an enduring commitment to understanding the intricate fabric of urban existence and the evolving interactions within it. With specific reference to the phenomenon of violence against women, as put by Stout (1992), "an ecological framework allows the opportunity to merge feminist world views with more traditional models on homicide and other forms of violence to maximize one's ability to understand the many facets which contribute to violence against women in today's complex society".

researchers report significant associations (O'Campo et al., 1995; Benson et al., 2004), others report non-significant effects (Li et al., 2010), and still, others report differential effects based on race/ethnicity (Cunradi et al., 2000), or confounding effects between race and neighborhood-level disadvantage (Van Wyk et al., 2003; Benson et al., 2004). The interpretation of factors elucidating the causative mechanisms and trajectories of homicides within intimate partner and family contexts has been proposed through the lens of two distinct hypotheses: the *exposure-reduction* and the *backlash* hypothesis (Russell, 1975; Williams and Holmes, 1981). These contrasting perspectives offer insights into the intricate dynamics underlying these tragic incidents. The exposure-reduction hypothesis contends that elevated levels of gender equality correspond with diminished violence, endowing women with the necessary resources to disengage from unhealthy relationships. On the other hand, the backlash hypothesis posits that heightened gender equality might initially trigger an escalation of violence against women, attributed to the perceived erosion of male privileges. Remarkably, both hypotheses, despite their seeming contradiction, find substantiating evidence within existing literature (Reckdenwald and Parker, 2010; Reckdenwald and Parker, 2012). In essence, understanding the fluctuations in intimate partner and family-related homicides might necessitate a nuanced perspective that navigates the convergence and divergence of theories, while acknowledging that the factors underpinning such incidents are deeply intertwined and contextually contingent. The interplay of societal dynamics, individual agency, and broader structural conditions collectively shapes the intricate mosaic of these trends.

4.1.1 Femicide: concept background and evolution

The phenomenon of femicide is not new; however, its dramatic rise in international attention is unprecedented. As put by Dawson and Carrigan (2021), one consequence of this attention is increasing global discussions about how femicide should be defined, how it is distinct from homicide, and how differences can be operationalized. As defined by Diana Russel (Radford and Russell, 1992), femicide is a term used to identify the murder of a woman just because of her gender. According to Sarmiento et al. (2014), this expression emerged as an alternative to the neutral term "homicide" with the political objective of recognizing and making visible the discrimination, oppression, inequality, and systematic violence against women that in its most extreme form culminates in death. On the other hand, the term femicide is a term coined by the Mexican researcher Marcela Lagarde, who built it with more intense political meaning. The aim was to denounce the lack of response from the state in these cases and its failure to fulfill its international obligations, including the duty to investigate and punish. For Lagarde, feminicide is a state crime. It speaks to a "fracture in the rule of law that favors impunity" (Lagarde, 2006). The concept, as clarified by Sarmiento et al. (2014), refers to the full set of facts that characterize the crimes and disappearances of girls and women in cases in which the response of the authorities is one of omission, inertia, silence, and a failure to act to prevent and eradicate these crimes. However, as stated by UN-Women within the Latin American Protocol for the Investigation of gender-related killings of women (femicide/feminicide) (Sarmiento et al., 2014), the term femicide may be understood as "the murder of women because they are women, whether it is committed within the family, a domestic partnership, or any other interpersonal relationship, or by anyone in the community, or whether it is perpetrated or tolerated by the state or its agents". Such a definition is at the same time precise and wide enough to allow Social Scientists to move across the aforementioned approaches when designing their own research.

The modern academic interest in the homicide of women can be traced back to the 1970s, more precisely to the work of Ryan titled *Blaming the Victim* (Ryan, 1976). The revolutionary change of paradigm consisted, basically, of understanding that victimization is mainly the perpetrators' responsibility. In other words, the victim should not be blamed *a priori* for what happened.

Ryan originated a debate that reshaped social and environmental criminology, as so as victimization as an academic discipline[4].

One of the first scientific attempts to explicitly analyze femicide in relationship with the environment in which it takes place, is the work of Stout, in 1992. The author examined the "factors within ecological settings which may be associated with the killing of women by male intimate partners" (Stout, 1992). She claims, as reported also by Corradi et al. (2016), that an ecological framework allows the opportunity to merge *feminist* perspectives with more traditional models of homicide and other forms of violence. The proposed quantitative approach is based mainly on the inclusion of controls such as marital and employment status, the victim's age, the rate of rape, and the presence of shelters or crisis centers. As noted by Corradi et al. (2016), 1992 marks a watershed in the academic literature. If before that year very few works used the term femicide, in the following years both the notion of and research on femicide expanded throughout scientific literature and sought to describe, analyze, and prevent the phenomenon of the violent death of women. Up to now, the research approaches that have been adopted to deepen the analysis of the phenomenon are, mainly, six: the law-related approach; a feminist approach, focused on disentangling the patriarchal domination; a sociological approach, focused on the phenomenon's social determinants; a criminological approach, analyzing femicide as a unique sector in the homicide studies; a human rights approach; and a decolonial approach. From the economics perspective, especially in applied economics, literature has been showing a growing interest in violence against women and traditional gender-role norms (Alesina et al., 2021; Denti and Faggian, 2022; González and Rodríguez-Planas, 2020; Tur-Prats, 2019). However, despite a few exceptions (Denti and Faggian,

[4]In the same year, Diana Russell coined the word 'femicide', during the proceedings of the First International Tribunal on Crimes against Women in Brussels, which she organized jointly with Nicole van de Ven, in March 1976. The ostensible goal of this new word was to raise awareness that the violent death of women was a crime *per se*, "not to be confused with the gender-neutral term 'homicide'" (Corradi et al., 2016).

2022; Tur-Prats, 2019 Tur-Prats, 2021), the evidence is mainly at the cross-country level. This holds true in particular regarding the case of Italy.

4.1.2 Italian Metropolitan Areas

In Italy, there are 14 metropolitan cities, or areas: Bari, Bologna, Cagliari, Catania, Florence, Genoa, Messina, Milan, Naples, Palermo, Reggio Calabria, Rome, Turin, and Venice[5]. They essentially are territorial areas, at times quite extensive, encompassing both the capital city and the neighboring municipalities of I and II levels, based on their distance from the urban center. Within these areas, which account for 15.4% of the national territory, reside 36.2% of the population (over 21.3 million people).

The metropolitan areas in Italy represents a peculiar geo-administrative reality which might be seen as a reflection of the Italian panorama[6]. If on the one hand, Italian metro areas are the expression of an administrative change mainly prompted by the so-called *Riforma Delrio*, as clearly noted and highlighted by Di Gennaro and Elce (2020) metropolitan areas correspond to the progression and expansion of varied territorial nuclei that have increased, extended, and differentiated over time due to a) the rising count of individuals, both residents and non-residents, who have chosen suburban areas or utilize central zones as commuters, b) the notable alterations in industries, alongside the new phase of information-based tertiary growth that has emancipated workers and small advanced

[5]In our sample, we also consider the observations regarding the territory of the recently-constituted province of Monza e della Brianza. This administrative area lies very close to the Milan hinterland, and from a socio-economic perspective, it is strictly interconnected. For this reason, and because of the availability of data on IPF in that territory, we decided to include it in the sample, ending up with fifteen NUTS 3-level geographical units.

[6]In this research, we use the term *metropolitan area* as a synonym of *metropolitan city*. To be precise, however, the concept of the metropolitan area was born slightly before the institution of the metropolitan cities by the *Riforma Delrio*, discussed below. The process of identification of these areas and the actual functional interconnections offered by the administrations are constantly evolving. For instance, it is worth noticing that the Province of Sassari is not included in the dataset because has been recognized the status of a metropolitan city only in 2021.

enterprises from the need to be located within large urban agglomerations (Castells, 1989; Martinotti, 1993; Haddock, 2010)[7]. Within major urban centers emerge numerous neighborhoods, some of which have experienced gentrification processes at different times. These cities showcase historic centers enriched with monuments and architectures, bustling central commercial districts facilitating economic activities, and focal centers offering a modern interpretation of tertiary functions within expansive cities. Additionally, there exist dispersed areas that mirror an ideal residential concept, disrupting the congested city core. Nonetheless, metropolitan regions instantly summon a lifestyle characterization influenced by industrial modernization and the extension of territorial zones, which, following suburbanization trends, have given rise to the outskirts. These outskirts, frequently supported by intensive public housing initiatives, often lack adequate infrastructure and the fundamental requisites conducive to social and familial life. Consequently, they have generated a multitude of diverse realities, collectively forming a convoluted and paradoxical landscape. This intricate landscape not only corresponds to the emergence of "bedroom communities" encircling major metropolises but also intermingles with traditional central elements comprising historic working-class neighborhoods, deteriorated sectors of historic centers (as observed in Genoa, Palermo, Naples), disregarded areas stemming from deficient urban planning, and community enclaves that resiliently withstand the fragmentation induced by urban anonymity (Di Gennaro and Elce, 2020).

The National Institute of Statistics (ISTAT) underscores that when comparing seven out of eleven indicators with those of 2010, the overall picture

[7] "Delrio reform," or the redesign of local administrative competencies once under the purview of provinces and now governed by Law 56 of April 7, 2014, which precisely envisions the creation of "Metropolitan Cities" with bodies and functions overseeing the unions and mergers of municipalities. Metropolitan cities are extensive territorial entities coinciding with the territories of the same province, and their functions encompass a) the strategic development of the metropolitan territory; b) the integrated promotion and management of services, infrastructure, and communication networks of metropolitan interest; c) the management of institutional relationships at their own level, including those with European metropolitan cities and areas.

that emerges is largely positive, to the extent that "the perception of social and environmental degradation in the living area diminishes, and the proportion of individuals who feel secure walking alone in the dark in their vicinity increases, albeit marginally" (ISTAT, 2019a, p. 101). Various sources have indeed indicated a general decline in criminality within our country, highlighting an improvement in indices related to various offenses, both against individuals and property, as shown in Figure 4.1.

However, the metropolitan areas register the highest crime rates with respect to the other Italian NUTS-3 level entities, as shown in Figure 4.3. The data elaborated by the Ministry of the Interior also yield reassuring signals, indicating at the very least a fluctuating trend within a framework that nonetheless confirms the stability of the taxonomy of various indicators of forms of violence and security protection. In this scenario of decreasing crime rates, the contrast of the rising trend in femicide becomes even more noticeable and worrisome (ISTAT, 2020a, p. 15; ISTAT, 2019a, p. 106)[8]. It is interesting, from this perspective, to see the trends of the different offenses against women, shown in Figure 4.2 .

[8] As reported by Vignali et al. (2021) Italy adopted several measures in order to combat gender-based violence. The enactment of Law 93 of 2013 aimed, in fact, to tackle crimes against females increasing the penalty for those who commit violence against women and femicide. The implementation plan was realized in 2015 with a budget of thirty million euros for teaching programs and territorial plans, both for the general population and for those professional figures who take care of gender violence victims. The budget was also used to sustain women's emancipation and cultural prevention of the phenomenon. In addition, the Parliamentary Committee of Inquiry into Femicide and All Forms of Gender-based Violence, created by the Italian Senate, designed a national map of the phenomenon which was discussed on the 62nd Commission on the Status of Women of ONU (Repubblica Italiana, 2018). Furthermore, the Italian National Institute of Statistics (ISTAT) recently contributed with statistical analysis on intimate partner relationship instability, knowledge of the phenomenon, anti-violence centers, and law enforcement's role in the protection of victims (ISTAT, 2019).

4.2 Data

Violence against women is a vast hidden issue since many victims tend not to report the abuses. In this sense, as already mentioned, we consider femicide to be a measure that does not suffer from under-reporting, although inadequate to proxy the real level of overall violence. For our dependent variable, we draw on Denti and Faggian (2022) dataset to retrieve the information on the IPFs recorded in the Italian metropolitan areas between 2012 and 2020. We updated and geo-coded each event at the street level and arranged a pooled version of the dataset, excluding the time variation[9].

Figures 4.12 - 4.25 represent the geographical distribution of the IPF rate (10,000 inhabitants) inhabitants across and within the metropolitan areas.. Figure 4.5 (*a*) summarizes the same geographical distribution of the aggregate rate, while Figure 4.5 (*b*) shows the same at the metropolitan city level. Due to the exploratory nature of the paper, our initial geographical sample is composed of more than 108,000 census tracts, distributed within 1376 municipalities, across 14 metropolitan areas[10]. Thanks to the geo-localization we are able to account for slightly more than 400 events, aggregated at the census tract level. Figure 4.7 visually represents the level of disaggregation obtained through the census-tract areas. Figure 4.6a and Figure 4.6b show the relative frequency distributions[11].

[9]The information on IPFs comes from web-scraping of newspapers, in the absence of other publicly available sources of data with such level of geographical disaggregation. What happens is that the information regarding the precise location of the event, might not always be immediately available, and this might be mainly due to reasons related to privacy and/or ongoing investigations or trials. We then checked all the records for potential updates, to make sure our dataset represents the most precise location possible.

[10]The shape-files are the official ones provided by ISTAT.

[11]We chose to base our analysis on the finest geographic unit at our disposal: the census tract area, in our effort to accurately represent the data and map the behavior of the variables at hand. Given that this work is primarily exploratory and still in its early stages — with its primary objective being to navigate a novel set of geocoded data — we claim that utilizing the finest area will offer more insights into correlations without the potential interference that could arise from the vast geographical variations associated with municipal-level analysis. This approach also mitigates potential complications that can emerge when data is aggregated at higher levels, such as the Simpson paradox. Having said that, we fully recognize the limitations of the census tract area. Indeed, it does not

With the aim of identifying the most relevant *ecological* factors related to the presence and intensity of the IPF across the municipalities within the Italian metropolitan areas, our estimation considers a broad set of potential risks and protective factors for IPF drawing on existing research. The main set of covariates comes from the 2011 Italian National Census. In compliance with the most relevant literature, we account for the demography, population composition, socioeconomic characteristics of the households, employment, and education of the female and male population, and for the characteristics of the urban fabric (Aizer, 2010; Anderberg et al., 2016; Bozzano, 2017; Alesina et al., 2021; Waldron, 2021; Hainmueller and Hopkins, 2014; González and Rodríguez-Planas, 2020; Dijkstra et al., 2020; Glaeser and Sacerdote, 2000). Specifically, we account for demographic factors such as the population size (taken in logarithm), the share of the female population, the share of divorced, the share of large families (with more than four members), and the share of the foreign population. We then include in the estimation variables which are meant to address the sphere of the socio-spatiality of the unit of analysis. In particular, we account for the percentage of households renting the house in which they live, the percentage of households that own the house in which they live, and the residential density, representing The ratio between dwellings occupied by at least one resident and the surface area of dwellings occupied by at least one resident. Furthermore, we include a buildings quality index (higher value, indicates higher quality of residential built environment), and the transience index, an indicator which includes the houses occupied by non-residents and the ones left empty. To account for the socio-economic characteristics of the population in our unit of analysis, we account for the share of illiterate males and females, as well as the share of male and female unemployment. Finally, as will be discussed further below, we also account for the number of shelters per 10,000 inhabitants, which have been collected and geocoded

serve as an accurate representation of a 'neighborhood' in the urban-sociological sense, nor does it enable us to identify significant urban patterns. At the same time, we acknowledge the complexities involved in defining *neighborhoods*, as presented in the Introduction of this chapter.

specifically by who is writing for the purposes of this study. Table 4.1 reports the descriptive statistics for the main covariates at the census tract level.

4.3 Empirical Strategy and Estimation

As main estimation strategy, we rely on a hurdle-like two-step estimation, comprising a Probit and a Truncated Poisson regression. The rationale behind opting for the Hurdle model is rooted in its suitability for the unique characteristics of our dataset. The Hurdle model addresses the dual nature of the data, distinguishing between areas with no femicides and those with varying frequencies[12]. As the first step, we run a Probit regression to identify the main factors significantly related to the probability of observing at least a femicide in a given area. We use the Probit model as a tool to detect the *red flags* identifying latent process, which surely involves factors and mechanisms that we are not able to fully account for at this stage of investigation (Paez, 2022). Such processes are here conveyed by the latent variable y_i^*, which is a function of the vector $x_i^{*'}$ as in Eq. 4.1

$$y_i^* = \alpha x_i^{*'} + \epsilon \tag{4.1}$$

$$y_{ij} = \beta x_{ij}^{'} + \epsilon \tag{4.2}$$

Let's now define the variable y_{ij} as the dependent variable associated with the probability of observing femicide in the same geographical unit. Based

[12]The Probit component specifically models the likelihood of femicide occurrence, while the Truncated Poisson efficiently captures the intensity of femicides in specific areas. This model choice is advantageous for handling highly skewed count data with genuine zeroes, without the need for data truncation. Unlike the Tobit model, which assumes a normal distribution and may not be well-suited for skewed count data, the Hurdle model accommodates the specific characteristics of femicide data more effectively. Moreover, the Hurdle model's ability to account for heterogeneity in the data is crucial, as it recognizes that the processes generating zeros and positive counts may differ.

on our assumption, y_{ij} is not always observed. Rather, the dependent variable for observation i in the unit j can be observed according to the conditions summarized in Eq. 4.3.

$$y_{ij} = \begin{cases} 1 & if \quad y_i^* \geq 0 \\ 0 & otherwise \end{cases} \tag{4.3}$$

The results of the first step, the Probit estimation, are summarized in Table 4.2, and discussed in the next session.

Following the hurdle logic, in the second step we then subset our sample and perform a truncated Poisson estimation (Cameron, Trivedi, et al., 2010)[13]. The general estimation model at the base of our analysis is represented by Equation 4.4:

$$IPF_j = \alpha_0 + \alpha_1 W_j^{'} + \epsilon_j \tag{4.4}$$

where $W^{'}$ is a vector including the set of risk and protective factors which could relate to IPF described above, at the level of census tract j. The results are summarized in Table 4.2, Column (3).

4.3.1 Early Stage Consistency Check

As anticipated, one of the main challenges related to this research regards the distribution of the dependent variable. Figure 4.6a and 4.6b show the frequency distribution of IPF respectively at the census-tract and municipal levels. In the attempt to run a benchmark estimation on the whole sample without applying the hurdle-like logic presented above, it might be difficult to defend the reliability of estimates produced by a straightforward

[13] See Figure 4.8 for the fit of the distribution

linear regression method, given such a skewed and unbalanced distribution. We opted for the adoption of a negative binomial as reference distribution which, in our case, fits the data better than a Poisson[14]. As shown in Figure 4.9, the Poisson does not represent a perfect fit[15].

$$\hat{k} = \frac{\bar{x}^2}{\sigma^2 - \bar{x}} \tag{4.5}$$

Furthermore, computing the so-called 'clumping parameter' as a measure of the degree of aggregation in the data (Crawley, 2012), as shown in Equation 4.5, we obtain a value of $k = 0.031$ and $k = 0.006$ for the distributions at the municipal and census tract level respectively, thus indicating a high level of aggregation in the data (Crawley, 2012). Another indication of a negative binomial being appropriate is given by comparing the observed and expected values shown in Figure 4.10. Again, this holds true both in the case of municipal level (a) and census tract level distributions.

As an alternative model specification, we performed a Zero-Inflated Negative Binomial regression, often suggested as the best way to deal with this kind of over-representation of zeroes (Crawley, 2012; Cameron, Trivedi, et al., 2010)[16]. The results are presented in Table 4.3, Column (1). We use the logarithm of the population as the inflation variable. With respect to the set of independent variables presented above, we include in the model the quadratic term of the logarithm of the population to check for the existence of a quadratic relationship between the distribution of IPFs and the population of the census tract areas. Moreover, as shown in Column (2),

[14] See for recent evidence and usage of the model Beckers and Boschman (2019); Moreira and Ceccato (2021); Wang et al. (2021).

[15] While the graphic evidence does have a limit, especially in the case of this research, to provide all the evidence needed to discard the Poisson option, the variance-mean ratio leaves no doubts, with a value of 10.292 and 1.670 at the municipal and census tract level respectively.

[16] The Zero-Inflation Negative Binomial regression (ZINB) provide a better model fit with respect to the Negative Binomial regression (NEGBIN) also according to the values of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Where lower value suggests better fit: AIC (NEGBIN) = *4460.365*; AIC (ZINB) = *4395.035*; BIC (NEGBIN) = *4748.11*; BIC (ZNIB) = *4721.146*.

we include the number of shelters for 10,000 inhabitants. An in-depth discussion of the methodology and the results are provided in the following section.

4.4 Results and Discussion

We rely on a hurdle estimation process to differentiate the variables correlated with an increased probability of observing at least an IPF in a given census tract area from the ones that might have a role in influencing the escalation of the phenomenon. Before proceeding we should clarify that the variables presented and discussed below have been found as the optimal set of variables that encompasses the literature and, at the same time, does not suffer from multicollinearity[17]. Table 4.2, Column (1), shows the estimates of the Probit regression[18]. The population, the share of foreigners, and the transience index appear related to an increased probability of observing at least a femicide.

It seems worth highlighting the evidence shown in Column (2) of Table 4.2. We indeed estimate the same Probit regression, substituting the total share of the foreign population, discriminating by their macro-region of origin[19]. The estimates show that the coefficients remain positive and significant in relation to people originally coming from Europe and Africa. While we are not able to say whether this correlation is due to the perpetrators or the victims, although has been proven that belonging to an ethnic minority is a common characteristic for both IPF victims and offenders (Matias et al., 2020), the results are consistent with the literature identifying differential

[17]Besides the set of correlations shown in Figure 4.4, our set of variables are robust to the VIF test, as shown by the coefficients reported in Table C1

[18]Given the peculiar characteristics, we run the run a Logistic regression as a robustness check, specifically designed to handle the analysis of rare events (Tomz et al., 2021), which estimates are shown in Table C2. The main results provided by the Probit regression still hold.

[19]The same exercise could not be performed in the second step of the hurdle estimation because, given the too low number of observations, the algorithm would not properly converge.

patterns across different ethnic groups Kubrin and Herting, 2003; Frye et al., 2008; Stansfield et al., 2021; Messing et al., 2022. On the other hand, the share of large families (with more than 4 members), the share of families that own the house in which they live, and the share of males with a low level of education, are correlated to a decreased probability[20].

Table 4.2, Column (3), reports the estimates of the second step of our hurdle-like estimation, performed keeping only the areas in which have been recorded at least one IPF. In this case, there are no significant coefficients, except the one related to the share of families that own the house in which they live. In other words, within the areas with a higher probability of registering an IPF, this is the only factor that is significantly correlated with a decreased *intensity* or *escalation* of the phenomenon. This evidence appears particularly interesting if considered in light of some relevant pieces of literature such as Sampson et al. (1997). In this study, the authors hypothesize that *collective efficacy*, defined as social cohesion among neighbors combined with their willingness to intervene on behalf of the common good, is linked to reduced violence. Specifically, they identify the share of families in owned houses as one of the main drivers for collective efficacy.

4.4.1 Alternative Model Specification

In order to assess the consistency of our estimates given the peculiar distribution of our dependent variable, we performed a Zero-Inflated Negative Binomial regression as an alternative model specification, often considered the best option when dealing with similar distributions (Cameron, Trivedi, et al., 2010; Crawley, 2012). As shown in Table 4.3 (Columns 1 and 2), we use the logarithm of the population as the inflation variable. In regions with a sparse population, the absence of femicides can often be attributed to the sheer lack of opportunity due to the small number of inhabitants. In other words, femicides may not occur in these areas simply because the population is too low to present significant opportunities for such events. On

[20] In all the estimations, the Metropolitan Area Fixed Effects are non-significant.

the other hand, in densely populated regions, the non-occurrence of femicides can be explained by different factors, unrelated to population size. Such areas may have zeros for reasons other than a lack of opportunity — perhaps due to effective preventive measures, cultural factors, or other socio-economic conditions. This would then allow us to account for the excess zeros in our data, as confirmed by the significance of the inflation coefficient. While the main results still hold, it seems worth highlighting that we have included the quadratic form of the variable related to the log of population, with the aim of checking for non-linear relationships[21]. The coefficients related to the log of population and its quadratic form appear both significant. However, while the former has a negative sign, the latter is positively correlated. This would suggest a *U* shaped distribution, in which the increasing level of the population starts showing a positive effect with the increased probability of observing IPFs after a certain threshold. We then computed this *turning point*, obtaining a value of approximately one hundred and twenty inhabitants, very close to the median of the distribution of population in our sample. Relying on a slightly increased stability of the model, we include in this estimation the presence of anti-violence shelters per 10,000 inhabitants. This geocoded data set, which has been collected and assembled specifically for the purposes of this paper, was initially excluded because of the concerns related to its potential endogeneity[22]. Despite the persistence of such concerns, we believe it is important to assess - even preliminary - the role of this factor, which relevance is also often highlighted by the related literature (Dugan et al., 2003; Reckdenwald and Parker, 2010; Voith, 2019). The coefficient is positive and slightly significant. Although this might seem counter-intuitive, similar results have already been found in previous studies. From a criminological perspective,

[21]Figure 4.11 shows the distribution of IPF over the population size.

[22]The presence of shelters (*Centri Anti-Violenza*) in Italy, is not mapped by a unique source. The data has been collected by who is writing through the web-scraping of publicly available websites of both institutions (regions and municipalities) and specialized associations managing the shelters and operating either at the local or national level.

the interpretation of this positive relationship usually falls under the conceptual framework offered by the so-called *Backlash Theory* (Russell, 1975; Williams and Holmes, 1981). In extreme synthesis, this perspective suggests that male violence leading to IPF increases in the presence of a perceived or real loss of power control (Vieraitis and Williams, 2002; Dugan et al., 2003; Browne, 2008 in Reckdenwald and Parker, 2010)[23].

4.5 Conclusions

In this Chapter, we present an attempt to understand the risk and protective factors associated with Intimate Partner Femicides in metropolitan areas by exploiting novel data while drawing on a mix of literature strands from criminology, urban studies, and applied economics. To the best of our knowledge, we are among the firsts proposing the adoption of a similar setting to the analysis of the case of *urban* Italy. As detailed in section 4.1.2, Italian metropolitan areas are unique administrative entities. While some exhibit more rural traits, others present an intricately complex urban landscape. One of the challenges related to the analysis of dynamics within these areas is related to the definition of a concept of pivotal importance in the studies dealing with urban ecology: the *neighborhood*. Coulton et al. (1999) defines neighborhoods as geographically bounded groupings of households and institutions connected through structures and processes. Arguably, the main challenge when it comes to applied social research is the identification of the *processes*, which in this case we might define as those non-physical ties or social factors shared by inhabitants or users. However, although researchers have been interrogating themselves and their communities regarding the need to overcome the use of pre-defined administrative boundaries (see for instance Clapp and Wang, 2006), they still represent one of the most straightforward and comparable geographical units available.

[23]This theoretical perspective, together with the *Exposure Reduction* theory (Dugan et al., 1999; Dugan et al., 2003; Reckdenwald and Parker, 2010), is one of the key approaches most commonly used to interpret the role of contextual (and personal) variables on the dynamics underpinning - and leading to - IPH and IPF.

Aware of this, we decided (at this stage) to base our analysis on the smallest unit available, the census tract, in order to address the potential connections among the data at the finest level possible.

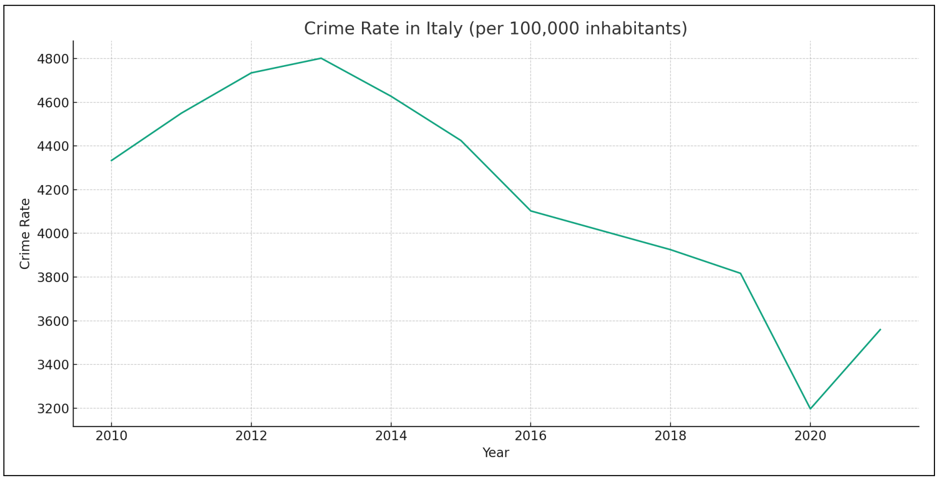
It is important to emphasize that the relationships highlighted in this study are correlational, and a causal interpretation is not warranted based on our evidence, which represents a first step in detecting which elements of the urban fabric appear to matter for the observed urban geography of IPF. Our findings contribute substantially to the existing body of research on this topic. By leveraging innovative geocoded data, we have embarked on an exploration of this pressing issue at a neighborhood level, a scale that has been largely uncharted in previous studies regarding the Italian context. Our study also aims to emphasize the need for further rigorous research, particularly to disentangle the intricate web of causality. In this regard, our next steps will move towards the identification of a more suitable definition of neighborhood, and the inclusion of other neighborhood-level (potentially) relevant factors that might be related to the social connections and the system of cultural and gender norms (as the presence of churches, for instance).

However, we must also acknowledge that this study faces some relevant issues, that might be difficult to fully address. First, our current research lacks an accounting of deterrence. We do not have data on the number of police officers, for instance. A measure which by the way would be difficult to place at the geographical scale our analysis is currently based on. Furthermore, even if we account for the geo-coded presence of shelters for women, we fear that our estimation strategy could not deal, at this stage, with the endogeneity connected to such a variable. Finally, our study is not able to provide a clear understanding of whether the dynamics of IPF identify a violent phenomenon *per se*, or it is linked to the dynamics of other forms of violence, such as 'common' violent or property crime (Frye et al., 2008). This is mainly due to the unavailability of these kinds of data[24]. In this regard, we must say that the generation and dissemination of such data become paramount. By sharing with researchers this kind of information, not only can we amplify our academic understanding of gender violence, but we can also equip policymakers, especially at the local level, with insights that can significantly inform and influence their decisions. The synergy of research and policy can pave the way for more informed actions, driving meaningful change in the realm of gender violence.

[24]Even though there might be these kinds of records disaggregated at the municipal level, they are managed by the Italian Ministry of the Interior, and obtaining them, at this moment, does not seem possible.

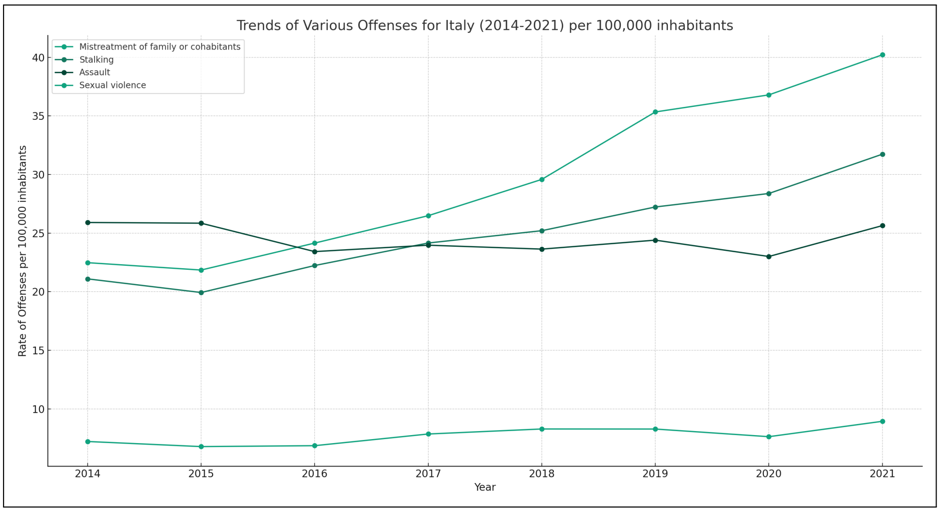
4.6 Figures and Tables

FIGURE 4.1: *Total Crime Rate - National Level*



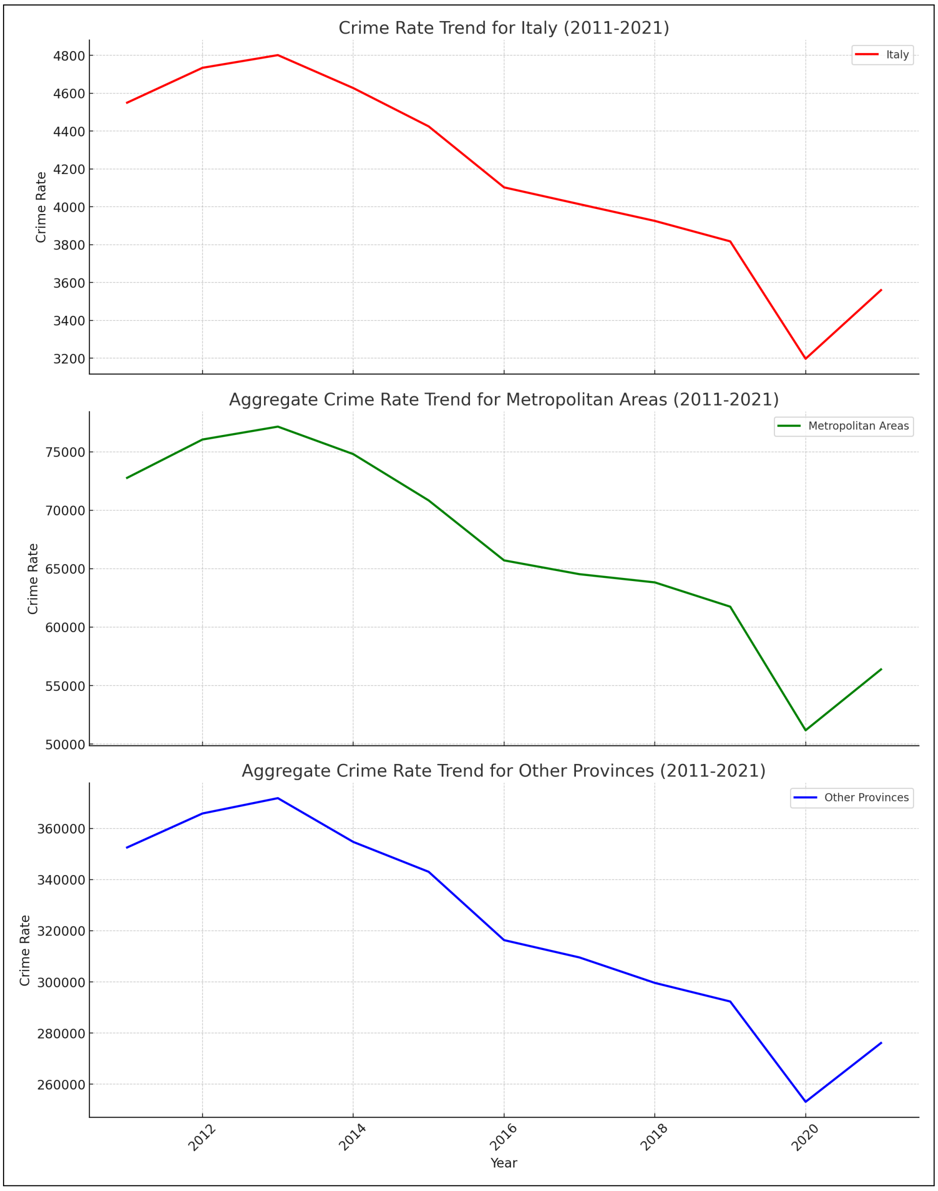
Note: Author's elaboration on ISTAT data.

FIGURE 4.2: *Various Offenses Against Women*



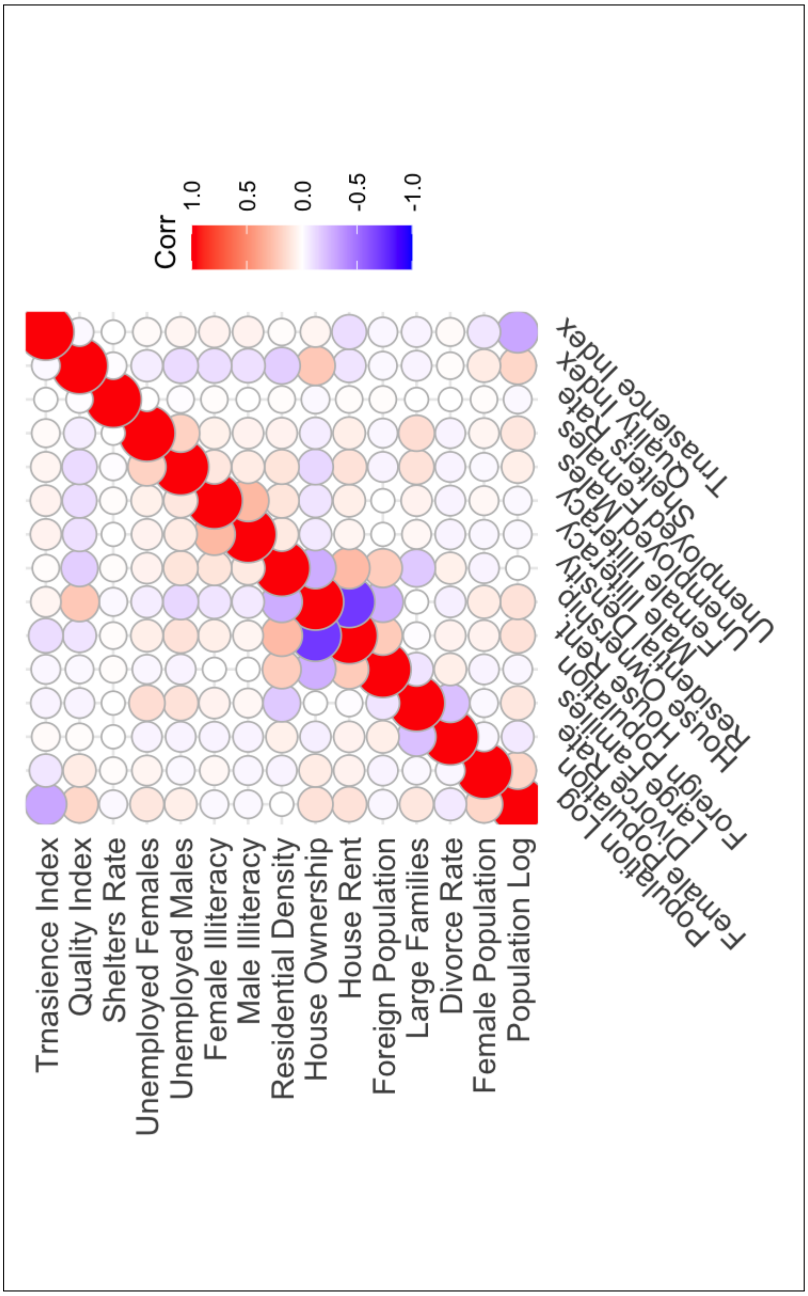
Note: Author's elaboration on ISTAT data.

FIGURE 4.3: *Total Crime Rates - NUTS-3 Level*



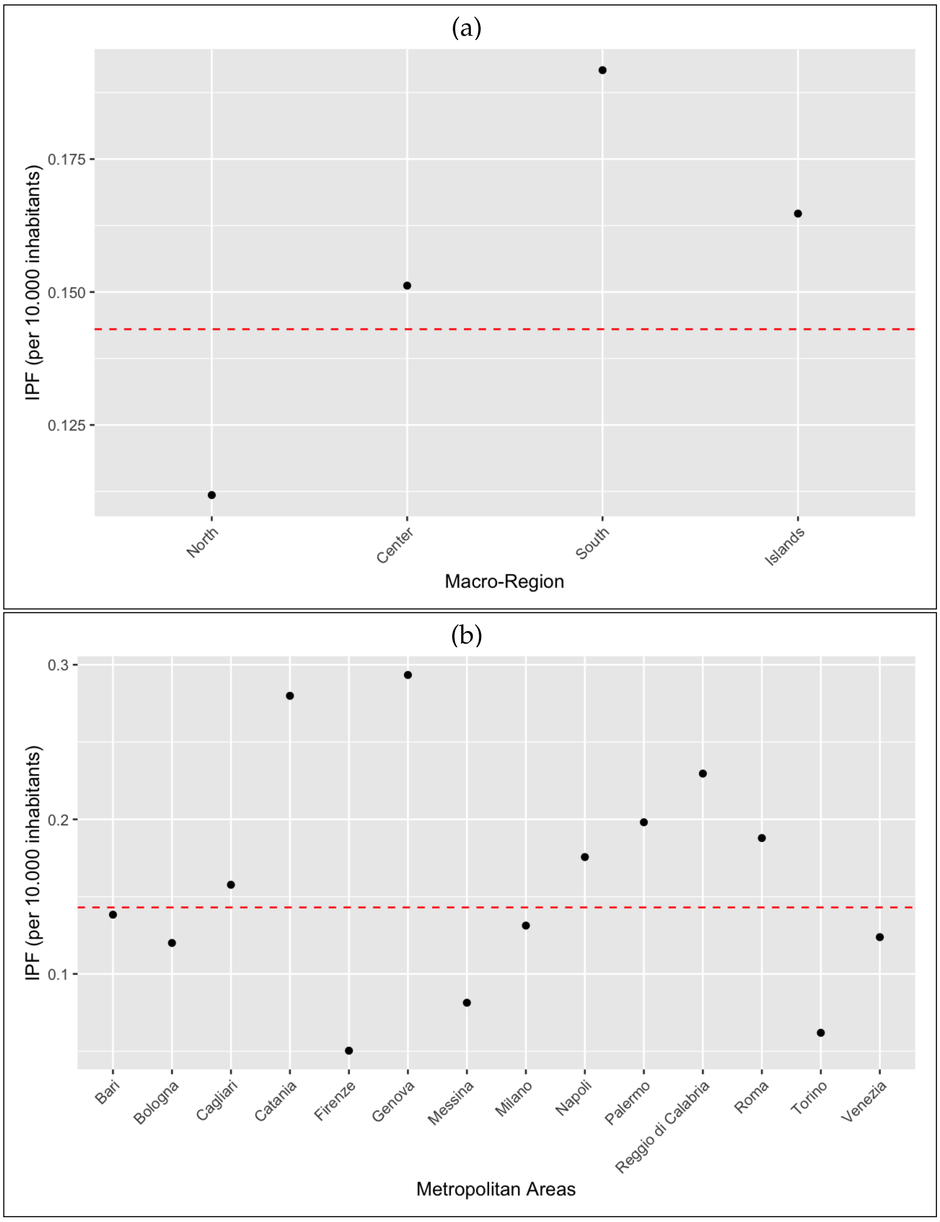
Note: Author's elaboration on ISTAT data. The graph offers a comparison between the total crime rate within the Italian Metropolitan Areas, the other Italian Provinces, and the total rate at the national level.

FIGURE 4.4: *Correlations Among Variables*



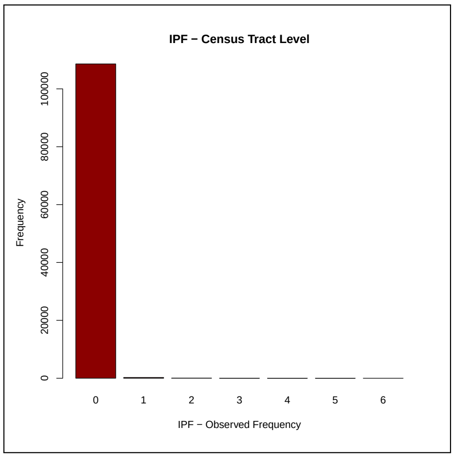
Note: The Figure offers a graphical representation of the correlations among the variables included in all the different stages of the estimation, including the indexes.

FIGURE 4.5: *IPF rate aggregated distribution*

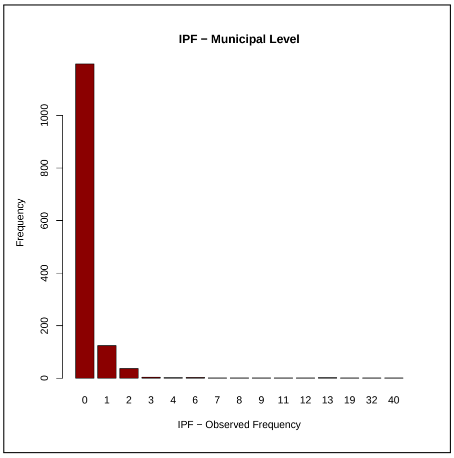


Note: The figure displays the distributions of IPF rates (number of IPFs per 10,000 inhabitants) across 'Macro-Regions' (North, Center, South, and Islands) and metropolitan areas. The red line represents the mean of each distribution.

FIGURE 4.6: *IPF - Frequency Distribution*



(a)



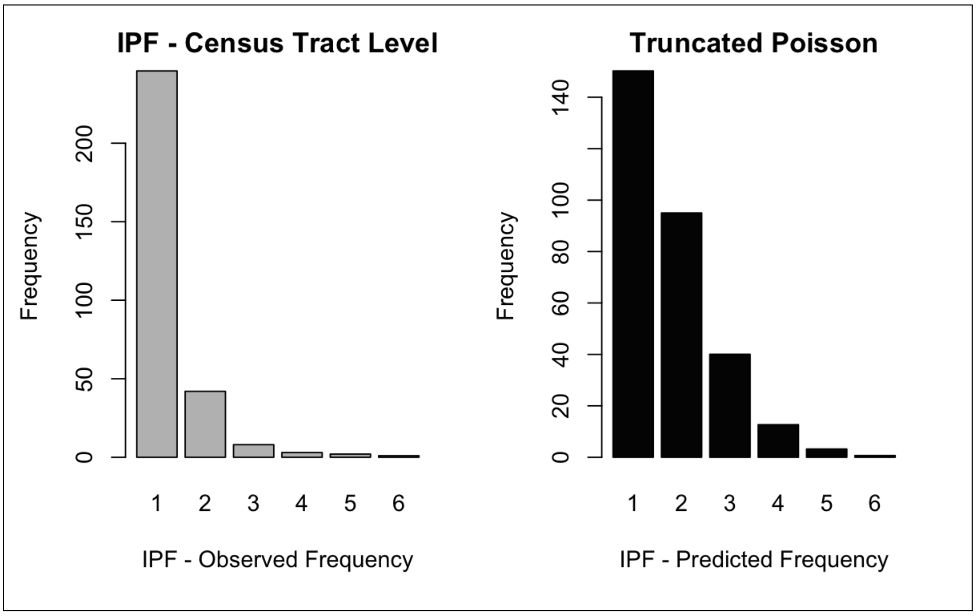
(b)

Note: The figure represents the distributions of IPFs, expressed as a count variable, at the census-tract level (a) and the municipal level (b). The extreme skewness of both distributions is evident, with a notable over-representation of zeroes.

FIGURE 4.7: *Census tract level geo-localization of IPF*

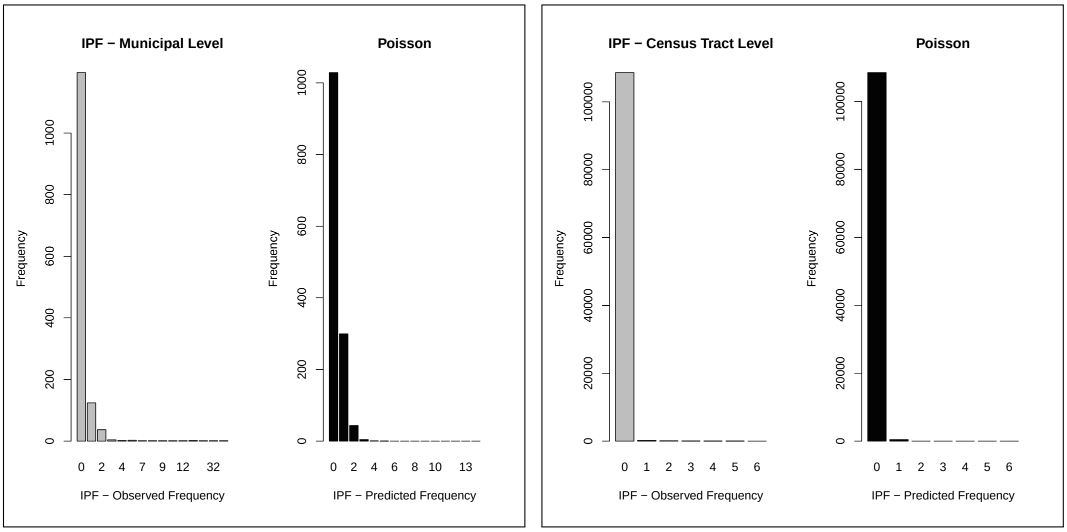
Note: The figure represents the level of geographical disaggregation provided by the Italian census tract areas. In this case, the image represents the historical city-center of Bari, in Puglia region.

FIGURE 4.8: *Truncated Poisson - Distribution Fit*



Note: The figure illustrates the actual distribution of IPF on the left side and the predicted frequency distribution of the truncated Poisson on the right. The truncated Poisson distribution is adjusted to align with the characteristics of the original distribution.

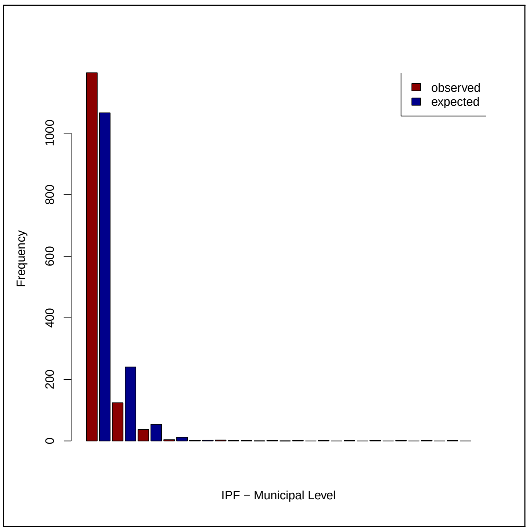
FIGURE 4.9: *Poisson distribution fit*



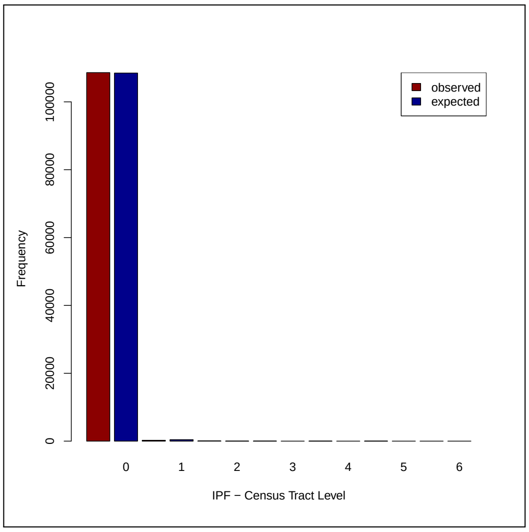
(a) (b)

Note: The figure illustrates the actual distribution of IPF and the predicted frequency distribution of the Poisson at both municipal (a) and census-tract (b) levels. The Poisson distribution is adjusted to align with the characteristics of the original distribution.

FIGURE 4.10: *Negative-Binomial distribution fit*



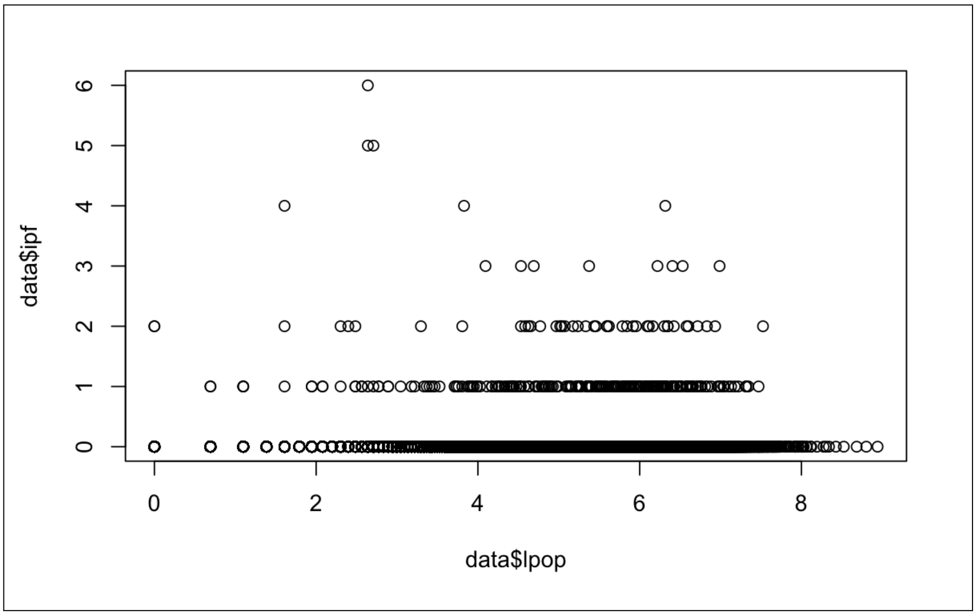
(a)



(b)

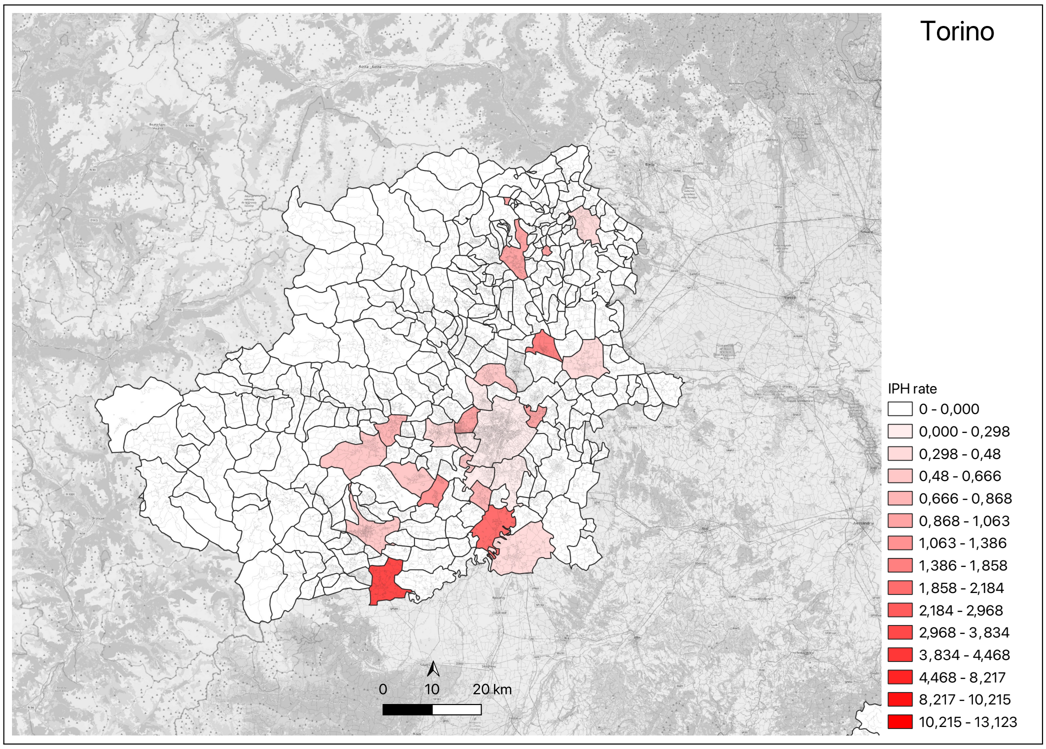
Note: The figure illustrates the actual distribution of IPF and the predicted frequency distribution of the Negative Binomial at both municipal (a) and census-tract (b) levels. The Negative Binomial distribution is adjusted to align with the characteristics of the original distribution.

FIGURE 4.11: *IPF distribution over population*



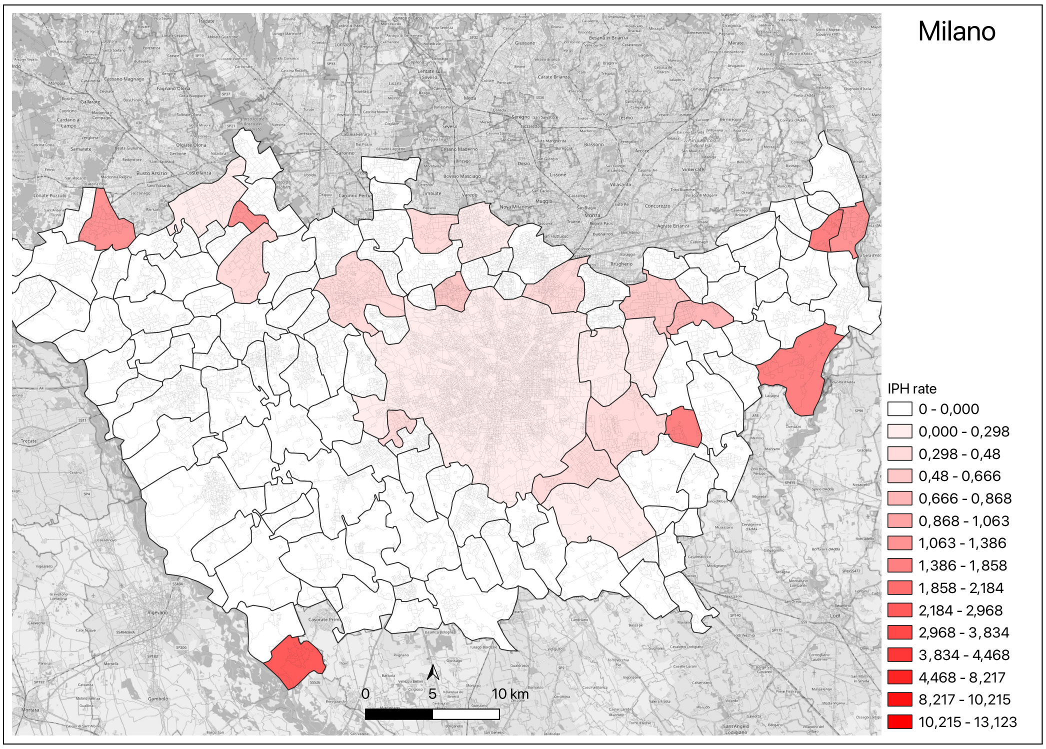
Note: The plot illustrates the distribution of IPF over the population (expressed in logarithm) of the census-tract areas considered in the sample. The distribution of values supports the need to check for a non-linear relationship between IPF and population. In this regard, see the results of the Zero-Inflated Negative Binomial regression in Table 4.3.

FIGURE 4.12: *Torino - IPF rate (10.000 inhabitants)*



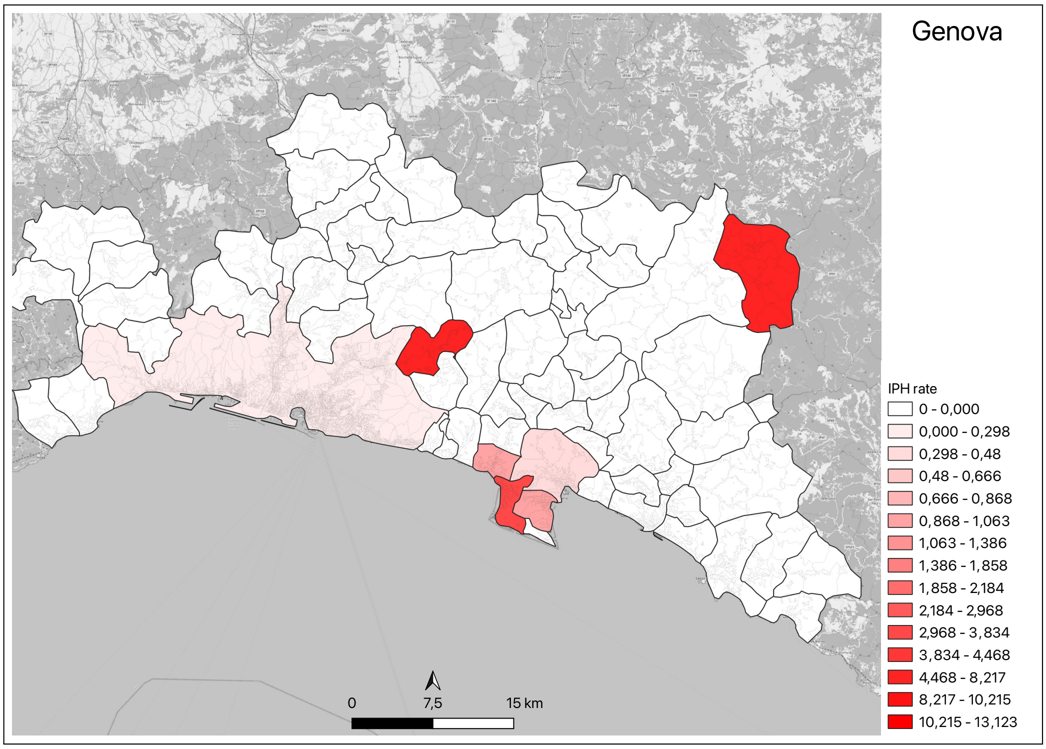
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.13: *Milano - IPF rate (10.000 inhabitants)*



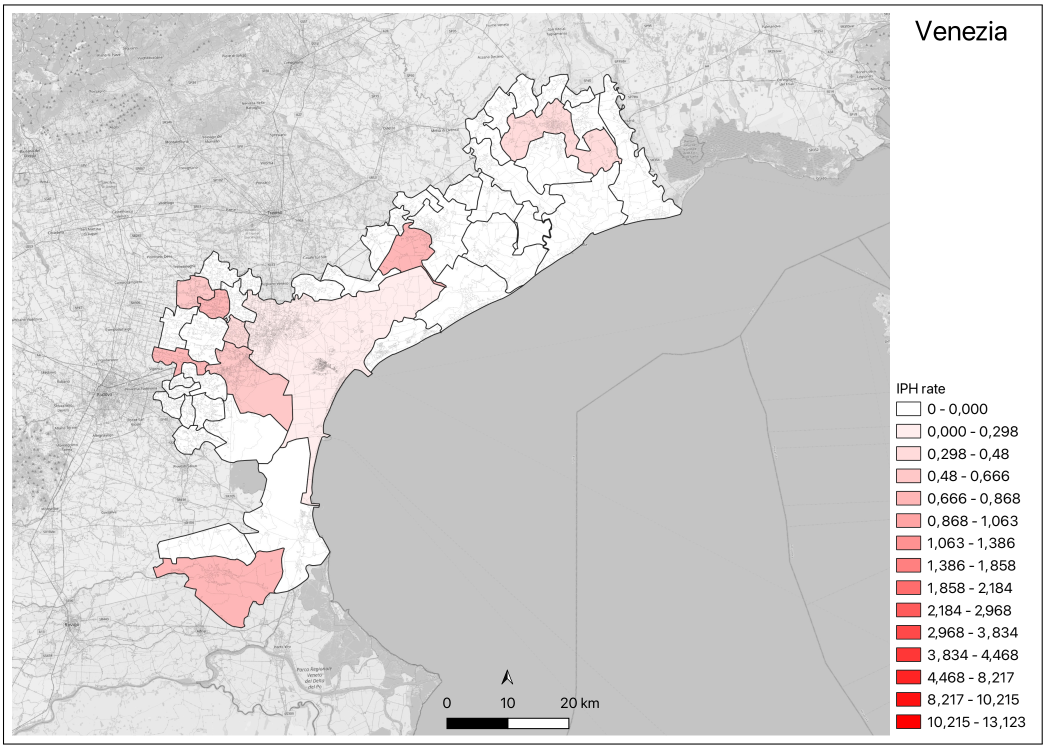
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.14: *Genova - IPF rate (10.000 inhabitants)*



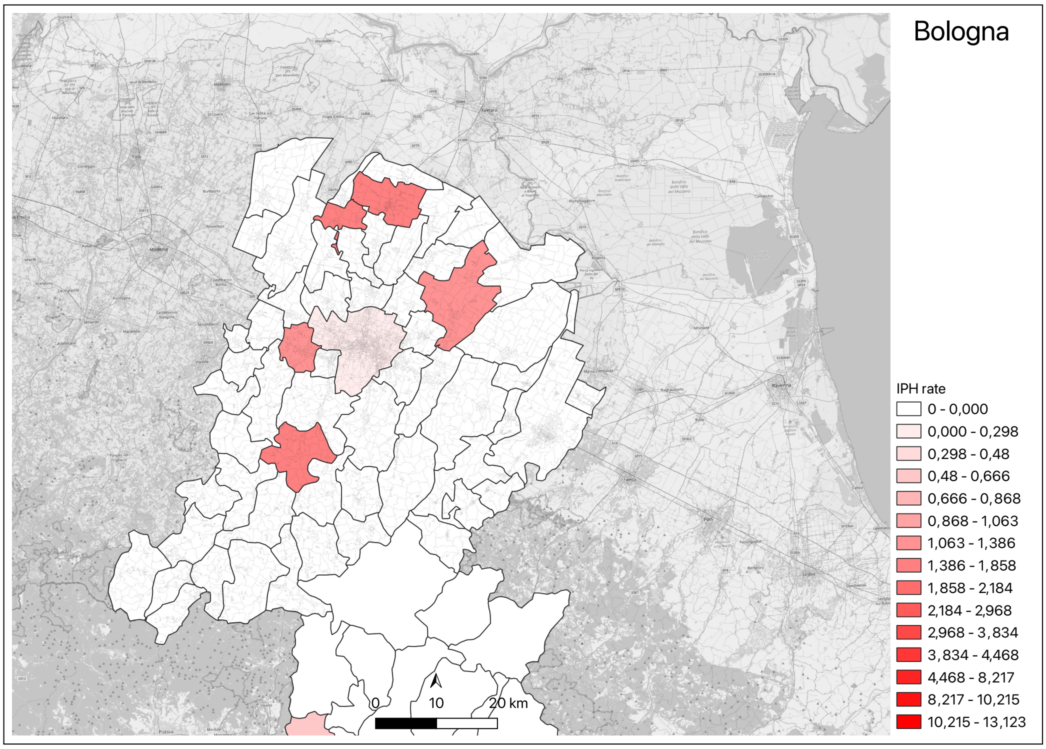
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.15: *Venezia - IPF rate (10.000 inhabitants)*



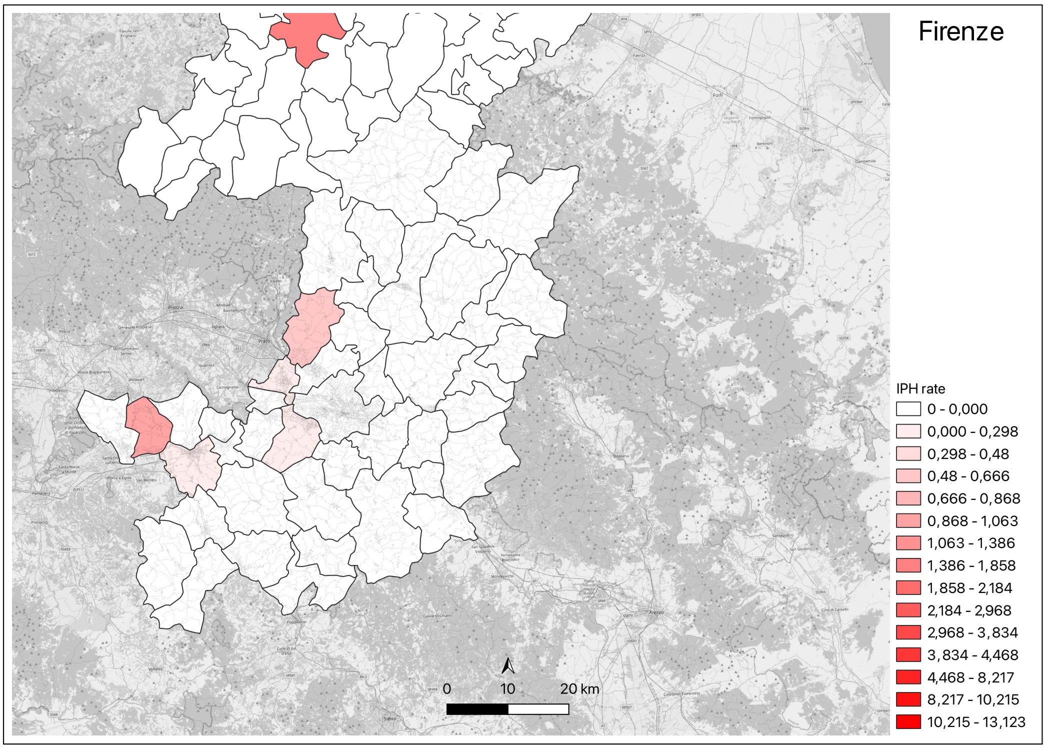
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.16: *Bologna - IPF rate (10.000 inhabitants)*



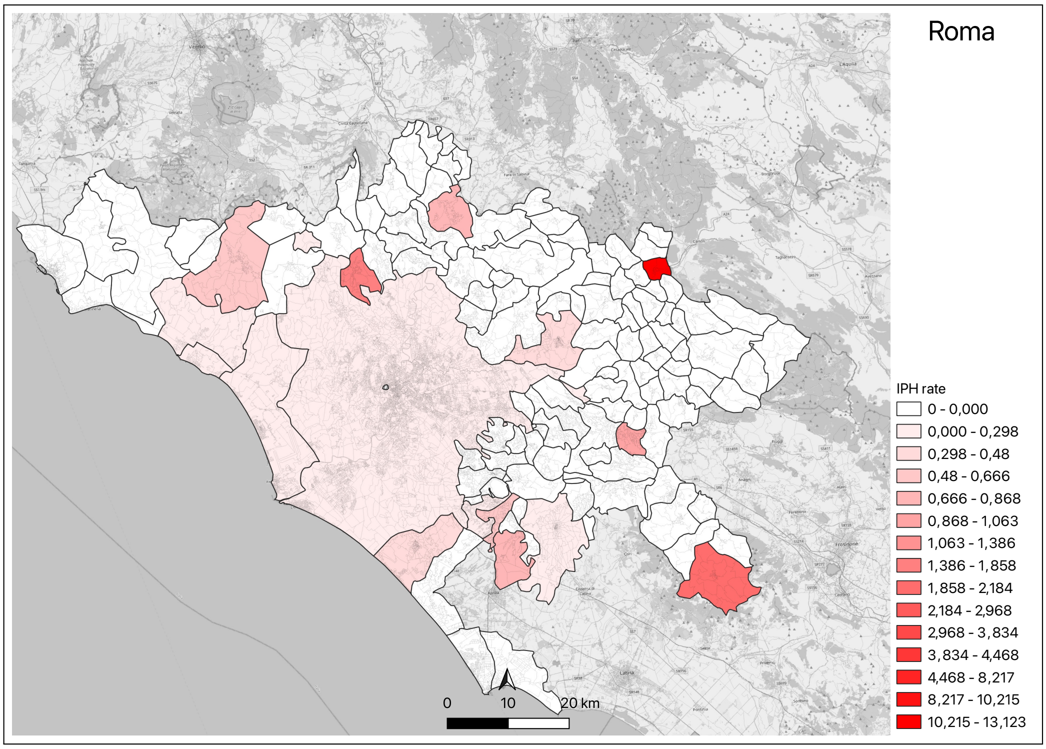
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.17: *Firenze - IPF rate (10.000 inhabitants)*



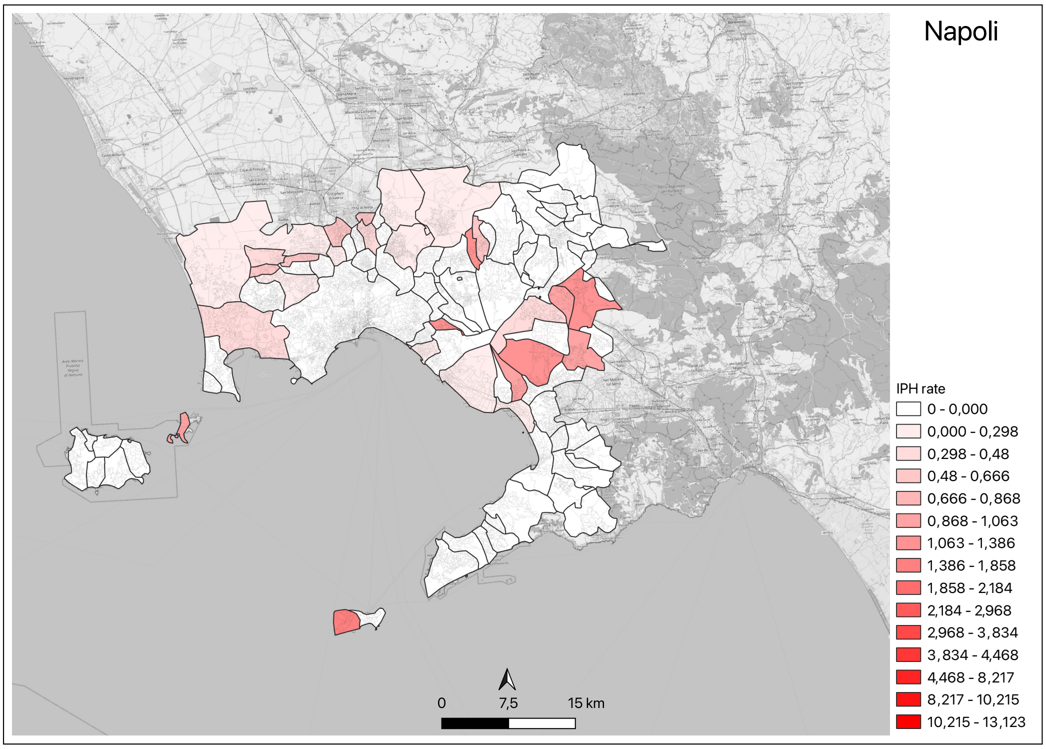
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.18: *Roma - IPF rate (10.000 inhabitants)*



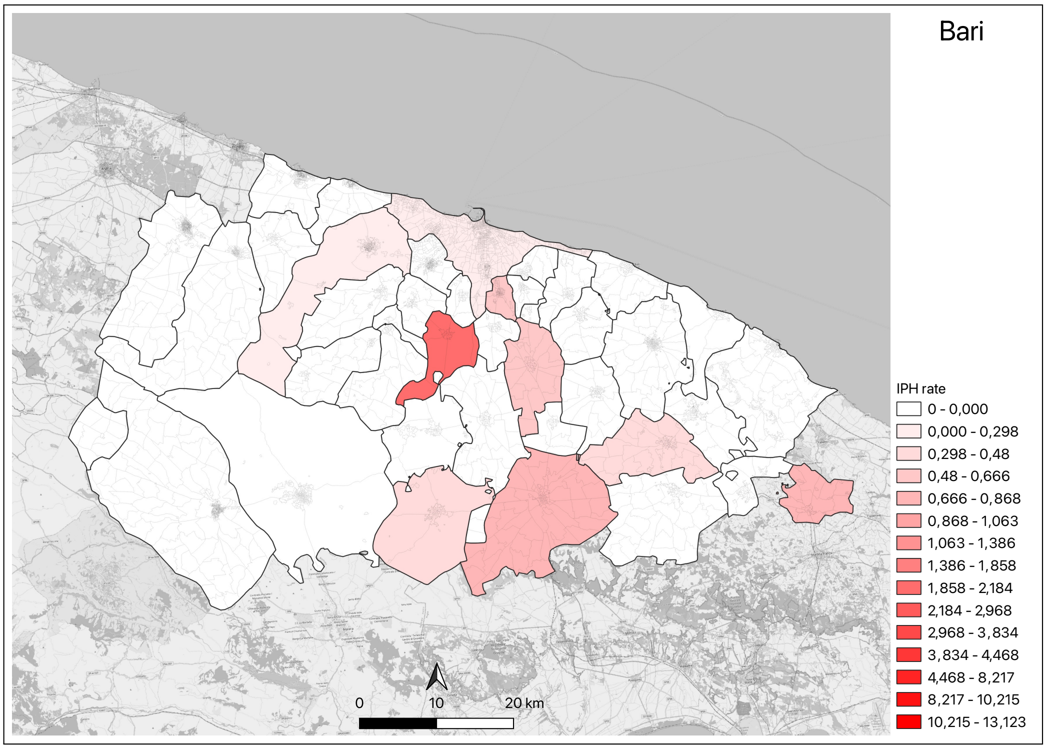
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.19: *Napoli - IPF rate (10.000 inhabitants)*



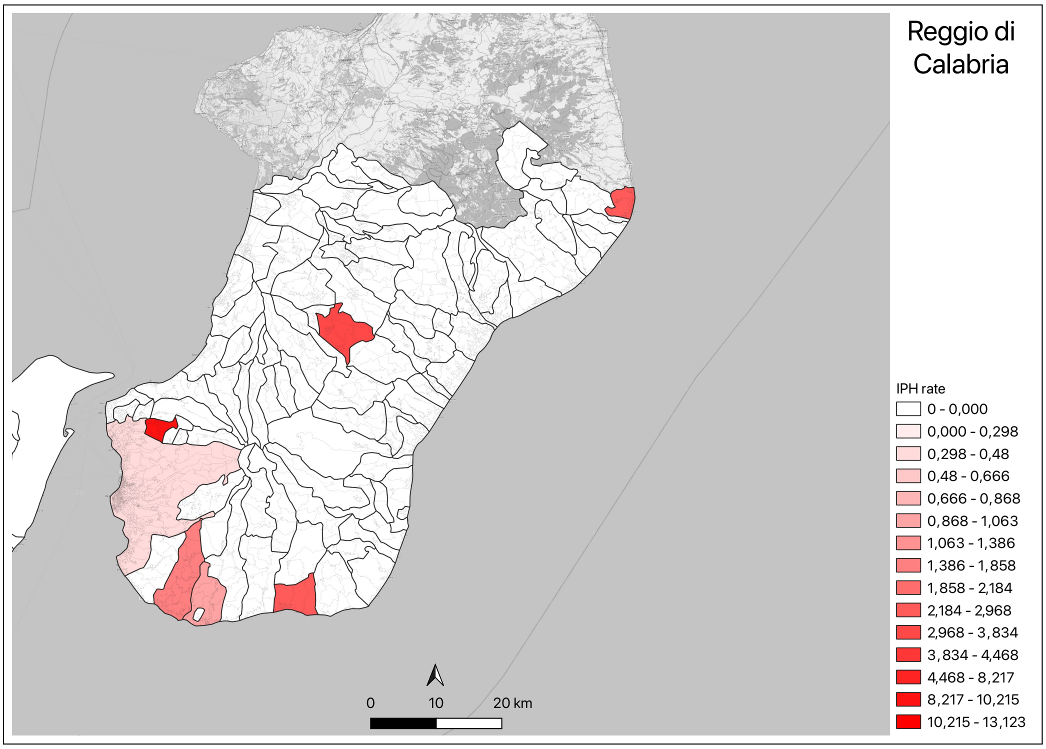
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.20: *Bari - IPF rate (10.000 inhabitants)*



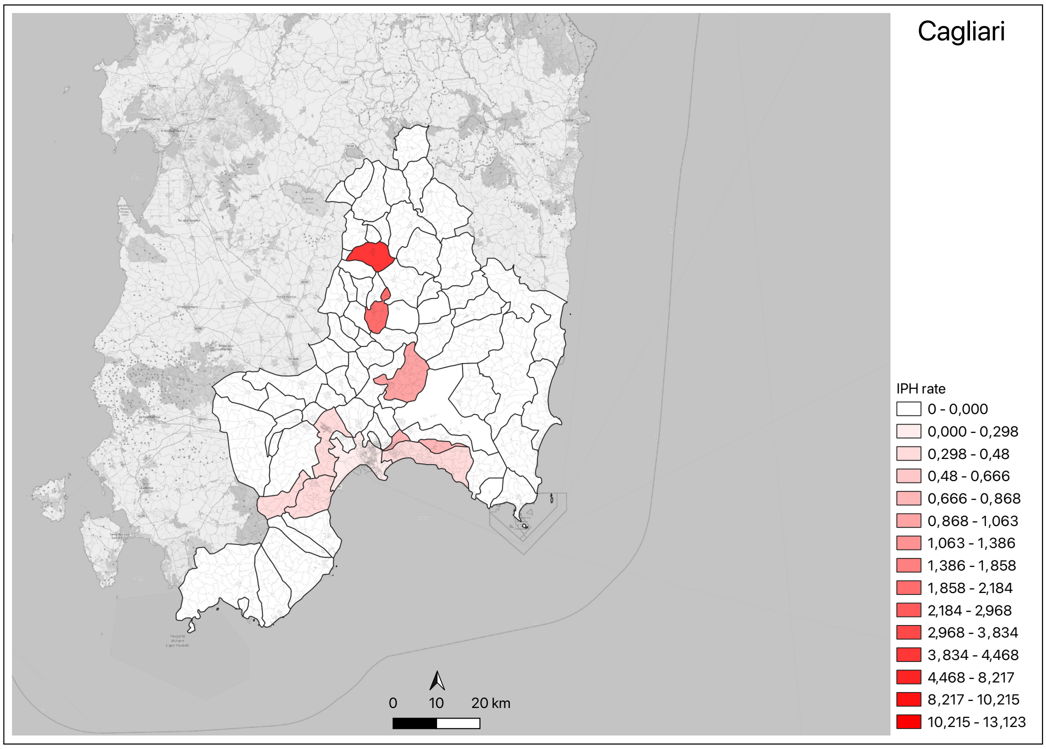
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.21: *Reggio di Calabria - IPF rate (10.000 inhabitants)*



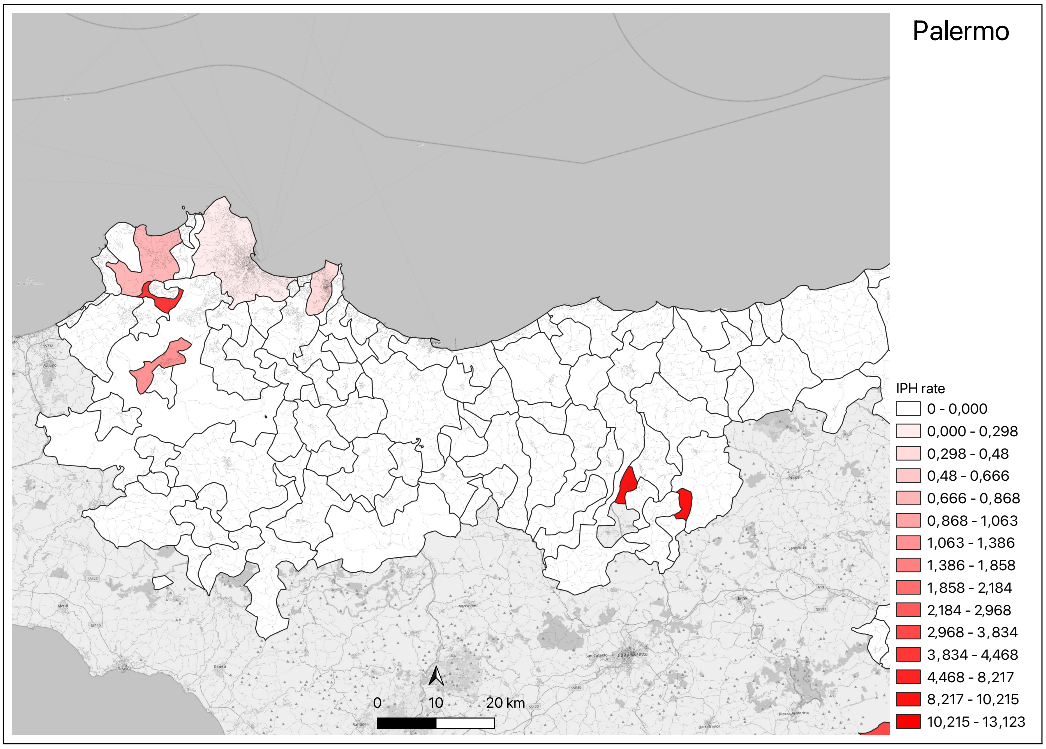
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.22: *Cagliari - IPF rate (10.000 inhabitants)*



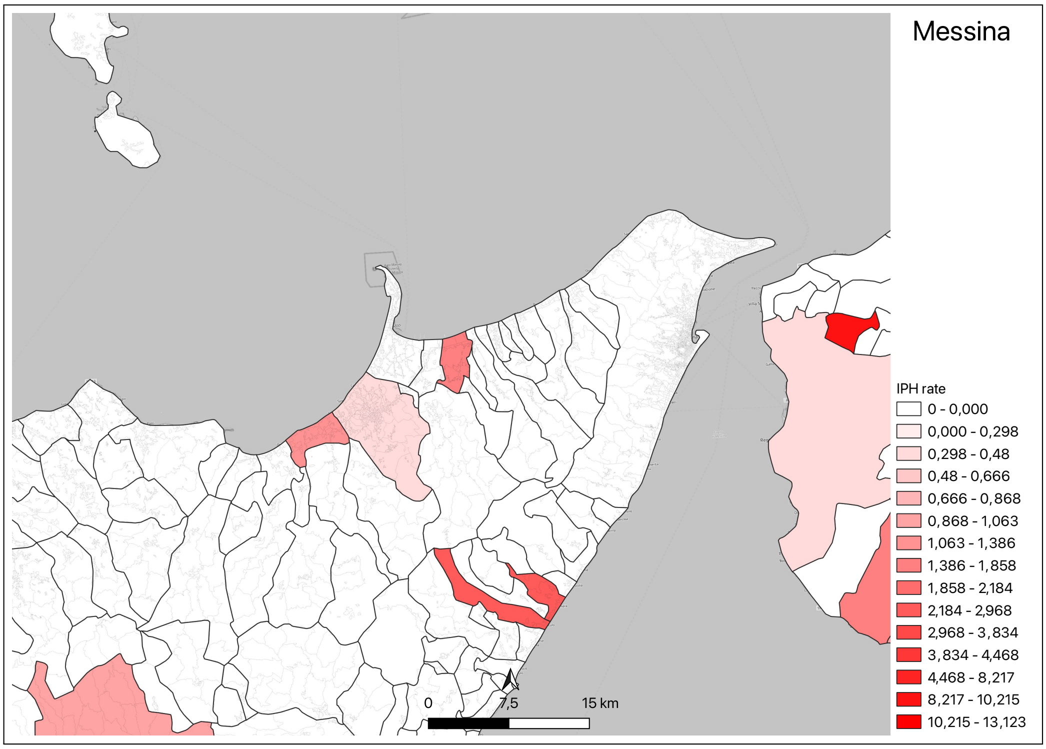
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.23: *Palermo - IPF rate (10.000 inhabitants)*



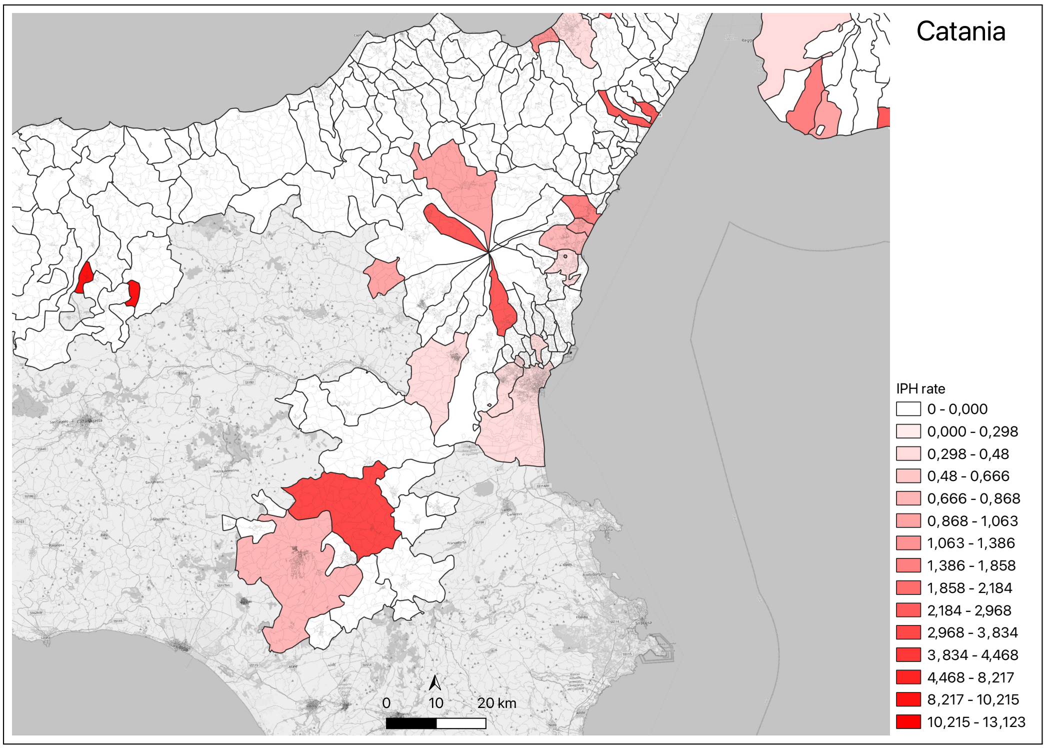
Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.24: *Messina - IPF rate (10.000 inhabitants)*



Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

FIGURE 4.25: *Catania - IPF rate (10.000 inhabitants)*



Note: The map illustrates the geographical distribution of IPF rates (per 10,000 inhabitants) across the municipalities within each Metropolitan Area. The layer depicting municipal borders is superimposed on the layer of census-tract areas (see Figure 4.7), whose concentration aids in approximating population density.

TABLE 4.1: Descriptive Statistics

					Total Sample							
vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
					Demographic Variables							
Population (Log)	108917	4.49	1.49	4.67	4.60	1.50	0	8.94	8.94	-0.63	0.10	0.00
Female (%)	108917	51.26	9.59	51.74	51.74	4.15	0	100.00	100.00	-1.15	13.43	0.03
Divorced (%)	108917	2.68	4.66	2.00	2.06	2.59	0	100.00	100.00	12.00	221.55	0.01
Large Families (%)	108917	21.51	15.29	19.23	20.16	12.04	0	100.00	100.00	1.61	5.35	0.05
Foreign Pop. (%)	108917	6.96	11.24	3.21	4.60	4.75	0	100.00	100.00	3.90	22.09	0.03
					Socio-Spatial Variables							
Hous. Rent (%)	108917	19.14	19.94	14.29	15.66	15.06	0	100.00	100.00	1.84	3.98	0.06
Hous. Ownership (%)	108917	67.79	22.97	72.31	70.73	16.96	0	100.00	100.00	-1.27	1.62	0.07
Residential Density	108173	0.01	0.00	0.01	0.01	0.00	0	0.04	0.03	1.12	5.31	0.00
Build. Quality Index	108917	3.06	0.62	3.00	3.10	0.42	0	4.00	4.00	-1.66	6.50	0.00
Transience Index	108917	17.27	21.04	10.53	13.36	15.61	0	1066.04	1066.04	3.78	88.80	0.06
					Socio-Economic Variables							
Male Illiteracy (%)	108917	0.78	3.05	0.00	0.25	0.00	0	100.00	100.00	16.81	445.81	0.01
Female Illiteracy (%)	108917	1.16	3.60	0.00	0.51	0.00	0	100.00	100.00	13.58	299.28	0.01
Male Unemployment (%)	108917	6.96	9.49	4.84	5.30	7.17	0	100.00	100.00	4.08	29.59	0.03
Female Unemployment (%)	108917	8.39	11.13	6.15	6.45	9.12	0	100.00	100.00	3.69	22.81	0.03
					Deterrence							
Shelters Rate (10,000 inhabitants)	108917	0.67	53.38	0.00	0.00	0.00	0	10000.00	10000.00	143.91	24412.79	0.16
					IPF = 1							
					Demographic Variables							
Population (Log)	302	5.20	1.45	5.51	5.38	1.21	0.0	7.53	7.53	-1.15	1.12	0.08
Female (%)	302	51.84	8.78	51.91	51.87	3.13	0.0	100.00	100.00	0.49	14.02	0.50
Divorced (%)	302	3.05	4.41	2.37	2.49	1.79	0.0	50.00	50.00	8.08	82.14	0.25
Large Families (%)	302	19.13	11.24	17.51	18.40	8.88	0.0	70.69	70.69	1.01	2.24	0.65
Foreign Pop. (%)	302	9.38	10.74	6.25	7.51	7.09	0.0	85.71	85.71	2.60	10.72	0.62
					Socio-Spatial Variables							
Hous. Rent (%)	302	23.75	19.13	20.15	21.36	14.58	0.0	100.00	100.00	1.49	2.98	1.10
Hous. Ownership (%)	302	63.63	21.07	67.96	66.20	15.28	0.0	100.00	100.00	-1.24	1.81	1.21
Residential Density	300	0.01	0.00	0.01	0.01	0.00	0.0	0.03	0.02	1.05	4.53	0.00
Build. Quality Index	299	3.06	0.47	3.00	3.07	0.35	1.5	4.00	2.50	-0.24	0.50	0.03
Transience Index	300	16.21	16.46	12.03	13.56	14.75	0.0	87.50	87.50	1.46	2.27	0.95
					Socio-Economic Variables							
Male Illiteracy (%)	302	0.85	1.61	0.00	0.46	0.00	0.0	12.50	12.50	3.35	14.58	0.09
Female Illiteracy (%)	302	1.34	2.19	0.63	0.86	0.93	0.0	16.67	16.67	3.28	14.42	0.13
Male Unemployment (%)	302	7.67	8.43	6.45	6.54	5.79	0.0	100.00	100.00	4.97	46.80	0.49
Female Unemployment (%)	302	8.61	7.29	7.41	7.73	5.49	0.0	50.00	50.00	1.89	6.87	0.42
					Deterrence							
Shelters Rate (10,000 inhabitants)	302	12.46	115.21	0.00	0.00	0.00	0.0	1666.67	1666.67	12.08	156.32	6.63

Notes: The table presents the descriptive statistics for the variables included in the estimations. It is organized by the type of variable (demographic, socio-spatial, socio-economic, or related to deterrence) and provides information for both the total sample and census tract areas where at least one femicide has been recorded in the considered period.

TABLE 4.2: Hurdle Estimation

	Probit	**Probit**	**Truncated Poisson**
	(1)	(2)	(3)
Variables	Estimates	Estimates	Estimates
Population (Log)	0,163 ***	0,165 ***	-0,116
	0,021	0,021	0,087
Female	0,002	0,002	-0,004
	0,004	0,004	0,012
Divorced	0,007	0,006	-0,032
	0,004	0,004	0,033
Large Families	-0,009 ***	-0,009 ***	-0,001
	0,002	0,002	0,012
Foreign Pop.	0,006 ***	-	-0,020
	0,001		0,013
Foreign Pop. by Region of Origin:			
- *Europe*	-	0,008 ***	-
		0,002	
- *Africa*	-	0,008 *	-
		0,003	
- *Americas*	-	-0,004	-
		0,008	
- *Asia*	-	0,003	-
		0,003	
- *Oceania*	-	-1,399	-
		0,831	
Residential Density	-6,274	-6,653	-47,118
	9,171	9,218	52,314
Build. Quality Index	-0,040	-0,041	-0,142
	0,036	0,036	0,271
Transience Index	0,001 *	0,001 *	-0,005
	0,001	0,001	0,007
Hous. Rent	-0,002	-0,002	-0,006
	0,002	0,002	0,009
Hous. Ownership	-0,004 *	-0,004 *	-0,022 *
	0,002	0,002	0,009
Male Unemployment	0,001	0,001	-0,009
	0,003	0,003	0,018
Female Unemployment	-0,002	-0,002	-0,009
	0,002	0,002	0,018
Male Illiteracy	0,000	0,000	0,040
	0,005	0,005	0,064
Female Illiteracy	0,005	0,005	0,031
	0,003	0,003	0,048
Observations:	108917	108917	302
Fixed Effects (NUTS-3 level):	YES	YES	YES
Cluster S.E.:	YES	YES	YES

Notes: The table presents the estimates from the hurdle estimation process, employing a Probit (1) followed by a subsequent Truncated Poisson (3). In column (2), the estimates are reported for the same Probit regression presented in column (1). However, in column (2), the foreign population variable is replaced with five different variables distinguishing foreigners based on their region of origin. Asterisks denote statistical significance:***$p < 0.01$,**$p < 0.05$,*$p < 0.1$.

TABLE 4.3: Alternative Model Specification

Zero-Inflated Negative Binomial regression:			
	(1)		(2)
Variables	Estimates	Variables	Estimates
Population (Log)	-1,267 **	*Population (Log)*	-1,543 ***
	0,459		0,446
$[Population\ (Log)]^2$	0,132 **	$[Population\ (Log)]^2$	0,167 ***
	0,047		0,045
Female	-0,001	*Female*	-0,001
	0,011		0,011
Divorced	0,012	*Divorced*	0,016
	0,033		0,032
Large Families	-0,028 ***	*Large Families*	-0,030 ***
	0,008		0,008
Foreign Pop.	0,021 **	*Foreign Pop.*	0,021 **
	0,008		0,008
Residential Density	-33,990	*Residential Density*	-27,226
	33,233		32,977
Build. Quality Index	-0,117	*Build. Quality Index*	-0,113
	0,142		0,140
Transience Index	0,010 *	*Transience Index*	0,010 *
	0,005		0,005
Hous. Rent	-0,006	*Hous. Rent*	-0,004
	0,008		0,008
Hous. Ownership	-0,017 *	*Hous. Ownership*	-0,015 *
	0,007		0,007
Male Unemployment	0,001	*Male Unemployment*	0,002
	0,012		0,011
Female Unemployment	-0,006	*Female Unemployment*	-0,006
	0,009		0,009
Male Illiteracy	0,022	*Male Illiteracy*	0,017
	0,045		0,043
Female Illiteracy	0,049	*Female Illiteracy*	0,046
	0,036		0,035
Shelters Rate	-	*Shelters Rate*	0,031 *
			0,012
Observations:	108917		108917
Fixed Effects: (NUTS-3 level)	YES		YES
Cluster S.E.:	YES		YES
Log(theta)	-2,979 **	Log(theta)	-3,632 ***
	1,094		0,368
Zero-inflation model coefficients (binomial with logit link):			
Population (Log)	-0,619 ***	lpop	-0,742 ***
	0,146		0,145
Theta	0,051	Theta	0,026
Number of iterations in BFGS optimization: 58		Number of iterations in BFGS optimization: 70	
Log-likelihood: -2175 on 33 Df		Log-likelihood: -2164 on 34 Df	

Notes: The table presents the results of the Zero-Inflated Negative Binomial estimation. In column (2), the estimates are displayed, including the shelter rate—a variable that is considered potentially endogenous at this stage, warranting caution and therefore included separately. Both the models corresponding to column (1) and column (2) utilize the logarithm of the population as the inflation variable. This choice aims to account for potentially different data-generating processes related to the over-represented zeros in our distribution. Asterisks denote statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix

TABLE C1: Test for Multicollinearity

Variance Inflation Factor - VIF test				
Model:	**Probit**	Values	**Truncated Poisson**	Values
	Population (Log)	1.259	*Population (Log)*	1.418
	Female	1.046	*Female*	1.176
	Divorced	1.059	*Divorced*	1.311
	Large Families	1.144	*Large Families*	1.532
	Foreign Pop.	1.125	*Foreign Pop.*	1.392
	Residential Density	1.213	*Residential Density*	1.525
	Build. Quality Index	1.094	*Build. Quality Index*	1.248
	Transience Index	1.135	*Transience Index*	1.233
	Hous. Rent	2.657	*Hous. Rent*	3.456
	Hous. Ownership	2.709	*Hous. Ownership*	3.474
	Male Unemployment	1.103	*Male Unemployment*	1.454
	Female Unemployment	1.072	*Female Unemployment*	1.240
	Male Illiteracy	1.107	*Male Illiteracy*	1.487
	Female Illiteracy	1.121	*Female Illiteracy*	1.658

Notes: The table displays the coefficients resulting from the Variance Inflation Factor (VIF) test for multicollinearity. These coefficients pertain to the variables included in the hurdle process, the Probit, and the Truncated Poisson regression, as presented in Table 4.2, columns (1) and (3) respectively. No values exceed 5, indicating the absence of collinearity issues among the variables.

TABLE C2: Rare Event Logistic Regression

Variables	Coefficient
Population (log)	0.461 ***
	(0.056)
Female	0.002
	(0.009)
Divorced	0.022 *
	(0.012)
Large Families	-0.020 ***
	(0.006)
Foreign Pop.	0.013 ***
	(0.004)
Residential Density	-1.278
	(24.841)
Build. Quality Index	-0.139
	(0.097)
Transience Index	0.002 *
	(0.001)
Hous. Rent	-0.004
	(0.005)
Hous. Ownership	-0.012 **
	(0.005)
Male Unemployment	0.007
	(0.008)
Female Unemployment	-0.002
	(0.006)
Male Illiteracy	0.012
	(0.013)
Female Illiteracy	0.021 **
	(0.010)
_cons	-6.778 ***
	(0.708)
Observations:	108917
Fixed Effects: (NUTS-3 level)	NO
Cluster S.E.:	NO

Notes: The table displays the coefficients obtained from the rare events logistic regression (Tomz et al., 2003). This serves as a robustness check for the estimates presented in the first part of the hurdle model, as shown in Table 4.2, column (1). We opted for a logit instead of a probit, as the same rare-events robust specification is not available for the probit model. Asterisks denote statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Summary and Conclusive Remarks

The thesis endeavors to navigate through the intricate challenges associated with analyzing various forms of violence and comprehending their foundational local dynamics. It does so through three research papers, which constitute the core of the dissertation: Chapter 2, Chapter 3, and Chapter 4. Respectively, each chapter explores the relationship between violence and international migration, the interplay between violence and electoral behaviors, and the complexities associated with mapping and analyzing gender violence in urban areas. These contributions are preceded by a detailed presentation and critical discussion in Chapter 1, which addresses challenges stemming from a general lack of understanding of the concept of violence, its causes, and consequences, as well as those arising from the (scarce) availability of reliable data at the sub-national level. Collectively, these chapters embody the author's effort to blend a qualitative socio-criminological background with the rigorous tools and methodology of applied economics, paying special attention to the spheres of regional sciences and urban studies.

In Chapter 2, the causal impact of authoritative violence on the propensity of individuals to migrate is investigated. Specifically, I focused on the migratory trends of Venezuelans amid the 2017-2018 political and economic crises. Insights are derived from regional-level data on civilian casualties incurred by security forces and data extracted from the ENCOVI-2018 survey, capturing migratory movements. Estimates leverage the travel time from the capital city as an instrumental variable and remain robust upon the inclusion of various household and socio-economic regional-level characteristics. The evidence robustly indicates that authoritative violence acts as a substantial non-economic push factor for international migration, with additional findings highlighting its influence on the skill composition of migrants, particularly within the context of South-to-South migratory flows.

In Chapter 3, I present a study designed to disentangle the (nuanced) causal linkage between terrorist violence during the *Anni di Piombo* and the subsequent decline in voter turnout in Italian political elections. The analysis encompasses electoral participation at the provincial level from 1972 to 1992 and draws upon data from the Global Terrorism Dataset, which provides details on terrorist attacks, casualties, victims, and a proxy for material damages. The Causal Mediation Analysis (CMA) - a methodological framework that remains relatively underutilized in regional and applied economics - is employed to assess the Average Treatment Effect of terrorism on voter turnout. Utilizing the Front Door Criterion (FDC), we identify the unbiased, albeit indirect, effect of terrorism on electoral participation, mediated by the size of the terrorist attack, approximated by the occurrence of deaths, injuries, and damages. A broad spectrum of time-lagged terrorism-related variables, spanning from 1 to 12 quarters preceding each election day, is considered in the analysis. The outcomes, corroborated by naive estimations performed using a regression model à la Barro (1991), unveil that while terrorism generally exerts a time-diminishing effect leading up to election day, this impact is predominantly prompted by physical damages. Contrary to our initial hypothesis, victims do not play a significant role, whereas the effect of terrorism, mediated by injuries, demonstrates a positive and significant impact on voter turnout in the medium-long run. Furthermore, our analysis confirms the literature concerning political party dynamics, especially regarding the erosion of consensus for the incumbent party.

In Chapter 4, an endeavor to map the distribution of Intimate Partner Femicide (IPF) across and within the fourteen Italian Metropolitan Areas is presented. By leveraging exclusive data on IPF incidents recorded between 2012 and 2020, I built a unique dataset of geo-coded events. I then merged it with other census-tract-level data to highlight the correlations between socio-economic, urban, and demographic characteristics and the occurrence of this particular form of violence. At this stage of the research, our principal estimation strategy hinges on the deployment of a hurdle-like model, supplemented with estimations from alternative model specifications. While causal effects cannot be established, a conscientious effort is made to account for a wide array of observable influences and factors. The core objective is to provide a thorough exploration of the contextual features associated with IPF in densely populated urban contexts, highlighting the paramount importance of undertaking such investigations. Additionally, the chapter underscores the criticality of affording researchers access to this type of data, thereby illustrating its indispensable value to institutions and policymakers.

One of the immediate implications emanating from the theoretical 'journey' embarked upon in Chapter 1, serving as the introduction to this thesis, is the notion that formulating general conclusions about violence may not merely be futile, but potentially impossible. The literature reviews presented in Chapters 2, 3, and 4 provide substantial evidence that seems to support this claim. Furthermore, while the contributions made in these chapters offer valuable insights into specific contexts, time frames, and manifestations of violent behavior, the unique nature of each scenario amplifies the complexity inherent in crafting wider generalizations.

In the landscape of economic and applied economic research, we often encounter the dichotomy between an insistence on the uniqueness of every case and an unwavering commitment to overarching theories that claim universal applicability. It's akin to a tug-of-war between the intricacies of particularities and the allure of sweeping generalizations. What this thesis strives to champion is the acknowledgment of a nuanced middle ground—a space where the idiosyncrasies of individual cases are not dismissed but rather embraced. In the realm of local violence, as explored in the preceding chapters, we navigate the complexities of unique contexts, temporal variations, and diverse manifestations. Yet, this exploration is not an argument against generalizability per se; rather, it calls for a judicious balance. The call for methodological flexibility is not an abandonment of universal insights but an invitation to recognize that while each case may dance to its own tune, there are choreographies that can be replicated and steps that yield valuable insights. It is within this delicate equilibrium that the true essence of applied economics unfolds a discipline capable of both appreciating the uniqueness of each economic dance and discerning the common rhythm that connects them all.

In essence, the singular characteristics intrinsic to each context imply that assertions of generalizability warrant meticulous scrutiny and a nuanced comprehension. The quest for universally applicable findings is often underscored, prompting a pivotal query: Is the pursuit of generalizability always of paramount importance? Particularly within the multifaceted realm of violence research, can the constant aspiration to attain what is often referred to as *external validity* always be justified? The answer, if there is one, is arguably delicate.

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