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Whatever one does,
one always rebuilds the monument in his own way.
But it is already something gained
to have used only the original stones.
Marguerite Yourcenar

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INTRODUCTION

And now prosecutions were brought not only on public grounds but against individual men; and when the state is most corrupt, the laws are most numerous.

Tacitus, c. 100–117 AD

To classify crime among the phenomena of normal sociology is not to say merely that it is an inevitable, although regrettable phenomenon due to the incorrigible wickedness of men; it is to affirm that it is a factor in public health, an integral part of all healthy societies.

Émile Durkheim, 1904

The trouble with Eichmann was precisely that so many were like him, and that the many were neither perverted nor sadistic, that they were, and still are, terribly and terrifyingly normal. From the viewpoint of our legal institutions and of our moral standards of judgment this normality was much more terrifying than all the atrocities put together.

Hannah Arendt, 2006

If one assumes that tendencies toward good and evil coexist within the human being, then in a large population the presence of deviant behavior - and, by extension, of criminal activity - appears almost a statistically inevitable consequence. Such an observation does not amount to a moral justification of crime but rather to a sociological finding: deviance is a recurring phenomenon that resists purely repressive measures (Durkheim, 1904). Despite the efforts of legislators, law-enforcement agencies, and judicial systems, crime tends to renew itself and to find novel ways to evade control strategies, thereby revealing the limits of exclusively punitive-repressive policies (Foucault, 1979).

The idea that crime is "a stable component" of social life does not imply scientific resignation. In contrast, it motivates an analytical approach: if crime cannot be completely eliminated, it becomes essential to understand its determinants, the mechanisms of its reproduction, and the conditions that amplify or attenuate its effects. In this context, the economics of crime emerges as a field of inquiry capable of transforming fatalism into actionable knowledge. The economic approach does not seek to reduce the moral complexity of the phenomenon to mere calculability, but it provides tools for modeling the incentives that shape deviant choices and for evaluating, both ex ante and ex post, the effectiveness of public policies (Becker, 1968).

The economic analysis of crime, therefore, responds to both practical and theoretical questions: What costs and benefits do offenders perceive? How do institutions and illegal markets interact with the formal economy? What externalities and constraints render certain countermeasures ineffective or counterproductive? Addressing these questions requires mixed methods and rigorous attention to the empirical difficulties inherent in the study of the phenomenon.

A primary methodological difficulty is intrinsic to the very nature of crime: it is largely "hidden" and deliberately evasive. For qualitative researchers, this implies the loss - or the radical limitation - of techniques such as participant observation, which require trust, proximity, and sustained presence in the field; for quantitative researchers, the problem is equally challenging, because official crime statistics reflect not only the true incidence of illicit behaviors but also institutional variables (e.g., investigative capacity, propensity to report) and cultural factors (reporting rates, local perceptions) (Heckathorn, 1997). For these reasons, the practice of the economics of crime rests on a plurality of empirical sources - official statistics, victimization surveys, administrative records, sampled studies of hidden populations, and network analyses

- and on methodological techniques designed to reduce selection bias and underestimation (Becker, 1968; Heckathorn, 1997).

The study of criminal behavior within the field of economics rests primarily on the paradigm of rational choice (Fiorentini, 1999; Savona, 2001; Lucarelli and Perone, 2018). In Becker's (1968) classical perspective, criminal actors are interpreted as decision-makers who evaluate costs and benefits: illicit conduct occurs when the expected utility of the violation exceeds the return the individual would obtain by investing time and resources in lawful activities. From this standpoint, the task of microeconomic theory is to explain the main patterns of deviant behavior and to suggest interventions that increase the costs or reduce the benefits of crime. However, empirical evidence - such as the higher crime rates observed in large urban areas compared with smaller centers - raises questions about the exhaustiveness of the purely microeconomic approach and points to the need to integrate analyses that account for structural and contextual factors, such as urbanization (Giacomelli and Rodano, 2001).

Italy represents an emblematic case study for the economics of crime, in which the dynamics between illicit phenomena and the local productive fabric assume particular significance. Mafia-type organizations, rather than autarkic and isolated entities, are characterized by their ability to weave ties with actors external to the criminal association-relations of proximity and exchange often grounded in mutual economic interests. These interconnections enable mafia organizations to consolidate their territorial presence, penetrate the legal economy, and expand their business interests, thereby generating durable spheres of power. In other words, the strength and persistence of the mafias derive not only from internal violence and coercion but, above all, from their capacity to build and maintain external networks of cooperation and collusion that sustain their reproduction and expansion over time.

Studying the mafia - and, more generally, criminality - poses significant identification challenges. The mafia phenomenon manifests itself in highly heterogeneous forms depending on spatial and temporal contexts: it is polymorphic and multilayered, with boundaries that are often blurred and difficult to capture through univocal definitions. It changes not only across time and space but also displays a variable-geometry structure that requires analytical tools capable of grasping its complexity and its contiguity with both legal and informal domains (Sciarrone, 2002).

The analysis developed in this dissertation adopts a progressive perspective: starting from a national level, it focuses on the processes of territorial diffusion of mafias in non-traditional areas; it then narrows attention to the historical territories where Italian mafia organizations originated; and finally, through microdata collected at the household level, it examines the extent to which families' perceptions of crime are influenced by contextual variables. This "concentric circles" approach allows for the integration of macro- and micro-level observations, with the aim of providing a more comprehensive picture of the dynamics of entrenchment and the social perception of the criminal phenomenon.

Thesis structure

The dissertation is organized into two complementary parts. The first (Chapters 1–2) examines the economic impacts of organized crime in Italy, analyzing how mafia infiltration affects local development indicators and market functioning. The second (Chapters 3–4) investigates the mechanisms linking crime as perceived by households to residential mobility dynamics and transformations in the housing market. The following section summarizes, chapter by chapter, the context, data, methodology, and objectives of each part of the dissertation.

Chapter 1 explores the relationship between mafia infiltration and the innovative capacity of Italian firms at the provincial level, contributing to the broader debate on how criminal presence influences local economic dynamics. The theoretical framework draws on studies of informal governance, territorial control, and the supports or barriers to entrepreneurship that characterize areas with different mafia traditions. From an empirical standpoint, the analysis uses a provincial panel dataset covering the period 2006–2021. The outcome variable is the intensity of industrial patenting, while mafia presence is summarized in a "Mafia Index" constructed via Principal Component Analysis on official indicators (ISTAT, data on confiscated assets, and other categories of mafia-related crimes). Methodologically, to address endogeneity and reverse causality - issues typically associated with the study of crime - System and Difference GMM estimators are employed, allowing the use of instrumental variables to purge the explanatory factors of their correlation with the error term. The innovative contribution is twofold: first, to reduce the spatial aggregation typical of prior literature by employing the provincial level of analysis; and second, to introduce estimation procedures and sample segmentations (overall sample; historical southern provinces; nontraditional central-northern provinces) capable of capturing contextual heterogeneity in mafia strategies and their potential effects on innovation.

Chapter 2 assesses the spillover effects of the judicial administration (JA) of mafia-affiliated firms on the performance of legal enterprises operating in the same area and same macro-sector. The theoretical framework focuses on the so-called "gray areas" (Sciarrone, 2024), where legal and illegal economies coexist through relationships of complicity, exchange, and informal services. The policy under examination - the JA procedure established under Italian law - aims to disrupt these channels without immediately removing the firm from the market, thus providing an ideal setting to observe real spillover effects within local markets.

From an empirical perspective, the study employs an unbalanced panel of firms (AIDA database) located in the four southern Italian regions - Campania, Apulia, Calabria, and Sicily - over the period 2006–2023. Neighboring firms are defined as follows: for each firm placed under JA, geographical distances to all other firms are computed (using the Vincenty formula), and those operating in the same macro-sector and located within a 10-kilometer radius are classified as treated (neighboring) firms. This choice is motivated by evidence that productive and informational interdependencies tend to be spatially concentrated over short distances. The control group consists of firms in the same macro-sector but located at least 50 kilometers away from JA firms, thereby minimizing the likelihood that they were affected by the same mafia channels or local investigative interventions.

The identification strategy combines propensity score matching (to ensure pre-treatment comparability between groups) with dynamic event evaluation approaches - an event-study design and a dynamic difference-in-differences (diff-in-diff) model that employs a continuous treatment variable, defined as the number of neighboring firms placed under JA in a given year. This approach allows for the analysis of varying intensities of institutional action. The framework makes it possible to test whether the exposure and neutralization of mafia networks generate positive spillovers (e.g., improved competition and market functioning) or transitory adverse effects (e.g., disruption of informal service provision, higher transition costs) for legal firms operating in close territorial proximity. To assess the robustness of the results, alternative distance thresholds and specifications controlling for sectoral characteristics and pre-trends are also explored.

Chapter 3 investigates the relationship between the housing market and perceptions of safety, focusing on how rental levels may both reflect and help shape an urban geography of fear. The theoretical framework draws on spatial equilibrium models and literature demonstrating how socio-economic deterioration and urban fragmentation foster crime, which in turn affects property values and residential choices (Roback, 1982; Sampson et al., 1997).

Empirically, the analysis uses Italian microdata from the EU-SILC (pooled cross-sections 2004-2023), incorporating household-level information on perceived insecurity, housing characteristics, and socio-economic conditions. To address key identification challenges - simultaneity between neighborhood quality and rental prices, and non-random selection within the tenant population - the methodological strategy combines an instrumental variables model (2SLS), with theoretically motivated instruments such as contract type, dwelling size, and a composite housing deprivation index (including tests for instrument validity and strength), and a Heckman selection model to correct for bias arising from the fact that the rent equation is observable only for renting households (Heckman, 1979; Kleibergen and Paap, 2006).

By integrating these techniques, the chapter aims to more credibly isolate the effect of rental levels on crime perception and, conversely, to assess the nature of feedback between the housing market and perceived insecurity. The findings have important implications for housing policies and urban regeneration interventions aimed at reducing spatial inequalities in safety.

Chapter 4 focuses on the spatial consequences of rising rents and the mechanisms through which housing price pressures affect household mobility decisions and, indirectly, conditions of vulnerability and perceptions of urban safety (Aalbers, 2017). The chapter begins with the theoretical hypothesis that increases in central-area rents push the most housing-cost-burdened households outward, exposing them to contexts with fewer services, weaker support networks, and potentially greater signals of social deterioration.

Empirically, the analysis uses the Italian EU-SILC panel (2004–2023) and incorporates household, housing, and territorial variables to model the propensity to move. To estimate the probability of relocation, a penalized logistic regression model (Firth, 1993) is employed, suitable for relatively rare events and designed to reduce separation bias. The specification controls for demographic and socio-economic characteristics, housing attributes (type, size, housing deprivation index), life-cycle events (changes in marital status, employment transitions, births), and territorial indicators (density, deprivation, environmental quality). The rationale is twofold: on one hand, to connect the residential mobility literature with studies highlighting the housing effects of financialization and tourism-driven pressures; on the other hand, to provide empirical evidence on the mechanisms that translate price pressures into relocations and, potentially, into new profiles of urban vulnerability, with direct implications for housing policies and urban regeneration interventions. To assess robustness, the chapter also explores alternative household configurations and different regression specifications.

The results emerging from the various analyses highlight important policy implications as well as potential new avenues for future research. Both aspects will be discussed in the concluding section.

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Chapter 1

THE EFFECTS OF MAFIA INFILTRATION ON THE INNOVATIVENESS OF ITALIAN PROVINCES

1.1 Introduction

The mafia has always found fertile ground in those areas where the government fails to guarantee the most basic conditions of personal security (Sciarrone, 2002a). However, quantifying the determinants and effects of mafia activity is particularly complex, given the impossibility of measuring with certainty its degree of penetration within the social, political and economic systems of territories; indeed, mafia activities are secret by definition and consequently escape any kind of statistical survey (Mocetti and Rizzica, 2021). In addition to the difficulties of measurement, determining the relationship between mafia presence and economic underdevelopment is also complex, as the two phenomena tend to reinforce each other through a reverse causality effect: on the one hand, the mafia thrives in underdeveloped contexts; on the other hand, its presence also perpetuates economic stagnation. Moreover, mafia organizations tend to expand their activities by also investing in areas other than their areas of origin, following economic strategies aimed at maximizing profits. This expansion is not a random or independent phenomenon, but is closely linked to the economic and social dynamics of the areas involved, demonstrating that the criminal presence is not an exogenous element of the local system. This mutual relationship between mafia infiltration and economic development makes it difficult to isolate the specific association of one variable with the other, and the estimates presented in this chapter should accordingly be interpreted as conditional correlations rather than causal effects.

Against this backdrop, this chapter addresses the following research question:

Is mafia presence associated with the innovative capacity of Italian provinces, and does this association differ depending on whether mafia organizations operate in territories of traditional entrenchment or of more recent expansion? The innovative capacity of businesses at the provincial level has been quantified by data on the number of registered patents per 100,000 inhabitants measured by UIBM (the acronym UIBM stands for: *Ufficio italiano brevetti e marchi*, Italian Patent and Trademark Office). For this purpose, a panel dataset was constructed in which Italian provinces were observed over the widest possible time window, namely the sixteen years from 2006 to 2021.

The empirical strategy adopted is based first of all on the creation of an index, the Mafia Index, which summarizes data on the main classes of crime that can be linked to the mafia matrix (ISTAT and Confiscatibene data). The procedure used follows the one devised by Mocetti and Rizzica (2021), but differs from the latter by using Principal Component Analysis (instead of simply averaging the indicators), including data on kidnapping of persons, usury and receiving stolen goods in the indicator set, and finally excluding subjective data on business perceptions from the set.

Compared with the previous empirical literature, the analysis proposed here brings several new elements. First, the smallest possible aggregation, i.e., the province, is used in order to capture as many differences as possible between territories; much statistical research dealing with crime uses regional data instead (Daniele, 2009; Parbonetti, 2021). Second, for the first time in this context of analysis, estimates are made using *System* (Blundell and Bond, 1998) and *Difference* (Arellano and Bond, 1991) Generalized Method of Moments (GMM), which are well suited to dynamic panel data prone to endogeneity and reverse causality. The endogeneity of the Mafia Index arises from two main sources: reverse causality, since mafias may selectively expand into provinces with higher innovative capacity; and the likely correlation between mafia presence and time-varying unobserved provincial characteristics, such as institutional quality and social capital, that independently affect patenting. The GMM addresses these concerns by exploiting internal instruments

— namely deeper lags of the endogenous variables — to purge the estimates of their correlation with the error term, under the assumption that such lags are uncorrelated with current innovation shocks (Roodman, 2009; Ullah et al., 2018). While this assumption may not hold in all circumstances, particularly if omitted variables exhibit strong serial correlation, the GMM estimates are more robust to these concerns than standard fixed-effects or OLS approaches. The validity of the instruments is assessed through the Hansen test and the Arellano-Bond tests for serial correlation, as discussed in Section 1.4. Finally, the empirical analysis is conducted across all Italian provinces and two further sub-samples: the first restricts the analysis to provinces where mafia-type organizations have historically been based (the traditional southern strongholds); the second contains provinces without an indigenous mafia tradition, i.e., areas where southern mafia groups have only more recently established a presence[1]. This three-fold split allows us to compare the conditional correlation between mafia activity and innovation across contexts with distinct historical trajectories of organized crime (Gambetta, 1992; Calderoni, 2011; Varese, 2011).

The results indicate that the association between mafia presence and innovation differs markedly across the two subsamples. In provinces of traditional mafia infiltration — primarily in the South — the Mafia Index is negatively and significantly associated with patent applications, consistent with the hypothesis that entrenched mafia activity suppresses the conditions necessary for innovative investment. In provinces of non-traditional infiltration — primarily in the Centre-North — the association is positive and significant, suggesting that mafia organizations tend to concentrate their activities in economically

[1]The term “provinces with traditional mafia penetration” refers to those provinces belonging to regions that have historically been the area of origin of structured mafia organizations: Campania (*Camorra*), Puglia (*Sacra Corona Unita*), Calabria (*’Ndrangheta*), and Sicily (*Cosa Nostra*). To these are added the provinces of Basilicata and Molise, where — although no indigenous form of organization comparable to that of the aforementioned regions has developed — there is a significant level of infiltration by organized criminal networks. The “non-traditional penetration areas” are those provinces where no indigenous mafia has taken root: this category includes the provinces of the remaining Italian regions.

dynamic areas with higher innovative capacity, without necessarily fostering innovation themselves. These findings are robust to the use of alternative estimators, alternative measures of mafia activity, and alternative definitions of the dependent variable.

Beyond its contribution to the empirical literature on organized crime and economic performance, this analysis carries direct implications for policy. The negative association between mafia presence and innovation in southern provinces reinforces the case for targeted anti-mafia enforcement in traditionally infiltrated areas, not only as a matter of public order, but as a precondition for unlocking local innovative potential. In the Centre-North, the positive association between mafia presence and innovative provinces calls for a different policy response: one focused on protecting the integrity of legal markets and preventing criminal organizations from exploiting and distorting the innovative capacity of wealthier territories. More broadly, the results suggest that regional innovation policy cannot be designed independently of the institutional and security environment in which firms operate.

The remainder of the chapter is organized as follows. Section 1.2 presents the theoretical framework and the hypotheses underlying the empirical analysis. Section 1.3 describes the data and the construction of the Mafia Index. Section 1.4 outlines the empirical strategy, including the GMM specification and the robustness checks. Section 1.5 discusses the results, and Section 1.6 concludes.

1.2 Theoretical and empirical framework

1.2.1 Theoretical Framework

According to an evolutionary perspective, in a market ideally free of interference by organized crime, businesses compete for limited resources and strive to attract customers. Natural selection favors survival, according to the *survival of the fittest*, rewarding companies capable of innovation. In fact, innovation makes it possible to optimize the allocation of resources, thus leading to competitive advantages. This means that through the introduction of new processes, products or services, companies can make the best use of available resources, ensuring a better chance of long-term survival (Schumpeter, 1942; Porter, 1985; Christensen, 1985).

Innovation flourishes as a winning strategic choice in those contexts where economic governance[2] is capable of ensuring the security of property rights (North, 1990) and fair competition between firms (Aghion et al., 2018). However, organized crime implements various practices to compromise property rights and distort the competitive play of markets, thereby discouraging firms from invest in innovative economic activities (Caglayan et al., 2019; Fiorentini and Peltzman, 1997). Key mafia activities with the greatest impact on innovation include the following.

- *Extortion and racketeering:* with the so-called '*pizzo*', a protection fee imposed by the mafia, these groups inflict an extra cost on businesses, reducing the funds available for innovation and generally discouraging any kind of investment beyond routine operations (Gambetta, 1992). These crimes are frequently accompanied by violence and intimidation, so agents who choose not to submit to mafia pressure are at risk of being victims of abuse such as damage, assault, murder, or arson. Extortion, therefore, erodes agents' property rights and dismantles those guarantees that are crucial for planning innovative strategies (Caglayan et al., 2019).

- *Government corruption:* mafias can infiltrate public institutions, bribing government officials and politicians to obtain favors, concessions, or advantageous conditions for their illegal activities. Mafias lead administrations to divert public investments from innovative projects to traditional low-tech activities, such as construction, as these are the sectors where it is easier to appropriate public money (Di Cataldo & Mastrorocco, 2021).

- *Money laundering and credit availability:* laundering money is necessary for mafias to exploit illegal profits. The business activities in which

[2] Economic governance, as defined by Dixit (2009), refers to the structure and functioning of legal and social institutions that support economic activity and economic transactions by protecting property rights, enforcing contracts and taking collective action to provide physical and organizational infrastructure.

the mafia invests its dirty money are those with the greatest potential for growth. According to the Transcrime Report (2013), these are low-innovation and low-tech firms, such as construction, catering, and hospitality firms. In this way, money laundering distorts fair competition within markets, creating a clear divide between businesses that have access to criminal funds and those that do not (Caglayan et al., 2019). The availability of credit allows mafias by rewarding companies that choose to cooperate. In this way, the mafias replace banks, which, according to Bonaccorsi di Patti (2009), tend to charge higher interest rates in the provinces where organized crime is most established.

- *Control of competition and territory:* In areas where organized crime is traditionally established, the mafia uses extortion and protection mechanisms to regulate the local economy and enhance its reputation (Sciarrone, 2002a). The episodes of mafia violence and intimidation used by the mafia to impose control over the territory discourage new businesses from entering or operating in certain sectors or geographical areas, thus making these territories economically unattractive. Moreover, as Schelling (1971) notes, one of the characteristics of the mafia system is 'exclusivity', i.e., the tendency to create monopolies within the market, thereby annihilating competition and hindering the natural processes of innovation (Gambetta, 1992; Aghion et al., 2018). This monopolistic logic has been analyzed from a price-theoretic perspective by Buchanan (1973), who argued that the consolidation of criminal activity under a single syndicate tends to internalize negative externalities, reducing competitive violence but potentially stabilizing criminal markets at the expense of legitimate economic activity. Backhaus (1979) further elaborated on this point, highlighting how syndicated crime benefits from economies of scale in the enforcement of illegal agreements, which lowers the costs of criminal activity and may ultimately increase its overall prevalence.

Ultimately, according to Dixit (2009; 2004), in the most vulnerable areas, where the government fails to act as a guarantor of private property rights, there is a risk that agents will resort to the forms of protection offered by organized crime[3]. Returning to the evolutionary perspective, in territories where the mafia is deeply entrenched, innovation is not the only strategy for survival, and natural selection offers businesses three possible choices: (A) to cooperate with the mafia, seeking to benefit and protect from it, (B) to suffer mafia intimidation passively, (C) to invest in innovative activities. Caglayan et al. (2019) used an approach based on evolutionary game theory model to analyze the relationship between mafia presence in the market and firm innovation. The authors theorize that among the three survival strategies mentioned above, innovation is the least advantageous in contexts where many firms cooperate with the mafia.

In the light of the theoretical framework outlined so far, it looms as a plausible hypothesis that there is less tendency to innovate in areas that are under mafia control. However, it should be borne in mind that when talking about organized crime, territorial boundaries can be extremely blurred: although Gambetta (1992) defines the mafia as a "*brand that is difficult to export*", insofar as it is strongly linked to the contextual conditions of the local environment[4]; other authors in the literature have focused their attention on

[3]It was precisely by providing protection services to threatened landowners that the Sicilian mafia established and enriched itself over the years. After the collapse of the feudal system, banditry became widespread in Sicily. Landowners began hiring bandits as guards to protect their property. Gradually, these bandit protectors formed associations that eventually became the modern mafia. While state protection was available to all equally, the mafia offered protection only to clients who paid for it, creating a significant negative externality: thieves began selectively targeting properties outside mafia control, which in turn increased demand for protection services, allowing the mafias to raise their prices (Dickie, 2004; 2009).

[4]Gambetta (1992) does not exclude the possibility that the 'Mafia' brand is actually counterfeited, given its success, even in areas that are not traditionally associated with organized crime. The counterfeiting phenomenon can also arise simply from the 'presence of strong, armed men' who use violence to enhance their criminal reputation. As Catanzaro (1992) and Dixit (2009) observe, the offer by criminal groups (even disorganized ones) of protection services creates its respective demand in the market: if companies or citizens feel

the mafia's ability to interfere in the economic fabric even outside its area of origin.

Mafias have a strong territorial specificity: the action of criminal organizations has always been strongly rooted in a localized social space. However, this does not mean that the range of criminal activities is restricted to the original territories (Sciarrone, 2002a). The mafia, in fact, adopts real 'expansion strategies' through processes of colonization. Varese (2011) identified the factors most conducive to the phenomenon of mafia transplantation, i.e., that dynamic whereby a mafia group runs illicit business in a territory outside its region of origin. Among the factors most favoring the phenomenon: the presence of Mafia members in the territory, the absence of other organized and established criminal groups, and the emergence of new markets and business opportunities over which state protection does not extend. Block (1980) identifies two types of criminal activity that most characterize the mafia matrix: *power syndicates*, involving the use of violence and coercion to control territory and spread generalized terror related to criminal activity, and *enterprise syndicates*, consisting of illicit economic activities through which the mafia enriches itself and achieves economic success. Expansion into new territory takes on different forms depending on whether mafia action is more oriented towards controlling the territory (*power syndicate*) or managing economic affairs (*enterprise syndicate*). In particular, the colonization of a new territory is often the consequence of expansionist economic strategies (therefore linked to the sphere of *enterprise syndicate*). In newly acquired territories, in fact, mafias initially tend to control one or more illegal markets and only after acquiring a position of competitive advantage do they begin to establish an extended form of control over the local community through extortion and violence (*power syndicate*).

Criminal organizations tend to behave according to cartel logic, destroying competition and establishing rules for dividing up territory or shares of the illicit market (Fiorentini and Peltzman, 1997; Buchanan, 1973). It is therefore

threatened by criminals, they may decide to pay for their protection.

possible for the mafia, after an initial phase of conquering illegal markets in new territories, to clear the field, entrusting the direct management of illicit trafficking to others and limiting itself to offering a protection service. In the presence of a particular permeability of the territory to mafia action, these protection services can then extend to the legal markets as well (Sciarrone, 2002a).

At this point, it is important to determine the criteria by which criminal organizations identify new territories or markets to conquer.

As mentioned above, criminal groups may find greater opportunities for permeability in territories where the protection of property rights and the enforcement of contracts are problematic (Dixit, 2009; 2004). In these cases, criminal groups enter the markets, presenting themselves to the local community as specialized in the provision of protection services, filling gaps in governance. The selection of territories to be conquered takes place on the basis of various factors, geographical, demographic, political-social, contingent[5], but above all economic. Indeed, a market, in order to be considered 'economically attractive' must be developed (Pellegrini, 2018) or at least developing (Massari, 1997). It is no coincidence that the presence in the Center-North of the mafia is more concentrated in the most industrialised regions of Italy (Parbonetti, 2021).

Ultimately, different types of territory can be distinguished in Italy, depending on mafia penetration: traditionally settled territories and non-traditional territories. Areas of traditional Mafia infiltration are those where the Mafia has historically originated: Sicily (*Cosa Nostra*), Calabria (*'Ndrangheta*), Campania (*Camorra*), Apulia (*Sacra Corona Unita*) (Dickie, 2004). As a matter of geographical proximity and in light of anti-mafia investigations, the provinces of Molise and Basilicata can also be included in this group. These

[5]Through the "*metaphor of contagion*", Sciarrone (2002a) points out how, according to a group of interpretations in the literature, mafia movement has also been favored by demographic and cultural issues as well as contingent factors such as the immigration of Southerners or forced residence.

territories, often perceived as marginal to the dynamics of organized crime, have actually represented over time areas of expansion, refuge or strategic junction for the activities of criminal organizations.
In traditionally besieged areas, the management and control of the territory (also through *power syndicate* activities) allow the mafias to create real headquarters from which to issue orders and plan strategies, whereas in non-traditional areas, economic objectives and business activities (*enterprise syndicate*) prevail over the mere search for power, also because it is actually the search for business opportunities that pushes the mafia beyond territorial boundaries (Sciarrone, 2002a).

The hypothesis underlying this study is that the effect of mafia activity on innovation depends not only on its intensity, but also on the different strategies adopted by mafia organizations in different territories. In contexts traditionally used as strongholds or "headquarters" by mafias, it is plausible that the impact on innovation is predominantly negative. This could be attributed to the fact that the mafia strategy in such areas tends to discourage any form of economic, technological, or social progress that could hinder the control exercised over the territory. Economic stagnation and the absence of significant change in these areas respond to the logic of preservation of local power by the mafias, who see innovation as a threat to their influence.

Otherwise, in non-traditional territories or those chosen as targets for expansion, the effect could be paradoxically positive. In these contexts, mafias tend to direct their activities toward economically attractive areas characterized by a high degree of industrialization, development or growth potential. The decision to invest and take root in such areas is motivated by an interest in taking advantage of the economic and technological opportunities already present, such as advanced infrastructure or innovative production systems. This phenomenon could thus be reflected in a greater concentration of mafia activities in economically dynamic areas and, consequently, in an apparently positive correlation between mafia presence and local innovativeness.

1.2.2 Old mafias and new mafias: the hypotheses

Until relatively recent times, the mafia phenomenon was firmly rooted in specific areas of Southern Italy, where criminal organizations built a strong territorial anchorage based on family networks, internal bonds of trust, and mechanisms of reciprocity (Sciarrone, 2021).

In these traditional strongholds, mafiosi are not primarily distinguished by entrepreneurial capacities; rather, they rely on the extortion–protection mechanism as the principal means of accumulating mafioso capital and as the foundation of their relational system. In such settings, organizations tend to consolidate territorial control, dominate low-innovation markets, and establish robust clientelistic networks and local "headquarters" that raise transaction costs, capture local institutions, and deter the entrepreneurial risk-taking necessary for the emergence of high-tech firms. Innovation is therefore perceived as potentially destabilizing to the established mafioso equilibrium and is commonly repressed (Gambetta, 1992; Calderoni, 2011). Accordingly, one of the hypotheses we test in this analysis is that mafia presence is negatively associated with innovation in provinces where mafia "headquarters" are historically established.

From the 1970s onward, however, the phenomenon expanded territorially: older mafias extended their reach and new mafias emerged modeled on the traditional ones, initiating a form of colonial expansion. Two main mechanisms drove the emergence of these new mafias (Sciarrone, 2021):

- *Colonization*: traditional mafia groups stabilized and extended their operations into new areas.
- *Imitation*: local criminal groups reproduced organizational models and practices of the traditional mafias in locally favourable niches.

These dynamics clearly shape different mafia strategies in the North compared with the South. In non-traditional contexts - particularly in the Centre and the North - mafia activity tends to be more entrepreneurial and opportunistic: organizations privilege entry into the most remunerative markets and control illicit trades that can be rapidly monetized. The drug trade is a telling example: in the North, trafficking concentrates "where the money is," i.e., in economically wealthier areas with more lucrative local markets; consequently, mafioso interests concentrate in zones with higher spending capacity, where clientele can afford higher prices.

For these reasons we expect the mafia-innovation relationship to differ in areas of recent mafia expansion. In such areas we hypothesize a qualitatively different (and potentially positive or ambiguous) association, insofar as concentrated mafia activity may, under some conditions, accompany or even anticipate local economic and innovative development. In short, while in traditional Southern strongholds the logic of territorial domination, clientelism, and institutional capture produces strongly adverse conditions for innovation (hence our expectation of a negative effect), in provinces of recent expansion mafias adopt profit-oriented strategies and concentrate activity where industrial and innovative capacities are higher - implying an ambiguous, and in some cases potentially positive, relationship between mafioso activity and innovation (Sciarrone, 2002b; Gambetta, 1992; Calderoni, 2011).

1.2.3 Empirical framework

Contributions in the field of scientific research on the relationship between organized crime and innovation are limited.

From an international perspective, Van Dijik (2007) produced a survey of 150 countries, quantifying the presence of organized crime through a composite index. The index combined data on the perceived prevalence of organized crime, unsolved homicides, grand corruption, money laundering, and the black economy. Sources included the World Economic Forum's annual CEO surveys, the Merchant International Group's investment risk assessments, World Bank Institute studies, and official crime statistics. The analysis shows that higher levels of organized crime are strongly and negatively correlated with national wealth and development, but this relationship operates largely through institutional channels: organized crime undermines the rule of law, fosters corruption, and ultimately depresses economic prosperity. The study concludes that tolerating criminal activity for short-term economic benefits is counterproductive, as it entrenches rent-seeking and weakens the institutional foundations of long-run growth.

Daniele (2009) used ISTAT regional data to analyze the relationship between organized crime activities, particularly extortion, and key economic indicators such as GDP growth, unemployment rates, and FDI inflows. The objective of the paper was to quantify, through LAD (least absolute deviation) estimations, the relationship between typical mafia activities (extortion, arson, attacks, mafia association) and indicators of economic development, including GDP, unemployment, and infrastructure status. The survey shows a positive relationship between mafia-related crimes and unemployment rates. In contrast, Scognamiglio (2018) observes that the mafia favored employment in particular in the construction sector. Scognamiglio's analysis is based on the use of diff-in-diff on data on the total number of individuals relocated in each province during 1961-1972 (IPAC, 1976-1982). The treatment group is the number of mobsters transferred to each province normalized per 100,000 population. The author also used data on the number of crimes (ISTAT) and data on employment by productive sector (Census of Industry and Services). Scognamiglio's investigation thus testified to the possibility that the relocation of mobsters to nontraditional territories generates positive impacts on employment. This effect could be caused by the mafia's ability to seize opportunities in the construction sector that would otherwise go untapped due to liquidity constraints.

The mafia transposition, i.e., the phenomenon whereby mobsters tend to extend their criminal activities into territories other than their home territories, can be favored by several factors (Varese, 2011). According to the investigations of Buonanno and Pazzona (2014) the transfer of mobsters has also been favored over the years by the large influx of migrants, which has led mafia influence in the Central and Northern regions of Italy. The authors analyzed aggregate data on crime and migration flows in Central and Northern Italian provinces from 1983 to 2000, focusing on two phenomena in particular:

i) the large influx of Southern immigrants during the period of the economic miracle and ii) the application of the confinement law, which required mafiosi to resettle far from their province of origin. The results obtained by Buonanno and Pazzona (2014), both through the method of OLS (Ordinary Least Squares) and IV estimates (Instrumental Variables), suggest that the interaction between forced resettlement and migration was a crucial factor in fostering the transplantation of criminal organizations to Central and Northern regions.

Bonaccorsi di Patti (2009), analysing by OLS the relationship between the terms on bank loans (employing a sample of over 300,000 bank-firm relationships, obtained from the Central Credit Register) and local crime rates (ISTAT data), shows that among the types of crime that most negatively affect the loan market are those linked to organized crime.

The negative externalities produced by organized crime are further highlighted in the analysis of Barone and Narciso (2013), who highlighted the extent to which the Mafia is able to influence the allocation of public funds. The investigation, conducted on public funds data made available in confidence by Italy's Ministry of Industry, a criminal dataset and a range of organized crime tools, shows that the Mafia pockets some of the public funds by setting up sham enterprises and bribing public officials.

Albanese and Marinelli (2013), analysing data from Italian companies, through the estimation of a production function over a stratified sample of Italian firms, found the negative impact of organized crime on productivity, which is not significantly different between small and large firms, or between industrial and services firms. The negative effects of the mafia on productivity (defined using Total Factor Productivity growth) were later confirmed by Ganau and Rodrıguez-Pose (2018), who, however, observed larger negative effects for small manufacturing firms.

Pinotti (2015) examined the postwar economic development of Apulia and Basilicata exposed to mafia activity after the 1970s, applying synthetic control methods to estimate their economic performance in the hypothetical absence of organized crime. A comparison of actual and counterfactual development from Pinotti's investigation shows that the presence of the Mafia lowers GDP per capita by 16 percent.

Caglayan and Flamini (2019) provide one of the earliest empirical contributions on the relationship between organized crime, technology, and innovation. Using data from northern Italian provinces over the period 2005–2012, the authors construct a technology index and a mafia index based on signalling crimes, and identify the causal effect of mafia presence by exploiting the historical episode of forced resettlement of high-ranking mafia bosses to Northern Italy as an exogenous source of variation. Their results show a negative and statistically significant impact of organized crime on both technology levels and innovation flows measured by patent applications: a 10% increase in the mafia index is associated with an approximately 9% decline in patents per capita. These findings are rationalized through an evolutionary game-theory framework, which highlights how mafia presence distorts innovation incentives and generates persistent effects.

Our study differs from Caglayan and Flamini (2019) along several methodological and conceptual dimensions, which explains why the empirical results need not coincide. First, while their identification strategy is well suited to capture the long-run effects of historical mafia rooting in northern provinces, we employ a longer dynamic provincial panel (2006–2021) estimated using *Difference* and *System* GMM models, allowing us to address dynamic endogeneity and to focus on contemporaneous marginal effects. Second, the measurement of mafia differs: whereas Caglayan and Flamini rely on historical instrumental variation, our Mafia Index is time-varying and constructed via PCA on a broad set of crime indicators, capturing the current intensity of infiltration. Finally, unlike their focus on the North and on mafia transplantation, we analyze the entire country and explicitly distinguish between provinces with traditional and non-traditional mafia penetration. As a result, while Caglayan and Flamini identify persistent structural effects of mafia rooting, our approach is better suited to uncover heterogeneous and short- to medium-run effects of mafia infiltration on innovation.

1.3 Data description

In order to analyze the effects of organized crime on innovation, in accordance with the availability of data, a panel data of Italian provinces (NUTS 3) was composed and monitored for the period 2006-2021[6].
The reason for choosing to use the provincial aggregation lies in the fact that the province is the smallest possible territorial aggregation.

Many studies on the same topic have used data based on regional aggregations (NUTS 2). However, as shown below, the significant differences, observed at the provincial level, even within the same region, suggest that the provincial aggregation is the preferred method for analyzes of this type, in order to capture as many differences as possible.

- **Innovation**: To measure the level of innovation across Italian provinces, data on patent applications were drawn from the Italian Patent and Trademark Office (UIBM, *Ufficio Italiano Brevetti e Marchi*) database. Patents represent a direct and widely accepted measure of innovation output, as they reflect the tangible results of inventive activity (Keller, 2004).

[6] The analysis draws on all Italian provinces for which data are available, covering 104 provinces until 2010 and 107 from 2011 onward. The Sardinian provinces of Ogliastra and Olbia-Tempio were excluded due to missing data and because both were formally abolished in 2016. The province of South Sardinia, established in 2016, was also excluded since consistent data series were unavailable. For Fermo (Marche), Barletta-Andria-Trani (Puglia), and Monza and Brianza (Lombardy), which became operational in 2009, data are available only from 2011; therefore, the reference period for these units covers 2011–2021. Over the observation period, several municipalities were administratively reassigned among provinces, altering population size and territorial composition. To ensure comparability across time, all variables were expressed in per capita terms and adjusted annually, so that the measures remained consistent despite administrative boundary changes.
The resulting dataset is unbalanced, as some provinces enter or exit the panel depending on data availability and institutional transformations. This feature does not compromise the estimation strategy, since system-GMM estimators are well-suited to unbalanced panels and yield consistent results under these conditions (Arellano and Bond, 1991; Blundell and Bond, 1998; Roodman, 2009).

To capture high-technology innovation, industrial patents were selected as the main indicator. This category primarily reflects product and process innovation in industrial sectors, providing a direct link between inventive activity and the productive structure of local economies. However, industrial patents are geographically concentrated in areas characterized by large manufacturing firms - predominantly in Northern Italy - whereas Southern provinces, which are more specialized in services and composed of smaller firms, are structurally underrepresented in this measure. For this reason, the total number of patent applications was also considered as an alternative dependent variable, in order to verify whether the effect of mafia presence on innovation changes when broader forms of technological activity are included.

Consistent with the literature, and to avoid bias due to differences in provincial demographic size, patent data were normalized by population (Falk, 2004; Bratti and Conti, 2014; Leogrande, 2024). Specifically, the number of industrial patents per 100,000 inhabitants was calculated for each province. This standardization ensures comparability across territories and enhances the robustness of the estimates, also accounting for potential administrative changes in provincial boundaries over time.

- **Mafia Index**: To measure the mafia phenomenon, which by definition is elusive to statistical surveys, a multidimensional approach is used in this chapter in an attempt to capture the different ways in which mafias operate in the territory. It was therefore chosen to calculate an index, the Mafia Index (MI), that measures the intensity of the mafia phenomenon in Italian provinces over the period from 2006 to 2021, including three types of elementary indicators. Following the definitions introduced by Block (1980) , the MI consists of objective indicators and two sets of spy indicators: power syndicates and enterprise syndicates. Each indicator represents a distinct category of crimes reported to the police authorities and refers to the Italian provinces observed between 2006 and 2021.

  The objective indicators include the number of reported crimes that are directly linked to the mafia matrix: mafia murders, mafia association crimes, number of municipal councils dissolved for mafia infiltrations, and number of properties confiscated. These are the crimes that are directly related to the activities of organized crime in the narrow sense. The use of these indicators has several complexities. These are low-frequency crimes, which are particularly concentrated in some Italian provinces (mainly those in the South) and totally absent in others. The risk is to introduce potential randomness in the phenomenon: a single incident of mafia association, for example, could significantly affect the mafia index, distorting the index estimate. In addition, there could be crimes committed by organized crime, e.g., murders, in which, however, the mafia matrix has not been officially identified and which are therefore entered in the generic category of "murders" rather than the more specific "mafia murders." This would result in an underestimation of the actual incidents. It should also be pointed out that the number of recorded mafia episodes could be directly proportional to the effectiveness of the authorities proposed to the anti-mafia, which is not homogeneously distributed across the territory. Therefore, if one were to limit the construction of the mafia index to only mafia crimes, one could obtain a measure of the ability of judicial authorities to recognize the mafia matrix of reported crimes, rather than the establishment of organized crime.

To address these problems, we chose to add the other two categories of crimes mentioned: enterprise syndicate crimes i and power syndicate crimes, which, while not directly attributable to mafias, summarize the characteristic activities by which organized crime enriches itself or strengthens its control of the territory. The first of these two categories, constituted by enterprise syndicate spy crimes, includes the mafia's characteristic businesses that allow it to benefit economically by exploiting illegal markets, such as drugs or prostitution. These crimes, while not officially recognized as 'mafia crimes,' require the existence of a structured and complex criminal organization, which in the Italian case coincides closely with the mafia. In particular, this category includes crimes related to: drug trafficking, smuggling, exploitation of prostitution, money laundering, receiving stolen goods and usury. The second category, consisting of spy crimes, power syndicate, on the other hand includes criminal activities used by mafias to exert their power through the tool of collective intimidation. These are crimes aimed at spreading generalized terror so as to trigger social phenomena such as omertà, corruption, and submission. The following fall into this category: murders, extortion, bombings, arson, and kidnappings. Using data related to activities that are not typically mafia-related allows the index to generalize, adding information related to the illicit activities through which mafias obtain their illicit proceeds, or parade their power, however, this choice is not immune to risk. Indeed, many of these crimes (such as intentional homicides, bombings, or prostitution and drug trafficking) could be attributable to cases not directly linked to the mafia, thus generating a potential problem with the index's statistical representativeness. Crime data refer to ISTAT (Italian National Institute of Statistics) computations, aggregated by province (NUTS 3), of crimes reported to the judicial authorities by the *Polizia di Stato* ("state police", one of Italy's primary police agencies) and the *Guardia di Finanza* ("financial police", the primary policing agency for financial crimes). The survey reports the operational activity of police forces. On the other hand, data on municipal councils dissolved for mafia infiltration are made public by the Ministry of the Interior and cover the same years as the ISTAT observations on crimes (2006-2021). While, data on confiscated property come from the Italian database *Confiscatibene*, which originated from a project of Libera (*Associazioni, nomi e numeri contro le mafie*). All data cover the widest possible time horizon ranging from 2006 to 2021 and are on provincial aggregation. To obtain measures that are not distorted by differences in provincial population size, a proportional adjustment was made based on the number of inhabitants, in order to express crime data per 100,000 inhabitants.

- **Covariates**: In light of the research on innovation and mafia presence, and taking into account the limited data availability regarding Italian provinces, we proceed with an empirical analysis that considers the following variables as covariates.

  Gross Domestic Product (GDP) was included as a control variable due to the substantial differences in GDP per capita across Italian provinces. In this study, GDP at the provincial level is considered a proxy for territorial wealth (Keller, 2004; Ghazal et al., 2015). The data were obtained from the SISREG database (System of Provincial Social and Regional Indicators), which provides information aggregated at the provincial level (NUTS 3) and spans the period from 2006 to 2021.

  The employment rate was included as a covariate, with data sourced from the SISREG (System of Provincial Social and Regional Indicators) database. The inclusion of the employment rate is based on the hypothesis that a robust labor market fosters an environment conducive to innovation. Specifically, a high employment rate may reflect greater availability of skilled human resources and a socioeconomic context favorable to the development of new ideas and technologies.

  However, this relationship may not be linear. On one hand, not all forms of employment contribute directly to innovation: a workforce dominated by low-skilled jobs or roles unrelated to innovative sectors may have limited impact on technological progress. On the other hand, the prevalence of informal or undeclared work, particularly significant in some Italian provinces, could distort the reported employment rate, reducing its ability to accurately capture economic dynamism and the territory's potential for innovation.

- **Instruments**: Regarding business investment in research and development (R&D), in the absence of available data at the provincial level we applied a proportional allocation procedure. Specifically, we took the regional R&D expenditure series published by ISTAT and re-proportioned it to provinces according to the number of firms in each province, thereby creating a province-level proxy of business R&D (Eliasson, et al., 2024; Lembcke et al., 2025). The imputed provincial R&D measure was employed as an instrument intended to approximate the investments that support patent proliferation. This choice reflects potential reverse causality (patenting activity may itself influence firms' R&D decisions), measurement error and omitted local factors correlated with both R&D and patenting (Crépon et al., 1998).

In addition, provincial and regional election dummies were included as exogenous instruments to capture institutional and political shocks that are plausibly unrelated to short-term innovation dynamics (Brender and Drazen, 2005).

1.4 Empirical Strategy

In this analysis, the relationship between the activity of organized crime (measured by the Mafia Index) and business innovativeness (expressed as the number of registered patents per 100,000 population) is tested through a panel data econometric model.

The empirical strategy involves two key steps: constructing the Mafia Index using Principal Component Analysis and estimating its impact through the GMM.

1.4.1 Calculation of the Mafia Index

The analysis of the effects of organized crime focuses on creating a measure that can represent the degree of mafia presence.

A procedure similar to the one adopted by Mocetti and Rizzica (2021) was followed to construct the mafia index, but it differs from the latter by including data on crimes of kidnapping, usury and receiving stolen property in the dataset and by excluding subjective data on perceptions of businesses.

In addition, unlike the authors mentioned above, who calculated the index using the simple average of indicators, the method chosen to construct the index is principal component analysis (PCA). This is a multivariate analysis technique to simplify the complexity of the data. The main objective is to reduce the number of the fifteen variables available, while retaining most of the original information contained in the index.

The choice of PCA over alternative dimensionality reduction techniques is motivated by several considerations. First, all the elementary indicators entering the Mafia Index are continuous variables, expressed as crime rates per 100,000 inhabitants. This rules out the use of Multiple Correspondence Analysis (MCA), which is specifically designed for categorical or nominal data and would therefore be inappropriate in this context (Greenacre, 1984). Second, PCA is preferred over exploratory factor analysis because the objective here is not to uncover a latent theoretical structure underlying the observed crimes, but rather to construct a composite summary measure that captures as much of the total variance in the indicator set as possible; PCA is better suited to this goal as it is a purely data-driven technique that maximizes explained variance without imposing prior assumptions on the covariance structure (Jolliffe, 1986; OECD, 2008). Third, simple averaging — the approach adopted by Mocetti and Rizzica (2021) — implicitly assigns equal weight to each indicator regardless of its informational content, whereas PCA weights each component by its contribution to overall variance, producing a more efficient and statistically grounded composite (Vyas and Kumaranayake, 2006). Finally, PCA is a well-established method for the construction of composite indices in the social science literature and has been widely employed in similar contexts involving the aggregation of heterogeneous crime indicators (Omrani et al., 2019; Wu, 2021).

Some of the crimes that make up the Mafia Index are correlated with each other; however, PCA allows the risk of multicollinearity in the data to be reduced by creating new variables that are linearly independent (Jolliffe, 1986).

To obtain values that are unit-independent, the indicators were standardized ($mean = 0$, $SD = 1$) prior to PCA (Jackson, 1993; Jolliffe, 1986; Abdi and

Williams, 2010). This standardization prevents variables measured on larger scales or with higher variance from dominating the principal components, so that each indicator contributes more comparably to the extracted components. It also makes component loadings and scores easier to interpret and compare across indicators, improving robustness when combining heterogeneous measures (Abdi and Williams, 2010; Jackson, 1993).

After performing PCA, the 15 elementary indicators were subjected to the Kaiser-Meyer-Olkin (KMO) test to assess the appropriateness of the selected variables for creating the index. The KMO values range from 0 to 1, and generally, values above 0.50 indicate a better fit of the data to the PCA (Constantin, 2014; Venturini & Graziano, 2016). The generic value of KMO is 0.72, this means that the indicators fit well with Principal Component Analysis. In addition, when taken individually, all fourteen variables have KMO values greater than 0.5 (the minimum KMO value is 0.60, while the maximum is 0.81).

To ascertain the adequacy of the variables, Bartlett's test of sphericity was also checked (Constantin, 2014; Galende et al., 2014). The test of sphericity assesses whether each sequential eigenvalue is significantly different from the other eigenvalues (Jackson, 1993). The test aims to test the null hypothesis (H_0) that the variables are not correlated with each other. The very low p-value (0.000) suggests that the elementary indicators that make up the Mafia Index are correlated with each other, providing support for the validity of using PCA (Jolliffe, 1986).

For the selection of the principal components to be included in the index, we chose to use Kaiser's criterion, that is, to retain those components to which an eigenvalue greater than 1 corresponded (Kaiser, 1960; Vyas et al., 2006; Dinno, 2009). In this way, the first six principal components were selected. The index was created using a methodology widely used in the literature, obtained by summing the selected principal components weighted by their respective eigenvalue (Omrani et al., 2019; Wu, 2021). In mathematical terms:

$$\sum_{k=1}^{6} PC_k * W_k \tag{1.1}$$

Where, PC_k is the k-th principal component and W_k is the k-th eigenvalue.

The final result is thus an index, associated with each province, proportional to the intensity of mafia activity for each year.

1.4.2 GMM Approach

The empirical models used to estimate the conditional association between mafia activity and innovation in Italian provinces were estimated through the Difference and System GMM and are formulated as follows:

Difference GMM:

$$\begin{aligned}\Delta \mathrm{Pat}_{i,t} = {} & \beta_1 \Delta \mathrm{Pat}_{i,t-1} + \beta_2 \Delta \mathrm{MI}_{i,t} + \beta_3 \Delta \mathrm{GDP}_{i,t} + \beta_4 \Delta \mathrm{Er}_{i,t} \\ & + \beta_5 \Delta \mathrm{MI}_{i,t-1} + \beta_6 \Delta \mathrm{GDP}_{i,t-1} + \beta_7 \Delta \mathrm{Er}_{i,t-1} + \Delta \epsilon_{i,t}\end{aligned} \tag{1.2}$$

System GMM:

$$\begin{aligned}\mathrm{Pat}_{i,t} = {} & \alpha + \beta_1 \mathrm{Pat}_{i,t-1} + \beta_2 \mathrm{MI}_{i,t} + \beta_3 \mathrm{GDP}_{i,t} + \beta_4 \mathrm{Er}_{i,t} \\ & + \beta_5 \mathrm{MI}_{i,t-1} + \beta_6 \mathrm{GDP}_{i,t-1} + \beta_7 \mathrm{Er}_{i,t-1} + \lambda_r + \gamma_t + \epsilon_{i,t}\end{aligned} \tag{1.3}$$

Where $i = 1, 2, ..., 107$ are the Italian provinces and $t = 2006, 2007, ..., 2021$ are the years of observation; $Pat_{i,t}$ is the number of industrial patents in province i at time t (for robustness checks, the total number of patents was also used as the dependent variable); $Pat_{i,t-1}$ is the number of patents lagged at time $t-1$, which captures the persistence of innovative capacity and controls for the dynamic nature of patenting activity; $MI_{i,t}$ is the Mafia Index in province i at time t; $GDP_{i,t}$ is the GDP; $Er_{i,t}$ is the employment rate; $MI_{i,t-1}$, $GDP_{i,t-1}$ and $Er_{i,t-1}$ are the explanatory variables lagged at time $t-1$; λ_r is the regional fixed effect, which captures systematic variations across regions (provinces in the same region); γ_t is the temporal fixed effect, which captures effects common to all provinces in the same year; α is the constant, removed from differencing in the Difference GMM model, but present in the System GMM; and finally $\epsilon_{i,t}$ is the stochastic error.

Both the contemporaneous value ($MI_{i,t}$) and the one-period lag ($MI_{i,t-1}$) of the Mafia Index are included in the specification for two reasons. First, from an economic standpoint, the relationship between organized crime and innovation is unlikely to operate instantaneously: while some mechanisms — such as extortion, credit distortion, and intimidation — may affect firms' investment decisions within the same period, others — such as the erosion of institutional trust, the displacement of skilled workers, and the long-run deterioration of the local business environment — are expected to manifest with a delay. Including both the contemporaneous and lagged values allows the model to capture the full short-run dynamic of the association. Second, from an econometric standpoint, including a lag of the Mafia Index helps to absorb potential autocorrelation in the relationship between mafia activity and patenting, reducing the risk that the contemporaneous coefficient captures spurious persistence in the data (Roodman, 2009).

The Difference GMM model (Arellano and Bond, 1991) begins by transforming the variables through first differencing to eliminate time-invariant unobservable fixed effects. This approach differentiates the dependent and independent variables with respect to the previous period, capturing their variations and addressing the component of endogeneity that arises from time-invariant provincial characteristics — such as structural differences in industrial composition or historical institutional quality — that are correlated with both mafia presence and patenting activity. Temporal and regional fixed effects are not included in this model because the differencing process inherently removes such components, as does the constant term.

However, while first differencing removes time-invariant confounders, it does not fully resolve endogeneity arising from time-varying omitted variables or from reverse causality between current mafia activity and current innovation shocks. For this reason, the Difference GMM uses deeper lags of the endogenous variables as internal instruments. The identifying assumption is that lags of order $t-2$ and beyond are uncorrelated with the differenced error term $\Delta\epsilon_{i,t}$. This assumption is plausible if the omitted determinants of patenting do not exhibit strong serial correlation; it may however be violated if mafias systematically target provinces with persistently favorable innovative characteristics, in which case lagged mafia activity would remain correlated with current innovation shocks through the omitted variable. This limitation is acknowledged and implies that the estimates should be interpreted as conditional correlations rather than causal effects.

A further limitation of the Difference GMM is that first differencing reduces the variability of the data, potentially weakening the precision of the estimates. For this reason, the System GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) is also employed. The System GMM combines equations in levels and in first differences, using lagged differences as instruments for the levels equations and lagged levels as instruments for the differenced equations. This augmented instrument set improves efficiency and is particularly valuable when the endogenous variables are highly persistent — as is the case for both patents and the Mafia Index. Regional and time fixed effects are explicitly included in the levels equation. The System GMM additionally requires that the differences used as instruments are uncorrelated with the unobserved unit-specific effects, a condition that is satisfied under joint mean stationarity of the dependent and independent variables (Kripfganz, 2019). Accordingly, all variables were subjected to the Fisher-type unit root test; the results indicated that the GDP variable was non-stationary and was therefore included in first-differenced form (Rosca, 2011).

In addition to the internal instruments generated by the GMM procedure, two sets of external instruments were employed. The first is a province-level proxy for business R&D expenditure, constructed by re-proportioning regional R&D data (ISTAT) to provinces according to the number of firms in each province. This variable is intended to capture the local innovation input environment and is included as an instrument for patenting activity on the grounds that R&D expenditure is a primary driver of patent output (Crépon et al., 1998). It should however be acknowledged that R&D expenditure and patenting are closely linked by construction, and that reverse causality — whereby higher patent output encourages further R&D investment — cannot be entirely ruled out. The second set consists of provincial and regional election dummies, included to capture institutional and political shocks that generate exogenous variation in the local institutional environment. The rationale is that election cycles can alter the composition and priorities of local governments, with potential downstream effects on the regulatory and enforcement environment in which mafias operate. However, as the referee notes, this exclusion restriction is not without risk: election cycles may also affect innovation indirectly through policy uncertainty, changes in public procurement, or variation in credit supply — channels that could independently influence patenting activity. These limitations are acknowledged, and the election dummies should be understood as imperfect instruments that improve the efficiency of the GMM estimator under the maintained assumptions, rather than as sources of clean exogenous variation.

In light of these considerations, the estimates presented in this chapter are best interpreted as conditional correlations: associations between mafia activity and patenting that are robust to time-invariant provincial heterogeneity and to the dynamic structure of the data, but that do not claim full causal identification.

STATA software was used for this analysis, specifically the `xtabond2` command (Roodman, 2009), which implements both the System GMM and Difference GMM estimators. The two-step procedure was preferred over the one-step procedure, as it provides more efficient estimates with lower bias in the standard errors (Windmeijer, 2005). To reduce the risk of instrument proliferation and overfitting, the *collapse* option was employed, which minimizes the size of the instrument matrix by aggregating moment conditions. The number of instruments was kept below the number of groups in all specifications, in accordance with standard practice (Roodman, 2009).

The System GMM and Difference GMM estimators were applied to the dataset, which was divided into three distinct samples: (1) the whole of Italy, which includes all Italian provinces; (2) Southern Italy, which includes provinces traditionally associated with mafia origins, belonging to Campania, Puglia, Calabria, Basilicata, Molise and Sicily; and (3) Central and Northern Italy, which covers provinces where there is no indigenous form of mafia organization. This geographically segmented approach allows for a more nuanced assessment of the conditional association between mafia infiltration and patent activity across contexts with structurally different trajectories of organized crime.

1.4.3 Robustness checks

To assess the robustness of the results, as anticipated in the previous section, each regression was conducted using both System GMM and Difference GMM estimators. In addition, for each of the regressions, some tests were performed, which were necessary to infer the consistency of the estimates obtained.

The Arellano-Bond tests examine the null hypothesis that there is no first- and second-order autocorrelation in the regression residuals. This test is crucial because it directly assesses one of the key assumptions underlying the Generalized Method of Moments (GMM) estimators (Rodman, 2009).

For the AR(1) test, a significant value ($p < 0.05$) is expected, as it indicates the presence of first-order serial correlation in the residuals, which is a common and generally acceptable feature in dynamic models such as GMM.

In contrast, for the AR(2) test, a non-significant value ($p > 0.05$) is desirable. This suggests the absence of second-order serial correlation, implying that the instruments used in the model are valid and uncorrelated with the residuals.

Hansen's test was employed to assess the validity of the instruments used in the model. This test is designed to verify whether the instruments chosen for the GMM model are valid, meaning they are uncorrelated with the error term and are not weak. In other words, it checks if the instruments are exogenous and appropriate for the model (Rodman, 2009). Generally, a p-value greater than 0.05 is considered preferable, as it suggests insufficient evidence to reject the null hypothesis, which posits that the instruments are valid. Although this test is robust, it can be affected by an excessive number of instruments.

To mitigate the 'too many instruments' problem, two precautions were taken: first, the number of instruments was kept smaller than the number of groups (a commonly accepted rule of thumb) (Rodman, 2009); second, the collapse option was used to reduce the number of instruments generated by the models.

All models are considered valid only if they pass the aforementioned tests successfully.

To assess the ability of the mafia index to synthesize the elemental indicators of which it is composed the regressions were further computed using the simple average of the crime indicators (Table A8).

In addition, the estimates were repeated using the total number of patent applications as the dependent variable, instead of focusing solely on industrial patents, in order to assess the effect of mafia activity on innovation in a broader context, encompassing other types of innovation, such as those related to technological and scientific research (Tables 1.2 & A8).

Figure 1.1: Geographical and Temporal Distribution of the Mafia Index Indicators

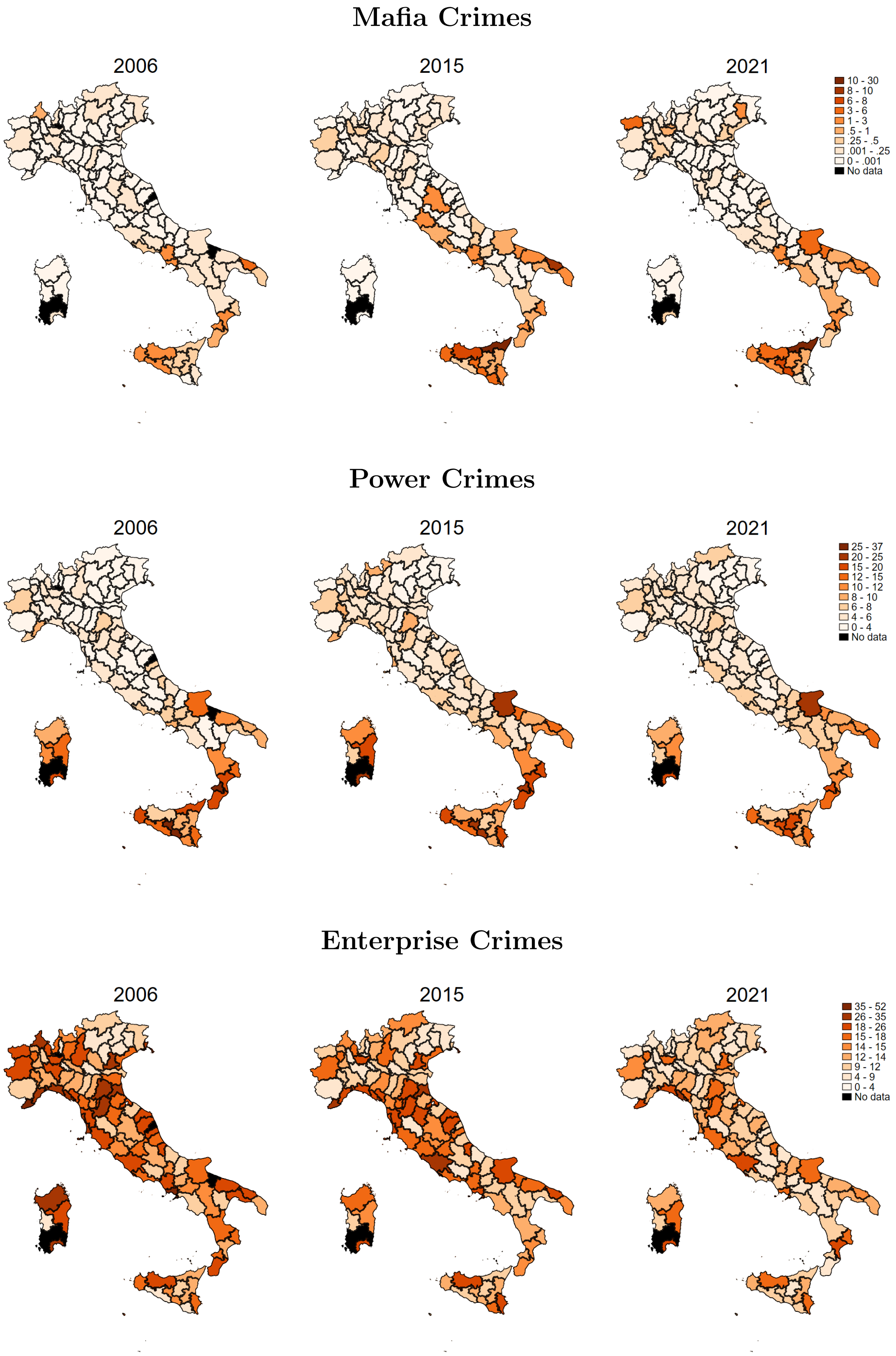

Figure 1.2: Heat Map of the Correlation Between Elementary Indicators of the *Mafia Index*

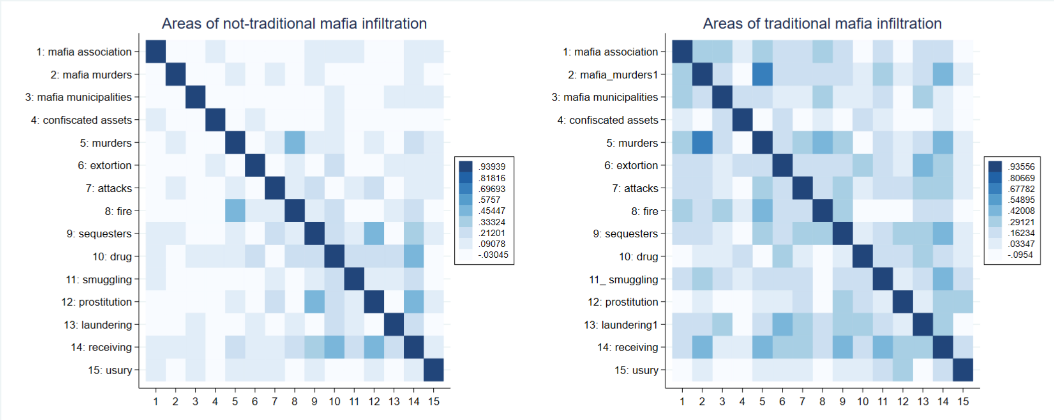

Figure 1.3: Geographical and Temporal Distribution of Patent Applications per 100,000 Inhabitants

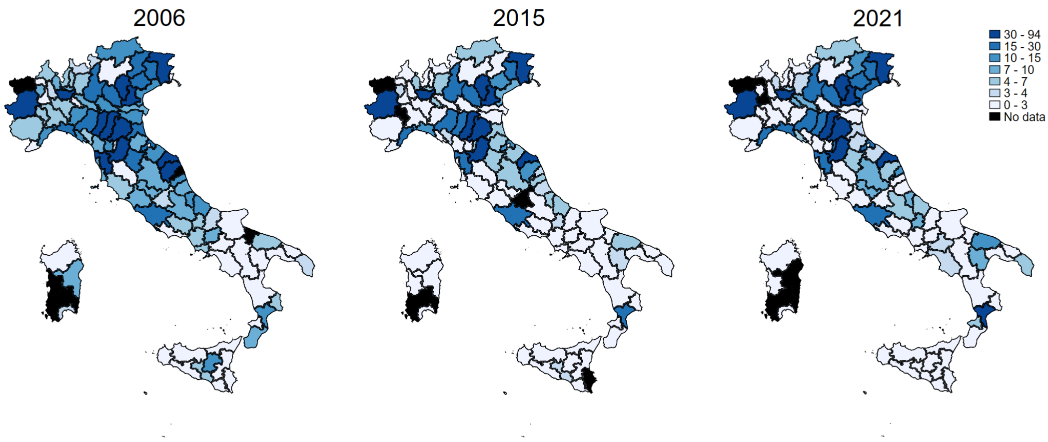

Table 1.1: Results of estimates with System GMM - Industrial patents

System GMM			
Areas:	All Italian Provinces	Provinces of Non-Traditional Mafia Infiltration	Provinces of Traditional Mafia Infiltration
Dependent Variable:	Industrial Patents	Industrial Patents	Industrial Patents
L1 Ind. patents	0.811***	0.819***	0.616***
	(0.0125)	(0.0105)	(0.149)
Mafia Index	0.326***	0.0788***	-0.0212
	(0.0746)	(0.0160)	(0.0334)
L1 Mafia Index	-0.156***	0.0304	-0.0712**
	(0.0516)	(0.0221)	(0.0359)
d.GDP	0.0000548	0.000287***	0.000661
	(0.0000620)	(0.0000600)	(0.000781)
L1 d.GDP	0.000306***	0.000350***	0.000415
	(0.0000657)	(0.0000622)	(0.000514)
Employment Rate	0.145***	0.138***	0.138**
	(0.0373)	(0.0421)	(0.0660)
L1 Employment R.	0.0765**	0.127***	-0.158
	(0.0324)	(0.0381)	(0.108)
Constant	-12.51***	-14.90***	2.112
	(2.270)	(2.314)	(3.969)
Years Dummies	YES	YES	YES
Regions Dummies	YES	YES	YES
N	1386	1007	379
AR(1) Test	0.000	0.000	0.009
AR(2) Test	0.362	0.360	0.146
Hansen Test	0.052	0.114	0.542

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The Provinces of Traditional Mafia Infiltration are those belonging to Campania, Calabria, Puglia, Basilicata, Molise, and Sicily, while the remaining provinces are classified as Provinces of Non-Traditional Mafia Infiltration.

Table 1.2: System GMM Results - All Patents

System GMM			
Areas:	All Italian provinces	Provinces of Non-Traditional Mafia Infiltration	Provinces of Traditional Mafia Infiltration
Dependent variable:	All patents	All patents	All patents
L1 All patents	0.903***	0.877***	1.022***
	(0.00422)	(0.00461)	(0.184)
Mafia Index	0.0975**	0.159**	0.392
	(0.0386)	(0.0651)	(0.405)
L1 Mafia Index	0.0237	0.0863	-0.956**
	(0.0388)	(0.0644)	(0.424)
d.GDP	0.000265**	0.000672***	0.00165*
	(0.000127)	(0.000150)	(0.000850)
L1 d.GDP	0.0000195	0.0000539	0.00140**
	(0.000122)	(0.000156)	(0.000608)
Employment rate	0.186**	0.267**	-2.417**
	(0.0790)	(0.116)	(1.088)
L1 Employment rate	0.189***	0.439***	1.184*
	(0.0674)	(0.107)	(0.636)
Constant	-23.90***	-39.85***	52.74**
	(6.111)	(10.50)	(22.23)
Years Dummies	YES	YES	YES
Regions Dummies	YES	YES	YES
N	1429	1037	392
AR(1) Test	0.37	0.043	0.011
AR(2) Test	0.161	0.147	0.971
Hansen Test	0.145	0.190	0.844

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The Provinces of Traditional Mafia Infiltration are those belonging to Campania, Calabria, Puglia, Basilicata, Molise, and Sicily, while the remaining provinces are classified as Provinces of Non-Traditional Mafia Infiltration.

1.5 Results

The analysis of the geographic distribution of indicators of mafia activity confirms the theoretical framework underlying this study, suggesting significant diversification in the operating patterns of mafias across Italian territory (Figure 1.1). The first two sets of indicators — the objective ones (crimes with an officially recognized mafia origin, such as mafia association or mafia-style murders) and the power syndicate indicators (violent crimes such as assaults, kidnappings, arson, and homicides) — show a greater concentration in Southern Italian provinces. This distribution reflects the historical entrenchment of traditional mafias, such as Cosa Nostra, 'Ndrangheta, and Camorra, in the South, where these organizations have historically operated as parallel systems of power to the state. In these provinces, mafias exert direct territorial control through intimidation and violence, employing methods like bombings or assassinations to assert and maintain their authority.

In contrast, the more uniform distribution of enterprise syndicate indicators — economic crimes such as drug trafficking, money laundering, usury, and the exploitation of prostitution — throughout the country underscores the entrepreneurial orientation of mafia organizations. These groups focus on wealth accumulation by exploiting illicit markets or by infiltrating the legal economy. In North-Central areas, direct territorial control (represented by the objective and power syndicate indicators) plays a less prominent role; instead, mafias operate more discreetly, prioritizing economic and financial activities that maximize profits while minimizing their risk of exposure.

This interpretation is further reinforced by the heat map of correlations between the crimes included in the Mafia Index (Figure 1.2). In areas of traditional mafia infiltration in the South, these crimes exhibit significantly stronger correlations compared to those in the North-Central regions. This indicates a deep interconnection between associative and violent crimes in Southern areas, where these activities are instrumental for mafias to establish a system of social control. Such systems ensure the loyalty and obedience of the local

population while enabling domination over regional economic activities. In contrast, areas of nontraditional infiltration reveal a primarily entrepreneurial orientation, which is less dependent on violent methods and more aligned with economic exploitation.
Thus, the objective of this analysis is to examine the conditional association between different mafia criminal strategies and local innovative capacity, using patent applications as a measure of economic and technological dynamism. To achieve this, the System GMM was applied, using the number of industrial patent applications as the dependent variable.

Analysis of the temporal and geographic distribution of patents reveals a clear disadvantage for provinces in Southern Italy and the islands, which correspond to areas with a higher incidence of mafia activity (Figure 1.3). The results of the System GMM model further reinforce this picture, suggesting that the conditional association between mafia infiltration and patenting differs markedly across Italian provinces (Table 1.1).

The coefficient of the lagged innovation variable demonstrates a significant persistence of innovative capacity across all areas analyzed: 0.811 for all provinces, 0.819 for the North-Center, and 0.616 for the South. These values suggest that past technological innovation is a strong predictor of future innovation. However, persistence is notably weaker in the South, likely due to structural weaknesses in the local economy.

As for the Mafia Index, a joint analysis of all provinces produces ambiguous results, showing a positive coefficient at time t and a negative one at time $t-1$. The picture becomes clearer when the sample is split between provinces of non-traditional mafia infiltration (North-Center) and traditional mafia infiltration (South). In the former, the Mafia Index is positively and statistically significantly associated with innovation at time t (0.0788); in the latter, the association is negative and statistically significant at time $t-1$ (-0.0712). These results are consistent with the theoretical framework outlined above. It should however be noted that the positive association observed in the North-Center does not imply that mafia presence fosters innovation: rather, it reflects the tendency of mafia organizations to concentrate their activities in more industrialized and innovative provinces, selecting into economically dynamic territories rather than generating dynamism themselves (Parbonetti, 2021; Sales & Melorio, 2017). In the South, by contrast, the negative association is consistent with the hypothesis that entrenched mafia activity is accompanied by conditions — extortion, institutional capture, suppression of competition — that are structurally unfavorable to innovative investment.

The control variables confirm the importance of the broader economic environment for patenting activity. The association between GDP growth and patents is positive and significant in most specifications, as is that of the employment rate. However, the positive association with employment is weaker or reverses sign in the South, which is consistent with a labor market characterized by low industrialization and a high share of informal and undeclared work — conditions that limit the formation of the skilled human capital necessary for innovation.

The Difference GMM model results (Table A7) corroborate the System GMM findings. For the North-Center, the Mafia Index is positively and significantly associated with innovation at both time t (0.144) and time $t-1$ (0.0728). For the South, the association is significantly negative at both time points — at time t (-0.121) and at time $t-1$ (-0.263) — highlighting a starkly contrasting pattern relative to the northern provinces.

Further analysis using the total number of patent applications per 100,000 population as a broader measure of innovative activity confirms the observed pattern: the Mafia Index is positively associated with patenting in the North at time t (0.159) and negatively associated in the South at time $t-1$ (-0.956), with both coefficients significant at the 5% level (Table 1.2).

Finally, to assess the robustness of the Mafia Index to its construction method, the analysis was replicated using an alternative index based on the simple average of the mafia-related indicators (Table A8). The results obtained with the System GMM approach closely replicate the main findings, with the Mafia Index negatively associated with innovation in the South and positively associated in the North-Center, lending further support to the robustness of the observed conditional correlations.

1.6 Final remarks

The empirical results presented in this chapter, obtained by analyzing data on Italian provinces for the period 2006–2021 using GMM estimators, are consistent with the theoretical framework that the conditional association between mafia activity and innovative capacity varies across territories depending on the objectives and strategies pursued by mafia organizations at the local level.

To better capture the diverse patterns of the mafia phenomenon, this analysis introduces, for the first time in the literature, a novel approach to data segmentation by dividing the dataset into three distinct panels: (1) a panel including all Italian provinces analyzed jointly; (2) a panel comprising only the provinces in the Center-North, characterized by non-traditional mafia infiltration, as they lack a deeply entrenched indigenous mafia association; and (3) a panel limited to the provinces in Southern Italy, specifically those where the mafia has historically originated, with particular focus on the regions of Campania, Calabria, Apulia, Basilicata, Molise, and Sicily.

The results of the System GMM model, corroborated by those from the Difference GMM model, indicate that a one-unit increase in the Mafia Index is associated with a significant increase in the number of industrial patent applications at time t for Center-North provinces (0.0788), and with a significant reduction in patenting activity in Southern provinces at time $t-1$ (-0.0712). These estimates are best interpreted as conditional correlations rather than causal effects, as discussed in Section 1.4.

The significance of the Mafia Index in relation to patenting activity highlights the degree to which mafia organizations are deeply embedded in market relations, to the point that they constitute a relevant correlate of local technological dynamism. This association, with opposite signs, is observed both in regions where the mafia is historically entrenched and in those where it has expanded its economic reach.

In areas of traditional settlement, mafias exert more direct and coercive control over the local economy. They enforce an extortion and protection mechanism to regulate local markets and propagate their criminal reputation, ensuring the silence of the population. Within these contexts, innovation is perceived by mafias as a potential threat to the established order. Outside their areas of origin, mafias concentrate their activities in territories with higher levels of industrialization, where there are more opportunities for innovation and technological development (Parbonetti, 2021). In this context, mafia concentration appears to be a correlate of economically dynamic areas rather than a driver of their development.

In Central-Northern Italy, mafias are more likely to integrate into legal economic circuits. This creates a situation in which criminal and legal enterprises merge, forming what is called a pooling equilibrium in game theory, a condition where it becomes difficult to distinguish between "good" and "bad" enterprises (Sciarrone, 2002a).

In these areas, the mafia is no different from the market. It increases its wealth, even though this wealth, fueled by corruption and violence, does not generate development in the areas from which it originates (Sales & Melorio, 2017).

The results are consistent with a picture in which mafia presence is associated with conditions structurally unfavorable to innovative investment in the South, while in the Center-North it tends to co-occur with — rather than generate — the economic and technological dynamism of the territories it infiltrates.

While the robustness of the estimates has been tested through various checks, further modifications could enhance the timeliness and interpretability of the results.

In this analysis, innovation was used as an indicator of economic well-being. The number of patent applications was chosen to quantify the innovativeness of provinces, thus measuring the output of innovation (Balland et al., 2017). However, as noted by Griliches (1990), using patents as a proxy for innovation has several limitations: (1) not all innovations are registered; (2) not all registered patents possess the same innovative value; and (3) the protection granted by patent registration can, in some cases, slow the diffusion of knowledge, potentially hindering innovation. To mitigate these limitations, only industrial patents were considered. However, the analysis could certainly be extended using more precise variables.

In general, the analysis is limited by the availability of provincial-level data for Italy. A possible future direction for research could involve the use of richer data sources, enabling the development of more comprehensive models and hypotheses. A further avenue worth exploring concerns the long-run dynamics of the relationship between mafia presence and innovation: since both variables exhibit persistent trajectories over time, future work could attempt to disentangle their longer-term interactions, assessing whether the negative association observed in traditionally infiltrated areas deepens or attenuates as mafia entrenchment accumulates over successive periods.

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APPENDIX A

Table A3: Kaiser–Meyer–Olkin test results

Variables	**KMO**
Crimes of Mafia association	0.797
Mafia murders	0.725
Municipal councils dissolved for mafia	0.811
Property confiscated from the mafia	0.648
Murders	0.708
Extortion	0.726
Attacks	0.813
Fire damages	0.725
Kidnapping	0.799
Production and trafficking of narcotics	0.604
Smuggling	0.656
Exploitation of prostitution	0.653
Money laundering	0.707
Receiving stolen property	0.699
Usury	0.654
Overall	**0.723**

Table A4: Descriptive statistics of the variables included in the Mafia index

Number of crimes per 100.000 population	**All italian provinces**				**Provinces of not-traditional mafia infiltration**				**Provinces of traditional mafia infiltration**			
Variables	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Mafia association	.1258321	.3697019	0	5.950631	.0184626	.0802323	0	.979995	.4116828	.6095475	0	5.950631
Mafia murders	.0617666	.2641529	0	3.513374	.0013353	.0199008	0	.5983456	.2226535	.4681975	0	3.513374
Municipal councils dissolved for mafia infiltration	.1927713	.9133943	0	14.81481	.0085716	.1140556	0	2.380952	.6831677	1.641357	0	14.81481
Assets confiscated from the mafia	1.18426	4.542215	0	87.3744	.3378634	1.238537	0	20.91572	3.437628	8.036791	0	87.3744
Murders	.7626804	.8442092	0	9.176627	.5991776	.6192136	0	9.176627	1.197976	1.153611	0	7.324934
Extortion	12.40688	5.51077	1.216597	38.76704	10.93334	4.857073	1.216597	30.44898	16.3299	5.223605	4.452404	38.76704
Attacks	.6213493	.7066262	0	8.427584	.5494752	.6120485	0	6.187579	.8127006	.8845455	0	8.427584
Fire	17.47131	21.47891	0	171.6512	10.05403	11.76971	0	99.82736	37.2184	28.02452	2.312433	171.6512
Sequesters	1.990202	1.196784	0	7.383888	1.819383	1.125647	0	6.086131	2.444975	1.261244	0	7.383888
Drug production and trafficking	53.93402	22.03628	12.36029	139.4918	55.90365	24.04268	12.36029	139.4918	48.69026	14.22239	21.40028	113.8083
Smuggling	.7295352	2.326356	0	21.65969	.5348761	1.829377	0	21.65969	1.247778	3.249537	0	19.48735
Exploitation of prostitution	1.800923	1.663101	0	15.3892	2.003535	1.826664	0	15.3892	1.261505	.9214649	0	5.613688
Laundering	.0023545	.0027606	0	.0410418	.0022875	.0030086	0	.0410418	.0025331	.0019437	0	.0131317
Receiving	34.9602	19.47716	3.961557	231.5668	34.98543	20.94609	3.961557	231.5668	34.89306	14.8957	6.241312	129.5854
Usury	.5380291	.6489434	0	11.63925	.455928	.6422618	0	11.63925	.7566074	.6157769	0	3.92941

Table A5: Descriptive statistics

	All italian provinces				Provinces of not-traditional mafia infiltration				Provinces of traditional mafia infiltration			
Variables	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Industrial patents	9.586351	14.97694	.2361342	93.43537	12.14428	16.74448	.2451876	93.43537	2.755655	3.255954	.2361342	36.58122
All patents	25.9585	69.06307	.2534437	670.7272	33.98507	79.49659	.4416864	670.7272	4.601466	4.62513	.2534437	42.67809
Mafia Index	-4.20e-09	6.821528	-13.29344	32.85549	-1.621489	5.947106	-13.29344	32.85549	4.316904	7.12103	-9.42028	29.61792
GDP	25296.92	6905.911	13900	61200	28240.42	5702.47	16000	61200	17513.15	2072.201	13900	26800
Employment rate	57.95798	9.987109	32	74.1	63.27717	5.00961	46.7	74.1	43.76572	4.677689	32	57.3

Table A6: Fisher-type unit-root test: p-value

Fisher-type unit-root test

H_0: All panels contain unit roots

H_a: At least one panel is stationary

Test	Industrial Patents (p-value)	All Patents (p-value)	Mafia Index (p-value)	Employment rate (p-value)	GDP (p-value)	d.GDP (p-value)
Inverse chi-squared(210)	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Inverse normal	0.0000	0.0000	0.0003	0.0000	1.0000	0.0000
Inverse logit t(529)	0.0000	0.0000	0.0001	0.0000	1.0000	0.0000
Modified inv. chi-squared	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Avg number of periods	15.59	15.83	15.86	15.86	15.95	14.95

Table A7: Results of estimates with Difference GMM - Industrial patents

Difference GMM			
Areas:	All Italian Provinces	Provinces of Not-Traditional Mafia Infiltration	Provinces of Traditional Mafia Infiltration
Dependent Variable:	Industrial Patents	Industrial Patents	Industrial Patents
L1 Ind. Patents	0.708***	0.747***	0.417***
	(0.0437)	(0.0397)	(0.0321)
Mafia Index	0.1357**	0.144**	-0.121***
	(0.0676)	(0.0704)	(0.0239)
L1 Mafia Index	0.0945**	0.0728*	-0.263***
	(0.0478)	(0.0417)	(0.0492)
GDP	0.000232**	0.000166**	0.000370**
	(0.000075)	(0.0000647)	(0.000185)
L1 GDP	0.000462***	0.000544***	-0.000430***
	(0.000089)	(0.0000977)	(0.000101)
Employment Rate	-0.292***	-0.173**	0.250***
	(0.0918)	(0.0852)	(0.0676)
L1 Employment R.	0.123	-0.0574	-0.169***
	(0.0963)	(0.109)	(0.0470)
Year Dummies	NO	NO	NO
Regions Dummies	NO	NO	NO
N	1386	1007	379
AR(1) Test	0.000	0.000	0.005
AR(2) Test	0.965	0.475	0.264
Hansen Test	0.035	0.044	0.658

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Results of estimates made using the average of crimes - System GMM

Areas	Provinces of Non-Traditional Mafia Infiltration	Provinces of Traditional Mafia Infiltration	Provinces of Non-Traditional Mafia Infiltration	Provinces of Traditional Mafia Infiltration
Dependent variable:	Industrial patents	Industrial patents	All patents	All patents
L1 Industrial patents	0.820***	0.528***		
	(0.0106)	(0.116)		
L1 All patents			0.884***	0.853***
			(0.00440)	(0.127)
Mean mafia	1.676***	-0.877	3.158**	4.333
	(0.335)	(1.075)	(1.272)	(3.654)
L1 Mean mafia	0.584	-0.946**	1.448	-9.929**
	(0.406)	(0.470)	(1.255)	(3.935)
d.GDP	0.000293***	0.00119*	0.000625***	0.00134**
	(0.0000587)	(0.000668)	(0.000145)	(0.000650)
L1 d.GDP	0.000355***	0.0000438	0.0000132	0.000892*
	(0.0000618)	(0.000175)	(0.000153)	(0.000456)
Employment	0.133***	0.0991	0.237**	-1.883**
	(0.0419)	(0.0736)	(0.113)	(0.832)
L1 Employment	0.122***	-0.200*	0.414***	1.034**
	(0.0376)	(0.118)	(0.104)	(0.475)
Constant	-15.54***	6.557	-39.24***	37.34**
	(2.364)	(6.598)	(9.983)	(16.50)
Years dummies	YES	YES	YES	YES
Regions dummies	YES	YES	YES	YES
N	1007	379	1037	392
AR(1) Test	0.000	0.017	0.043	0.005
AR(2) Test	0.343	0.159	0.145	0.814
Hansen Test	0.125	0.440	0.212	0.627

Chapter 2

THE SPATIAL IMPACT OF JUDICIAL ADMINISTRATION ON FIRMS' PERFORMANCE

2.1 Introduction

In the past, the Italian Mafia was not regarded as a threat in the societies where it operated (Sciarrone, 2002b). The relationship between the Mafia and the state was characterised by a symbiotic coexistence, with the logics of extralegal order intertwined with those of public order (Pizzorno, 1987).

The Italian state's struggle against the Mafia has often been marked by a chronic delay in intervention, with responses coming only after serious escalations of violence. State measures against mafia expansion have historically been reactive, aimed more at responding to events than preventing them. This delay has allowed mafia organisations to become deeply embedded in the social and economic fabric, transforming themselves into essential actors within markets. As a result, genuine "gray areas" have emerged within the legal economy, areas in which the legal and illegal spheres collude to such an extent that the boundary between them becomes indistinguishable (Sciarrone and Storti, 2024).

The markets where the Mafia operates as an economic actor represent the most sensitive targets for intervention in the fight against organised crime. Anti-mafia efforts in these gray areas must therefore focus on unravelling the intricate connections between the Mafia and the economy, distinguishing the various degrees of compromise and complicity between legal and illegal actors. One of the intervention models developed by the Italian legislative system to curb mafia economic activity is judicial administration (JA), which forms the basis of the empirical analysis in this chapter.

Judicial administration, governed by Article 34 of the Italian Anti-Mafia Code and fully reformulated by Article 10 of Law No. 161/2017, stipulates that if an enterprise's economic activity is directly or indirectly influenced by mafia dynamics, a new administrator (the judicial administrator) is appointed to work alongside the enterprise's legal administrator, thereby curtailing opportunities for collusion or cooperation with the mafia. Unlike seizure or confiscation, which remove the involved enterprise from the market, judicial administration was designed to safeguard business activity and inhibit mafia infiltration without undermining the pre-existing competition among enterprises. Because it does not directly reassign market shares through asset removal, judicial administration is particularly well-suited for pre/post analyses: it allows us to observe whether discouraging mafia activity generates positive spillovers (improved competition and market functioning) or negative ones (an economic vacuum, higher transaction costs, and temporary declines in productivity) for neighbouring legal firms.

The consequences of judicial administration can be distinguished into direct and indirect effects. The direct effects — those falling on the mafia-infiltrated firm itself — have been documented by Calamunci, De Benedetto, and Silipo (2021), who show that firms entering judicial administration experience a 19% reduction in bank credit and a decline in value added of approximately 6.6%, reflecting the loss of illegally acquired competitive advantages once the judicial administrator severs ties with criminal networks. The objective of this chapter is to investigate the *indirect* effects: the disruption of the mafia firm's network does not remain confined to that firm but may propagate outward to neighbouring legal firms that had, even inadvertently, benefited from the same relational and productive infrastructure. Specifically, we examine the impact of judicial administration on the performance of neighbouring firms operating in the same area and in the same macrosector, within a 10-km radius of the sanctioned firm.

The analysis is conducted using data from Italian firms located in the four main regions of southern Italy, namely Campania, Puglia, Calabria, and Sicily, observed over the period 2006–2023. The data, collected from the Italian AIDA database, constitute an unbalanced panel exploited for a pre/post analysis.

Within the economic literature, the indirect effects of JA have been studied most directly by Calamunci and Drago (2020), who examine the impact of a mafia firm's entry into judicial administration on legal firms in the same industry and province, finding positive spillovers at the provincial level.

Consistent with Calamunci and Drago (2020), the analysis presented in this chapter examines the spillover effect on legal firms (i.e., those that have never entered JA) resulting from a neighbouring firm's entry into JA. Unlike that work, which considered firms as neighbours if they belonged to the same province and macrosector, this analysis defines neighbours as firms that not only operate in the same macrosector but are also located within a maximum distance of 10 km. By incorporating a spatial component through distances calculated using Vincenty's formula (Hijmans, 2020), we more accurately identify spillover effects among truly neighbouring firms, reducing distortions that would inevitably arise from using a static territorial criterion such as province membership (Cainelli and Lupi, 2010).

The treated group consists of 4,280 unique firms operating in the same macrosector and located within a 10 km radius of at least one mafia firm subject to JA. The control group includes firms situated at least 50 km away from any enterprise placed under judicial administration. The 10 km threshold is not arbitrary: it reflects empirical evidence that productive and informational interdependencies tend to concentrate spatially within short distances, so that the disruption of such links provides strong theoretical grounds for expecting adverse effects particularly among firms in close proximity (Cainelli and Lupi, 2010; Bhattacharjee et al., 2023). Both groups operate in the so-called gray areas of the economy — firms active in the traditionally mafia-affected provinces of southern Italy — characterised by high levels of complicity and compromise between legal and mafia actors (Sciarrone and Storti, 2024). The key difference is that in the markets of treated firms, defined by belonging to the same macro-sector within a 10 km area, anti-mafia investigations at some point lead to judicial administration, whereas in control markets such events are not observed within at least 50 km.

The underlying assumption is that, prior to the intervention, mafia activity in the markets of treated firms was stable and operated without disruption. The investigations carried out by the *Guardia di Finanza* (Italian Financial Police) and the subsequent judicial administration lead to a contraction of such activity, as the discovery and disruption of mafia channels weaken their influence. The research question is therefore: what happens when a mafia enterprise is uncovered and its influence is obstructed, particularly for neighbouring firms that may have relied, to some extent, on that criminal channel?

Building on the existing literature (Lebert and Vercellone, 2006; Esposito et al., 2014; Sobering and Auyero, 2019; Sciarrone, 2024), we hypothesise that the exposure and subsequent disruption of a mafia firm's influence generate negative spillover effects on nearby enterprises. Law enforcement interventions are often characterised by chronic delays that allow mafia organisations to consolidate informal economic channels and key positions within local competitive dynamics. The sudden closure of these channels may create a vacuum of services and relationships that legal firms struggle to replace, leading to declines in productivity and increased operational uncertainty.

Our main results confirm this hypothesis. Using the De Chaisemartin and D'Haultfœuille (2024) estimator with a continuous treatment variable measuring the number of neighbouring JA events per year, we find an average cumulative effect of -2.24% on sales revenues, -2.05% on employment, and a small but significant decline in net income per unit of treatment in the first three years following the JA event. Placebo tests support the validity of the parallel trends assumption throughout.

Beyond the reduced-form effect, we provide evidence on the operative mechanism through three complementary analyses. First, we estimate the effect on value added, finding an average cumulative decline of -4.98%, substantially larger than the revenue effect, indicating that the disruption compresses productive margins rather than merely reducing demand. Second, effects on the liquidity ratio are statistically indistinguishable from zero, ruling out a purely financial channel and pointing instead toward the disruption of informal relational and commercial networks. Third, we exploit variation in the sectoral definition of treatment to disentangle the mafia network channel from standard market mechanisms. When treatment is defined as proximity to any JA firm regardless of sector, the estimated effects on revenues, employment, and value added are all statistically indistinguishable from zero, ruling out generalised demand or uncertainty shocks, which would affect all nearby firms equally. By contrast, as the sectoral definition becomes progressively more granular, the negative effects on all three outcomes grow in magnitude, consistent with the disruption of sector-specific relational networks built on shared suppliers, subcontracting arrangements, and informal market intermediation. A complementary spatial gradient shows that effects on employment intensify as physical distance from the JA firm decreases, from $-2.18\%^{***}$ at 9 km to $-3.51\%^{***}$ at 4 km. These results contrast with the positive provincial-level spillovers documented by Calamunci and Drago (2020). We argue that the two findings are not contradictory: provincial-level analyses capture a reputational or signalling mechanism operating over large administrative areas, whereas our 10 km radius identifies the market-level disruption of relational and productive networks that is inherently spatial and attenuates with distance.

The remainder of this chapter is organised as follows. Section 2.2 sets out the institutional framework. Section 2.3 reviews the related literature. Section 2.4 presents the hypotheses. Section 2.5 describes the data and sample construction. Section 2.6 outlines the empirical strategy. Section 2.7 presents the main results. Section 2.8 discusses the operative mechanism and alternative market definitions. Section 2.9 reports robustness checks. Section 2.10 concludes.

2.2 The judicial administration in the fight against the Mafia

The origins of the Italian Mafia, understood as "mafia acting," date back to the end of Sicilian feudalism (Gambetta, 1992; Bandiera, 2003), when landowners, in an effort to defend their property rights, hired bandits for protection (Dixit, 2009).

During the early postwar period, the Mafia continued to manifest itself as banditry, focusing primarily on matters related to land management. It was not until the late 1950s that Mafia interests began to shift toward the construction contracting business. Nevertheless, at that time, the Mafia was not yet perceived as a threat by the state.

The true extent of *Cosa Nostra*'s danger became apparent with the numerous Mafia murders in Palermo in 1962. Confronted with a growing awareness of *Cosa Nostra*'s economic ambitions, the Parliamentary Anti-Mafia Commission was established. However, the work of the first Commission culminated in three final reports in 1968, including a majority report that reduced the Mafia to a criminal organisation devoid of political entanglements, attributing its existence largely to regional customs.

Legislatively, the state ceased to ignore the Mafia phenomenon only after the tragic events of 1982, which culminated in the murders of the regional secretary of the Communist Party, Pio La Torre, and Palermo's prefect, Carlo Alberto Dalla Chiesa. On September 13, 1982, Law No. 646 was enacted, introducing Article 416 bis into the Italian Penal Code and, for the first time, defining "Association of Mafia-type."

From that point forward, the balance of power between the state and the Mafia changed radically. The Palermo anti-Mafia pool, composed of Giovanni Falcone, Paolo Borsellino, Leonardo Guarnotta, and Giuseppe Di Lello, launched an unprecedented offensive against *Cosa Nostra*. Through bank investigations and arrests, this team implemented the insights of Boris Giuliano and Cesare Terranova, who were among the first to examine the links between the Mafia and the economy. Law 416 bis also provided the legal basis for the indictment of 475 defendants in the *Maxiprocesso* (the largest trial ever held in the history of Italy's fight against organised crime), which was conducted in the bunker room of Palermo's Ucciardone prison between February 10, 1986, and December 16, 1987.

However, in the subsequent years, a decline in state and media attention allowed *Cosa Nostra* to reorganise. In 1992, the Mafia embarked on a spree of massacres, with bombings that claimed the lives of, among others, Giovanni Falcone and Paolo Borsellino.

In response to these atrocities, the state launched a new wave of legislative interventions. Legislative Decree No. 306 of 1992 introduced the institution of judicial administration (JA). However, this measure initially remained unused, partly due to ambiguity regarding its objectives and implementation procedures.

Currently, judicial administration is regulated by Article 34 of the Italian Anti-Mafia Code, as reformulated by Article 10 of Law No. 161/2017. This measure is applied when asset investigations by the financial police or the Judicial Police reveal that an enterprise's economic activity is, directly or indirectly, subject to intimidation or forms of subjugation attributable to the mafia dynamics described in Article 416 bis of the Criminal Code. JA may also be imposed when an economic activity, including business operations, risks facilitating individuals subject to personal or asset prevention measures, or those under investigation for crimes such as mafia association, extortion, usury, money laundering, and the use of goods of illicit origin.

In such cases, the management of companies and assets that could, even indirectly, be exploited for economic activities linked to organised crime is entrusted to a judicial administrator, who is appointed by the competent court together with a delegated judge. The judicial administrator assumes all the powers held by the legal owners of the properties and companies subject to the measure.

This measure may be adopted for a period not exceeding one year. Upon the expiration of the JA period, several options are available: (a) if the judicial administrator's report indicates the need for an extension, the measure may be renewed for a period not exceeding two years; (b) judicial administration may be revoked; (c) the measure may be replaced by judicial control; (d) the assets involved may be permanently confiscated if the attempt at rehabilitation through JA proves ineffective.

By implementing this preventive measure, which removes from the involved parties the management and availability of assets and economic activities that serve criminal interests, the aim is to counter the expansion of the mafia phenomenon by limiting its influence on the legal economy while preserving the operational continuity of the business. In this way, the institution seeks to shield healthy enterprises from mafia contamination, emphasising prevention rather than mere repression (Sciarrone and Storti, 2024).

From a sociological perspective, judicial administration emerges as a critical tool for countering mafia activity within what Sciarrone and Storti (2021) refer to as the "gray areas" of the economy, that is, markets where mafiosi operate as economic actors and forge relationships with legitimate businesses. These markets predominantly consist of traditional sectors characterised by stringent public regulation and limited competition (Lavezzi, 2008; Sciarrone, 2002a, 2021; Transcrime, 2013). In these contexts, mafiosi are not distinguished by exceptional entrepreneurial, managerial, or financial skills; rather, their strength lies in their ability to establish strategic relationships, leveraging the expertise of entrepreneurs, professionals, and public officials. In exchange, they provide significant economic resources and exert violence for personal protection or to resolve private disputes (Sciarrone and Storti, 2024).

These dynamics yield mixed outcomes: while the removal of mafia influence may enhance competitive quality, it can simultaneously harm businesses that have, either intentionally or inadvertently, relied on the services provided by organised crime. This duality raises important questions about the indirect effects of anti-mafia measures on the local economy. Although judicial administration is designed to rehabilitate infiltrated enterprises, it also carries the risk of destabilising the market by disrupting established networks of relationships and economic mechanisms that have long benefited many participants.

Ultimately, the impact of judicial administration, whether positive or negative, hinges critically on the timeliness of intervention. Delayed action may allow the Mafia to become deeply entrenched in the market, build robust relational networks, and ultimately transform into an indispensable component of the local economic system.

2.3 Literature review

Mafia influence within the legal economy has been analysed from various perspectives in the economic literature. The study conducted by Transcrime (2013) was the first to identify the distinctive traits of criminal enterprises, that is, those firms found by judicial investigations to be linked to mafia organisations. Transcrime (2013) found that these firms are primarily concentrated in sectors characterised by low openness to foreign markets, limited technological innovation, high labour intensity, and a predominance of small and medium-sized enterprises. In addition, these sectors are marked by high deregulation, strong territorial specificity, and significant involvement of public and government resources.

The report also indicates that the profitability of these firms is similar to, or even lower than, that of their legal competitors, owing to inefficient management. This occurs despite their employment of typical mafia practices, such as the intimidation of workers, competitors, and suppliers, as well as the manipulation of public contracts. In fact, the economic and financial management of such enterprises appears to be oriented more toward money laundering and the concealment of illegal activities than toward profit maximisation.

Parbonetti (2021) later reconfirmed the "identikit" of the mafia enterprise by analysing data on mafia-linked firms, identified based on judicial police operations and related convictions. He demonstrates that the distinctive traits of these criminal enterprises have remained largely unchanged from those highlighted by Transcrime (2013), despite the passage of time. Additionally, Parbonetti (2021) emphasises that events related to the SARS-CoV-2 pandemic have provided an opportunity for the Mafia to further develop and become entrenched.

Building on this characterisation, Arellano-Bover et al. (2024) introduce a conceptual framework distinguishing between three motives for OCG infiltration of legal firms: a functional motive, whereby newly established firms are used primarily for criminal activities; a competitive motive, whereby infiltration provides firms with criminal advantages such as intimidation of rivals and privileged access to resources; and a pure motive, whereby large and established firms are exploited for pecuniary returns and political connections without being directly involved in criminal activities. The competitive motive is of particular relevance to our analysis: it is precisely the channel through which neighbouring legal firms may derive indirect benefits from the presence of a mafia firm in their market. When judicial administration severs these ties, the competitive advantages artificially generated by the OCG disappear, and neighbouring firms that had, even inadvertently, benefited from the same relational network may suffer the consequences.

Several authors have examined the impact of policies and measures against organised crime on local economies. Most studies focus on so-called criminal enterprises, those operating in the gray area of the economy (Sciarrone and Storti, 2024; Transcrime, 2013; Parbonetti, 2021), but have produced mixed results. Among these, Operti (2018) investigates the effects of confiscating assets linked to criminal organisations on the rate of new business formation at the provincial level in Italy between 2009 and 2013. The study identifies two opposing dynamics. On the one hand, the removal of economic assets associated with organised crime reduces irregular competition and stimulates entrepreneurial innovation, thereby fostering new business creation; on the other hand, the confiscation of operational assets of the Mafia can create an institutional vacuum, weaken territorial control, and generate uncertainty, which negatively impacts the emergence of new businesses.

Daniele and Dipoppa (2022) examine the effectiveness of a screening mechanism introduced by the Italian government in 2013 to exclude businesses potentially linked to the Mafia from applying for subsidies exceeding 150,000 euros. Their findings indicate that approximately 3.8 percent of firms strategically reduced the subsidy amounts requested in order to avoid audits, thereby highlighting the capacity of mafia-linked firms to circumvent anti-corruption measures.

Donato, Saporito, and Scognamiglio (2013) analyse the credit and management profile of mafia-related firms following confiscation. The authors highlight that the reduction in credit by banking institutions begins as early as four years before confiscation, likely coinciding with the onset of judicial investigations.

Calamunci, De Benedetto, and Silipo (2021), using a diff-in-diff approach, assess how the placement of firms linked to organised crime under judicial administration affects their access to credit. The results indicate that, prior to the court order, the financing terms granted to mafia-affiliated firms do not differ significantly from those of legal firms. However, once firms enter judicial administration, banks significantly reduce lending to these firms, suggesting that the measure mitigates information asymmetry between lenders and firms.

Fabrizi and Parbonetti (2021), analysing data on Italian firms through a difference-in-differences procedure, observe that the removal of a mafia firm from the market through judicial confiscation leads to improved performance among legal firms operating in the same industry and municipality. This improvement is quantified as a 20.4% increase in normalised EBITDA relative to total assets. However, assessing the indirect effects of removing a mafia firm from the market presents a methodological challenge: the observed improvement in the performance of neighbouring legal firms could stem from a reduction in competition rather than the cessation of mafia influence.

Le Moglie and Sorrenti (2022) provide complementary evidence by documenting how provinces with a high organised crime presence were less affected by the 2007 financial crisis in terms of the establishment of new enterprises, which they interpret as evidence of mafia investment in the legal economy as a substitute for formal credit. This finding corroborates our interpretation that legal firms operating in gray areas may rely, at least in part, on informal financial and relational services provided by mafia networks, services that become unavailable when those networks are dismantled through judicial administration.

In a similar vein, Castelluccio and Rizzica (2025) examine the risk of mafia infiltration into legal firms exploiting the sharp revenue drop caused by the Covid-19 lockdowns of 2020. They find that a 10 percent drop in revenues increases the probability of mafia infiltration by approximately 4.9 percent, and that firms in temporary financial difficulty are more likely to resort to mafia-linked lending. Their results illuminate the two-way relationship between organised crime and the legal economy, showing how financial vulnerability opens the door to criminal infiltration. Our chapter studies the reverse side of this relationship: the consequences for the legal economy when mafia networks, once established, are disrupted by institutional intervention.

Fenizia and Saggio (2024) study city council dismissals in mafia-infiltrated municipalities and find positive effects on employment, firm creation, and institutional trust. Their results operate through a different channel from ours, namely the restoration of institutional legitimacy rather than the disruption of firm-level relational networks, but they provide further evidence that the relationship between organised crime and economic activity is causally significant and empirically tractable.

The study most closely related to the present chapter is Calamunci and Drago (2020), who examine the indirect effects of judicial administration, a measure that severs a firm's mafia ties without disrupting its operations. Using financial data from corporations in Southern Italy, they assess the impact of a mafia firm's entry into judicial administration on legal firms in the same sector and province through an event study analysis, finding a 2.2% increase in performance and a 0.7% rise in turnover in the first four years following the JA event.

This chapter differs from Calamunci and Drago (2020) and the broader econometric literature on this topic in several key aspects:

- *Definition of the local market*: Unlike Calamunci and Drago, who define "neighbouring" businesses based on their location in the same province, our study uses latitude and longitude data to define the local market within a 10 km radius (Cainelli and Lupi, 2010; Bhattacharjee et al., 2023). This finer geographical definition allows for a more accurate understanding of the interdependencies between firms and possible spillover effects, reducing the risk of artificial spatial aggregations that could mask the actual dynamics observed in the data.

- *Selection of control firms*: While Calamunci and Drago (2020) identify control firms as those operating in the same city but in different macro-sectors, our control group consists of firms that have never had competitors enter into judicial administration within a 50 km radius. The control sample was then refined through propensity score matching to enhance comparability with treated firms.

- *Methodology of analysis*: In addition to event study analysis, we use a dynamic difference-in-differences estimator (de Chaisemartin and d'Haultfoeuille, 2024), which is robust to heterogeneity and applicable to unbalanced panels. Unlike traditional difference-in-differences models, this method accommodates non-binary treatments, represented by discrete or continuous variables that can fluctuate over time. In our case, the treatment variable is the number of neighbouring firms (within a 10 km radius) in the same industry that enter judicial administration each year.

2.4 Definition of hypotheses

While Calamunci and Drago (2020) report positive spillover effects of judicial administration at the provincial level, we expect an adverse short-run impact on firms located in the immediate vicinity of the sanctioned mafia firm. This expectation rests on theoretical and empirical considerations indicating that, in the so-called "gray areas" of the economy, mafia-controlled enterprises often concentrate substantial shares of local economic activity and perform operational and relational functions (such as informal protection, access to unregulated credit, intermediation in market networks, and facilitation of contracts) that operate as local hubs and reduce certain transaction costs for colluding actors (Sciarrone, 2024; Giordano, 2017). Judicial administration, although designed to dismantle these networks without immediately removing business activity from the market, abruptly severs such channels; the resulting gap in services and relationships can be difficult for neighbouring legal firms to replace quickly, producing declines in productivity and heightened operational uncertainty (Lebert and Vercellone, 2006; Esposito et al., 2014).

Moreover, agglomeration evidence shows that productive and informational interdependencies concentrate spatially within relatively short distances, which reinforces the prediction that adverse effects will be strongest among firms proximate to the event (Cainelli and Lupi, 2010). For this reason, our geographically precise market definition, based on distances computed from coordinates, is likely to capture local spillovers that province-level analyses may miss, explaining why our findings may diverge from those of Calamunci and Drago (2020), who rely on broader administrative units.

2.5 Data

The empirical analysis is based on an annual unbalanced panel dataset of Italian firms operating in the southern regions of Italy (Calabria, Campania, Puglia, and Sicily), observed over the period 2006–2023. The data are sourced from AIDA, Bureau Van Dijk's Italian database, which provides detailed company information, including firm identifiers, financial data from annual financial statements, and geographic coordinates (address, latitude, and longitude). The database also includes information on legal proceedings involving the companies, specifying the years in which these proceedings began and concluded.

The analysis deliberately focuses on Southern Italy for both theoretical and empirical reasons. Theoretically, the concept of "gray areas" of the economy, namely markets where legal and illegal actors operate in structural collusion, characterises Southern Italian regions, where organised crime has been embedded in the local economy for generations. Northern Italy presents a fundamentally different institutional context in which mafia infiltration operates primarily through financial channels and public procurement rather than through the territorial relational networks that are central to our mechanism. Including Northern firms would introduce substantial institutional heterogeneity that would complicate identification and interpretation. Empirically, JA events in Northern Italy are relatively rare compared to the South, meaning that extending the sample northward would add a disproportionately large number of potential control firms relative to treated firms, with no meaningful gain in statistical power.

All outcomes are measured at the firm level, as provided by the AIDA database, which reports consolidated financial statements for each legal entity. Geographic coordinates used to compute distances between firms refer to the registered address, which is the only location information available in AIDA. This is a limitation shared by all studies relying on Italian firm-level administrative data. It is, however, unlikely to materially affect our results, since the vast majority of firms in our sample are micro and small enterprises for which having multiple geographically dispersed establishments is uncommon.

By cross-referencing AIDA with the Italian Court of Cassation's judgments portal, 440 enterprises were identified as having been subject to judicial administration in at least one of the years considered (see Appendix B for descriptive statistics on the sectoral and geographic distribution of these firms). For each of these enterprises, data were available on their sector of activity (six-digit Ateco codes), geographic location (latitude and longitude), and the year of entry into JA.

The following criteria were used to identify treated enterprises:

1. *Definition of geographic proximity*: A legal enterprise is considered "close" to a firm placed under JA if the distance between them is less than or equal to 10 km. The shortest distance between two firms (i.e., the great-

circle distance or as-the-crow-flies distance) is calculated using the Vincenty (sphere) method (Hijmans, 2020).[1] The choice of a 10 km radius is consistent with the findings of Cainelli and Lupi (2010), which show that agglomeration economies and inter-firm spillovers operate on very small spatial scales, typically within about 10 km. As a robustness check, we verify that the results hold under alternative distance thresholds ranging from 4 to 9 km, documenting a spatial gradient.

2. *Industry classification*: Proximity is considered only among firms operating within the same macrosector.[2]

If a legal firm has at least one firm entering JA within a 10 km radius and operating in the same macrosector, it is classified as treated. This procedure results in the definition of two variables: a binary indicator JAt_i that takes value 1 in years when firm i has at least one nearby firm placed under JA, and 0 otherwise; and a continuous variable counting, year by year, the number of firms within a 10 km radius and active in the same macrosector that are placed under JA. The continuous variable is used as the treatment variable in the De Chaisemartin and D'Haultfœuille (2024) estimator.

Following an intent-to-treat (ITT) design, treatment is defined as an absorbing state: once a firm is exposed to a neighbouring JA event, it remains classified as treated in all subsequent periods. This is the standard approach recommended for staggered difference-in-differences designs with heterogeneous treatment effects.

Using this procedure, 4,280 unique treated firms are identified.

The control enterprises are defined and selected based on the following criteria:

1. *Absence of proximity to enterprises in JA*: The control enterprise must

[1] The `distVincentySphere` function, available in the statistical software R via the `geosphere` package, was used to calculate the distance between legal firms and those in JA.

[2] The AIDA database contains information on the six-digit Ateco activity code of enterprises. Official ISTAT linking tables were used to move from activity codes to macrosectors.

not have any mafia-related enterprises in JA or confiscated within a 50 km radius. This threshold ensures sufficient spatial separation from firms involved in anti-mafia measures while maintaining an adequate number of control firms for each province. The choice is consistent with the empirical results of Bhattacharjee et al. (2023), who find that spillover effects substantially attenuate within a radius of less than 50 km.

2. *No judicial history*: Control firms must not have been involved in judicial proceedings, as verified through information in the AIDA database.

3. *Belonging to the same macrosector, period, and geographic area*: Control firms must be active in Southern Italy, operate in the same macrosectors as the treated firms, and be active in the same years.

At the end of this procedure, 77,241 control enterprises were identified.

Following the approach of Calamunci, De Benedetto, and Silipo (2021), propensity score matching[3] was applied to refine the control group and enhance comparability with treated firms. A probit regression was estimated, where the dependent variable equals 1 if the firm is located near a firm placed under judicial administration and 0 otherwise. Province dummies, sector dummies, and firm size dummies (classified according to EU standards as micro, small, medium, or large enterprises) were used as independent variables. We acknowledge that treated and control firms may differ in their baseline exposure to mafia activity even after matching, since spatial proximity to a JA event may be correlated with underlying organised crime presence. However, this concern is mitigated by two features of our design. First, control firms are required to be located at least 50 km from any JA episode, ensuring structural separation from mafia-exposed markets. Second, the province×year and sector×year fixed effects included in all specifications fully absorb any time-varying mafia intensity that operates at the province or sector level, which is the level at which publicly available proxies for organised crime presence are measured. Adding such measures to the matching procedure would therefore

[3] The `psmatch2` command in Stata proposed by Leuven and Sianesi (2018) was used.

not alter identification. To determine the appropriate caliper for matching, Stuart and Rubin's (2008) rule of thumb was followed, setting it equal to one-fourth of the standard deviation of the propensity score. This procedure significantly reduced the number of firms in the control group but optimised their similarity to the treated firms.

Table 2.1 presents the standardised bias for the dummies related to firm size, provinces, and macrosectors after matching. The difference between the sample means in the treatment and control subsamples is expressed as a percentage of the square root of the mean of the sample variances of the two groups (Rosenbaum and Rubin, 1985). According to Caliendo and Kopeinig (2008), standardised biases below the 5% tolerability threshold, as observed in our case, are considered sufficient to confirm the effectiveness of the matching procedure. The absence of statistically significant differences in the t-tests further confirms the reliability of the propensity score matching.

Table 2.1: Comparison between treated and control group

Variable	Treated	Control	%Bias	t-test (p-value)
Self employed	0.23435	0.23435	0.0	1.000
Micro	0.6051	0.60197	0.6	0.831
Small	0.07424	0.07648	-0.8	0.777
Medium	0.00313	0.00447	-1.7	0.466
Big	0.00313	0.00268	0.6	0.781
Manufacturing	0.02862	0.02952	-0.5	0.859
Energy	0.00134	0.00134	0.0	1.000
Water & Waste	0.00089	0.00134	-0.5	0.655
Construction	0.42755	0.42934	-0.4	0.904
Wholesale & Retail	0.36628	0.37030	-0.8	0.780
Transport	0.02862	0.02594	1.3	0.582
Accommodation	0.00850	0.00716	0.6	0.611
Finance	0.00045	0.00045	0.0	1.000
Real Estate	0.12165	0.11896	0.8	0.783
Healthcare	0.01565	0.01521	0.3	0.903
Arts	0.00045	0.00045	0.0	1.000
Agrigento	0.00045	0.00045	0.0	1.000
Avellino	0.02415	0.02370	0.3	0.922
Bari	0.00850	0.00805	0.2	0.869
Barletta-Andria-Trani	0.00224	0.00224	0.0	1.000
Catania	0.81082	0.81038	0.1	0.970
Catanzaro	0.00179	0.00224	-0.4	0.739
Enna	0.00045	0.00045	0.0	1.000
Messina	0.02191	0.02057	0.9	0.756
Napoli	0.00045	0.00045	0.0	1.000
Palermo	0.00089	0.00089	0.0	1.000
Ragusa	0.02236	0.02057	1.1	0.680
Reggio di Calabria	0.05590	0.05635	-0.3	0.948
Salerno	0.02191	0.02370	-0.7	0.689
Taranto	0.00045	0.00045	0.0	1.000
Trapani	0.02147	0.02191	-0.3	0.918
Vibo Valentia	0.00447	0.00492	-0.7	0.827

The table reports standardised bias and t-test p-values for all matching variables after propensity score matching.

2.6 Empirical strategy

The empirical strategy relies on a panel of financial data that distinguishes between two groups of enterprises: treated and control. Treatment of a legal enterprise (i) is defined as proximity (within a radius of 10 km) to a mafia enterprise active in the same macrosector that is placed under judicial administration. In other words, treatment occurs in years when a law enforcement action against organised crime disrupts or weakens mafia ties in the market surrounding enterprise i. Here, the market is defined as the set of firms operating in the same macrosector and located within a 10 km radius.

The objective is to analyse the spillover effects generated by the judicial administration of a mafia enterprise and the subsequent disruption of its criminal ties on neighbouring enterprises. To this end, two different models are estimated: an event study analysis (Sun and Abraham, 2021) and a dynamic difference-in-differences (de Chaisemartin and d'Haultfoeuille, 2024).

The firms under observation are predominantly small or medium-sized, active in traditional industries (Table B7), and characterised by limited involvement in extraordinary financial transactions (Transcrime, 2013; Parbonetti, 2021).

Because many of the analysed firms are sole proprietorships, typically small, owner-managed businesses with limited diversification, our analysis prioritises metrics that reflect ongoing business operations. We therefore select three primary outcome variables: (1) revenue from the sale of goods and services, as the principal indicator of operating scale and market activity; (2) net income, as a summary measure of profitability after expenses and taxes; and (3) number of employees, as a proxy for labour input and organisational size. We intentionally exclude extraordinary or non-operating financial items (such as one-off capital gains, exceptional grants, or other irregular financial windfalls) because such events can disproportionately distort the financial profiles of small firms and would not reliably indicate their underlying operational performance. In addition to these primary outcomes, we estimate effects on four supplementary variables to investigate the operative mechanism: value added, as a measure of productive efficiency net of intermediate inputs; intermediate costs, to reconcile the revenue and net income results; the current ratio, as an indicator of short-term liquidity; and a binary indicator of firm exit, to assess whether JA exposure affects the probability of economic closure of neighbouring firms.

We assume that the entry into JA is not randomly assigned, but is influenced by environmental, political, and judicial factors beyond our control. The causal interpretation is based on the fact that, conditional on fixed effects for unit, year, province, and industry, the timing of a firm's entry into JA related to organised crime is exogenous to the performance of its competitors. This conditional independence hypothesis is supported by several circumstances, including the long duration of criminal investigations and the high variability in the timing of judicial disposition among districts, which suggests that the timing of judicial administration is driven largely by uncontrollable exogenous factors rather than by the economic performance of neighbouring firms. Additionally, we assume that, in the absence of such an event, the treated and control units would have followed parallel trends.

As noted in Section 5, treatment is defined following an intent-to-treat (ITT) design: once a firm is exposed to a neighbouring JA event, it remains classified as treated in all subsequent periods, regardless of whether further JA events occur nearby.

The interaction-weighted (IW) estimator of Sun and Abraham (2021) is employed to estimate the dynamic effects of placing a mafia firm under judicial administration on nearby legally operating firms. This estimator is preferred because it corrects biases that can afflict the canonical two-way fixed-effects (TWFE) event study when treatment effects are heterogeneous across cohorts. In the presence of cohort-specific heterogeneity, TWFE coefficients may be expressed as weighted averages whose weights are generally not interpretable. By contrast, the IW procedure constructs, for each relative period, a weighted average of cohort-specific estimates with weights that reflect the empirical distribution of cohorts in the panel; consequently, the period-by-period IW estimates admit a transparent interpretation as the dynamic treatment effects.

The IW estimator is implemented in three stages. First, an interacted regression is estimated (via `reghdfe`), including interactions between cohort indicators and relative-time dummies. Second, cohort-specific shares that underpin each relative period are estimated. Third, for each relative period a weighted average of the cohort-specific estimates from stage one is computed using the estimated cohort shares as weights. This procedure yields event-study estimates that are robust to heterogeneity of treatment effects across cohorts (Baum and Schaffer, 2015; Correia, 2017; Sun and Abraham, 2021).

Formally, the model we estimate can be written as:

$$Y_{it} = \sum_{k\in\{-3,\ldots,3\}} \sum_{c\in\mathcal{C}} \delta_{c,k}\, \mathbf{1}\{\text{cohort}_i = c\}\, \mathbf{1}\{\text{JA}_{it} = k\} + \alpha_i + \lambda_t + \Gamma_{p(i),t} + u_{it}, \tag{2.1}$$

Y_{it} Outcome for firm i in year t (e.g. log sales revenues, log net income, log number of employees).

$\mathcal{C}$ The set of treatment cohorts, where each cohort c is defined by the specific year of first exposure to the treatment. Units that remain untreated throughout the entire sample period constitute the never-treated control group and serve as the reference category. This implies that all relative-time periods, including $t = -1$, are identified as deviations from the never-treated group rather than from a specific pre-treatment period, and can therefore be estimated and reported as additional pre-trend diagnostics.

$\mathbf{1}\{\text{cohort}_i = c\}$ Indicator equal to 1 if firm i belongs to cohort c (first exposure to JA proximity in that year).

$\mathbf{1}\{\text{JA}_{it} = k\}$ Relative-time indicator equal to 1 if observation (i, t) is k years away from the JA event ($k \in \{-3, -2, -1, 0, 1, 2, 3\}$). The event study is estimated over a symmetric $\pm$3-year window. Observations outside this window are not binned but are simply excluded from the event-study indicators. The panel is unbalanced, so cohorts treated in early years may have fewer pre-treatment periods available; this is accommodated naturally by both estimators.

$\delta_{c,k}$ Cohort-specific effect for cohort c at relative time k (estimate from the interacted regression). These coefficients are then combined with cohort weights to obtain the IW estimators $\hat{\beta}_k^{\mathrm{IW}}$.

α_i Firm fixed effect, which absorbs all time-invariant characteristics of firm i.

λ_t Year fixed effect, which absorbs shocks common to all firms in year t.

$\Gamma_{p(i),t}$ Province×year fixed effect, where $p(i)$ denotes the province of firm i.

u_{it} Idiosyncratic error term. Standard errors are clustered at the firm level in the baseline specification. Alternative clustering strategies are discussed in Section 8.

To ensure the causal validity of the post-event estimates, the analysis relies on the parallel trends assumption: in the absence of treatment, treated and control units are expected to follow equivalent trajectories over time. To reinforce the plausibility of this assumption, the control group was constructed using propensity-score matching in order to balance observable characteristics between treated and control firms (Caliendo and Kopeinig, 2008). Moreover, two diagnostic checks were implemented to directly assess the absence of anticipation effects and the validity of the parallel trends condition. First, the pointwise significance of the coefficients on the lead (pre-treatment) indicators was examined. Second, joint placebo (pre-trend) tests were conducted on the set of lead coefficients, that is, tests of their joint nullity, to provide a global assessment of whether systematic pre-trends were present (Callaway and Sant'Anna, 2021; Roth et al., 2023).

Following the event study analysis, we estimate the dynamic difference-in-differences (DiD) model developed by de Chaisemartin and d'Haultfoeuille (2024) as our preferred specification. We adopt this estimator rather than a standard TWFE regression for two reasons. First, it is robust to heterogeneous treatment effects across groups and over time, a concern that is particularly relevant in our staggered adoption setting where JA events occur in different years and the composition of treated firms varies across cohorts. Under treatment effect heterogeneity, TWFE estimates may assign negative weights to some treatment effects, potentially biasing the estimated average effect away from the true treatment effect. Second, the estimator naturally accommodates a non-binary, non-absorbing continuous treatment variable, in our case the number of neighbouring JA firms per year, while providing valid placebo tests for the parallel trends and no-anticipation assumptions. A TWFE specification with continuous treatment is reported as a robustness check in Section 8 and confirms the direction and significance of the main findings.

The key estimand proposed by de Chaisemartin and d'Haultfoeuille (2024) is:

$$\delta_{g,\ell} = \mathbb{E}\left[Y_{g,F_g-1+\ell} - Y_{g,F_g-1+\ell}(D_{g,1},\ldots,D_{g,1})\right] \tag{2.2}$$

where $\delta_{g,\ell}$ quantifies the treatment effect for group g after ℓ periods relative to the hypothetical scenario where treatment remained at its pre-switch level; $Y_{g,t}$ is the potential outcome for group g at time t; $D_{g,t}$ is the treatment (number of neighbouring JA firms), which can vary continuously and does not follow a staggered binary structure; F_g is the first period in which group g experiences a change in treatment; and $Y_{g,F_g-1+\ell}(D_{g,1},\ldots,D_{g,1})$ is the counterfactual outcome the group would have exhibited had treatment remained constant at its initial level.

In practice, this estimand is computed from the following regression:

$$Y_{it} \;=\; \alpha_i \;+\; \lambda_t \;+\; \sum_{\ell=1}^{L} \beta_\ell \,\Delta D_{i,t-\ell+1} \;+\; \varepsilon_{it} \tag{2.3}$$

where $\Delta D_{i,t}$ denotes the change in the number of neighbouring JA firms for firm i between $t-1$ and t, α_i and λ_t are firm and year fixed effects, and ε_{it} is an idiosyncratic error term. The coefficients β_ℓ capture the dynamic treatment effects at each lag ℓ, and their weighted average yields the average cumulative effect per treatment unit reported throughout the paper. This average cumulative effect is normalised by the average number of periods over which each treatment unit's effect is accumulated (approximately 3 in our setting), and therefore captures the average effect per unit of treatment intensity, namely per additional neighbouring JA firm, rather than the simple average of the annual point estimates. The annual effects (Effect_1 through Effect_3) and the average cumulative effect are therefore complementary objects: the former describe the dynamics of the effect over time, while the latter provides a single summary measure of the overall impact.

Unlike the Sun and Abraham (2021) estimator, which uses a binary 0/1 variable to identify treatment years, the de Chaisemartin and d'Haultfoeuille (2024) estimator allows for the use of a continuous variable that quantifies the number of neighbouring firms that entered JA. This approach enables the measurement of the event's effect by assigning different intensities to each observation based on the number of judicial interventions recorded each year. The underlying idea is that the greater the number of mafia-owned firms identified and placed under judicial administration within a given area and sector, the stronger the intensity of public attention directed toward anti-mafia enforcement in that year.

2.7 Main results

Before turning to the estimates, it is useful to recall the broader context in which the spillover effects are expected to materialise. Calamunci, De Benedetto, and Silipo (2021) document that firms directly subject to judicial administration experience a 19% reduction in bank credit and a decline in value added of approximately 6.6%, reflecting the loss of illegally acquired competitive advantages once the judicial administrator severs ties with criminal networks. Our results document the mirror-image effect: the disruption of the mafia firm's network does not remain confined to that firm but propagates outward to neighbouring legal firms that had, even inadvertently, benefited from the same relational and productive infrastructure.

The first estimated model is the interaction-weighted event study of Sun and Abraham (2021), tested under two fixed effects specifications: one including firm and year fixed effects only, and one additionally absorbing province-by-year interactions to control for unobserved time-varying provincial shocks.

The findings reported in Table 2.2 and Figure 2.1 indicate that judicial administration, by disrupting mafia ties in the local market, is associated with significant negative effects on the performance of neighbouring legal firms. For sales revenues, the estimated coefficients are negative and statistically significant in the first two post-treatment years across both specifications, indicating a persistent deterioration in operating scale following the JA event. The inclusion of province-by-year fixed effects leaves the sign and significance of the estimates largely unchanged, suggesting that the effect is not driven by time-varying provincial factors.

A similar pattern emerges for employment, where a significant decline is observed in the first two post-treatment years, with the effect somewhat more pronounced in the specification with province-by-year fixed effects. For net income, the estimated coefficients are negative throughout the post-treatment period, though the magnitude is smaller and significance is less stable across specifications, a result that we discuss further below in light of the cost channel.

Crucially, the pre-treatment coefficients ($JA{-}3$, $JA{-}2$, $JA{-}1$) are small, do not display any systematic trend, and are statistically indistinguishable from zero in all specifications. The joint pre-trend p-values range from 0.197 to 0.841 across outcomes, providing strong support for the parallel trends assumption and the absence of anticipation effects.

The results obtained using the estimator proposed by de Chaisemartin and d'Haultfoeuille (2024) confirm and strengthen the findings from the event study. This estimator is preferred as the main specification because it is robust to heterogeneous treatment effects across cohorts and over time, and because it naturally accommodates the continuous treatment variable (the number of neighbouring JA firms per year) while providing valid placebo tests for the parallel trends and no-anticipation assumptions.

For sales revenues (Table 2.3), the estimated effects in the first three post-treatment years are -4.28%, -5.00%, and -4.87% respectively, all significant at the 1% level. The average cumulative effect is -2.24% per unit of treatment ($p < 0.001$). For employment, the estimated effects are -3.26%, -5.50%, and

-3.14%, with an average cumulative effect of -2.05% ($p < 0.001$). For net income, the annual effects are small in magnitude but consistently negative, with an average cumulative effect of approximately -0.000029 ($p < 0.001$).

A clarification on the interpretation of these estimates is in order. The annual effects (Effect_1 through Effect_3) and the average cumulative effect reported by the estimator are complementary but distinct objects. The annual effects capture the dynamic trajectory of the impact in each post-treatment period and are the appropriate measures for assessing persistence. The average cumulative effect, by contrast, is normalised by the average number of periods over which each treatment unit's effect is accumulated (approximately 3 in our setting) and captures the average effect *per unit of treatment intensity*, that is, per additional neighbouring JA firm per year. It therefore does not represent the simple average of the three annual point estimates, but rather a weighted summary of the overall impact that accounts for variation in treatment intensity across switcher-period observations. The apparent discrepancy between the annual effects (around -4% to -5%) and the average cumulative effect (-2.24%) reflects precisely this normalisation.

The placebo tests confirm the validity of the identifying assumptions: the joint nullity tests for the pre-treatment placebo periods yield $p = 0.196$ for revenues, $p = 0.072$ for net income, and $p = 0.113$ for employment, all comfortably above conventional significance thresholds.

It should be noted that, while our dataset records the year in which each firm enters judicial administration, information on the subsequent outcome of the procedure — whether the measure was extended, revoked, replaced by judicial control, or led to permanent confiscation — is not systematically available in the public records used to construct our sample. This prevents us from analysing heterogeneous effects by post-JA trajectory, as the relevant administrative acts are not uniformly disclosed upon conclusion of the procedure.

Table 2.2: Event Study estimates (Sun and Abraham estimator)

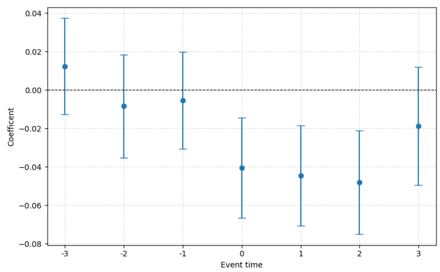
	ln Sales		**ln Net Income**		**ln Employees**	
	(1)	(2)	(3)	(4)	(5)	(6)
$JA-3$	0.0115	0.0116	0.00000738	0.00000895	-0.00428	-0.000214
	(0.0129)	(0.0142)	(0.0000149)	(0.0000158)	(0.0162)	(0.0175)
$JA-2$	-0.0100	-0.00924	-0.00000132	0.0000168	-0.01404	-0.01182
	(0.0138)	(0.0146)	(0.0000172)	(0.0000287)	(0.0174)	(0.0182)
$JA-1$	-0.00647	-0.00292	0.0000292	0.0000382*	-0.03018*	-0.02184
	(0.0128)	(0.01298)	(0.0000192)	(0.0000206)	(0.01696)	(0.01733)
JA	-0.0427***	-0.0465***	-0.00000657	-0.0000178	-0.05544***	-0.06662***
	(0.01325)	(0.01335)	(0.0000168)	(0.0000200)	(0.01658)	(0.01706)
$JA+1$	-0.04610***	-0.05410***	-0.0000494	-0.0000540*	-0.07460***	-0.08218***
	(0.01356)	(0.01390)	(0.0000300)	(0.0000309)	(0.01742)	(0.01792)
$JA+2$	-0.04399***	-0.04354***	-0.0000172	-0.0000110	-0.04252**	-0.03951*
	(0.01437)	(0.01526)	(0.0000228)	(0.0000251)	(0.01930)	(0.02053)
$JA+3$	-0.02114	-0.02101	-0.0000198	0.0000210	-0.04128**	-0.03572
	(0.01604)	(0.01699)	(0.0000263)	(0.0000458)	(0.01988)	(0.02119)
Joint pre-trend p-value	0.1973	0.2721	0.8409	0.7965	0.6935	0.7329
FE: ID	Yes	Yes	Yes	Yes	Yes	Yes
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Province × Year	No	Yes	No	Yes	No	Yes
Observations	428,845	428,843	428,818	428,816	298,844	298,839
R^2	0.9055	0.9057	0.4116	0.4118	0.8744	0.8747

Robust standard errors clustered at the firm level are in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (1), (3), and (5) include firm and year fixed effects. Columns (2), (4), and (6) also include province-by-year fixed effects.

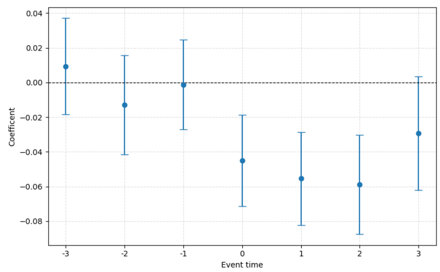
Figure 2.1: Judicial Administration Spillover Effects: Event Study Plots (Sun and Abraham estimator)

Sales Revenue (ln)

FE: id and years

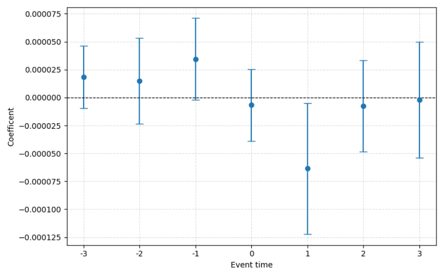


FE: id, years and province by year

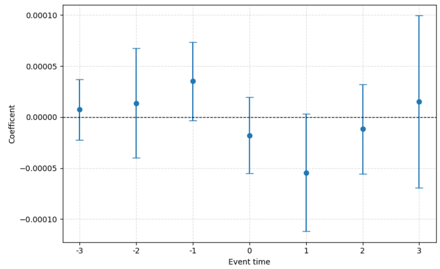


Net Income (ln)

FE: id and years

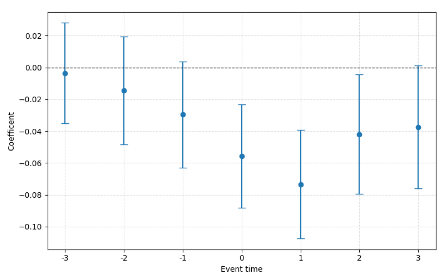


FE: id, years and province by year



Number of employees (ln)

FE: id and years



FE: id, years and province by year

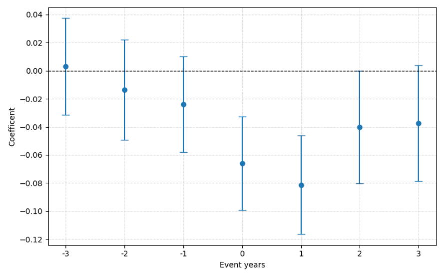


Table 2.3: Results of dynamic diff-in-diff
(De Chaisemartin and d'Haultfoeuille estimator)

	Revenue	Net income	Employees
Effect 1	-0.0428***	-0.0000408***	-0.0326***
	(0.0095)	(0.000015)	(0.0113)
Effect 2	-0.0500***	-0.0000833***	-0.0550***
	(0.0113)	(0.000029)	(0.0136)
Effect 3	-0.0487***	-0.0000528***	-0.0314
	(0.0160)	(0.000018)	(0.0198)
Average tot. effect	-0.0227***	-0.0000286***	-0.0208***
	(0.0047)	(0.000007)	(0.0060)
Placebos			
Placebo 1	-0.0038	-0.0000358**	0.0130
	(0.0101)	(0.000014)	(0.0116)
Placebo 2	0.0192	-0.0000356*	0.0220
	(0.0132)	(0.000021)	(0.0177)
Placebo 3	-0.0120	-0.0000451	0.0843**
	(0.0241)	(0.000035)	(0.0361)
Joint nullity test			
Effects Test	0.000006	0.000801	0.000355
Placebos Test	0.1955	0.0720	0.1127
Observations	352844	352825	240717

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The treatment variable is the number of neighbouring firms (within a 10-km radius, same macrosector) entering judicial administration each year.

2.8 Mechanisms and market definition

Provincial-level analysis

As a first step in understanding the operative channel, we replicate the identification strategy of Calamunci and Drago (2020) as closely as possible. Treatment is defined as proximity to a firm under judicial administration within the same province and 2-digit sector, regardless of physical distance, which corresponds to the broadest and least geographically precise definition of the local market. Control firms are all legal firms in the same provinces and sectors, with no distance restriction and no propensity score matching applied, in order to mirror the original sample construction as faithfully as possible. The estimation follows an OLS panel regression with firm and year fixed effects, augmented in the most saturated specification with sector-by-year interactions, consistent with Calamunci and Drago's approach.

The results, reported in Table 2.4, show no statistically significant effect on revenues, net income, or employment in any specification. Notably, the point estimate on revenues in the most saturated specification (Spec 2) is slightly positive (+0.45%), consistent in sign with the positive spillovers found by Calamunci and Drago (2020), though far from statistical significance. We interpret this finding as evidence that the provincial-level analysis captures a different mechanism from the one identified in our main specification. The judicial administration of a mafia firm in the same province may signal to external actors — banks, investors, public authorities — that the area is subject to active anti-mafia enforcement, potentially improving the perceived institutional quality of the province and generating a diffuse reputational benefit for legal firms operating there. This mechanism does not require physical proximity and is therefore consistent with a province-wide analysis. Our main results, by contrast, identify the market-level disruption of relational and productive networks that occurs in the immediate vicinity of the JA firm, a mechanism that is inherently spatial and attenuates with distance.

Table 2.4: Provincial-level analysis — OLS Estimates

	Sales Revenue (ln)	Net Income (ln)	Employees (ln)
Spec 1: Firm + Year FE			
JA treatment (binary)	-0.0162	-0.0000357	-0.0168
	(0.0115)	(0.0000201)	(0.0141)
Spec 2: + Sector × Year FE			
JA treatment (binary)	0.0045	-0.0000273	0.0021
	(0.0117)	(0.0000210)	(0.0144)
Spec 3: Continuous treatment			
N. firms in JA (count)	-0.0032	-0.0000046	-0.0029
	(0.0036)	(0.0000042)	(0.0043)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Obs. (Spec 1)	801,441	801,431	534,724
Obs. (Spec 2–3)	801,312	801,302	534,599

Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Alternative Geographic Market Definition: Local Labour Market Areas

As a second step, we test whether the negative spillover effect identified at 10 km is confirmed under an intermediate geographic definition of the local market. We use ISTAT's *Sistemi Locali del Lavoro* (SLL), commuting-zone-based aggregations constructed on the basis of observed commuting flows between municipalities. SLL areas are substantially smaller than provinces — and therefore economically more homogeneous — but larger than our baseline 10 km radius, representing a natural intermediate aggregation that balances geographic precision with sample size. Treatment is defined as the number of firms entering JA in the same SLL and macrosector each year, with PSM applied following the same procedure as the baseline.

The results, reported in Table 2.5, show negative and statistically significant effects on revenues (-1.82%, $p < 0.01$) and net income (-0.0000205, $p < 0.01$), with clean placebo tests for both outcomes. The effect on employment is also negative and significant (-2.25%, $p < 0.001$), though the joint placebo test for this outcome yields $p = 0.039$, which we note explicitly in the interest of transparency. These results confirm that the negative spillover identified in our main specification is not an artefact of the 10 km threshold and is detectable at the SLL level, which is meaningfully tighter than the provincial aggregation used by Calamunci and Drago (2020).

Table 2.5: Local Labour Market Definition — De Chaisemartin & D'Haultfœuille (2024)

	Sales Revenue (ln)	Net Income (ln)	Employees (ln)
Effect 1	-0.0341***	-0.0000123	-0.0340***
	(0.0106)	(0.0000153)	(0.0120)
Effect 2	-0.0389***	-0.0001085***	-0.0593***
	(0.0129)	(0.0000366)	(0.0158)
Effect 3	-0.0515***	-0.0000104	-0.0534**
	(0.0175)	(0.0000150)	(0.0222)
Average tot. effect	-0.0182***	-0.0000205***	-0.0225***
	(0.0049)	(0.0000073)	(0.0064)
Placebos			
Placebo 1	-0.0110	-0.0000072	0.0105
	(0.0117)	(0.0000112)	(0.0132)
Placebo 2	0.0250	0.0000025	0.0298
	(0.0177)	(0.0000208)	(0.0220)
Placebo 3	-0.0483	-0.0000719	0.2503***
	(0.0611)	(0.0000442)	(0.0891)
Joint nullity test			
Effects Test	0.003	0.027	0.002
Placebos Test	0.059	0.153	0.039
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Province×Year FE	YES	YES	YES
Observations	208,374	208,368	140,815

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

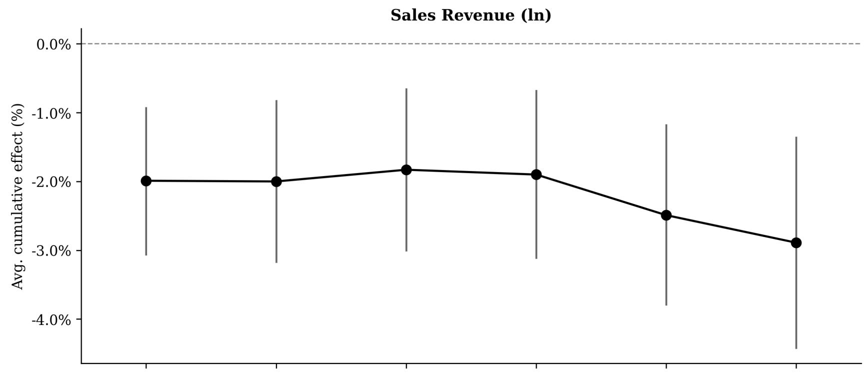
Spatial gradient

To further characterise the geographic scope of the spillover effect, we progressively restrict the treatment radius from 9 km down to 4 km and re-estimate the main model at each threshold. If the mechanism operates through the disruption of local relational and productive networks — whose territorial reach is inherently limited — we would expect the estimated effect to intensify as the radius shrinks and the sample of treated firms becomes increasingly concentrated around the JA event.

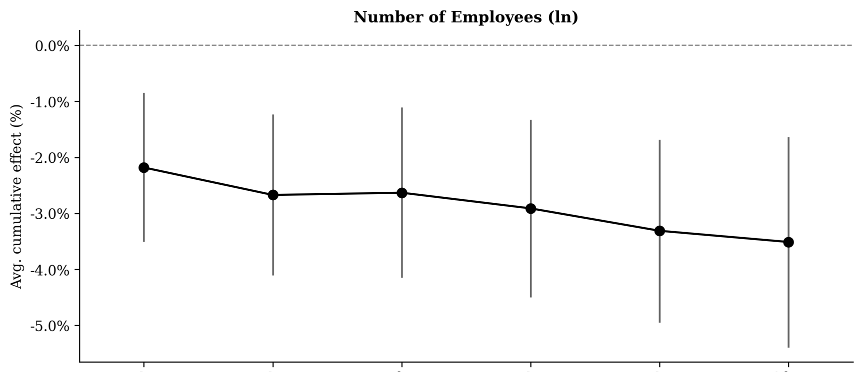
Figure 2.2 reports the average cumulative effect on revenues and employment at each distance threshold. For employment, the spatial gradient is monotonic and clear: the estimated effect grows in magnitude from $-2.18\%^{***}$ at 9 km to $-3.51\%^{***}$ at 4 km, with clean placebo tests throughout. This pattern is precisely what one would expect if the disruption of mafia-controlled networks attenuates with physical distance from the JA firm.

For revenues, the pattern is broadly consistent but exhibits some non-monotonicity at intermediate distances ($-1.83\%^{***}$ at 7 km, $-1.90\%^{***}$ at 6 km) that likely reflects sampling variability in the composition of treated firms across different radii, rather than a substantive deviation from the gradient. We note in the interest of transparency that the placebo test for revenues at 4 km yields $p = 0.048$, which is borderline significant; the remaining thresholds all produce clean placebos. The overall pattern nonetheless points in the same direction: the closer a firm is to a JA event, the more severely it is affected, consistent with the territorial and relational nature of mafia networks.

Figure 2.2: Spatial Gradient of JA Spillover Effects



	9 km	8 km	7 km	6 km	5 km	4 km
Av. cum. effect	-1.99%***	-2.00%***	-1.83%**	-1.90%**	-2.49%***	-2.89%***
Treated firms	4,091	3,805	3,230	3,001	2,722	2,475
p (effects)	0.003	0.006	0.015	0.013	0.001	0.002
p (placebos)	0.067	0.104	0.110	0.211	0.259	0.048



	9 km	8 km	7 km	6 km	5 km	4 km
Av. cum. effect	-2.18%***	-2.67%***	-2.63%***	-2.91%***	-3.31%***	-3.51%***
Treated firms	4,091	3,805	3,230	3,001	2,722	2,475
p (effects)	0.002	<0.001	0.001	<0.001	<0.001	0.001
p (placebos)	0.044	0.145	0.121	0.143	0.155	0.067

Average cumulative effect per treatment unit (De Chaisemartin and D'Haultfœuille, 2024). PSM applied. Standard errors clustered at the firm level.

Channels: costs, firm exit, and value added

We now turn to a direct investigation of the channels through which the JA spillover propagates. Table 2.6 reports estimates for three additional outcomes: value added, the current ratio (a measure of short-term liquidity), and a binary indicator of firm exit.

We begin with intermediate costs, which are not reported in Table 2.6 but are relevant for reconciling the revenue and net income results. The average cumulative effect on intermediate costs is -2.42%, negative in sign but statistically indistinguishable from zero. This finding suggests that the JA-induced shock affects both the revenue and the cost side of neighbouring firms, with the two effects partially offsetting each other. The resulting net income decline is therefore small in absolute magnitude — consistent with our estimates — but remains statistically significant, indicating that the cost reduction does not fully compensate for the revenue loss.

Turning to firm exit, the average cumulative effect is -0.001 and statistically indistinguishable from zero ($p = 0.329$), with clean placebo tests. This result rules out the hypothesis that the estimated performance decline is driven by the selective exit of more productive firms from the sample, which would introduce upward survivorship bias into the remaining panel. We note, however, that firm exit in AIDA-based panels is not straightforwardly observable: firms may disappear from the dataset either because they genuinely cease operations or because AIDA discontinues coverage for administrative reasons entirely unrelated to firm performance. Our exit indicator is defined conservatively as the first year in which revenues are zero for two consecutive years, excluding firms that disappear with missing revenues. This definition is likely to undercount true economic closures, and the null result should therefore be interpreted as evidence against large-scale exit rather than as conclusive evidence of no exit whatsoever.

The most informative outcome for the identification of the mechanism is value added. The average cumulative effect on value added is $-4.98\%^{***}$ ($p < 0.01$), with point estimates of -9.71%, -11.1%, and -10.0% in the three years following the JA event. Placebo tests are clean (joint nullity $p = 0.156$). Crucially, the decline in value added is substantially larger in magnitude than the corresponding decline in revenues (-2.24%), indicating that the disruption of mafia-controlled networks compresses productive margins rather than merely reducing demand. If the effect operated purely through a demand channel — fewer clients, lower orders — we would expect revenues and value added to decline by similar proportions. The fact that value added declines by more than twice as much as revenues indicates that the cost structure of neighbouring firms deteriorates relative to their output, consistent with the loss of informal productive services (access to input networks, subcontracting arrangements, informal market intermediation) that the mafia firm had been providing to firms in the same local market.

Table 2.6: Mechanisms

	Value Added (ln)	Liquidity Ratio	Firm Exit
Effect 1	-0.0971***	-0.0033	0.0024
	(0.0319)	(0.0058)	(0.0046)
Effect 2	-0.1110***	-0.0077	-0.0040
	(0.0319)	(0.0077)	(0.0041)
Effect 3	-0.1000***	-0.0178	-0.0057
	(0.0387)	(0.0106)	(0.0047)
Average tot. effect	-0.0498***	-0.0041	-0.0010
	(0.0131)	(0.0031)	(0.0017)
Placebos			
Placebo 1	-0.0090	0.0074	0.0036
	(0.0278)	(0.0063)	(0.0054)
Placebo 2	0.0608	0.0018	0.0166**
	(0.0383)	(0.0096)	(0.0068)
Placebo 3	0.0981	0.0022	-0.0009
	(0.0706)	(0.0203)	(0.0107)
Joint nullity test			
Effects Test	0.002	0.421	0.329
Placebos Test	0.156	0.644	0.105
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Province×Year FE	YES	YES	YES
Observations	365,483	339,420	365,483

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Sectoral gradient

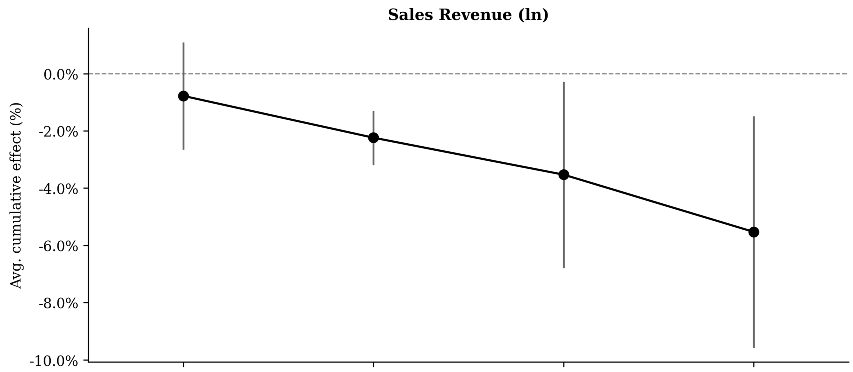
The final piece of mechanism evidence exploits variation in the sectoral definition of the local market to distinguish the mafia network channel from standard market channels such as competition, demand reallocation, or aggregate uncertainty shocks. The key observation is that the latter channels operate across product market boundaries — if a JA event generates uncertainty or demand contraction, all nearby firms should be affected regardless of their sector. The mafia network channel, by contrast, is inherently sector-specific: the relational and productive ties that mafia firms maintain (with suppliers, subcontractors, and local intermediaries) operate within the same industry, and their disruption should be concentrated among firms in the same product market.

To test this prediction, we estimate the main model under four alternative sectoral definitions of treatment, ranging from the broadest (all sectors, regardless of industry) to the most granular (3-digit sector classification). Figure 2.3 reports the average cumulative effect on revenues, employment, and value added under each definition.

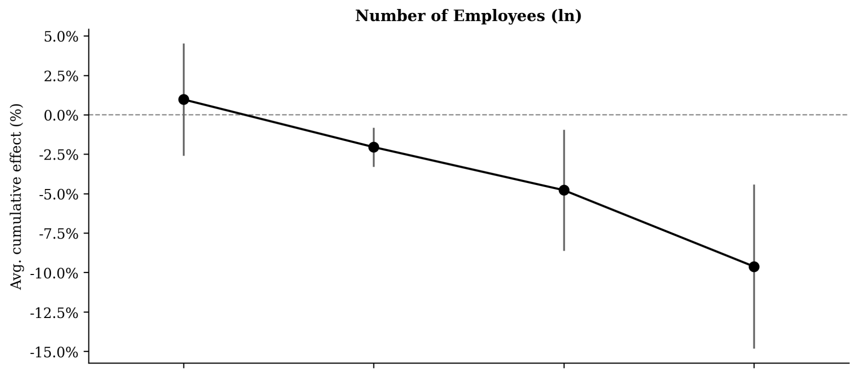
The results provide strong support for the mafia network interpretation. When treatment is defined using cross-sector proximity — including all neighbouring firms regardless of industry — the average cumulative effects on revenues, value added and employees are statistically indistinguishable from zero. This rules out standard market channels as the primary driver of the spillover. As the sectoral definition becomes more granular, the estimated effects grow monotonically in magnitude: for revenues, from $-2.24\%^{***}$ at the macrosector level, to $-3.53\%^{**}$ at 2-digit, to $-5.53\%^{**}$ at 3-digit. The same gradient is even more pronounced for employment and value added, with the value added effect reaching $-18.1\%^{**}$ at the 3-digit level.

This pattern is precisely consistent with what Arellano-Bover et al. (2024) describe as the competitive motive for OCG infiltration: mafia organisations leverage criminal expertise to benefit the infiltrated firm through sector-specific mechanisms — intimidation of rivals, privileged access to sector-specific inputs and subcontractors, informal market intermediation — that operate within well-defined product markets. When judicial administration severs these ties, the competitive advantages disappear, and the firms that had been operating in the same sector-specific relational network suffer the consequences. The sectoral gradient is thus not merely a robustness check but direct empirical evidence that the mechanism is sector-specific, as one would expect if it operates through the disruption of mafia-controlled relational networks rather than through generalised demand or uncertainty shocks.

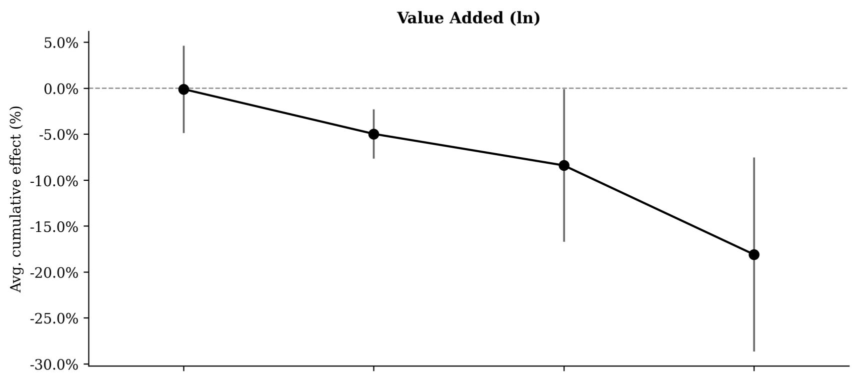
Figure 2.3: Sectoral Gradient of JA Spillover Effects



	All sectors	Macro-sector	2-digit	3-digit
Av. cum. effect	-0.78%	-2.24%***	-3.53%**	-5.53%***
Treated firms	8,979	4,280	3,010	1,864
p (effects)	0.407	<0.001	0.032	0.007
p (placebos)	0.007	0.193	0.051	0.043



	All sectors	Macro-sector	2-digit	3-digit
Av. cum. effect	0.97%	-2.05%***	-4.78%**	-9.62%***
Treated firms	8,979	4,280	3,010	1,864
p (effects)	0.588	0.001	0.013	<0.001
p (placebos)	0.687	0.119	0.623	0.608



	All sectors	Macro-sector	2-digit	3-digit
Av. cum. effect	-0.11%	-4.98%***	-8.41%**	-18.10%***
Treated firms	8,979	4,280	3,010	1,864
p (effects)	0.963	<0.001	0.044	0.001
p (placebos)	0.194	0.156	0.044	0.134

Notes: Average cumulative effect per treatment unit estimated using the De Chaisemartin and D'Haultfœuille estimator.

2.9 Robustness checks

To assess the reliability of the main estimates, we conduct a series of sensitivity analyses addressing alternative estimators, different assumptions on the clustering of standard errors, and potential concerns about sample composition. All tables referenced in this section are reported in Appendix B.

As a first robustness check, we re-estimate the event study using the Callaway and Sant'Anna (2021) estimator, which differs from Sun and Abraham (2021) in that it directly estimates average treatment effects for each group and time period (group-time ATT) using not-yet-treated units as the comparison group in addition to never-treated units. The results, reported in Figure A.8, are consistent with the main estimates in sign, magnitude, and significance, confirming that the findings are not sensitive to the choice of event-study estimator.

As a further verification, we apply the Clarke and Tapia Schythe (2021) approach, which allows for the estimation of event-study models under different configurations of fixed effects and facilitates the assessment of sensitivity to alternative choices of absorbed shocks. Three configurations are tested: (i) sector-by-year fixed effects, (ii) province-by-year fixed effects, and (iii) firm and year fixed effects. Across all configurations, the estimated coefficients remain stable in sign and magnitude (Table B12), confirming that the main results do not depend on a particular choice of fixed effects structure.

The baseline specification clusters standard errors at the firm level for the Sun and Abraham (2021) estimator. For the De Chaisemartin and D'Haultfœuille (2024) estimator, standard errors are computed analytically based on the variance of first differences between switchers and comparison units, as implemented in the `did_multiplegt_dyn` package. To assess the robustness of inference to alternative clustering assumptions, we re-estimate the Sun and Abraham (2021) models under two alternative clustering strategies.

The first alternative clusters at the level of the nearest JA firm, assigning each treated firm to the JA event that first triggered its treatment status and grouping control firms into a residual cluster. While it is not possible to assign a unique JA-firm cluster to all observations — control firms by construction have no JA firm within 50 km, and some treated firms fall within 10 km of multiple JA firms simultaneously — clustering by the nearest JA firm captures much of the within-treatment correlation and represents the closest feasible implementation of treatment-level clustering. The second alternative clusters at the municipality-by-sector level, which provides a theoretically grounded and symmetric criterion applicable to both treated and control firms. Firms in the same local product market are likely subject to correlated shocks regardless of treatment status, making this a natural unit for inference.

Table B13 reports the dynamic estimates under all three clustering strategies for revenues and employment. The coefficients are identical across specifications by construction, as clustering affects only standard errors. Pre-trend tests remain clean under all three strategies (joint χ^2 p-values ranging from 0.212 to 0.706), and the post-treatment effects remain negative and statistically significant. The main findings are therefore robust to alternative clustering assumptions.

Our preferred specification uses the full unbalanced panel, which exploits the complete time-series variation available in the data and is consistent with the design of the De Chaisemartin and D'Haultfœuille (2024) estimator for staggered adoption settings. As a complementary check, we also estimate the model on a balanced sub-sample of treated firms observed in all post-event periods from $t = 0$ to $t = 4$, which addresses the concern that the estimated performance decline might reflect the selective exit of more productive firms from the panel rather than a genuine treatment effect.

The results, reported in Table B15, confirm the main findings. The average cumulative effect on revenues is $-1.18\%^*$ (joint placebo $p = 0.050$) and on employment $-1.55\%^{**}$ (joint placebo $p = 0.067$). The somewhat smaller magnitude relative to the baseline specification is expected, as the balanced sample restriction reduces the number of usable treated firms. The direction and significance of the results are nonetheless preserved, providing further reassurance that the main findings are not an artefact of compositional change in the panel.

Finally, we estimate a standard two-way fixed effects model with a continuous treatment variable — the number of neighbouring JA firms per year — as a transparent benchmark for our preferred estimator (Table B14). The estimated coefficient is negative and statistically significant for revenues (-0.44%) and employment (-0.63%), consistent in sign and significance with the De Chaisemartin and D'Haultfœuille (2024) estimates. Net income is not significant in the TWFE specification ($p = 0.735$), a result attributable to the well-known limitations of TWFE under treatment effect heterogeneity: in staggered adoption settings, TWFE may assign negative weights to some treatment observations, attenuating the estimated average effect relative to more robust estimators. The confirmation of the revenue and employment results under TWFE nonetheless provides additional support for the main findings.

2.10 Final remarks and Policy implications

The analyses presented in this chapter examine the economic dynamics that unfold in what Sciarrone and Storti (2024) define as the gray areas of the legal economy, namely those segments of the market where mafiosi and entrepreneurs collaborate in mutually beneficial relationships, each deriving material advantages from the arrangement.

The extralegal power of mafia organisations is highly territorial in nature: control over the territory is a defining characteristic of criminal organisations entrenched in their traditional strongholds (Sciarrone, 2002b). Given this context, the present study investigates the economic impact of anti-mafia interventions on the local economy, focusing on the market segment most immediately adjacent to mafia-affiliated enterprises. The analysis examines the spillover effects triggered when a mafia-affiliated firm is placed under judicial administration, observing the consequences for neighbouring firms operating in the same macrosector within a 10-km radius.

The empirical results consistently indicate that the judicial administration of a mafia-affiliated firm generates negative spillover effects on nearby legal firms. Using the estimator of De Chaisemartin and D'Haultfœuille (2024), we find an average cumulative effect of -2.24% on sales revenues, -2.05% on employment, and a small but statistically significant decline in net income, per unit of treatment in the first three years following the JA event. These results are robust across alternative estimators, clustering strategies, geographic market definitions, and sample restrictions.

Beyond the reduced-form effects, the analysis provides strongly suggestive evidence on the operative mechanism. The disruption caused by judicial administration does not operate through standard market channels such as demand contraction or competitive reallocation — the estimated effect is statistically indistinguishable from zero when treatment is defined across all sectors regardless of industry, ruling out generalised demand or uncertainty shocks. Instead, the evidence points to the disruption of sector-specific relational networks: the negative effect on revenues grows monotonically as the sectoral definition becomes more granular, from $-2.24\%^{***}$ at the macrosector level to $-5.53\%^{**}$ at the 3-digit level, and the same gradient is confirmed for value added, which declines by $-4.98\%^{***}$ on average — more than twice the revenue effect — indicating that productive margins, rather than merely demand, are compressed. The spatial gradient reinforces this interpretation: effects on employment intensify monotonically as physical distance from the JA firm decreases, from $-2.18\%^{***}$ at 9 km to $-3.51\%^{***}$ at 4 km, consistent with the territorial and relational nature of mafia networks.

These findings are consistent with the framework proposed by Arellano-Bover et al. (2024), who distinguish between competitive, functional, and pure motives for OCG infiltration of legal firms. The competitive motive — whereby mafia organisations leverage criminal expertise to benefit the infiltrated firm through sector-specific advantages, including access to input networks, subcontracting arrangements, and informal market intermediation — is precisely the channel through which neighbouring legal firms may derive indirect benefits from the presence of a mafia firm in their market. When judicial administration severs these ties, the competitive advantages artificially generated by the OCG disappear, and firms that had, even inadvertently, benefited from the same relational network suffer the consequences.

The results also carry implications for the design of anti-mafia policy. The evidence suggests that the immediate vicinity of a judicially administered firm is characterised by a sudden vacuum of informal economic services that surrounding legal firms struggle to replace. This finding supports the argument, developed in the broader sociological literature (Sciarrone and Storti, 2024), that interventions targeting mafia-controlled firms must be accompanied by measures designed to sustain the economic vitality of the surrounding market. Policies that sever the criminal ties of an infiltrated enterprise without simultaneously providing legal substitutes for the informal functions that enterprise performed risk producing collateral damage on firms that had, even inadvertently, benefited from those functions. In this sense, judicial administration — though valuable as a preventive, non-destructive instrument — should be embedded in a broader strategy that combines regulatory intervention with targeted support for the formal institutional infrastructure of local markets: access to credit, market intermediation, and network formation among legal operators.

As the sociological literature has argued, and as the empirical evidence here suggests, the removal of mafia influence from a local economy is a necessary but not sufficient condition for the emergence of healthy market dynamics. The transition from a gray-area economy to a fully legal one requires a sustained, coordinated, and long-term policy effort — not simply the application of coercive instruments — capable of building the trust, institutions, and relational capital that legal markets require to function.

This study presents several complexities and identification challenges that suggest potential future extensions. The identification of mafia firms is based on legal proceedings, which may exclude firms linked to organised crime that have not yet been formally discovered, potentially contaminating the control group. Additionally, the administrative records available for this study record only the year in which a firm enters judicial administration, without information on the subsequent outcome of the procedure — whether the measure was extended, revoked, replaced by judicial control, or led to permanent confiscation. Constructing such a dataset from systematically disclosed administrative acts would allow future research to examine heterogeneous effects by post-JA trajectory, providing a more granular understanding of how different institutional responses to mafia infiltration shape the subsequent evolution of the surrounding local economy.

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APPENDIX B

Figure A.4: Geographic distribution of firms in JA

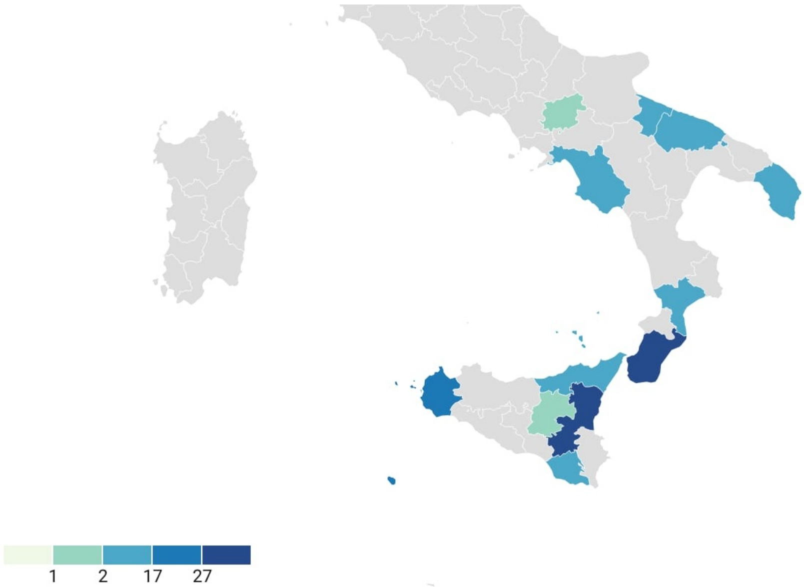


Table B7: Macrosectors of enterprises in JA

Sector	Freq.	%	Sector	Freq.	%
Manufacturing	24	5.45%	Transport	46	10.45%
Energy	2	0.45%	Accommodation	23	5.23%
Water & Waste	12	2.73%	Finance	2	0.45%
Construction	148	33.64%	Real Estate	33	7.50%
Wholesale & Retail	119	27.05%	Public Services	7	1.59%
Healthcare	11	2.50%	Arts	13	2.95%
				Total	**440**

The geographical and sectoral distribution confirms the findings of Transcrime (2013) and Parbonetti (2021), showing a higher concentration of mafia firms in low-tech sectors and in provinces where mafia infiltration is more entrenched.

Table B8: Distribution of Treated Firms by Year

Year	**Neighbouring firms treated (10 km, same macrosector)**
2006	3
2007	16
2008	10
2009	0
2010	12
2011	87
2012	62
2013	298
2014	222
2015	55
2016	1,657
2017	210
2018	154
2019	43
2020	44
2021	1,383
2022	10
2023	14
Total	**4,280**

Neighbouring firms treated counts the number of legal firms experiencing their first exposure to a JA event within a 10-km radius and in the same macrosector in each year. Each firm is counted only once, in the year of first exposure.

Table B9: Descriptive statistics

	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**
Panel A: Treated firms					
Revenues (€K)	21,656	1,302	8,678	0	475,764
Value added (€K)	21,656	228	699	0	30,854
Employees (N)	21,656	5.1	12.5	0	530
Net income (€K)	21,656	25.3	349	0	15,098
Interm. costs (€K)	21,656	1,074	8,470	0	472,786
Exit probability	19,471	0.124	0.330	0	1
Panel B: Control firms					
Revenues (€K)	422,518	1,985	14,983	0	2,605,703
Value added (€K)	422,518	411	2,987	0	358,812
Employees (N)	422,518	8.4	45.9	0	6,244
Net income (€K)	422,490	55.1	1,045	0	114,084
Interm. costs (€K)	422,518	1,574	13,554	0	2,589,252
Exit probability	370,502	0.099	0.299	0	1

Revenues, value added, net income, and intermediate costs are expressed in thousands of euros. Employment is number of employees. Exit probability is defined as the share of firm-year observations with zero or negative revenues for two consecutive years. Negative values of revenues, value added, employment, net income, and intermediate costs, which arise from accounting adjustments and are economically implausible, are set to zero before computing summary statistics. Statistics computed on the PSM-matched sample.

Table B10: Unconditional means by treatment status and event time

	Revenues (€K)	Value added (€K)	Employment (N)	Net income (€K)	Interm. costs (€K)	Exit prob.
Treated firms by event time						
$t = -3$	1,140	186	4.5	15.99	954	0.057
$t = -2$	1,250	193	4.8	15.83	1,057	0.044
$t = -1$	1,218	202	5.0	25.90	1,016	0.017
$t = 0$	1,281	221	4.9	30.80	1,060	0.017
$t = +1$	1,404	238	5.2	24.31	1,165	0.016
$t = +2$	1,227	263	5.4	38.00	965	0.011
$t = +3$	1,225	255	6.0	18.41	971	0.022
Full sample means						
Treated firms	1,302	228	5.1	25.3	1,074	0.124
Control firms	1,985	411	8.4	55.17	1,574	0.099

Mean outcomes for treated firms in each period relative to the JA event ($t = 0$). Control firms have no natural event time and are reported as full-panel averages.

Figure A.5: Dynamic diff-in-diff estimates on sales revenue (ln)

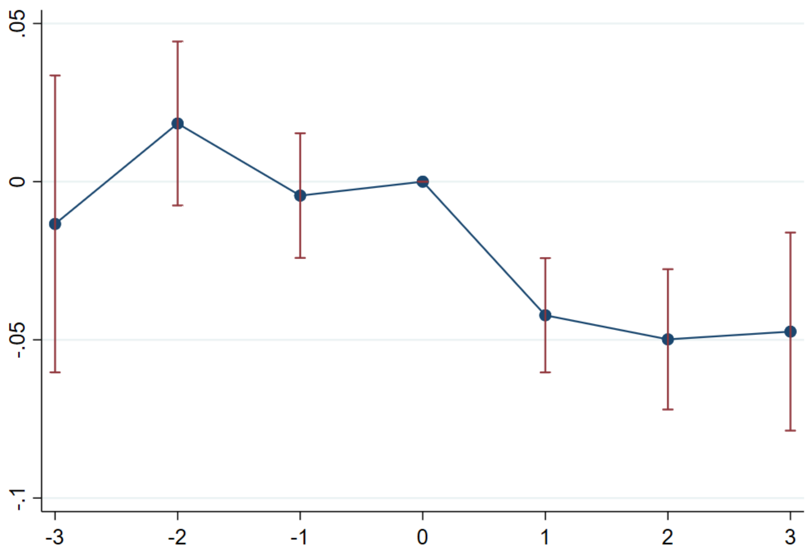


Figure A.6: Dynamic diff-in-diff estimates on net income (ln)

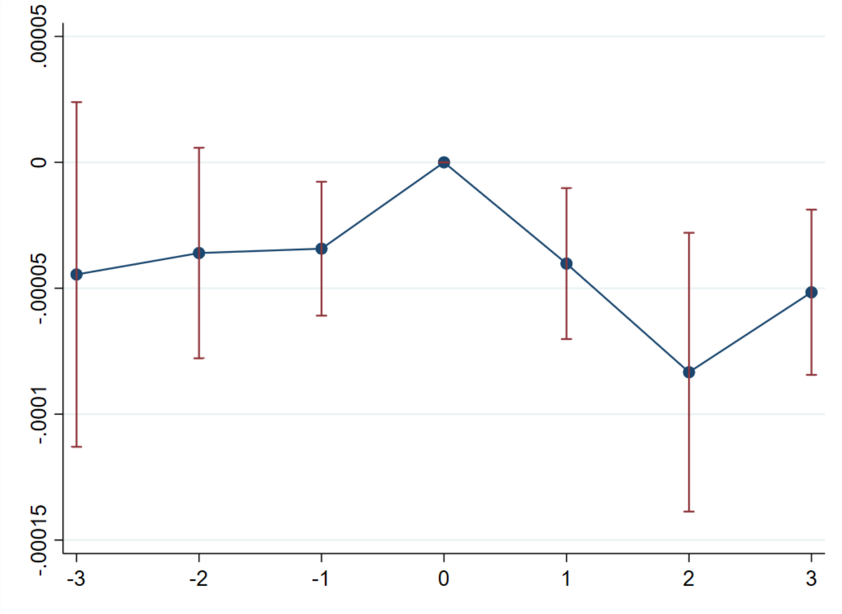


Figure A.7: Dynamic diff-in-diff estimates on employees (ln)

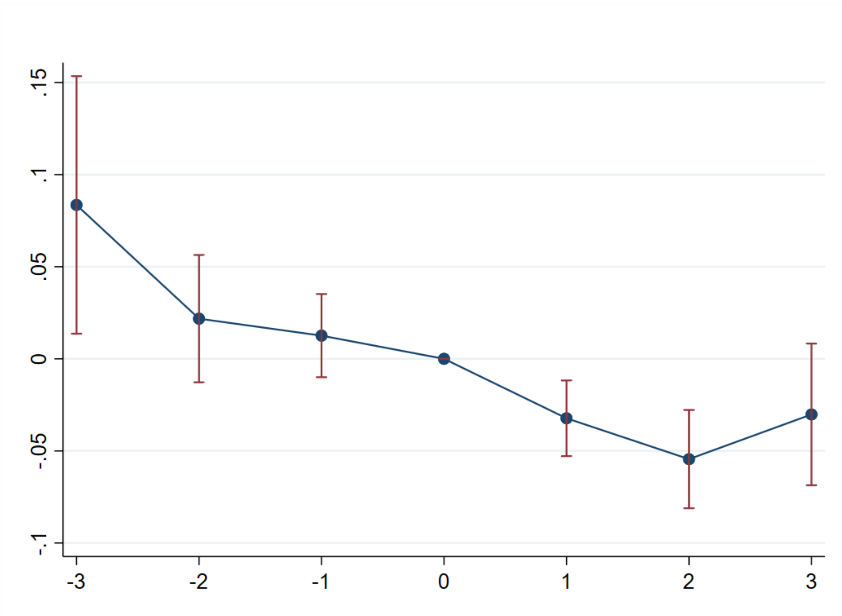
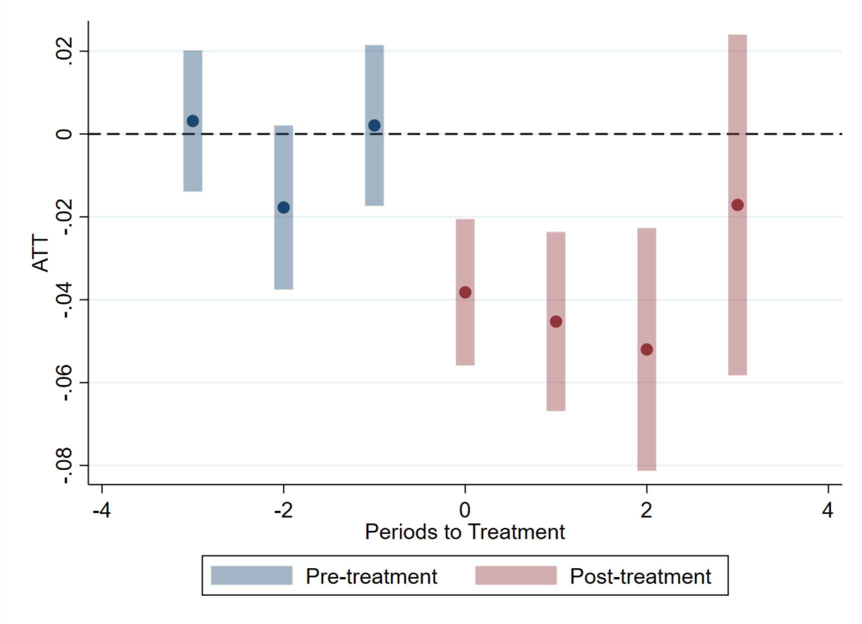
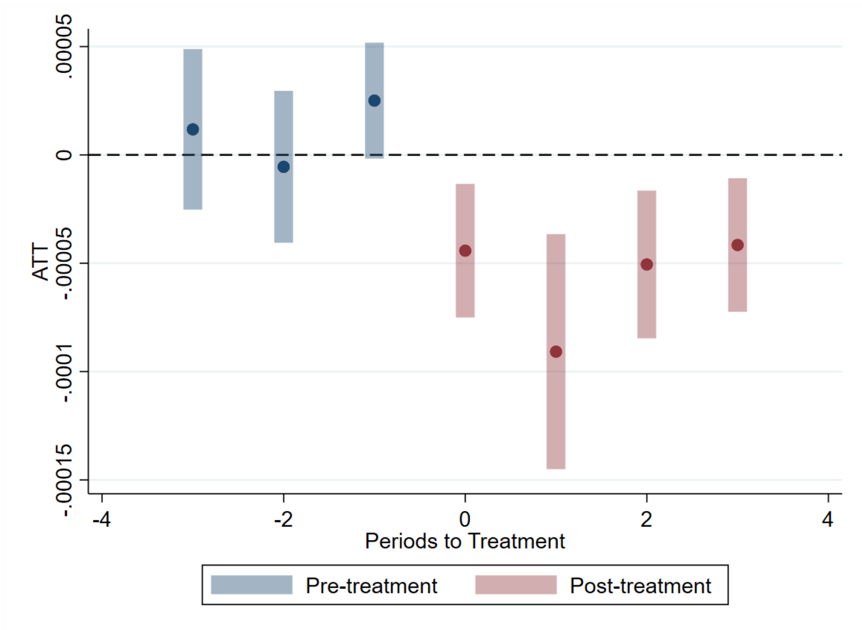


Figure A.8: Judicial Administration Spillover Effects: Event Study Plots (Callaway & Sant'Anna)

Sales revenue (ln)



Net income (ln)



Number of employees (ln)

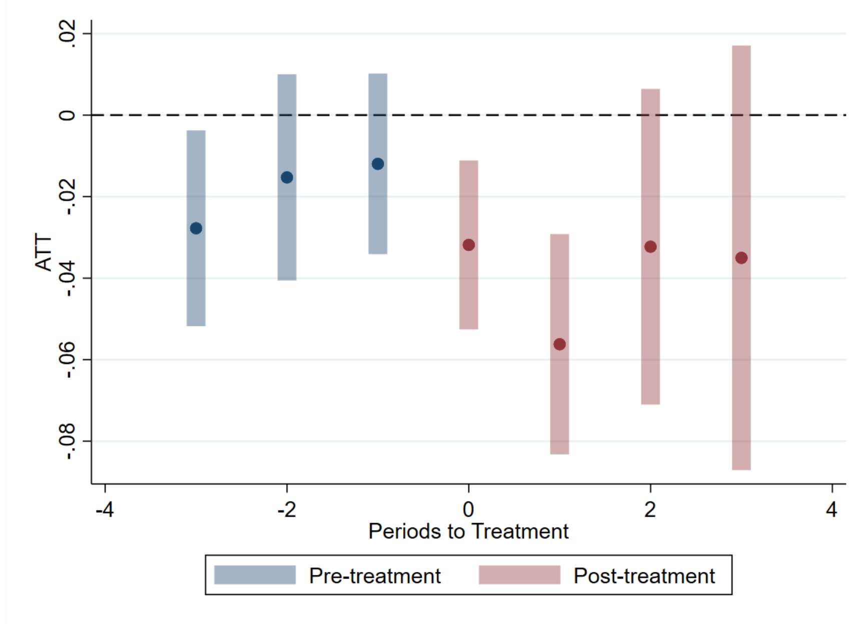


Table B11: Event Study estimates (Callaway & Sant'Anna)

	Sales revenue (ln)	Net income (ln)	Employment (ln)
Pre_avg	-0.0042 (0.0050)	0.0000 (0.0000)	-0.0183** (0.0065)
Post_avg	-0.0381*** (0.0113)	-0.0001*** (0.0000)	-0.0388** (0.0146)
$JA-3$	0.0031 (0.0087)	0.0000 (0.0000)	-0.0278** (0.0123)
$JA-2$	-0.0177 (0.0101)	0.0000 (0.0000)	-0.0153 (0.0129)
$JA-1$	0.0021 (0.0099)	0.0000* (0.0000)	-0.0120 (0.0113)
JA	-0.0382*** (0.0090)	-0.0000** (0.0000)	-0.0318** (0.0106)
$JA+1$	-0.0453*** (0.0110)	-0.0001*** (0.0000)	-0.0562*** (0.0138)
$JA+2$	-0.0520*** (0.0149)	-0.0001** (0.0000)	-0.0323 (0.0198)
$JA+3$	-0.0171 (0.0210)	-0.0000** (0.0000)	-0.0350 (0.0266)

Notes: Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B12: Event Study Results (Clarke and Tapia Schythe estimator)

	Sales Revenue (ln)			Employees (ln)			Net Income		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
lag3	-0.01962	-0.01308	-0.04397**	-0.02587	-0.02900	-0.04273*	-0.0000583**	-11.67469	-0.380161
	(0.01737)	(0.01935)	(0.01793)	(0.02253)	(0.02492)	(0.02352)	(0.0000251)	(9.12819)	(7.42314)
lag2	-0.04569***	-0.03685**	-0.00437	-0.03516*	-0.03549*	-0.00240	-0.0000575***	-9.38628	-5.34997
	(0.01482)	(0.01613)	(0.01541)	(0.01815)	(0.02008)	(0.01888)	(0.0000177)	(9.90677)	(5.52067)
lag1	-0.04318***	-0.04828***	0.00282	-0.04827***	-0.06049***	-0.02389	-0.0000792***	-36.33964***	-24.70475**
	(0.01137)	(0.01247)	(0.01171)	(0.01417)	(0.01599)	(0.01470)	(0.0000270)	(12.21113)	(12.13252)
lag0	-0.03965***	-0.04607***	-0.01325	-0.02582**	-0.04132***	-0.00553	-0.0000363**	-20.50693*	-15.06783*
	(0.00942)	(0.01026)	(0.00991)	(0.01122)	(0.01299)	(0.01179)	(0.0000153)	(9.77851)	(7.02592)
lead3	0.01848	0.01315	0.03759***	0.06145***	0.05747***	0.05872***	-0.0000115	-17.67469	-0.380161
	(0.01364)	(0.01548)	(0.01382)	(0.01780)	(0.02067)	(0.01832)	(0.0000171)	(9.12819)	(7.42314)
lead2	-0.00334	-0.00109	0.01853*	0.01819	0.01953	0.01656	-0.0000297**	-9.38628	-5.34997
	(0.01008)	(0.01069)	(0.01044)	(0.01175)	(0.01313)	(0.01221)	(0.0000134)	(9.90677)	(5.52067)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector-by-year	NO	NO	YES	NO	NO	YES	NO	NO	YES
Province-by-year	NO	YES	NO	NO	YES	NO	NO	YES	NO
Observations	428,845	428,843	427,318	298,844	298,839	297,413	428,818	428,817	427,292
R-squared	0.9055	0.9056	0.9107	0.8743	0.8747	0.8792	0.4115	0.2445	0.2756

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B13: Alternative Clustering — Sun & Abraham (2021) Estimates

	Cluster: Firm ID (baseline) ($N_{\text{cl}} = 47{,}535$)		**Cluster: Nearest JA firm** ($N_{\text{cl}} = 76$)		**Cluster: Municipality × Sector** ($N_{\text{cl}} = 19{,}650$)	
	Sales Revenue (ln)	Employees (ln)	Sales Revenue (ln)	Employees (ln)	Sales Revenue (ln)	Employees (ln)
$t = 0$	-0.0391***	-0.0549***	-0.0391***	-0.0549***	-0.0391**	-0.0549***
	(0.0134)	(0.0166)	(0.0146)	(0.0135)	(0.0156)	(0.0167)
$t = 1$	-0.0447***	-0.0741***	-0.0447***	-0.0741***	-0.0447***	-0.0741***
	(0.0136)	(0.0174)	(0.0165)	(0.0231)	(0.0171)	(0.0182)
$t = 2$	-0.0426***	-0.0419**	-0.0426***	-0.0419	-0.0426***	-0.0419**
	(0.0144)	(0.0193)	(0.0149)	(0.0254)	(0.0145)	(0.0209)
$t = 3$	-0.0204	-0.0407**	-0.0204*	-0.0407*	-0.0204	-0.0407**
	(0.0160)	(0.0199)	(0.0122)	(0.0232)	(0.0153)	(0.0200)
Pre-trend p-value	0.212	0.689	0.316	0.391	0.408	0.706
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	443,798	308,340	443,798	308,340	443,798	308,340

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B14: Two-Way Fixed Effects Estimates — Continuous Treatment

	Sales Revenue (ln)	Net Income (ln)	Employees (ln)
	-0.44**	-0.00009	-0.63***
	(0.17)	(0.00027)	(0.0020)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Province×Year FE	YES	YES	YES
Observations	443,796	443,767	308,335

Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B15: Balanced Sample — De Chaisemartin & D'Haultfœuille (2024)

	Sales Revenue (ln)	Net Income (ln)	Employees (ln)
Effect 1	-0.0352**	0.0000098	-0.0311
	(0.0163)	(0.0000193)	(0.0185)
Effect 2	-0.0122	-0.0000800*	-0.0430**
	(0.0173)	(0.0000457)	(0.0215)
Effect 3	-0.0453**	-0.0000073	-0.0411*
	(0.0200)	(0.0000184)	(0.0240)
Average tot. eff.	-0.0118**	-0.0000098	-0.0155**
	(0.0057)	(0.0000073)	(0.0075)
Placebos			
Placebo 1	0.0078	-0.0000106	0.0228
	(0.0181)	(0.0000141)	(0.0206)
Placebo 2	0.0676**	0.0000161	0.0376
	(0.0283)	(0.0000303)	(0.0399)
Placebo 3	-0.0179	-0.0000786	0.2117***
	(0.0587)	(0.0000490)	(0.0826)
Effects Test	0.036	0.269	0.221
Placebos Test	0.051	0.069	0.067
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Province×Year FE	YES	YES	YES
Observations	270,388	270,369	180,458

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

RENT LEVELS AND CRIME: EMPIRICAL EVIDENCE FROM EU-SILC IN ITALY

3.1 Introduction

The analyses presented in the first two chapters have shown that organized crime affects the formal economy, influencing both territorial innovative capacity and the stability of local markets. In particular, the presence of hierarchical and entrenched organizations produces heterogeneous effects on the productive and institutional fabric, generating economic opportunities as well as systemic vulnerabilities - especially in areas where such organizations are an integral part of the local economy (Pinotti, 2015; Gambetta, 1992).

Extending this reflection beyond the strictly economic dimension, the exploratory analysis of the territorial data reveals that, in areas historically affected by mafia infiltration, the correlation between different crime categories is higher (see correlation plot, Figure 1.2). This finding suggests that mafia presence is associated with a greater co-occurrence of distinct criminal phenomena, not only crimes typically linked to the mafia (e.g. extortion, usury), but also forms of common crime such as homicide and prostitution, indicating a possible normalization of criminal behaviour in highly penetrated contexts (Calderoni, 2011; Battisti et al., 2019). In other words, mafia settlement tends to embed itself in milieus where criminal conduct is socially normalized, thus nurturing an ecosystem of diffuse illegality (Calamunci et al., 2022).

This interplay between economic context, criminal presence and social behaviour is corroborated by the urban and criminological literature. Several studies have documented that poverty, physical decay and social fragmentation foster the establishment of criminal activities, while, conversely, higher crime levels depress property values and exacerbate residential segregation processes (Monthly et al., 2015; Sampson et al., 1997; Aliprantis and Hartley, 2015). A cumulative cycle thus emerges: socioeconomic deterioration breeds crime; crime increases insecurity; and insecurity, in turn, affects residential choices and housing prices.

In light of these interactions, this chapter shifts the focus from the dynamics of organized crime to the perceptual dimension of diffuse criminality. In this framework, perceptions of crime play a central role: often it is perceived insecurity - rather than only measured crime incidence - that drives demand shifts and discounts in property values. Official crime statistics are often affected by underreporting and variability over time and space, while residents' perceptions provide a measure that is closer to the reality experienced in that particular neighborhood (Buonanno et al., 2013).

Using EU-SILC microdata for the period 2004–2023, I analyse the relationship between rental levels and households' perception of insecurity. The aim is to assess the extent to which housing costs reflect - or contribute to shaping - a geography of urban fear in which housing markets and perceived safety mutually equilibrate via economic and social channels.
From an empirical standpoint, the analysis is structured into two complementary modeling frameworks designed to disentangle the bidirectional relationship between housing costs and insecurity, while addressing endogeneity and sample selection bias. First, the study investigates the determinants of perceived crime. To estimate the causal effect of rental levels on safety perception, an Instrumental Variables model (Two-Stage Least Squares, 2SLS) is employed to correct for simultaneity. Crucially, this specification augments the standard IV approach by integrating a Heckman correction: the Inverse Mills Ratio (IMR), derived from a preliminary probit model of tenure choice, is included as a regressor to control for the non-random selection of tenant households. Second, the analysis reverses the perspective to model the determinants of rental prices. Here, a Heckman Maximum Likelihood selection model is implemented to test whether perceived crime is capitalized into housing costs

(hedonic pricing).

The chapter is structured as follows: after a review of the relevant literature, the chapter describes the data (pooled cross-sections from EU-SILC) and sets out the econometric methods in detail. The subsequent sections present the estimation results and conclude with a discussion of the main findings and their interpretative implications.

3.2 Crime, Rents and Urban Decline: A Circular Model

The economic literature on the impact of crime on housing markets consistently indicates that elevated levels of crime - whether actual or perceived - tend to depress house prices and rents. For instance, Gibbons (2004) finds sizeable negative effects of crime on housing valuations in the Greater London area. Similarly, Ceccato and Wilhelmsson (2011), analyzing roughly 9,000 apartment transactions in Stockholm with a hedonic pricing model, report that nearby crime strongly affects sales prices across crime types and that these effects are particularly pronounced for housing values in peripheral areas.

Buonanno et al. (2013), using hedonic techniques (OLS and quantile regressions) on Barcelona data, estimate that a one-standard-deviation increase in perceived safety is associated with a roughly 0.57% increase in district valuation.

Several contributions exploit exogenous shocks or hedonic approaches to demonstrate risk capitalization: for example, Linden and Rockoff (2008), using a quasi-experimental design that leverages regulatory and placement variation for registered sex offenders, document localized and statistically significant declines in property values following notification/registration events.

These findings provide theoretical justification for using prices or rents as summary indicators of neighbourhood quality: in spatial equilibrium, deficits in safety and public goods are capitalized into prices, with consequent effects on demand and on the socio-economic composition of residents (Roback, 1982; Gibbons, 2004).

The relationship is, however, not unidirectional. A substantial body of work posits and documents that low property values or low rents can, in turn, foster conditions conducive to higher crime. The main mechanisms are multiple. (I) physical decay and poor maintenance typical of low-value areas reduce environmental barriers to crime (the "broken windows" hypothesis), thereby initiating a vicious cycle of incivility and offending (Monthly et al., 2015); (II) low levels of social cohesion and weak social capital - frequent in deprived neighbourhoods - undermine informal social control (collective efficacy) and thus increase the likelihood of deviant behaviour (Sampson, et al., 1997); (III) socioeconomic sorting implies that low prices attract or retain households with fewer legitimate economic opportunities, raising the relative prevalence of illicit activity (Sampson and Wilson, 2013; Buonanno, 2003; Wilson, 2022); (IV) the depreciation of property values diminishes incentives for both private and public investment in services and rehabilitation, further degrading the provision of local public goods and the security environment (Fischel, 2002; Glaeser and Gyourko, 2005); (V) low prices operate as signals: they stigmatize places, discouraging investment and facilitating the emergence of local illicit economies (Sampson et al., 1997; Monthly et al., 2015).

More generally, the literature has shown that the relationship between crime and property prices is typically circular: on the one hand, crime (whether actual or perceived) is capitalized into prices, meaning that the presence of, or fear of, crime reduces housing demand for an area; on the other hand, lower prices or rents shape the neighbourhood's socio-economic composition and the physical and institutional conditions that can facilitate illicit activity. Empirical literature has documented each causal direction depending on the identification strategy employed.

Regarding the impact of housing market dynamics on crime, Palmer et al. (2017) exploit the exogenous shock provided by the 1995 rent control removal in Cambridge, Massachusetts, to isolate the amenity value of public safety. By implementing a difference-in-differences design on detailed incident-level data (1992–2005), the authors find that the gentrification process triggered by deregulation led to a roughly 16% decline in overall crime (approximately 1,200 fewer annual incidents). Crucially, regarding the capitalization of safety into market prices, they estimate that this reduction in criminal activity generated a direct economic benefit that explains approximately 15% of the total property value appreciation attributable to the end of rent control. This finding provides robust evidence that lower crime rates translate directly into higher willingness to pay and housing valuations. Aliprantis and Hartley (2015) examine the effects of large-scale public-housing demolitions on crime indicators and, using time-series and spatial comparisons, report significant reductions in some offences after the removal of high-disadvantage housing concentrations - results that suggest changes in housing supply and neighbourhood composition can affect crime dynamics. Collectively, these studies motivate the adoption of tailored empirical strategies to address the endogeneity that links rents/prices and criminality. Complementing Aliprantis and Hartley (2015), Sandler (2017) investigates negative externalities from public housing by comparing block-level crime rates before and after public-housing demolitions in Chicago (1995–2010). Merging incident-level crime data with detailed geographic demolition records, he implements a difference-in-differences design and an event-study and finds an 8.8% decline in crime following demolitions - concentrated in violent crime, occurring around the eviction date and persisting for at least five years - with the largest reductions observed for large demolitions and poorly maintained projects.

In the Italian context, the entrenched presence of organized crime groups capable of systematically infiltrating productive markets - including the real estate sector (Transcrime, 2013; Parbonetti, 2021) - adds an additional layer of complexity to the study of the crime-rent nexus. Calamunci et al. (2022), for instance, analyze a sample of about 7,000 Italian municipalities from 2002 to 2019 and, using a difference-in-differences approach, find that anti-mafia interventions involving the confiscation and reassignment of firms previously controlled by criminal organizations generate positive spillover effects on commercial property values, increasing prices by roughly 4% on average. The appreciation is strongest in small and medium-sized municipalities located in provinces with a pronounced mafia presence. These dynamics reinforce the idea that, where organized crime is deeply entrenched, the rent–crime relationship operates through intertwined economic, institutional, and social channels that complicate empirical identification.

3.2.1 Hypotheses

Building on the preceding theoretical and empirical review, the following research hypotheses are formulated and tested using pooled cross-sections of EU-SILC microdata on Italian households for the period 2004–2023 (IT-SILC).

- **H1: Neighborhood quality effect: Perceived Crime** = f(**Rent**)
  It is further hypothesized that perceived crime acts as a function of rental levels, acknowledging that rents serve as proxies for neighborhood quality. Lower rents are expected to capture physical decay, limited service provision, and weak social cohesion (1979; 1982; 2005). Consequently, a negative relationship is expected even after addressing the endogeneity inherent in the rent-crime nexus, indicating that low-value housing areas function as attractors of criminal activity or social disadvantage.

- **H2: Capitalization effect: Rent** = f(**Perceived Crime**)
  It is hypothesized that households' perceived insecurity is capitalized into rental levels. Specifically, a negative relationship is expected, whereby higher levels of perceived insecurity reduce households' willingness to pay and, consequently, the market value of rents.

For both hypotheses, the estimated effects are expected to remain stable and robust when controlling for extended socio-economic and spatial factors and under alternative model specifications.

3.3 Data

The data used derive from the cross-sectional waves of the EU-SILC survey for Italy. The analysis is based on a pooled cross-section dataset, motivated by the fact that the dummy variable HS190 (perception of crime, violence or vandalism in the area of residence) is available only in the cross-section files.

Because HS190 was not collected in the 2021–2022 waves but is again available in 2023, estimations were first conducted on the 2004–2020 sample and subsequently replicated including 2023. The analysis is restricted to renting households: tenants are identified using tenure information (HH0212) and the question on rent payment (HH060), which also records the rent amount. After applying the selection criteria, the pooled sample comprises 60,721 renting households.

Table 3.1: Descriptive statistics of main variables (EU-SILC 2004–2023, tenants only)

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Core variables					
Perceived crime (dummy)	60,721	0.156	0.363	0	1
Monthly rent (€)	60,721	376.76	207.21	11	4,500
Household disposable income (€)	60,721	23,823.35	17,736.69	3	697,203
Number of workers	60,721	0.588	0.751	0	5
Any chronic diseases (dummy)	60,721	0.287	0.452	0	1
Household characteristics					
Mean head age (years)	60,721	51.78	15.80	18	81
Seniority (years)	56,179	13.15	13.20	0	96
Family size	60,721	2.27	1.32	1	11
Rooms per member	60,721	1.57	0.91	0.13	6
Housing discomfort index	60,721	0.050	1.523	0	33.712
Dwelling and area characteristics					
Car ownership (dummy)	60,721	0.729	0.445	0	1
Dense urban area (dummy)	60,721	0.471	0.499	0	1
Rural/deserted area (dummy)	60,721	0.161	0.368	0	1
Detached house (dummy)	60,721	0.080	0.272	0	1
Apartment in small building (dummy)	60,721	0.398	0.490	0	1
Apartment in large building (dummy)	60,721	0.376	0.484	0	1
High market price area (dummy)	60,721	0.506	0.500	0	1
Poverty (dummy)	60,721	0.257	0.437	0	1

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Table 3.1 Descriptive statistics of main variables (EU-SILC 2004–2023)

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Material deprivation index	60,721	0.536	1.143	0	6.580
Noise from neighbours (dummy)	60,721	0.233	0.423	0	1
Polluted area (dummy)	60,721	0.186	0.389	0	1

Note: All statistics refer to tenant households from the pooled IT-SILC cross-sections (2004–2020 and 2023). Rent and income are expressed in euros. Dummy variables take value 1 if condition holds, 0 otherwise.

3.4 Empirical Strategy

We investigate the link between households' perceived crime in their area and contemporaneous rental levels by exploiting repeated cross-section waves of IT-SILC for tenant households.

The estimated equations are:

$$\text{crime}_{i,t} = \beta_0 + \beta_1\,\widehat{\text{rent}}_{i,t} + \beta_2\mathbf{X}_{i,t}^{\top} + \theta\lambda_{i,t} + \delta_{\text{year}_t} + \delta_{\text{area}_i} + u_{i,t} \tag{3.1}$$

$$\text{rent}_{i,t} = \pi_0 + \pi_1\,\text{market\_price}_{i,t} + \pi_2\,\text{rooms}_{i,t} + \pi_3\,\text{housing\_discomfort}_{i,t} + u_{i,t} \tag{3.2}$$

Where the structural equation (Second Stage IV (3.1)) is given by:

$crime_{i,t}$ is the dependent variable, a dummy variable that indicates with 1 the households that perceive crime, violence, and vandalism in the area where they live.

β_0 is the intercept term.

$\beta_1\,\widehat{rent}_{i,t}$ is the instrumented effect of rent: β_1 is the coefficient on the predicted (instrumented) component of rent. It measures the average change in perceived crime associated with a one-unit increase in the exogenous component of rent.

$\boldsymbol{\beta_2}\mathbf{X}_{i,t}^{\top}$ is the vector of controls: $\mathbf{X}_{i,t}$ is the column vector of observed covariates and $\boldsymbol{\beta_2}$ is the corresponding coefficient vector. Each element of $\boldsymbol{\beta_2}$ reports the partial effect of the associated covariate on $\text{crime}_{i,t}$, holding other controls constant.

$\lambda_{i,t}$ is the Inverse Mills Ratio (IMR), derived from the first-stage probit estimation of the tenure choice (selection equation). It is included to control for potential sample selection bias arising from the fact that rents are observed only for tenants (Heckman, 1979).

θ is the coefficient associated with the Inverse Mills Ratio. A statistically significant estimate of θ would indicate the presence of selection bias; its inclusion corrects the estimates of the primary coefficients of interest (β_1) for this bias.

$\delta_{\mathbf{year}_t}$ are year fixed effects, which absorb common shocks affecting all households in a given year.

$\delta_{\mathbf{area}_i}$ are area fixed effects (NUTS1), which absorb time-invariant differences in crime perception and housing costs across macro-regions. It should be noted that the inclusion of area fixed effects absorbs all cross-sectional variation at the NUTS1 level; identification therefore relies on within-area, within-year variation in the instruments. A potential concern is whether region-specific time trends — that is, differential trajectories of rents and crime perceptions across macro-regions over the sample period — may confound the estimates. This limitation is acknowledged: the preferred specifications control for year and area effects jointly, but do not include region-by-year interactions, which would absorb any residual trend variation at the cost of substantially reducing the identifying variation. The stability of the core coefficient across specifications with different fixed-effects configurations (columns 1–6 of Table 3.2) provides some reassurance that the results are not driven by differential regional trends.

$u_{i,t}$ is the idiosyncratic error term for observation i in year t.

The objective is to estimate the association between perceived crime and a set of household characteristics and contextual variables related to areas of residence ($\mathbf{X}_{i,t}^{\top}$).
The set of covariates includes demographic and socioeconomic information that has been reconstructed at the family level by manipulating individual data, such as: *Mean head age*, the average age of the couple (or of the respondent in the case of single-person households); *Number of workers*, the number of household members engaged in employment; and *Chronic diseases*, an indicator for the presence of at least one household member with a severe disability. The variable *seniority*, included among the covariates capturing personal information ($P_{i,t}$), is computed as the difference between the observation year (t) and the year in which the rental contract started (HH031). Since this variable is available in the EU-SILC data only up to 2020, it was excluded from the models covering the 2023 wave.
Variables capturing residential density are also included: *Cities*, for highly populated areas, and *Rural areas*, for sparsely populated areas (reference category: medium-density areas). Housing type is represented by dummy variables such as *Detached*, *Apartment in a building*, and *Apartment in a big building*. Contextual conditions include *Polluted area*, an indicator for residence in a polluted area, and *Noise neighbours*, which signals the presence of noisy neighbours. Finally, the variable *Poverty* (HX090) identifies households at risk of poverty, defined as those whose equivalised disposable income falls below 60% of the national median income. An additional measure of poverty employed in the analysis, as an alternative to the variable *poverty*, is *Material deprivation*, an index proportional to the level of material deprivation experienced by households. The index was constructed using Multiple Correspondence Analysis (MCA). Specifically, starting from survey variables related to the availability of goods and the quality of domestic living conditions - ability to afford a one-week annual holiday (HS040); ability to afford a meal with meat, fish, or a vegetarian equivalent every other day (HS050); ability to meet unexpected

expenses (HS060); ownership of a telephone (HS070); ownership of a colour television (HS080); ownership of a computer (HS090); ownership of a washing machine (HS100); ownership of a car (HS110); and difficulty in making ends meet (HS120) - binary indicators were created, taking the value 1 when respondents reported a lack or difficulty. MCA was then applied to these indicators, and the first dimension was extracted, summarising the joint pattern of material deprivation.

To estimate equation (3.1), an instrumental variables (Two-Stage Least Squares, 2SLS) procedure was employed using the `ivreg2` command in Stata. The 2SLS estimation was carried out with heteroskedasticity-robust standard errors (robust) to ensure inference remains valid in the presence of variance heterogeneity (Baum et al., 2007).

Based on both theoretical considerations and empirical evidence, *Rent* is treated as a potentially endogenous regressor in the specification for perceived crime. Empirically, the orthogonality test implemented in `ivreg2` (option `orthog()`) indicates the non-exogeneity of rent with respect to the structural error term, thereby justifying the adoption of an instrumental variables strategy (Baum et al., 2007).

This choice is also grounded in economic theory: in spatial equilibrium, area characteristics - including insecurity and crime - are capitalized into property prices and rental values, generating potential reverse causality and simultaneity between rent and perceived crime (Roback, 1982). Empirical evidence shows that higher crime levels reduce property values and, consequently, rental prices (Gibbons, 2004; Ihlanfeldt and Mayock, 2010; Linden and Rockoff, 2008).

Endogeneity may therefore arise both from reverse causality (crime influencing rents) and from unobserved common determinants - such as processes of urban decay or renewal, shifts in the socio-economic composition of residents, or environmental factors - that simultaneously affect rental prices and perceptions of crime.

In the first stage (3.2), rent was explained using three instruments measured in the survey: (i) *Market price*, a dummy variable equal to 1 if the rent is paid at market price (as opposed to atypical or subsidized contracts); (ii) *Number of rooms*, a measure of dwelling size; and (iii) *Housing discomfort*, a composite index of housing inadequacy constructed via MCA on housing quality variables. MCA was applied to six dichotomous variables describing potentially problematic housing conditions: presence of humidity (HH040), difficulty in heating (HH050), absence of a bathroom or presence of a shared bathroom (HH081), and absence of an indoor flushing toilet or presence of a shared indoor flushing toilet (HH091). MCA was chosen over alternative dimensionality reduction techniques — such as Principal Component Analysis — because the input variables are binary indicators rather than continuous measures; MCA is specifically designed to handle categorical and dichotomous data, extracting latent dimensions that capture the joint pattern of variation across such variables (Greenacre, 1984). From this analysis, a continuous indicator was derived, with higher values corresponding to greater levels of housing discomfort.

The relevance of the three instruments is well established: contract type, dwelling size, and housing quality are among the primary determinants of rent levels, and this is confirmed by the first-stage diagnostics (Kleibergen–Paap rk Wald F statistic well above conventional thresholds for all specifications; see Table 3.2). The exclusion restriction — that these instruments affect perceived crime only through their effect on rent — requires more careful discussion, as it cannot be directly tested and rests on theoretical assumptions that may not hold in all cases.

Regarding *Market price*: the distinction between market-rate and subsidized contracts is primarily determined by dwelling and contract characteristics, and its direct effect on crime perception — conditional on the full set of covariates including area and year fixed effects — is theoretically limited. However, a potential concern arises from the fact that subsidized housing in Italy is not randomly allocated: it tends to be concentrated in specific neighborhoods and assigned to low-income households, who may inhabit areas with structurally higher crime rates. To the extent that the market-price dummy proxies for this neighborhood-level sorting, it may carry a direct association with crime perception that is not fully absorbed by the area fixed effects. This represents a potential, though partial, violation of the exclusion restriction. Its severity is mitigated by the inclusion of poverty and material deprivation controls in specifications (5) and (6), which absorb part of the socioeconomic gradient that drives sorting into subsidized housing.

Regarding *Housing discomfort*: the index captures structural deficiencies of the dwelling (humidity, inadequate heating, absence of sanitary facilities). Its direct effect on crime perception may operate through a channel in which physical housing deterioration is associated with neighborhood decay and poverty, which in turn are correlated with crime. This potential pathway — discomfort $\rightarrow$ poverty $\rightarrow$ crime — represents a possible violation of the exclusion restriction, particularly in the specifications that do not control for poverty or material deprivation. In the specifications that include these controls (columns 5 and 6 of Table 3.2), this channel is partially closed. The stability of the core coefficient on instrumented rent across all six specifications, including those with and without poverty controls, provides some reassurance regarding the robustness of the estimates to this concern.

Regarding *Number of rooms*: dwelling size is a standard hedonic determinant of rent and its direct association with crime perception, conditional on housing type, urbanization, and area fixed effects, is theoretically less obvious. This instrument is therefore considered the most credibly excludable of the three.

In light of these considerations, the estimates from the IV specification are best interpreted as capturing the association between the rent-driven component of neighborhood quality and perceived insecurity, rather than as strictly causal effects. The overidentification test (Hansen's J) does not reject the joint validity of the instruments in any specification (p-values ranging from 0.15 to 0.69), providing formal, though imperfect, support for the exclusion restrictions under the assumption that at least one instrument is valid.

The predicted variable $\widehat{\text{rent}}_{i,t}$ from this first stage (3.2) was then used in the second stage of the 2SLS procedure (3.1).

To support the IV approach, standard diagnostic tests provided by `ivreg2` were conducted: (i) the under-identification test (Kleibergen–Paap rk LM) to verify that the reduced-form matrix has full rank (Kleibergen and Paap, 2006); (ii) the weak instruments test (Cragg–Donald / Kleibergen–Paap rk Wald F), with comparison to the critical values proposed by Stock and Yogo (Stock and Yogo, 2002); (iii) the over-identification test (Hansen's J) to evaluate the collective validity of the excluded instruments with respect to the structural error term (Hansen, 1982).

Furthermore, to assess the potential endogeneity of individual covariates, the `orthog()` option in `ivreg2` was employed; this procedure guided the decision on which variables to treat as exogenous or potentially endogenous in the final model. To verify the absence of multicollinearity among the independent variables, both centered and uncentered Variance Inflation Factors (VIF) tests were employed, alongside collinearity diagnostic procedures as described by Belsley et al. (2005) (table C4).

Finally, as already mentioned, the Heckman correction (1979) addresses the bias arising from the fact that the rent equation is observed only for a non-random subsample of the population (i.e., tenants). The procedure involves a first-step selection equation that specifies the probability of being a tenant as a function of demographic and socioeconomic characteristics, including household size, mean age of household heads, number of workers, family type, health status, and car ownership, alongside fixed effects for area and year. These variables serve as the necessary exclusion restrictions for identification. From this probit estimation, the Inverse Mills Ratio ($\lambda_{i,t}$) is computed and inserted into the structural equation (Equation 3.1). This additional regressor corrects for unobserved heterogeneity affecting both the tenure choice and the structural relationship between rent and perceived crime.

To fully capture the bilateral nature of the relationship between rental prices and neighborhood safety, we complement the previous analysis by estimating a structural equation for rent, where perceived crime enters directly as an explanatory variable. This specification is designed to test the reverse causality hypothesis - namely, that higher crime perceptions may depress rental values (hedonic price theory) - while accounting for the non-random nature of the sample.

Similarly to Ceccarelli et al. (2009), a Heckman selection model was employed to investigate the determinants of rental prices. Unlike the cited authors, who limited their analysis to the 2005 EU-SILC wave, the present study extends the observation period to cover all years from 2004 to 2020. Consequently, due to slight variations in the questionnaire over time, only variables consistently observed across all years were retained.

Crucially, the selection equation used in this model - which estimates the probability of a household being a tenant versus a homeowner - adopts an identical specification to the one described above for the equation 3.2. This ensures consistency in identifying the demographic and socioeconomic drivers of tenure status across both stages of the analysis. The structural rent equation is specified as follows:

$$ln\text{rent}_{i,t} = \beta_0 + \beta_1 \mathbf{X}_{i,t}^\top + \theta\lambda_{i,t} + \delta_{\text{year}_t} + \delta_{\text{area}_i} + u_{i,t} \tag{3.3}$$

Where:

$lnrent_{i,t}$ is the natural logarithm of the rent paid;

β_0 is the intercept;

$\boldsymbol{\beta_2}\mathbf{X}_{i,t}^\top$ is the vector of controls: $\mathbf{X}_{i,t}$ is the column vector of observed covariates and $\boldsymbol{\beta_2}$ is the corresponding coefficient vector. The covariates included variables relating to the structure of the apartment and contextual variables relating to the area in which it is located.

$\lambda_{i,t}$ is the Inverse Mills Ratio (IMR), derived from the first-stage probit estimation of the tenure choice (selection equation).

θ is the coefficient associated with the Inverse Mills Ratio.

$\delta_{\mathbf{year}_t}$ is the year fixed effects.

$\delta_{\mathbf{area}_i}$ is the area fixed effects (e.g. NUTS1).

$u_{i,t}$ is the Idiosyncratic error term for observation i in year t.

The model was estimated using the Maximum Likelihood (ML) method (via the *ml* option in Stata's *heckman* command). This approach yields joint estimates of the outcome equation (rent), the selection equation (tenure choice), and the correlation between their error terms. The statistical significance of the parameter λ (the correlation between the errors of the two equations) serves as a test for the presence of sample selection bias; a significant λ confirms that the unobserved factors influencing the decision to rent are correlated with those affecting rental prices, thereby justifying the applied correction.
It is worth noting that, while sample selection is addressed via the Heckman correction, crime is entered as an exogenous variable in the rent equation. An instrumental variable approach was not feasible in this stage due to the lack of available variables in the dataset that could plausibly affect crime perceptions without directly influencing the housing market. The estimates from this equation should therefore be interpreted as conditional associations rather than causal effects. Future research could refine these estimates by exploiting richer datasets that offer plausible exclusion restrictions for the crime variable.

Table 3.2: The determinants of crime perception (IV 2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Core covariates						
$\widehat{rent}$ (endogenous, IV)	−0.095***	−0.072***	−0.101***	−0.083***	−0.082***	−0.080***
	(0.0085)	(0.0075)	(0.0084)	(0.0069)	(0.0070)	(0.0070)
Mean head age	−0.00088***	−0.00088***	−0.00076***	−0.00050***	−0.00042***	−0.00032**
	(0.00016)	(0.00016)	(0.00012)	(0.00013)	(0.00014)	(0.00014)
Number of workers	0.001	0.002	−0.002	0.000	−0.001	−0.002
	(0.0031)	(0.0029)	(0.0026)	(0.0029)	(0.0030)	(0.0029)
Chronic diseases	0.028***	0.031***	0.027***	0.025***	0.025***	0.023***

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Table 3.2 – *The determinants of crime perception (IV 2SLS)*

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0039)	(0.0039)	(0.0038)	(0.0034)	(0.0034)	(0.0034)
Family income (centered)	0.005**	0.001	0.005*	0.003*	0.006**	0.006***
	(0.0025)	(0.0024)	(0.0025)	(0.0020)	(0.0024)	(0.0020)
Poverty	—	—	—	—	0.008*	—
					(0.0039)	
Material deprivation	—	—	—	—	—	0.010***
						(0.0013)
Seniority	0.001***	0.001***	0.001***	—	—	—
	(0.00016)	(0.00015)	(0.00017)			
Car	−0.005	−0.008	0.001	−0.006	−0.004	0.004
	(0.0051)	(0.0051)	(0.0037)	(0.0044)	(0.0045)	(0.0045)
Area / local characteristics						
Cities (vs Towns and suburbs)	0.101***	0.097***	0.103***	0.088***	0.088***	0.089***
	(0.0034)	(0.0034)	(0.0034)	(0.0029)	(0.0029)	(0.0029)
Rural areas (vs Towns and suburbs)	−0.039***	−0.034***	−0.039***	−0.034***	−0.034***	−0.033***
	(0.0035)	(0.0034)	(0.0035)	(0.0029)	(0.0029)	(0.0029)
Detached (vs Semi-detached)	−0.016**	−0.018***	−0.012**	−0.015***	−0.015***	−0.016***
	(0.0053)	(0.0052)	(0.0052)	(0.0046)	(0.0046)	(0.0046)
Apart. in a building (vs S.-detached)	0.002	0.002	0.002	0.003	0.003	0.002
	(0.0038)	(0.0038)	(0.0038)	(0.0034)	(0.0034)	(0.0034)
Apart. in a big building (vs S.-detached)	0.037***	0.037***	0.032***	0.033***	0.033***	0.033***
	(0.0043)	(0.0043)	(0.0043)	(0.0039)	(0.0038)	(0.0038)
Polluted area	0.217***	0.218***	0.219***	0.225***	0.225***	0.224***
	(0.0056)	(0.0056)	(0.0056)	(0.0054)	(0.0054)	(0.0054)
Noise from neighbours	0.154***	0.153***	0.154***	0.155***	0.155***	0.154***
	(0.0048)	(0.0048)	(0.0048)	(0.0047)	(0.0047)	(0.0047)
λ (Inverse Mills ratio)	0.010	0.012	−0.003***	0.015**	0.010	0.006
	(0.0082)	(0.0080)	(0.00124)	(0.0071)	(0.0076)	(0.0072)
Constant	0.565***	0.432***	0.625***	0.484***	0.484***	0.471***
	(0.0502)	(0.0467)	(0.0480)	(0.0420)	(0.0420)	(0.0426)
Fixed effects						
Year fixed effects	Yes	No	Yes	Yes	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes	No	Yes	Yes	Yes
Model statistics						

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Table 3.2 – *The determinants of crime perception (IV 2SLS)*

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	56,179	56,179	56,179	60,721	60,721	60,721
Kleibergen–Paap rk LM (underid.)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J (overid. test)	0.6884	0.1453	0.1755	0.5413	0.6768	0.4216

Notes: Standard errors (robust) in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Models (1)–(3) were estimated on years 2004–2020 with different fixed-effects configurations. Models (4)–(6) are estimated with all the combinations of fixed-effects on the expanded sample that includes 2004–2020 and 2023. In models (5) and (6), variables relating to poverty and the material deprivation index were added respectively.

3.4.1 Robustness checks

All estimates of the rent–crime relationship were subjected to an extensive battery of robustness checks to assess identification strength and coefficient stability.

Models were estimated on two pooled cross-section samples (2004–2020 and 2004–2020 plus 2023) to check sensitivity to the temporary absence of HS190 in 2021–2022.

The baseline was two-stage least squares (2SLS, implemented with `ivreg2`); results are reported in Table 3.2. As robustness, we re-estimated the specification without instruments using logistic regression for the binary perception outcome (Table C5) and compared OLS and alternative link functions.

The rent equation (equation (3.3)) was estimated with and without a Heckman two-step correction to account for non-random selection into renting; these results appear in Table 3.3.

For the IV strategy we ran the full suite of diagnostics (Kleibergen–Paap rk LM for under-identification; Cragg–Donald / Kleibergen–Paap rk Wald F with Stock–Yogo critical values for weak instruments; and Hansen's J for over-identification). We also used `ivreg2`'s `orthog()` option to test the exogeneity of rent and individual covariates. Diagnostic statistics and p-values are reported alongside the IV estimates (Table 3.2).

Estimates were replicated across alternative fixed-effects configurations (year, NUTS1, and their combinations), with and without poverty and material-deprivation controls, and using alternative instrument sets.

Across these exercises the IV diagnostics were satisfactory, and the core coefficient on rent remained stable in sign and magnitude. Together, the diagnostic results and the consistency of estimates across samples, estimators and specifications provide strong evidence of robustness for the reported findings.

Table 3.3: Determinants of rent - OLS vs Heckman (2004-2020)

	(1) OLS without Heckman	(2) OLS with Heckman	(3) OLS without Heckman	(4) OLS with Heckman
Number of rooms	0.10850***	0.10902***	0.08095***	0.09864***
	(0.00254)	(0.00239)	(0.00246)	(0.00237)
Seniority	−0.01266***	−0.01117***	—	—
	(0.00021)	(0.00019)		
Humidity	−0.13521***	−0.11489***	−0.15353***	−0.12951***
	(0.00588)	(0.00530)	(0.00583)	(0.00517)
Cold	−0.11904***	−0.10696***	−0.12705***	−0.12549***
	(0.00653)	(0.00588)	(0.00635)	(0.00572)
No bathroom (vs private indoor bathroom)	−0.02240	−0.05970**	−0.08205***	−0.11825***
	(0.02922)	(0.02988)	(0.02792)	(0.02877)
Shared bathroom (vs private indoor bathroom)	−0.11900	−0.10283	−0.06879	−0.10578
	(0.10049)	(0.09741)	(0.09768)	(0.09336)
No indoor flushing (vs private indoor flushing)	−0.00570	−0.00070	−0.00245	0.00025
	(0.03492)	(0.03689)	(0.03473)	(0.03457)
Shared indoor flushing (vs private indoor flushing)	−0.11325	−0.12856	−0.10474	−0.12574
	(0.10092)	(0.09550)	(0.09818)	(0.09103)
Cities (vs Towns and suburbs)	0.15575***	0.15704***	0.12265***	0.12694***
	(0.00545)	(0.00526)	(0.00533)	(0.00507)
Rural areas (vs Towns and suburbs)	−0.18999***	−0.17833***	−0.18673***	−0.17422***
	(0.00654)	(0.00670)	(0.00652)	(0.00656)

continued on next page

Table 3.3 – *Determinants of rent - OLS vs Heckman*

	(1)	(2)	(3)	(4)
Detached				
(vs Semi-detached or terraced house)	0.00332	−0.00431	0.00168	−0.00668
	(0.00935)	(0.00977)	(0.00932)	(0.00960)
Apart. in a bulding				
(vs Semi-detached)	−0.00310	0.00432	−0.01268*	−0.00390
	(0.00667)	(0.00681)	(0.00672)	(0.00671)
Apart. in a big bulding				
(vs Semi-detached)	−0.01246*	0.00671	−0.03579***	−0.00745
	(0.00749)	(0.00718)	(0.00749)	(0.00706)
Crime, violence or vandalism in the area	−0.12302***	−0.09595***	−0.15285***	−0.11673***
	(0.00830)	(0.00684)	(0.00835)	(0.00675)
Polluted area	0.02538***	0.02526***	0.01314	0.01930***
	(0.00789)	(0.00683)	(0.00798)	(0.00675)
Noise neighbours	0.04832***	0.05012***	0.05077***	0.05061***
	(0.00700)	(0.00620)	(0.00704)	(0.00612)
λ (Inverse Mills ratio)	—	0.09938***	—	−0.24137***
		(0.01368)		(0.01585)
Constant	5.42883***	5.31041***	5.38495***	5.47320***
	(0.01552)	(0.01577)	(0.01585)	(0.01677)
Fixed effects				
Year fixed effects	Yes	Yes	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes	Yes	Yes
Observations	57,028	57,028	61,633	61,633

Notes: Standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Models (1) and (2) were estimated on years 2004–2020. Models (3)–(4) are estimated on the expanded sample that includes 2004–2020 and 2023.

3.5 Results

We first present the estimates for the structural equation of perceived crime (equation 3.1), where rental levels are instrumented to account for endogeneity. In the baseline model, estimated on the pooled cross-sections and including all available years (from 2004 to 2020) with year and NUTS1 fixed effects, the coefficient on ln(rent) is negative, sizeable and highly significant.

Interpreted as a marginal effect in the linear specification, this implies that a one-unit increase in ln(rent) is associated with a reduction in the probability that the household perceives crime problems in the area of approximately 9.5 percentage points. In more concrete terms, a 10% increase in rent corresponds approximately to a change of $0.1 \cdot (-0.095) \approx -0.0095$ (≈ -0.95 percentage points), whereas a doubling of rent (logarithmic change $\ln 2 \approx 0.693$) translates into an estimated decrease of about $0.693 \cdot (-0.095) \approx -0.066$ (≈ -6.6 percentage points).

The other covariates confirm expected patterns: city living is strongly and positively associated with perceived crime (coeff. $\approx +0.101$), polluted areas and the presence of noisy neighbours show sizeable positive effects (approximately $\approx +0.217$ and $\approx +0.154$, respectively), while some housing types (e.g. detached units) are associated with lower probabilities of perceiving crime (coeff. ≈ -0.016). The analysis also confirms that living in large buildings, perhaps due to greater diversity among neighbors, is significantly associated with a higher perception of crime (coeff. $\approx +0.037$).

Among household characteristics, the presence of serious health cases is associated with a higher probability of feeling unsafe, whereas the average age of the household head exhibits a small but statistically significant negative effect. Finally, the results show that family income is positively associated with the likelihood of perceiving crime problems (coeff. $\approx +0.005$), suggesting that families with greater economic resources tend to report higher levels of perceived insecurity, all other conditions being equal. This result may reflect greater sensitivity to urban decay or a different tolerance threshold for phenomena considered threatening to quality of life. Similarly, the variables *Poverty* and *Material deprivation* (Models 5 and 6) also have positive and statistically significant coefficients, indicating that, at the opposite end of the socioeconomic distribution, conditions of economic vulnerability and material deprivation are associated with a higher probability of perceiving crime in one's neighborhood. Overall, these results highlight a non-linear relationship between economic status and the perception of insecurity, in which both affluence and economic fragility can amplify, for different reasons, subjective sensitivity to criminal risk.

From an interpretative perspective, the results suggest that, once endogeneity is accounted for, higher rent levels are associated with lower perceived crime in the area of residence: this is consistent with the idea that higher rents partly reflect local quality and service provision (services, informal surveillance, public/private investments) that reduce the feeling of insecurity. When the model is estimated without any correction for endogeneity (Logit specifications shown in table C5), the coefficient on *rent* is always negative and statistically significant but substantially larger in magnitude than the IV specification. This indicates a strong negative raw association between rent and perceived crime. The difference between uncorrected logit models and IV-instrumented models indicates that a sizeable portion of the relationship observed in the uncorrected regressions is likely attributable to endogeneity (reverse causation, omitted confounders, or measurement error), which amplifies the negative correlation in the absence of instrumental correction. Despite the different scales, the stability of the sign (always negative) and the significance of `rent` across specifications provide coherent evidence of an inverse relationship between rents and perceived crime.

An additional interpretative element arises from comparing these results with regressions that take rent as the dependent variable, both in the OLS specification and in the Heckman selection-corrected model (Table 3.3, columns 3 and 4). In both cases, the coefficient on crime is negative and significant. In the simple OLS regression (Model 3), the estimate is:

$$\hat{\beta}^{OLS}_{\text{crime}} = -0.15285 \quad (\text{robust s.e.} = 0.00835)$$

whereas in the two-stage Heckman specification (Model 4), which corrects for non-random selection into the subsample with observed market prices, the coefficient is slightly smaller in magnitude but remains robust:

$$\hat{\beta}^{Heckman}_{\text{crime}} = -0.11673 \quad (\text{robust s.e.} = 0.00675)$$

These results confirm that, holding other housing and contextual characteristics constant, areas where households report crime problems display lower rents on average - roughly 11.7% lower than otherwise comparable areas based on the Heckman estimate. This is therefore a negative and robust effect that survives correction for potential sample-selection biases.

Interpretively, the parallelism between the two sets of estimates is particularly informative. On the one hand, the IV model points toward a causal effect from higher rents to lower perceived crime; on the other hand, the regressions with rent as the outcome indicate that perceived crime is systematically associated with lower values of *rent*. In other words, the relationship appears bidirectional: higher rents reflect housing and neighbourhood attributes that reduce perceived insecurity, while the presence of crime reduces willingness to pay and hence observed rent levels.

3.6 Final remarks

Using EU-SILC data on Italian households observed for all years available from 2004 to 2023, this analysis examines the conditional associations between rent levels and households' perception of crime in their area of residence.

The empirical results presented here are consistent with the existence of a systemic link between the housing market and perceived insecurity, in line with the theoretical framework of spatial equilibrium and the mechanisms of capitalization of urban amenities. Rather than establishing a single causal direction, the analysis documents how rents and perceptions of crime are associated in a feedback process: prices incorporate neighborhood qualities and characteristics that are correlated with lower feelings of insecurity, while the presence and spread of crime is associated with reduced willingness to pay and can contribute to social and economic decline. The estimates from both the IV and the Heckman specifications should however be interpreted with appropriate caution, as the exclusion restrictions underlying the IV approach rest on assumptions that cannot be fully verified. In particular, the *market price* dummy may partly reflect the non-random sorting of low-income households into subsidized housing in high-crime areas, and the *housing discomfort* index may carry a direct association with crime perception through its correlation with poverty and neighborhood deterioration. The stability of the core coefficient across all specifications — including those that control for poverty and material deprivation — provides partial reassurance, but does not fully resolve these concerns. Additionally, the models do not include region-by-year interactions, which means that differential time trends in rents and crime perceptions across macro-regions cannot be entirely ruled out as a confounding factor.

A further limitation concerns the measurement of the outcome variable. The dependent variable in the crime equation — households' perception of crime, violence, or vandalism in the area of residence — is inherently subjective. Individuals who were born and raised in a particular environment may perceive changes in crime levels differently from those who have moved residences and experienced a different baseline level of insecurity in their place of origin. This heterogeneity in perception thresholds implies that the variable captures not only objective neighborhood conditions but also individual reference points shaped by prior residential experiences, which may introduce measurement error and attenuate the estimated associations.

With regard to the perception of crime, the results further highlight that households reporting higher levels of insecurity are often those already in fragile circumstances — for example, because they live with a family member in poor health or are experiencing financial hardship. At the same time, the *income* variable reveals a distinct profile for wealthier households, which also tend to report higher perceived crime: in this case, the perception of risk may be linked to fear of property crime or, more generally, to a greater sensitivity to threats to personal and financial security. Overall, these results suggest a non-linear relationship between economic status and perceived insecurity, in which both economic fragility and relative affluence can amplify subjective sensitivity to criminal risk, for different reasons.

This feedback system has profound social consequences, especially in terms of urban equity: security becomes a luxury good, and low-income and more vulnerable segments of the population are at greater risk of crime. Furthermore, this mechanism accentuates the development of polarized cities, with islands of high quality and safety — often guarded or gated communities — in contrast to peripheral or degraded areas, where insecurity is not only perceived but often real.

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APPENDIX C

Table C4: Variance Inflation Factors (VIF) - Determinants of log rent

	No *seniority*		**With *seniority***	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**
Rent	1.21	0.823	1.27	0.786
Income (centered)	1.86	0.536	1.90	0.526
Detached	1.43	0.698	1.42	0.704
Apartament in a big bulding	2.43	0.411	2.38	0.420
Apartament in a bulding	2.27	0.440	2.22	0.451
Poverty	1.69	0.591	1.71	0.586
Material deprivation	1.30	0.770	1.30	0.770
Polluted area	1.39	0.721	1.38	0.722
Noise neighbours	1.36	0.736	1.35	0.738
Mean head age	1.35	0.738	1.80	0.555
Car	1.32	0.760	1.33	0.755
Cities	1.33	0.750	1.35	0.738
Rural areas	1.25	0.803	1.25	0.798
Chronic diseases	1.23	0.815	1.23	0.815
Number of workers	1.20	0.832	1.25	0.802
Seniority	—	—	1.54	0.649
Mean VIF	1.51		1.51	

Notes: The columns on the left refer to the model without seniority, those on the right to the model with seniority. The values of 1/VIF are the reciprocal of the VIFs. Figures rounded.

Table C5: The determinants of crime perception (Logistic regression)

	(1)	(2)	(3)	(4)	(5)	(6)
Core covariates						
Rent	−0.3563***	−0.3636***	−0.4113***	−0.3934***	−0.3873***	−0.3683***
	(0.02179)	(0.02138)	(0.02124)	(0.02105)	(0.02111)	(0.02122)
Mean head age	−0.00608***	−0.00632***	−0.00674***	−0.00153	−0.00132	−0.00053
	(0.00114)	(0.00113)	(0.00113)	(0.00096)	(0.00096)	(0.00097)
Number of workers	−0.05449**	−0.06567***	−0.05265*	−0.05404**	−0.05784**	−0.05308*
	(0.02552)	(0.02090)	(0.02541)	(0.02549)	(0.02547)	(0.02541)
Chronic diseases	0.3273***	0.3372***	0.2954***	0.3299***	0.3263***	0.2970***
	(0.03087)	(0.03060)	(0.03062)	(0.03033)	(0.03033)	(0.03048)
Family income (centered)	−0.02088	−0.01845	−0.04289**	−0.01667	0.02639	0.01846
	(0.01876)	(0.01833)	(0.01847)	(0.01842)	(0.02257)	(0.01909)
Poverty	—	—	—	—	0.1265***	—
					(0.03637)	
Material deprivation	—	—	—	—	—	0.13097***
						(0.01245)
Seniority	0.00903***	0.00883***	0.01035***	—	—	—
	(0.00117)	(0.00116)	(0.00115)			
Car	−0.03699	−0.03465	−0.02798	−0.02992	−0.03064	0.06797**
	(0.03118)	(0.03099)	(0.03101)	(0.03037)	(0.03042)	(0.03183)
Area / local characteristics						
Cities (vs Towns and suburbs)	0.8415***	0.8435***	0.8772***	0.8606***	0.8601***	0.8719***
	(0.03158)	(0.03148)	(0.03133)	(0.03073)	(0.03075)	(0.03076)
Rural areas (vs Towns and suburbs)	−0.5999***	−0.5917***	−0.5941***	−0.6066***	−0.6051***	−0.5946***
	(0.05730)	(0.05719)	(0.05693)	(0.05637)	(0.05638)	(0.05637)
Detached (vs Semidetached/terraced house)	−0.1527**	−0.1794**	−0.09293	−0.1568**	−0.1588**	−0.1634**
	(0.06971)	(0.06978)	(0.06907)	(0.06884)	(0.06890)	(0.06900)
Ap.ment in a building (vs s.det./terr.)	0.07996	0.07059	0.06221	0.07590	0.07674	0.08087
	(0.04566)	(0.04554)	(0.04545)	(0.04510)	(0.04512)	(0.04521)
Ap.ment in a big building (vs s.det./terr.)	0.3744***	0.3695***	0.3080***	0.3737***	0.3755***	0.3846***
	(0.04558)	(0.04545)	(0.04514)	(0.04505)	(0.04506)	(0.04517)
Polluted area	1.2219***	1.2273***	1.2351***	1.2533***	1.2533***	1.2469***
	(0.03136)	(0.03121)	(0.03117)	(0.03080)	(0.03081)	(0.03083)
Noise from neighbours	1.0664***	1.0752***	1.0697***	1.0792***	1.0787***	1.0696***

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Table C5 – *The determinants of crime perception (Logistic regression, robust SE)*

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.03085)	(0.03056)	(0.03067)	(0.03026)	(0.03027)	(0.03028)
Constant	-1.0071^{***}	-0.9853^{***}	-0.5673^{***}	-0.9529^{***}	-1.0077^{***}	-1.2570^{***}
	(0.1517)	(0.1477)	(0.1451)	(0.1492)	(0.1502)	(0.1522)
Fixed effects						
Year fixed effects	Yes	No	Yes	Yes	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes	No	Yes	Yes	Yes
Model statistics						
Observations	56,179	56,179	56,179	60,721	60,721	60,721
Pseudo R^2	0.2254	0.2227	0.2190	0.2295	0.2297	0.2315
Wald / LR chi2	8831.60	8707.14	8759.24	9600.79	9613.33	9611.53

Notes: Robust standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Models (1)–(3) were estimated on years 2004–2020 with different fixed-effects configurations (see the fixed-effects block). Models (4)–(6) are estimated on the expanded sample (2004–2020 and 2023). In models (5) and (6), variables relating to poverty and the material deprivation index were added, respectively.

Chapter 4

RENT AND RELOCATION: HOUSEHOLD MOBILITY IN ITALY

4.1 Introduction

In recent years a number of events have had a significant impact on urban housing markets, producing important social transformations. Among these, the phenomenon of rising rents - namely the concentrated increase in rental prices in central and semi-central urban areas - has contributed to a substantive reconfiguration of residential geography and distributive pressures on housing demand (Aalbers, 2017).

By "rising rents" we refer to the process by which rental rates grow substantially in high-demand locations, thus creating an economic incentive for households to relocate to peripheral or otherwise less expensive areas. The drivers of this phenomenon are multiple and often overlapping: the transformation of the housing stock in response to tourist demand and the diffusion of short-term rentals (e.g. B&Bs, Airbnb), which remove units from the long-term market (Cocola-Gant and López-Gay, 2020; Amore et al., 2022); the increasing financialization of the housing market, characterized by the growing influence of institutional investors (such as real estate funds and financial corporations) that prioritize short-term returns over social housing needs, combined with structural constraints on housing supply - including bureaucratic delays in new construction, limited land availability, and restrictive urban planning regulations - contributes to a reduction in the stock of affordable dwellings and exacerbates upward pressure on rents (Aalbers, 2017; Barron et al., 2021).

One of the most visible consequences of rising rents is the increase in cost-burdened renters and cost-related movers: households that relocate for affordability reasons and that often experience deterioration in social capital and relational well-being (Desmond, 2012; Beck, 2024). In many European cities - including those in Italy - this has translated into residential moves towards peripheral or suburban areas, where rents are lower and therefore more affordable for low-to-middle income households (Wyly et al., 2010; Beck, 2024).

As discussed in the chapter 3, it should be noted, however, that lower-rent areas are not necessarily free of problems: they frequently coincide with neighbourhoods showing higher signs of urban decay, lower provision of services and, at times, elevated levels of perceived insecurity (Atkinson and Wulff, 2009; Zuk et al., 2018). For this reason, the displacement induced by rising rents can produce, among others, ambivalent social effects: on the one hand it relieves the economic pressure on relocated households; on the other, it can expose them to weaker support networks, inadequate infrastructure and heightened perceptions of insecurity, with social costs that are not immediately quantifiable.

The aim of this chapter is to identify common mechanisms that link the findings reported in Chapter 3 - which examines the relationship between rental levels and perceived crime - with the determinants of residential mobility. Put differently, the chapter bridges two research strands that have typically been treated separately: the literature on how housing conditions and costs shape social distress and perceptions of insecurity, and the literature on the drivers of household relocation. By bringing these literatures together, I assess whether rising rents prompt households to move and whether those moves, on average, expose households to neighborhoods with different levels of perceived crime, thereby offering an integrated account of the trade-offs between housing cost and neighborhood quality (Bennett et al., 2022; Clark, 2013; Skobba and Goetz, 2013; Gibbons, 2004; Buonanno et al., 2013).

The empirical analysis draws on EU-SILC panel microdata for Italy from 2004 to 2023 and addresses two related but distinct research questions. First, it estimates the propensity to relocate using a penalized logistic model (Firth, 1993), which is suitable for estimating relatively rare events and reducing separation bias, in order to isolate the net effect of pre-move rent levels on the probability of moving. Second, among households that do relocate, it examines how rental costs change after the move and whether this change varies systematically with household income — thereby shedding light on the distributional consequences of cost-driven mobility. The specification controls for family characteristics, housing attributes and territorial characteristics. Alternative model specifications and robustness checks, including an instrumental variable approach to assess the exogeneity of rent, are also presented.

4.2 Literature review

Academic literature analyzing the phenomenon of residential mobility has identified four main categories of reasons that prompt families to move house:

- *Individual characteristics*: Individual characteristics (such as age, income, health status, marital status, education) can be important predictors of the propensity to move.

  Bennett et al. (2022), using data from the ARIC cohort and applying optimal subset algorithms, identify the main predictors of residential mobility, also taking into account the interactions between different individual variables. The results show that, in the case of short-distance moves, the most significant predictors are marital status, level of education, and age of the head of household. For long-distance moves, however, the most important variable appears to be the length of previous residence in the area of departure (*seniority*): those who have lived in a place for a short time are more likely to move far away (Bennett et al., 2022).

  The effect of health status on the propensity to relocate appears less straightforward than that of other factors. Larson et al. (2004), analyzing two waves of the Australian Longitudinal Study on Women's Health (1996) using logit models, found that poor chronic health was associated with a higher likelihood of residential mobility, particularly toward urban areas. Specifically, women who frequently consulted medical specialists were more likely to move between cities or migrate from rural to urban settings. In contrast, Zhang (2024), using data from the China Family Panel Studies (2012–2018), observed that among elderly Chinese individuals, those with better self-rated health had higher rates of residential mobility. This suggests that good health may enhance both the capacity and, potentially, the willingness to relocate in later life.

As for perceived income, it does not appear to be a reliable predictor of residential mobility, as it is frequently found to be statistically insignificant or associated with ambiguous effects (Diaz-Serrano and Stoyan, 2010; Causa and Pichelmann, 2020).

- *Life cycle events*: Significant events in family life (such as marriage, separation, or the birth of a child) or in the professional sphere (such as a job change) can suddenly alter housing needs, prompting individuals to relocate in order to adapt their residence to the new circumstances.

  Several studies have highlighted how life-cycle events can influence residential mobility (Rabe and Taylor, 2010; de Groot et al., 2011).

  Clark (2013), analyzing an Australian sample, found that changes in marital status-with the exception of widowhood-significantly increase the likelihood of relocating. The same results obtained by Clark (2013) were then verified by Coulter and Scott (2015) on a sample from the United Kingdom.

  Morris (2017), using detailed data from the Avon Longitudinal Study of Parents and Children (ALSPAC), applies a multilevel recurrent-event history analysis to examine the impact of life events on residential mobility. The results show that most life events - such as separations, births, or job changes -increase the likelihood of moving, although not necessarily into more or less socioeconomically deprived neighborhoods. Furthermore, the study finds that families living in poor housing or disadvantaged neighborhoods are more likely to remain "stuck in place" following negative life events, compared to those residing in more favorable environments.

- *Housing discomfort*: Housing insecurity - defined as poor housing conditions, with structural problems, safety issues, or poor maintenance - is one of the main reasons behind decisions to move house (Bartlett, 1997; Crowley, 2003; Skobba and Goetz, 2013). In particular, Skobba and Goetz (2013), through a qualitative analysis of 47 interviews with people who frequently change accommodation, highlight numerous cases in which the move was determined by a sense of insecurity within the home, which made it unsustainable to remain there.

- *Neighborhood features*: Perceived insecurity in one's neighborhood can be a key factor influencing the decision to move (Coulton et al., 2012; Skobba and Goetz, 2013).
  Coulton et al. (2012), using panel data from the Making Connections initiative across ten disadvantaged neighborhoods, apply cluster analysis to classify families based on life cycle, economic resources, and neighborhood attachment. Their findings show that residents with fewer resources tend to move only short distances without improving their housing conditions, while more stable families (more resources, better working conditions, greater social capital) are able to relocate to more desirable neighborhoods. Therefore, the perception of insecurity may prompt some people to seek change, but if they lack the means to do so, the result is often "intra-area mobility" (short moves, without any real improvement).

- *Housing costs*: The unaffordability of housing is often cited as the most common cause of involuntary residential mobility (Beck, 2024). In particular, Wyly et al. (2010), using New York City as a case study, analyze the spatial evolution of displacement pressures and identify difficulty paying rent as the leading cause of residential displacement.
  Desmond (2012), analyzing a sample of tenants in Milwaukee, finds that falling behind on rent is among the most common reasons tenants are summoned to eviction court and ultimately evicted.
  Beck (2024), drawing on data from the California Health Interview Survey, identifies a group of "cost-related movers" - renters who recently relocated due

to unaffordable rent increases. Analyzing this nationally representative sample, the study finds that individuals who move for housing cost reasons report significantly lower levels of trust in neighbors and social cohesion compared to other renters, including both non-movers and those who moved for other reasons. These findings suggest that high rental costs not only act as a push factor for involuntary residential mobility but also lead to moves associated with diminished social well-being.

In the Italian context, several studies have investigated the main determinants of individual residential mobility, highlighting specific features compared to other European countries.

Diaz-Serrano and Stoyan (2010), through a comparative analysis using panel data (1994–2001) from twelve European countries, find that the effect of job changes on residential mobility is significantly weaker in Italy than in the other countries analyzed. Furthermore, in all contexts examined, household income plays only a marginal role in influencing the decision to move.

Gabrielli and Buonomo (2016) apply logistic regression models to Italian data from population registers and the Labour Force Survey (LFS). Their findings show a higher incidence of residential moves in Northern and Central Italy, a greater propensity to relocate among individuals aged 25 to 34, as well as a positive and significant effect of cohabitation and employment changes on the likelihood of moving.

Finally, the study by Causa and Pichelmann (2020), based on the special module of EU-SILC 2012 on housing mobility, provides a comparative analysis across several European countries, including Italy. The results indicate that actual and expected residential mobility is significantly lower in Southern European countries - such as Italy and Spain - compared to Northern Europe. In Italy, in particular, homeowners - especially those without a mortgage - are considerably less mobile than renters. Moreover, recipients of housing allowances are more likely to move, a pattern also observed in Sweden and Spain. Temporary workers are the most likely to relocate, while high transaction costs (e.g., property taxes) serve as a major deterrent to mobility, particularly among young first-time homebuyers, including in Italy (Causa and Pichelmann, 2020).

Building on this evidence, the present chapter contributes to the Italian literature by exploiting the full longitudinal structure of EU-SILC data over the period 2004–2023 to estimate the causal effect of rent levels on relocation propensity, while also examining the distributional consequences of cost-driven moves in terms of post-relocation rental expenditure.

4.3 Data

The analysis draws on the IT-SILC longitudinal microdata for Italy (2004–2023). To estimate relocation propensity, I constructed an annual panel that follows the same household units where possible, so as to relate housing conditions at time t to the decision to move in the subsequent year $t+1$. The final sample used for estimation comprises 21,237 observations; of these, 880 correspond to households that actually moved within the following year ($\approx$ 4.14% of the sample), a low incidence that motivates the use of estimation techniques tailored to rare events (King and Zeng, 2001).

The use of a different sample than in the analysis in the previous chapter stems from the availability of key variables: DB110[1] (household status), which identifies households that have moved, is available only in the panel component; whereas HS190 (perceived crime, violence and vandalism in the area) is available only in the cross-sectional component. Nevertheless, the use of the same EU-SILC data source ensures that both samples remain nationally representative, thereby strengthening the comparability and consistency of results across chapters.

[1] The variable DB110, which records household status, comprises 11 possible categories, among them: 1 - "*Hhld from prev. wave: At the same address as last interview*"; and 2 - "*Hhld from prev. wave:Entire household moved to a private hhld within the country*". If the household has moved outside the country (code 4) or into an institution (code 3), the entire household is excluded from the survey's scope.

Table 4.1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Personal characteristics					
Rent (€/month)	21,591	386.89	209.68	24	3,000
Family income (€/year)	21,591	23,383.72	18,001.26	-15,568	547,646
Family size	22,517	2.1928	1.2915	1	10
Chronic family diseases	22,517	0.2782	0.4481	0	1
Car ownership	22,517	0.7212	0.4484	0	1
Seniority (years)	18,937	13.46	13.34	0	96
Life cycle events					
New birth	22,517	0.0196	0.1387	0	1
Wedding	22,517	0.0145	0.1195	0	1
Separation or divorce	22,517	0.0067	0.0816	0	1
Widowed	22,517	0.0068	0.0819	0	1
Work condition change	22,517	0.3271	0.4692	0	1
Housing characteristics					
Rooms per member	22,517	1.5992	0.9243	0.11	6
Housing discomfort index	22,517	0.0739	1.7527	0	35.11
Detached house	22,517	0.0862	0.2807	0	1
Apartment (small building)	22,517	0.4064	0.4912	0	1
Apartment (large building)	22,517	0.3690	0.4825	0	1
Area characteristics					
High-density area	22,517	0.4697	0.4991	0	1
Rural or low-density area	22,517	0.1541	0.3611	0	1
Market price high	22,517	0.5744	0.4944	0	1

4.4 Empirical strategy

The empirical objective of this study is to estimate the effect of rental costs, along with other housing and household characteristics, on the probability that a family changes its residence. The analysis draws on longitudinal EU-SILC data for Italy covering the period 2004–2023, observing the same households over time where possible.

Given the binary nature of the event (move vs no-move), the baseline specification is a non-linear probability model (logit/probit).

The estimated model can be expressed as:

$$\log\left(\frac{p_{i,t+1}}{1-p_{i,t+1}}\right) = \beta_0+\beta_1\ln(\text{Rent})_{i,t}+\mathbf{P}_{i,t}^{\top}\beta_2+\mathbf{E}_{i,t}^{\top}\beta_3+\mathbf{H}_{i,t}^{\top}\beta_4+\mathbf{N}_{i,t}^{\top}\beta_5+\delta_{\text{year}_t}+\delta_{\text{area}_i}+\varepsilon_{i,t} \tag{4.1}$$

where:

$\log\left(\frac{p_{i,t+1}}{1-p_{i,t+1}}\right)$ is the log-odds of household i moving in the period $t+1$. This transformation maps the probability $p_{i,t+1}$ from the $(0,1)$ interval to the entire real line, allowing a linear specification in the parameters.

β_0 is the intercept term.

$Rent_{i,t}$ is the rent paid by household i at time t (so before deciding to move), with associated coefficient β_1. The natural logarithm of the rent was used.

$\mathbf{P}_{i,t}$ is a vector of personal or household-level demographic characteristics (e.g., income, family size, health), with associated coefficient vector β_2.

$\mathbf{E}_{i,t}$ is a vector of recent events affecting the household (e.g., employment changes, changes in marital status, new births), with coefficient vector β_3.

$\mathbf{H}_{i,t}$ contains housing characteristics (e.g., dwelling type, number of rooms per member, housing discomfort variables), with coefficient vector β_4.

$\mathbf{N}_{i,t}$ is a vector of neighborhood characteristics (e.g., population density of the area of residence), with coefficient vector β_5.

$\delta_{\mathbf{year}_t}$ are year fixed effects capturing common shocks across all households in a given year.

$\delta_{\mathbf{area}_i}$ are area fixed effects capturing time-invariant differences between geographic areas (NUTS1).

$\varepsilon_{i,t}$ is the idiosyncratic error term.

Families that move from a rented dwelling to an owned property have been excluded from the analysis, as such moves are presumed to be primarily driven by reasons related to home purchase. Accordingly, the dependent variable takes the value of 1 if, in the following year ($t+1$), the household relocates to a new dwelling while remaining in rental tenure. Observing the future move allows us to examine which characteristics of the dwelling at time t ($H_{i,t}$) contributed to the household's decision to relocate at time $t+1$. To construct a synthetic indicator of housing discomfort, as in the previous chapter, a Multiple Correspondence Analysis (MCA) was employed. This statistical technique reduces the information contained in a set of correlated categorical variables by identifying latent dimensions that summarize their overall variability (Clarke and Greenacre, 1985; Milan and Whittaker, 1995).

The MCA was applied to six dichotomous variables describing potentially problematic housing conditions: presence of humidity (HH040), difficulty in heating (HH050), absence of a bathroom or presence of a shared bathroom (HH081), and absence of an indoor flushing toilet or presence of a shared indoor flushing toilet (HH091). From this analysis, a continuous indicator was derived, with higher values corresponding to greater levels of housing discomfort.

Regarding the set of variables related to family life cycle events ($E_{i,t}$), due to the impossibility of definitively establishing whether the move occurs before or after a given predictable event, dichotomous variables were constructed which take the value 1 for families in which one of the considered events occurs either at time t or at time $t+1$. Based on this criterion, variables were created to indicate the occurrence of weddings, separations or divorces, the death of a

spouse, changes in employment status, and new births within the family[2].
The variable *seniority*, belonging to the set of covariates related to personal information ($P_{i,t}$), is calculated as the difference between the year of observation (t) and the year the rental contract began (HH031). However, this variable is available in the EU-SILC data only up to 2020. Therefore, estimations were performed both including and excluding this variable, in order to assess its partial effect without sacrificing the completeness of the sample.
Among the personal information variables of the households ($P_{i,t}$), the dichotomous variable *Chronic diseases* was also included. This variable was constructed by aggregating the individual health status variable (PH010) at the household level and identifies households in which at least one member reported a very serious health condition.
Finally, the variable *Income* (HY020) is a continuous measure representing the total disposable household income and, due to the structure of the EUSILC dataset, is observed at time $t-1$. To mitigate the risk of collinearity, detected through the diagnostic procedures of Belsley et al. (2005), and given the positive, albeit moderate, correlation with Rent (0.2415), the Income variable was mean-centered. This transformation reduces linear correlation among predictors and improves the numerical stability of the estimation, without altering the interpretation of the coefficients associated with the other covariates (Aiken and West, 1991).
In the dataset, comprising 21,237 observations, only 879 cases (approximately 4.14% of the total) involve households changing residence, representing a typical instance of rare events data. In settings where the event of interest has low incidence, estimating a standard logit model via maximum likelihood is prone to producing biased coefficients and inaccurate confidence intervals due to the so-called small-sample bias (King and Zeng, 2001). This issue can be

[2]The variables concerning changes in marital status (PB190) and employment status (PL031) were aggregated at the household level from individual data. The variable indicating the birth of a new family member was derived by examining the ages of household members (RB080); if any member is recorded as having an age of zero, they are identified as a newborn.

particularly severe in the presence of rare predictors or quasi-separation in the data (Albert and Anderson, 1984).

To address this issue, equation (4.1) was estimated using the Firth penalized likelihood regression (Firth, 1993), an extension of the logistic model that applies a Jeffreys-type penalty to the likelihood function. This approach reduces the bias inherent in maximum likelihood estimates and improves the finite-sample properties of the estimators, thereby ensuring more stable and reliable inference in contexts characterized by rare events (Heinze and Schemper, 2002).

A potential concern with the baseline specification is that rent levels may be correlated with unobservable household or market characteristics that also affect the propensity to move. This issue is assessed through an instrumental variable approach, presented among the robustness checks below. The model presented in equation (4.1) may be subject to sample selection bias, as it is estimated solely on the subset of households that pay rent for their primary residence, which may differ systematically-and in unobservable ways-from the rest of the sample.

To assess the potential impact of such bias, as in the previous chapter, the two-stage procedure proposed by Heckman (1979) was applied, which allows for the integration of potential sample selection effects into the estimation process. In the first stage, a probit model was estimated in which the dependent variable captures the tenancy status, defined as paying rent for the current dwelling and, in the case of relocation, moving to another rented property.

To correctly identify the selection equation and address the limited knowledge of the determinants of tenancy status, the following covariates were included: fixed effects by household type[3], an indicator variable for whether the tenant

[3] In the absence of a variable identifying family type, provided by EU-SILC for cross-sectional data but not for panel data, the distinction between the different types of families was made using the following methodology. Using the variables Father ID (PB160) and Mother ID (PB170), families with children were identified. The age of family members was calculated using variable PB140. Combining this information, six family types were classified: young singles without children, adult singles without children, young couples without children, adult couples without children, young couples with children, and adult couples with chil-

also owns a property that is rented out (HY040N), and the binary variable *Market price*, which identifies households paying rent at market rates.

In the Heckman probit model, the parameter ρ measures the correlation between the error terms of the selection and outcome equations. In our case, the non-significant value of ρ ($SE = 0.323$) suggests the absence of selection bias, indicating independence between the selection and outcome processes (table D.7) . Moreover, the comparison between probit models estimated with and without the Heckman correction reveals no substantial differences that would raise concerns regarding selection bias. For these reasons, the model estimated using Firth's penalized likelihood regression was retained as the primary specification, given its suitability for rare events data.

Finally, to exclude the risk of multicollinearity, particularly among variables likely to be strongly correlated (e.g., rent and household income), two types of diagnostic tests were conducted: the calculation of Variance Inflation Factors (VIF), both centered and uncentered, and the application of collinearity diagnostic procedures as described by Belsley et al. (2005). The results, with VIF values below 5 and condition indices below 30 according to Belsley et al. (2005), provide a robust basis to rule out the presence of significant multicollinearity (table D.4).

A second, complementary empirical question concerns what happens to rental expenditure after the move. To address this, the analysis is extended to the subsample of households that relocated within the following year. For these movers, a variable is constructed measuring the log-difference between the rent paid in the new dwelling at time $t+1$ and the rent paid in the dwelling of origin at time t:

$$\Delta \text{Rent}_i = \ln(\text{Rent}_{i,t+1}) - \ln(\text{Rent}_{i,t}) \tag{4.2}$$

This variable is used as the dependent variable in an OLS regression with robust standard errors, estimated on the mover subsample only. The same

dren. "Young singles" are defined as individuals under 40 years of age, while "young couples" refer to couples with an average age below 40.

set of covariates used in the main specification - income, pre-move rent, life cycle events, housing and territorial characteristics - is included as regressors, measured at time t. The purpose of this analysis is twofold: first, to assess whether cost-driven moves systematically lead to lower rental expenditure; second, to examine whether the direction and magnitude of this change vary with household income, thereby shedding light on the distributional consequences of residential mobility.

Table 4.2: The determinants of family relocation - Firth logistic regression

	(1)	(2)	(3)	(4)
Personal characteristics				
Rent	0.296***	0.595***	0.634***	0.561***
	(0.080)	(0.072)	(0.074)	(0.075)
Family income (centered)	−0.105**	−0.164***	−0.201***	−0.182***
	(0.052)	(0.046)	(0.043)	(0.046)
Seniority	−0.071***	—	—	—
	(0.006)			
Family size	−0.099**	−0.160***	−0.078*	−0.147***
	(0.041)	(0.040)	(0.039)	(0.040)
Chronic diseases	−0.019	−0.226**	−0.023	−0.234**
	(0.085)	(0.081)	(0.081)	(0.081)
Car	0.151	0.175*	0.184**	0.169*
	(0.095)	(0.090)	(0.089)	(0.090)
Market price	0.219	0.241*	−0.557***	0.265*
	(0.156)	(0.143)	(0.078)	(0.144)
Life cycle events				
New birth	0.580***	0.835***	1.035***	0.817***
	(0.162)	(0.160)	(0.159)	(0.161)
Wedding	0.565***	0.717***	0.879***	0.718***
	(0.203)	(0.199)	(0.196)	(0.199)
Separation or divorce	1.269***	1.287***	1.477***	1.298***

continued on next page

Table 4.2 – *The determinants of family relocation - Firth logistic regression*

	(1)	(2)	(3)	(4)
	(0.254)	(0.249)	(0.244)	(0.249)
Widowed	0.407	0.164	0.216	0.165
	(0.405)	(0.390)	(0.381)	(0.391)
Work condition change	0.224**	0.231***	0.290***	0.237**
	(0.090)	(0.086)	(0.076)	(0.086)
Housing characteristics				
Rooms for members	−0.131**	−0.248***	−0.237***	−0.246***
	(0.061)	(0.057)	(0.056)	(0.057)
Housing discomfort index	0.036**	0.044**	0.033*	0.044**
	(0.014)	(0.014)	(0.014)	(0.014)
Detached	0.032	−0.043	−0.135	−0.041
	(0.154)	(0.150)	(0.148)	(0.150)
Apartament in a bulding (vs Semi-detached or terraced house)	−0.164	−0.174*	−0.291**	−0.181*
	(0.108)	(0.103)	(0.102)	(0.104)
Apartament in a big bulding (vs Semi-detached or terraced house)	−0.131	−0.233**	−0.322**	−0.240**
	(0.115)	(0.110)	(0.109)	(0.110)
Area characteristics				
Cities (vs Towns and suburbs)	−0.193**	−0.361***	−0.239**	−0.341***
	(0.086)	(0.080)	(0.080)	(0.081)
Rural areas (vs Towns and suburbs)	−0.298***	−0.206*	−0.110	−0.203*
	(0.115)	(0.108)	(0.107)	(0.108)
Fixed effects				
Year fixed effects	Yes	Yes	No	Yes
Area (NUTS1) fixed effects	Yes	No	Yes	Yes
Observations	17,771	21,237	21,237	21,237

Notes: Standard error in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. In model (1), the seniority variable was used among the regressors, therefore the years from

2021 to 2023 were excluded due to the unavailability of the variable in those years. Models (2), (3), and (4) test different fixed effects configurations. Model (4) is considered the main model.

4.4.1 Robustness checks

To assess the robustness of the results, the baseline specification was subjected to a series of robustness checks.

Equation (4.1) was estimated using three different models: Firth regression, adopted as the main model (Table 4.2), and both the logit (Table D.5) and probit models, each estimated with and without the Heckman correction (Table D.7). Furthermore, equation (4.1) was estimated using Firth regression separately for different subgroups of the sample identified on the basis of family type (Table D.6). Additionally, each estimated model was tested using alternative specifications of fixed effects.

To address the concern that rent levels may be correlated with unobservable household or market characteristics, an instrumental variable probit (IV-Probit) was estimated, instrumenting individual rent with a leave-one-out mean rent constructed for each cell defined by region, population density and year - that is, the average rent paid by all other renting households observed in the same area and period. This instrument captures local market-level rent variation while remaining orthogonal to household-specific characteristics. The instrument is strongly relevant in the first stage ($F = 229$, well above conventional thresholds). The Wald test of exogeneity fails to reject the null hypothesis of rent exogeneity ($\chi^2 = 0.54$, $p = 0.46$), indicating that the Firth baseline estimates are not materially affected by endogeneity bias. Full results are reported in Table D.8.

The favorable results of the diagnostic tests, together with the stability of the estimates across different specifications, provide strong evidence supporting the robustness of the findings.

Table 4.3: Changes in rent after moving house

	(1)	(2)	(3)	(4)
Personal characteristics				
Rent	-0.4306^{***}	-0.4292^{***}	-0.4574^{***}	-0.4633^{***}
	(0.03420)	(0.03532)	(0.03539)	(0.03664)
Family income (centered)	0.0382^{**}	0.0390^{**}	0.0318^{*}	0.0321^{*}
	(0.01674)	(0.01659)	(0.01631)	(0.01594)
Seniority	—	—	—	—
Family size	0.0050	0.0065	0.0135	0.0164
	(0.01599)	(0.01630)	(0.01638)	(0.01660)
Chronic diseases	−0.0217	−0.0151	−0.0334	−0.0260
	(0.02629)	(0.02691)	(0.02618)	(0.02664)
Car	0.0552^{*}	0.0534	0.0514	0.0491
	(0.03354)	(0.03493)	(0.03303)	(0.03442)
Market price	0.0423^{*}	0.0408	0.0525^{**}	0.0737
	(0.02460)	(0.05632)	(0.02481)	(0.05878)
Life cycle events				
New birth	0.0751	0.0793	0.0760	0.0828
	(0.05211)	(0.05331)	(0.05015)	(0.05175)
Wedding	0.1022^{*}	0.1172^{**}	0.1065^{*}	0.1252^{**}
	(0.05461)	(0.05599)	(0.05479)	(0.05758)
Separation or divorce	−0.0998	−0.0785	-0.1172^{*}	−0.0958
	(0.06324)	(0.06329)	(0.06466)	(0.06437)
Widowed	-0.1992^{*}	−0.1919	-0.2191^{*}	-0.2085^{*}
	(0.11878)	(0.12431)	(0.12349)	(0.12678)
Work condition change	−0.0145	−0.0018	−0.0182	−0.0048
	(0.02436)	(0.02643)	(0.02414)	(0.02603)
Housing characteristics				
Rooms for members	0.0267	0.0258	0.0318^{*}	0.0318^{*}

continued on next page

Table 4.3 – *Changes in rent after moving house*

	(1)	(2)	(3)	(4)
	(0.01904)	(0.01875)	(0.01891)	(0.01842)
Housing discomfort index	0.00224*	0.00158	0.00027	−0.00053
	(0.00122)	(0.00161)	(0.00130)	(0.00172)
Detached (vs Semi-detached)	−0.0466	−0.0356	−0.0370	−0.0257
	(0.05410)	(0.05428)	(0.05323)	(0.05330)
Apart. in a building (vs S.-detached)	0.0182	0.0183	0.0148	0.0142
	(0.03295)	(0.03332)	(0.03232)	(0.03260)
Apart. in a big building (vs S.-detached)	0.0497	0.0524	0.0458	0.0489
	(0.03593)	(0.03710)	(0.03540)	(0.03652)
Area characteristics				
Market price	0.0423*	0.0408	0.0525**	0.0737
	(0.02460)	(0.05632)	(0.02481)	(0.05878)
High-density area (dense)	0.0254	0.0268	0.0383	0.0407
	(0.02666)	(0.02671)	(0.02703)	(0.02692)
Rural/low-density (deserte)	−0.0620*	−0.0639*	−0.0598*	−0.0623*
	(0.03292)	(0.03339)	(0.03247)	(0.03284)
Fixed effects				
Year fixed effects	No	Yes	No	Yes
Area (NUTS1) fixed effects (region dummies)	No	No	Yes	Yes
R-squared	0.339	0.339	0.335	0.335
Observations	880	880	880	880

Notes: Robust standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Models: (1) baseline; (2) adds year fixed effects; (3) adds area fixed effects; (4) includes both year and region fixed effects.

The dependent variable is the change in rent after moving ($Rent_{t+1} - Rent_t$). All variables are at time t.

4.5 Results

The analyses of the determinants of household relocation, estimated using a Firth logistic regression, produce a picture that is consistent with the empirical evidence reported in the literature, largely confirming those findings for the Italian context over the period 2004–2023.

Life-cycle events emerge as the main mobility triggers: the birth of a child substantially increases the odds of moving (coeff. $= 0.817$, $e^{0.817} \approx 2.26$), as does marriage (coeff. $= 0.718$, $e^{0.718} \approx 2.05$) and, even more markedly, separation/divorce (coeff. $= 1.298$, $e^{1.298} \approx 3.66$). A change in employment status is also associated with a higher probability of moving (coeff. $= 0.237$, $e^{0.237} \approx 1.27$). These findings are readily interpretable within standard theory: events that redefine housing needs or the spatial organization of work increase the propensity to search for a new dwelling.

Among individual and household characteristics, income, household size and health status emerge as stabilising factors: an increase in (demeaned) income is associated with a lower probability of moving (coeff. $= -0.182$, $e^{-0.182} \approx 0.83$), as is a larger household size (coeff. $= -0.147$, $e^{-0.147} \approx 0.86$) and the presence of serious health problems in the household (*chronic diseases*: coeff. $= -0.234$, $e^{-0.234} \approx 0.79$). These effects suggest that higher economic resources and health constraints reduce mobility, plausibly due to costs, organisational difficulties and a greater aversion to the risks associated with relocation.

With respect to dwelling and neighbourhood characteristics, the composite housing-discomfort indicator is associated with a higher propensity to move (*housing discomfort index* coeff. $= 0.044$, $e^{0.044} \approx 1.045$: roughly $+4.5\%$ in the odds per unit), whereas some building typologies, such as large condominium blocks, exhibit lower observed mobility (*apartament in a big bulding* coeff. $= -0.240$, $e^{-0.240} \approx 0.79$).

An increase in rooms per household member further reduces the probability of moving (*rooms for members* coeff. $= -0.246$, $e^{-0.246} \approx 0.78$), indicating that greater space availability mitigates the pressure to change residence.

The variable of interest, the rent expressed in logarithmic form, is positive, sizable and highly significant (coeff. = 0.561, $z = 7.48$, $p < 0.001$). In practical terms, a one-unit increase in ln(rent) is associated with an increase in the odds of moving of approximately 75% ($e^{0.561} \approx 1.75$). More concretely, a 10% increase in rent corresponds approximately to a 5.8% rise in the odds of moving, while a doubling of rent would be associated with roughly a 47.6% increase. This pattern is consistent with a rent-adjustment mechanism: higher rental burdens push households to seek alternative housing solutions in order to contain expenditure. However, causal interpretation requires caution: the observed relationship may also incorporate selection or simultaneity mechanisms (for example, more dynamic markets with higher rents or temporary choices of more expensive housing prior to moving), which is why subsequent sections employ correction strategies (IV, Heckman) to explore causal robustness.

The specifications that correct for selection and the standard probit models confirm the qualitative picture emerging from the Firth regression but show some relevant quantitative adjustments. In particular, the coefficient on ln(rent) attenuates from 0.561 (Firth) to about 0.259 (heckprob) and 0.275 (probit), while remaining positive and highly significant in all specifications: this indicates that part of the observed association between rents and mobility is attributable to sample composition or selection-related covariates, but a robust and economically meaningful effect persists.

Moreover, the main results remain substantially unchanged across different fixed-effects specifications: life-cycle shocks (birth, marriage, separation) and key housing characteristics (rent, rooms per members, housing-discomfort index) remain robust and significantly associated with the probability of relocating. By contrast, some covariates - in particular the dummy *market price* and certain building types - exhibit marked sensitivity to the inclusion of geographic area fixed effects, suggesting that part of their variation is absorbed by local contextual factors.

The robustness of the principal relationships to the switch from Firth to conventional logit specifications (across various fixed-effects configurations) further supports the reliability of the findings.

A second set of results concerns the distributional consequences of relocation. The OLS regression estimated on the mover subsample (Table 4.4.1) shows that the pre-move rent level is strongly and negatively associated with the change in rent after relocation (coeff. = -0.461, $p < 0.001$): households paying higher rents before moving tend to achieve larger reductions in rental expenditure after the move. At the same time, household income is positively and significantly associated with the rent change (coeff. = 0.032–0.041, $p < 0.05$ across specifications): higher-income households tend to experience less negative or even positive rent changes after relocation. These two effects, operating in opposite directions, suggest that cost-driven moves lead to systematically different outcomes depending on household resources - with lower-income households moving toward cheaper dwellings and higher-income households maintaining or upgrading their rental expenditure.

4.6 Crime and mobility: Joint interpretations

Combining the results obtained in this chapter with those that emerged in the previous chapter (determinants of relocation and the relationship between rent and perceived crime), yields several plausible, non-mutually exclusive mechanisms that can account for the co-occurrence of low rents, low mobility and high perceived crime in some areas. Below we present the main interpretations suggested by the estimated coefficients.

1. **The phenomenon of housing stagnation in potentially criminal areas.**
   The analysis in the previous chapter shows that areas with lower rents have a higher concentration of perceptions of crime. At the same time, the study of the determinants of housing mobility highlights a lower propensity to move in those same contexts - a phenomenon of residential stagnation consistent with the findings of Morris (2017). In summary, where rents are lower, a double effect is observed: a greater sense of insecurity and, at the same time,

a tendency for households to remain anchored to their homes, which can contribute to consolidating situations of local socio-economic vulnerability.

2. **Cost–safety trade-off and selection into moves.**
   Looking at the results of the OLS regression on the sample of households that moved (table D.8), it emerges that a higher starting rent (measured at time t) is associated with a greater reduction in rent in the new home $(t+1)$. At the same time, household income shows a positive and significant effect: higher-income households tend to experience smaller reductions - or even increases - in rent after relocation. This suggests that cost-driven moves lead to systematically different outcomes along the income distribution: lower-income households tend to move toward cheaper dwellings, while higher-income households are able to maintain or upgrade their rental expenditure. This has two potentially significant consequences: firstly, price-induced moves tend to channel the most vulnerable households toward lower-rent neighbourhoods, which may be perceived as less safe; secondly, this mechanism could reinforce housing inequalities, contributing to the socio-economic stagnation of fragile areas.

3. **Seniority / exposure effect.**
   The seniority variable allows for a dual and complementary interpretation. On the one hand, longer tenure is associated with a lower propensity to move: established households tend to remain in the same home for longer. On the other hand, longer tenure corresponds to a higher probability of reporting crime in the area. This does not necessarily imply that crime increases over time, but rather that the perception of risk requires a period of exposure and knowledge of the context: families need to 'familiarize' themselves with the neighborhood - observing its dynamics, events, and signs of degradation - before stable assessments of insecurity emerge. Consequently, the effect on the perception of crime following a move may be delayed, making the timing of surveys crucial in assessing housing impacts.

4.7 Possible implications, the case of rising rents

The analyses of relocation determinants and of the relationship between rent levels and perceived crime point to a plausible mechanism rather than a proven causal link: it can be hypothesized that households forced to leave their dwellings because they can no longer afford high rents relocate to areas where, ceteris paribus, lower rents are associated with a higher perceived sense of insecurity. This proposition is inferred from microeconomic evidence and should therefore be treated as a testable hypothesis, not as an established causal fact.

At the macro level, this mechanism may generate a redistributive pressure across urban space: rising rents shift housing demand outward, prompting particularly young people and low–to–middle income families to abandon the urban core for peripheral rings or suburban markets, with potentially long-lasting effects on the socio-spatial composition of metropolitan areas. Such outward movement is unlikely to be neutral for the receiving neighbourhoods: areas characterized by lower average rents may, all else equal, exhibit greater perceived insecurity or higher incidence of physical and social deterioration, thereby increasing the economic and social costs borne by incoming households (Atkinson and Wulff, 2009; Zuk et al., 2018).

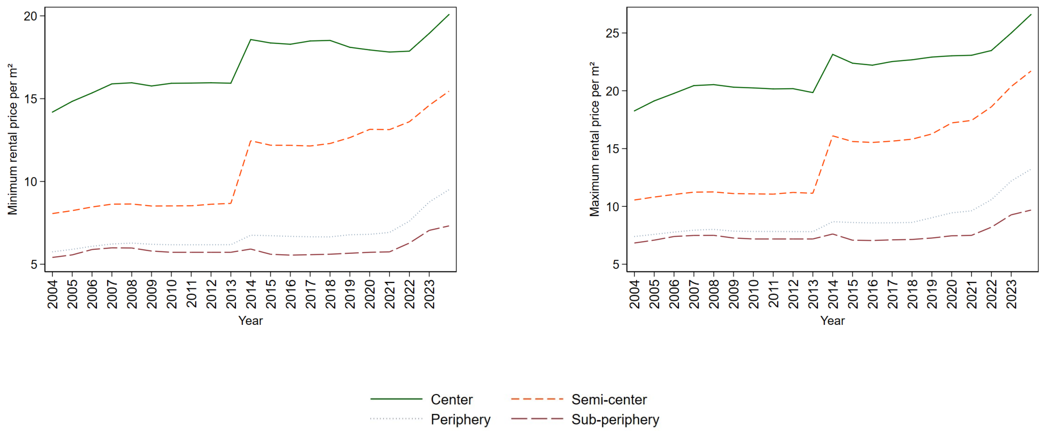
The structural drivers of upward pressure on rents include a chronic mismatch between housing supply and demand (underbuilding), regulatory and planning constraints that limit new supply, the financialization of the housing market (entry of large institutional investors), and demand shocks linked to concentration of jobs and services in central locations (Aalbers, 2017; Barron, Kung and Proserpio, 2021). In particular, a significant component of this dynamic is the transformation of the housing stock caused by growing tourist demand and the spread of short-term rentals (B&Bs, Airbnb, and similar platforms): the conversion of long-term housing into tourist accommodation reduces the supply available to residents and creates a tourism-driven "rent gap" that fuels rising rents in desirable neighbourhoods, accelerating displacement and "touristification" (Amore et al., 2022; Cocola-Gant and López-Gay, 2020). The observable and potential macro consequences are multiple and interlinked: (i) displacement and greater housing instability (evictions, loss of support networks) (Desmond, 2017); (ii) longer commuting times and fragmentation of work–home relations, with growing social and economic costs(Albouy et al., 2015); (iii) risk of infrastructural overload and neighbourhood deterioration in peripheral areas if inflows are not matched by investments in services and social integration (Zuk et al., 2018); (iv) heightened socio-economic segregation and concentrated vulnerability (Massey, 1990); and (v) the facilitation of "dormitory towns," with possible implications for crime and urban disorder (Kneebone and Berube, 2013). That said, current empirical evidence does not support a simple, mechanical relationship whereby relocation to the periphery automatically raises crime rates: several studies find no positive association - and in some contexts even a decline in crime- where migration is accompanied by employment opportunities and integration (Ousey and Kubrin, 2018). Perceptions of insecurity, moreover, tend to be highly sensitive to contextual factors (services, lighting, physical decay) and can worsen even in the absence of changes in recorded crime (Buonanno et al., 2013).

4.7.1 A possible case study: high rents in Milan

In line with the mechanisms discussed in the previous section, Milan constitutes a highly relevant urban laboratory. In recent years the city has exhibited clear signs of mounting pressure in the housing market, fuelling spatial exclusion and a reconfiguration of residential demand. Local evidence points to a marked increase in rents and a deterioration in housing affordability for lower-middle income groups, with an acceleration often dated to the post–Expo 2015 period and the city's subsequent rise in international attractiveness (Bricocoli and Paverini, 2024).

Figures 4.1 and 4.2 report our own elaborations based on the annual OMI rental quotations for the Municipality of Milan released by the Italian Revenue Agency (*Agenzia delle Entrate*). Figure 4.1 shows that maximum rents rose between 2004 and 2024 across all parts of the city, albeit at dif-

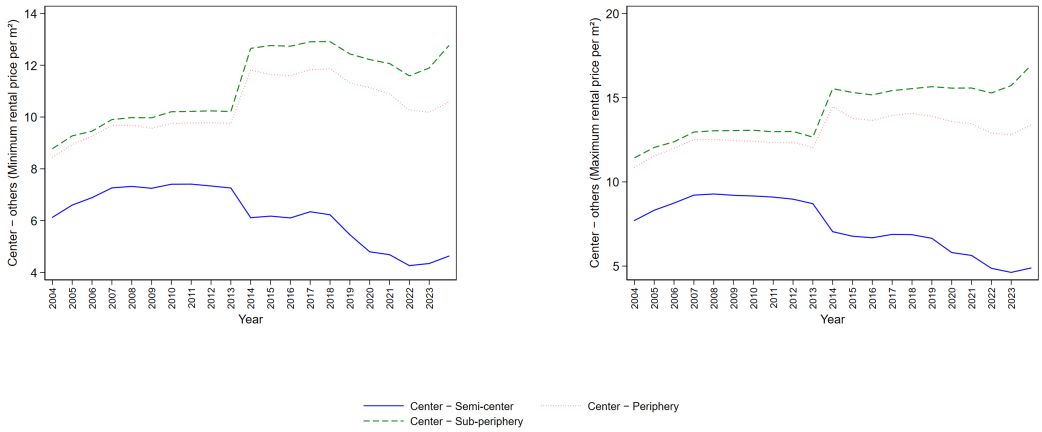
Figure 4.1: Evolution of minimum and maximum annual rents in Milan



ferent intensities: the strongest growth in peak rents occurred in semi-central areas, while the sub-periphery recorded a more contained increase. Figure 4.2 tracks the evolution of rent differentials between the centre - historically the most expensive - and other zones. The centre–periphery gap appears comparatively stable, with an uptick around 2014 followed by a mild easing, fluctuating broadly between €11 and €14 per m^2. By contrast, the centre–sub-periphery gap rises markedly, with a clear jump around 2014-2015 (Expo years) and a sustained upward trend through 2023. The centre-semi-centre gap narrows over time - from roughly €7–9 per m^2 in 2004-2012 to about €5 per m^2 or less by 2022–2023 - suggesting convergence of maximum rents in semi-central areas towards central levels and, consequently, a shrinking "central premium" at the top end of the rental market. It is therefore plausible that rent pressures are expanding and becoming increasingly pronounced in the semi-central belt.

To measure the direction and intensity of within-city residential flows, we construct a displacement index using administrative registrations ("*Iscrizioni anagrafiche*") by NIL (*Nuclei di Identificazione Locale*, the city's official neighbourhood units). The dataset - sourced from the Municipality of Milan's open data portal - provides annual inflows to Milan from Italy and abroad by neighbourhood. For each NIL we compute distance from the Duomo; units within 3 km are classified as centre/semi-center, the remainder as *periphery*. The 3-km threshold is intended to delineate a highly accessible, service-rich core from the

Figure 4.2: Evolution of differences in rents by area in Milan from the city center

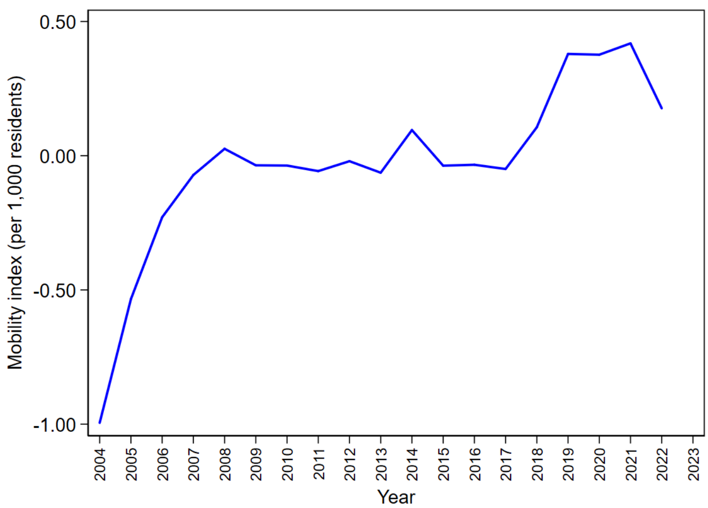


The graphs were produced using official data from the Italian Real Estate Market Observatory (OMI): agenziaentrate.gov.it.

outer urban belt; its robustness can be assessed with alternative cut-offs. For each zone we calculate a registration rate (inflows excluding births divided by resident population) and define the Displacement Index as the periphery rate minus the centre rate. Positive values indicate more registrations per capita in the periphery than in the centre; negative values indicate the opposite. Figure 4.3, depicting the time path of the index, shows predominantly negative values over 2004 -2013. A temporary inversion appears in 2014 - signalling a short-lived tilt towards the periphery - followed by a reversion in 2015. These oscillations may reflect transitory dynamics and anticipatory behaviour around events whose effects are heterogeneous or lagged (e.g., the preparatory phase and subsequent impact of Expo 2015 on housing and residential choices). From 2019 onwards the index rises sharply and remains elevated during 2020–2021, indicating that the periphery attracted substantially more registrations per capita than the centre - an evident phase of net outward relocation. This pattern aligns with two classes of factors highlighted in the literature: (i) intensified rent pressures and a widening rent gap in the core - amplified by the spread of short-term rentals -making peripheral areas a “reserve” option for households (Aalbers, 2017; Amore et al., 2022); and (ii) preference and behavioural shocks associated with the COVID-19 pandemic, notably increased demand for larger dwellings, lower-density environments, and the diffusion of remote work, which reduced the need to reside near the workplace (2020–2021) (Mondragon and Wieland, 2022).

In conclusion, the evidence indicates a recent spatial reconfiguration of housing demand in Milan. Rising prices and rents in the core - together with the diffusion of short-term rentals and pandemic - related preference shifts - coincide with a phase in which population-normalised registrations point to a greater propensity to settle in peripheral areas. This dynamic carries potential social implications: the growing attractiveness of outer areas may have divergent effects, either amplifying local vulnerabilities and weakening support networks or, conversely, improving safety and quality of life when matched by adequate services and investment. However, on current evidence, and in the absence of crime data broken down by district in Milan, it is not yet possible to assert a tangible change in the security conditions of peripheral neighbourhoods; these remain plausible hypotheses that require rigorous empirical verification.

Figure 4.3: Evolution of the difference index of registry entries for Milan



The index represents the difference between registry entries in peripheral areas and those in the city center, both normalized by the resident population. Data are sourced from the official database of the Municipality of Milan: dati.comune.milano.it.

4.8 Final remarks

The analyses presented in this chapter and in the previous chapter examined, using an integrated approach and EU-SILC microdata for Italy (2004–2023), two closely related relationships in the urban housing market: (i) the relationship between rent levels and perceived crime in the area of residence; and (ii) the role of rent levels in households' decisions to relocate among renters.
The main empirical findings are clear and consistent. Higher rent levels increase the probability of moving - an effect that remains positive and statistically significant after corrections for selection and across robustness checks, including an instrumental variable probit that confirms the absence of endogeneity bias - while the exogenous component of rent, estimated via instrumental-variables procedures, is associated with a lower probability of reporting crime problems. Moreover, among households that do relocate, pre-move rent levels are strongly and negatively associated with post-move rent changes, while household income shows the opposite effect: lower-income movers tend to move toward cheaper dwellings, while higher-income households maintain or upgrade their rental expenditure. Conversely, regressions that take the natural logarithm of rent as the dependent variable indicate that higher perceptions of insecurity are reflected in lower average rents.
A joint interpretation of these results points to several non-mutually exclusive mechanisms. First, price pressures in the urban core operate as a push factor, displacing economically vulnerable households and thereby contributing to the spatial persistence of inequality and local vulnerability. Second, there is a cost–safety trade-off: cost-driven moves can lead households to settle in neighbourhoods with worse perceived conditions. Third, the observed "seniority" (length of residence) effect indicates that greater attachment to place reduces mobility but may increase exposure to local problems and sensitivity to contextual deficiencies, translating into higher perceived insecurity among more long-standing residents. These mechanisms are aligned with empirical and theoretical contributions on displacement, touristification and the financialization

of housing markets (Aalbers, 2017; Barron et al., 2021; Amore et al., 2022). The Milan case study corroborates the practical relevance of these findings. Analysis of OMI rental quotations and of the displacement index constructed from administrative registration data shows a recent phase (2019–2021) of net outward movement, in a context where semi-central and sub-peripheral areas have experienced divergent rent dynamics - phenomena likely amplified by short-term rentals and by pandemic-related shifts in preferences (Amore et al., 2022; Cocola-Gant and López-Gay, 2020). Such an urban pattern entails a concrete risk of concentrated vulnerability if residential flows are not accompanied by supply-side policies and investments in local services.

On the basis of these considerations, clear policy implications emerge: (i) regulate and monitor short-term rentals to limit the conversion of long-term housing into tourist accommodation and thereby mitigate the rent gap in central neighbourhoods (Barron et al., 2021; Amore et al., 2022); (ii) implement eviction-prevention instruments and targeted support for cost-burdened renters (e.g. targeted subsidies, tenancy mediation programmes); (iii) invest in services and infrastructure in peripheral areas to prevent outward flows from producing degradation or concentrated vulnerability; and (iv) promote integrated territorial policies that connect housing, mobility and urban safety strategies.

Finally, the study identifies concrete avenues for future research: merge EU-SILC with administrative datasets on criminal offenses and evictions to distinguish perception from reality; adopt event-study or difference-in-differences designs to evaluate the effects of localized shocks (e.g. the introduction of Airbnb regulations, anti-eviction policies, major events, new construction, or university decentralization); develop spatial and network models to capture diffusion and concentration of effects across territories; and conduct qualitative research to document cost-related movers' lived experiences and the role of social networks in household adaptation processes.

In sum, this work shows that rising rents are an important driver of the spatial reconfiguration of housing demand and that the relationship between rents and perceived crime is robust and bidirectional. Effective policy must therefore operate on multiple levels - combining supply-side interventions, regulation of short-term markets and investments in local services - to prevent the spatial reshuffling of demand from translating into weakened social cohesion and concentrated vulnerability in peripheral neighbourhoods.

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APPENDIX D

Table D.4: Variance Inflation Factors (VIF)

	No *seniority*		With *seniority*	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**
Rent	1.31	0.764	1.36	0.734
Income (centered)	1.25	0.797	1.27	0.789
Apartament in a big bulding	2.53	0.395	2.43	0.412
Apartament in a bulding	2.38	0.421	2.27	0.440
Detached	1.48	0.674	1.45	0.689
Family size	2.03	0.491	2.05	0.488
Rooms for members	1.80	0.556	1.86	0.539
Cities	1.28	0.780	1.30	0.769
Rural areas	1.23	0.815	1.23	0.812
Market price	1.28	0.781	1.31	0.763
Car	1.20	0.836	1.21	0.828
Seniority	—	—	1.19	0.841
Work change	1.09	0.918	1.14	0.880
Chronic diseases	1.08	0.930	1.11	0.897
New birth	1.03	0.973	1.03	0.968
Widowed	1.01	0.993	1.01	0.987
Wedding	1.01	0.994	1.01	0.993
Separation or divorce	1.00	0.996	1.00	0.996
Housing discomfort	1.01	0.994	1.01	0.992
Mean VIF	1.39		1.38	

Notes: The columns on the left refer to the model without seniority, those on the right to the model with seniority. The values of 1/VIF are the reciprocal of the VIFs. Figures rounded.

Table D.5: The determinants of family relocation - Logistic regression

	(1)	(2)	(3)	(4)
Personal characteristics				
Rent	0.298***	0.597***	0.636***	0.564***
	(0.0797)	(0.0723)	(0.0745)	(0.0751)
Family income (centered)	−0.103**	−0.163***	−0.199***	−0.181***
	(0.0517)	(0.0463)	(0.0436)	(0.0466)
Seniority	−0.071***	—	—	—
	(0.0058)			
Family size	−0.101**	−0.162***	−0.079**	−0.149***
	(0.0413)	(0.0399)	(0.0390)	(0.0405)
Chronic diseases	−0.020	−0.228***	−0.024	−0.236***
	(0.0852)	(0.0814)	(0.0809)	(0.0815)
Car	0.153	0.176*	0.186**	0.171*
	(0.0956)	(0.0906)	(0.0888)	(0.0906)
Market price	0.226	0.248*	−0.558***	0.271*
	(0.1563)	(0.1439)	(0.0778)	(0.1449)
Life cycle events				
New birth	0.576***	0.831***	1.030***	0.814***
	(0.1630)	(0.1614)	(0.1599)	(0.1619)
Wedding	0.556***	0.708***	0.869***	0.709***
	(0.2052)	(0.2010)	(0.1979)	(0.2012)
Separation or divorce	1.261***	1.277***	1.466***	1.289***
	(0.2574)	(0.2514)	(0.2463)	(0.2521)
Widowed	0.352	0.104	0.153	0.105
	(0.4174)	(0.4028)	(0.3940)	(0.4036)
Work condition change	0.226**	0.232***	0.290***	0.238***
	(0.0898)	(0.0858)	(0.0758)	(0.0859)
Housing characteristics				
Rooms for members	−0.133**	−0.251***	−0.239***	−0.248***

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Table D.5 – *The determinants of family relocation - Logistic regression*

	(1)	(2)	(3)	(4)
	(0.0607)	(0.0572)	(0.0562)	(0.0573)
Housing discomfort index	0.034^{**}	0.042^{***}	0.030^{**}	0.042^{***}
	(0.0149)	(0.0147)	(0.0142)	(0.0147)
Detached (vs Semi-detached)	0.029	-0.045	-0.138	-0.044
	(0.1549)	(0.1501)	(0.1481)	(0.1503)
Apart. in a building (vs S.-detached)	-0.163	-0.173^{*}	-0.290^{***}	-0.180^{*}
	(0.1086)	(0.1037)	(0.1022)	(0.1039)
Apart. in a big building (vs S.-detached)	-0.130	-0.232^{**}	-0.321^{***}	-0.240^{**}
	(0.1150)	(0.1101)	(0.1087)	(0.1105)
Area characteristics				
Cities (vs Towns and suburbs)	-0.194^{**}	-0.362^{***}	-0.240^{***}	-0.342^{***}
	(0.0858)	(0.0803)	(0.0796)	(0.0817)
Rural areas (vs Towns and suburbs)	-0.301^{***}	-0.209^{*}	-0.113	-0.206^{*}
	(0.1149)	(0.1085)	(0.1069)	(0.1086)
Fixed effects				
Year fixed effects	Yes	Yes	No	Yes
Area (NUTS1) fixed effects	Yes	No	Yes	Yes
Observations	17,771	21,237	21,237	21,237

Notes: Standard error in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. In model (1), the seniority variable was used among the regressors, therefore the years from 2021 to 2023 were excluded due to the unavailability of the variable in those years. Models (2), (3), and (4) test different fixed effects configurations.

Table D.6: The determinants of family relocation - Firth logistic regression by family type

	Single (no children)	Single (with children)	Couple (no children)	Couple (with children)
Personal characteristics				
Rent	0.586***	0.480**	0.661***	0.515***
	(0.140)	(0.213)	(0.171)	(0.132)
Family income (centered)	−0.083	−0.352***	−0.160	−0.155
	(0.0856)	(0.1032)	(0.1387)	(0.0961)
Family size	—	−0.121	—	−0.262***
		(0.179)		(0.079)
Chronic diseases	−0.381**	−0.254	0.153	−0.187
	(0.162)	(0.231)	(0.177)	(0.139)
Car	0.448***	−0.210	−0.225	0.212
	(0.143)	(0.237)	(0.212)	(0.207)
Market price	−0.219	1.247**	0.456	0.217
	(0.238)	(0.528)	(0.342)	(0.245)
Life cycle events				
New birth	0.361	0.906	1.451***	0.647***
	(0.929)	(0.608)	(0.379)	(0.194)
Wedding	1.475***	0.510	0.472	0.399
	(0.336)	(0.539)	(0.453)	(0.405)
Separation or divorce	1.903***	0.151	1.330**	1.290***
	(0.655)	(0.734)	(0.530)	(0.446)
Widowed	0.397	0.944	−0.144	0.003
	(0.919)	(0.937)	(0.688)	(0.692)
Work condition change	0.113	0.326	0.400*	0.146
	(0.167)	(0.244)	(0.191)	(0.147)
Housing characteristics				
Rooms for members	−0.217***	−0.474*	−0.318*	−1.005***

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Table D.6 – *The determinants of family relocation - Firth logistic regression by family type*

	(1)	(2)	(3)	(4)
	(0.073)	(0.268)	(0.184)	(0.248)
Housing discomfort index	0.066***	0.011	0.027	0.066
	(0.015)	(0.047)	(0.049)	(0.055)
Detached (vs Semi-detached)	−0.074	0.530	−0.134	−0.094
	(0.305)	(0.391)	(0.343)	(0.237)
Apart. in a building (vs S.-detached)	−0.093	−0.100	−0.415*	−0.146
	(0.189)	(0.312)	(0.242)	(0.169)
Apart. in a big building (vs S.detached)	−0.136	−0.207	−0.474*	−0.279
	(0.202)	(0.329)	(0.250)	(0.184)
Area characteristics				
Cities (vs Towns and suburbs)	−0.345**	−0.694***	−0.217	−0.320**
	(0.147)	(0.240)	(0.188)	(0.139)
Rural areas (vs Towns and suburbs)	−0.091	−0.742**	−0.179	−0.209
	(0.187)	(0.349)	(0.277)	(0.176)
Fixed effects				
Year fixed effects	Yes	Yes	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes	Yes	Yes
Observations	7,760	2,887	3,534	6,399

Notes: Standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table D.7: The determinants of family relocation – Probit vs Heckman selection

	(1) Probit	(2) Heckman (selection)
Personal characteristics		
Rent	0.275***	0.259***
	(0.0284)	(0.0371)
Family income (centered)	−0.051**	−0.066**
	(0.0203)	(0.0262)
Family size	−0.056***	−0.080***
	(0.0162)	(0.0197)
Chronic diseases	−0.145***	−0.094**
	(0.0339)	(0.0412)
Car	0.158***	0.098**
	(0.0377)	(0.0465)
Life cycle events		
New birth	0.495***	0.394***
	(0.0718)	(0.0893)
Wedding	0.409***	0.390***
	(0.0870)	(0.1181)
Separation or divorce	0.563***	0.637***
	(0.1283)	(0.1692)
Widowed	−0.061	0.022
	(0.1848)	(0.2114)
Work condition change	0.103***	0.128***
	(0.0346)	(0.0428)
Housing characteristics		
Rooms for members	−0.088***	−0.114***
	(0.0219)	(0.0272)
Housing discomfort index	0.016**	0.023***
	(0.0069)	(0.0073)

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Table D.7 – *The determinants of family relocation – Probit vs Heckman selection*

	(1) Probit	(2) Heckman (selection)
Detached	-0.030	-0.054
(vs Semi-detached or terraced house)	(0.0621)	(0.0777)
Apartment in a building	-0.059	-0.083
(vs Semi-detached or terraced house)	(0.0425)	(0.0527)
Apartment in a big building	-0.109^{**}	-0.122^{**}
(vs Semi-detached or terraced house)	(0.0453)	(0.0563)
Area characteristics		
Cities	-0.165^{***}	-0.134^{***}
(vs Towns and suburbs)	(0.0330)	(0.0411)
Rural areas	-0.085^{*}	-0.045
(vs Towns and suburbs)	(0.0436)	(0.0540)
Fixed effects		
Year fixed effects	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes
_cons	-2.721^{***}	-2.633^{***}
	(0.1798)	(0.2661)
ρ		-0.0382072
		(0.323)
Observations	21,237	21,237

Notes: Standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table D.8: IV-Probit robustness check

	Firth (main)	IV-Probit
Personal characteristics		
Rent	0.561***	0.538
	(0.075)	(0.349)
Family income (centered)	−0.182***	−0.086*
	(0.046)	(0.050)
Family size	−0.147***	−0.066***
	(0.040)	(0.021)
Chronic diseases	−0.234**	−0.106
	(0.081)	(0.064)
Car	0.169*	0.129**
	(0.090)	(0.056)
Life cycle events		
New birth	0.817***	0.463***
	(0.161)	(0.088)
Wedding	0.718***	0.390***
	(0.199)	(0.092)
Separation or divorce	1.298***	0.537***
	(0.249)	(0.134)
Work condition change	0.237**	0.105***
	(0.086)	(0.034)
Housing characteristics		
Rooms per member	−0.246***	−0.108***
	(0.057)	(0.035)
Housing discomfort index	0.044**	0.016**
	(0.014)	(0.008)
Apartment in a big building (vs Semi-detached or terraced house)	−0.240**	−0.119**
	(0.110)	(0.046)

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Table D.8 – *IV-Probit robustness check*

	Firth (main)	IV-Probit
Area characteristics		
Cities (vs Towns and suburbs)	-0.341^{***}	-0.196^{***}
	(0.081)	(0.051)
Diagnostics		
ρ (corr. error terms)	—	-0.135
		(0.181)
First-stage F-statistic	—	229.45
Wald test of exogeneity (p-value)	—	0.462
Year fixed effects	Yes	Yes
Area (NUTS1) fixed effects	Yes	Yes
Observations	21,237	23,034

Notes: Standard errors in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. The IV-Probit instruments individual rent with the leave-one-out mean rent computed within cells defined by region, population density and year. The Firth estimates correspond to model (4) of Table 4.2.

CONCLUSIONS

This dissertation provides an integrated and nuanced account of the relationships among organized crime, the functioning of local markets, and transformations in the housing market, highlighting not only the immediate economic effects but also the spatial, social, and institutional mechanisms that amplify or mitigate them. Below I summarize the main interpretative findings, accompanied by a brief note on the methods used in each chapter.

- Chapter 1 - Mafia and regional innovative capacity

  The first chapter demonstrates that mafia presence is not homogeneous: it manifests differently according to a territory's history and economic structure and, consequently, produces correspondingly varied effects on local innovation. In historically entrenched areas, mafia organizations exercise control and forms of power that compress entrepreneurial initiative, rendering innovation potentially disruptive to the predatory equilibrium; conversely, in areas where infiltration is more recent or of an "integrative" type, criminal groups penetrate production networks, distort incentives, and can give rise to apparently positive but fragile forms of development grounded in illicit capital and collusive relations. In both settings, mafia presence reshapes market signals, impedes the accumulation of stable human and social capital, and distorts trajectories of territorial specialization. Methodologically, the chapter relies on a provincial-level analysis, constructs a composite mafia-presence index, and employs GMM estimators (System and Difference GMM) to address endogeneity and temporal dynamics; this strategy allows the capture of persistence and spatial heterogeneity processes that would be obscured at higher aggregation levels.

- Chapter 2 - Local effects of judicial administration on legitimate firms

  The second chapter examines the micro-territorial consequences of public interventions against mafia-controlled firms and shows that judicial action, while aimed at disrupting illicit networks, produces ambivalent short-term effects in local markets: neutralizing firms under mafia control can cause interruptions of informal services, transition costs, and temporary contractions in sales and employment among neighboring legitimate firms, yet it also opens space for competition and the potential virtuous reconfiguration of markets over longer horizons or across larger territorial scales. The evidence therefore suggests that intervention policies should be accompanied by support measures for legitimate firms and targeted spatial monitoring to avoid undesirable side effects. On the methodological side, the analysis uses a firm-level panel (AIDA), defines territorial proximity with precise spatial criteria (a 10-km threshold), and combines propensity score matching with dynamic impact-evaluation designs (event study and a dynamic diff-in-diff with a continuous treatment), an approach that permits estimation of localized and graduated effects of judicial intervention while acknowledging limits arising from potential anticipation of investigations and identification of crime-linked firms.

- Chapter 3 - Rents and perceived safety: feedbacks and inequalities

  The third chapter foregrounds subjective and market dimensions: the relationship between rent levels and perceived safety is bidirectional and constructs a geography of fear that overlays socio-economic fault lines. Rents capitalize local qualities - services, informal surveillance, public and private investment - that reduce perceived insecurity; at the same time, increases in actual or perceived crime lower willingness to pay and can trigger processes of decline and stigmatization. Importantly, perceptions are heterogeneous: more vulnerable households and, in different ways, wealthier households may both exhibit heightened sensitivity to risk, producing opposing but convergent effects on urban polarization. Methodologically, the chapter draws on EU-SILC microdata and integrates tools to address simultaneity and selection: IV (2SLS) models with theoretically motivated instruments (contract type, dwelling size, housing deprivation indices) and Heckman selection corrections for the subsample of renters, thereby more credibly isolating the relationship between price and perception.

- Chapter 4 - Price pressures, residential mobility, and vulnerability

  The final chapter describes how upward pressure on housing costs acts as a driver of spatial reorganization: rising central rents push the most cost-burdened households outward, weakening support networks and amplifying signs of deterioration in receiving areas. Mobility choices are primarily driven by life-cycle events (births, marriages, separations), but they are also sensitive to cost pressures; residential "seniority" produces a dual effect, reducing the propensity to move while increasing exposure and sensitivity to local problems, with a lag in the formation of perceptions. The Milan case study corroborates the concrete risk of concentrated vulnerability when residential flows occur without accompanying housing and service policies. Methodologically, this chapter exploits the EU-SILC panel and employs models suited to relatively rare events and to reducing separation bias (Firth penalized logistic regression), controlling for a rich set of demographic, housing, and territorial variables; for the urban case, it also integrates local administrative sources (OMI rental quotations, displacement indices) to link micro evidence to the urban context.

Policy implications and new horizons for research

Studies highlight how organized crime can assume a decisive - and sometimes regulatory - role within the economic contexts where it operates. To curb mafia infiltration of markets, the Italian legal framework has developed instruments that fall broadly into two categories: ex ante measures, designed to reduce the risk of criminal penetration, and ex post measures, aimed at limiting the damage and coercively removing mafia activity.

The instrument of judicial administration, examined in detail in Chapter 2, is intended as an ex ante intervention in the so-called "gray area" of firms. Specifically, it targets entrepreneurs who, while initially legitimate, have over time shown themselves to be conditioned or infiltrated by organized crime. Its purpose is therefore preventive rather than purely punitive, unlike confiscation or seizure: judicial administration seeks to extract such firms from mafia influence as swiftly as possible and to return them to the legal market once they have been cleansed of contaminating elements.

By contrast, instruments aimed at repressing and removing mafia infiltration from the market follow a different logic. This category includes judicial confiscation, whose goal is to prevent illegally accumulated mafia capital from being reinvested - whether into illicit activities or into ostensibly legal enterprises - in ways that distort normal market functioning. These firms had been able to survive thanks to competitive advantages conferred by the protective umbrella of the mafia. Once that protection is removed, their decline often appears inevitable: after an anti-mafia intervention, such firms typically must rebuild from scratch their networks of suppliers, partners, and clients in a market environment constrained by low levels of generalized trust and by pronounced institutional instability associated with entrenched organized crime.

As shown in previous chapters, in markets where the mafia systematically regulates market mechanisms and strategies (as in provinces characterized by traditional infiltration), the removal or disruption of mafia influence produces ambivalent effects on the networks of proximity immediately surrounding the "sanitized" firms. The measures adopted by the Italian political system appear, to some extent, to be informed by an idealistic stance according to which assets seized from mafia control tend to be valued primarily for their symbolic significance (Sciarrone, 2024). The symbolic dimension, while unquestionably important, must not become an end in itself. This risk materializes when confiscated assets are preserved with an almost museal logic - as if they were a warning - without fully exploiting the economic potential of the firms to which those assets have been returned (Sciarrone, 2024). The underlying premise is that concrete examples of firms that have successfully exited the mafia circuit and subsequently prospered can play a catalytic role by demonstrating that non-cooperation with criminal organizations is a viable path to development. To effectively intervene in the "gray areas," therefore, systemic measures are required to sever the ties between the licit economy and illicit activity, leveraging what appears to be the only sustainable strategy to reduce mafia influence: non-cooperation with mafias (Crouch and Galesm, 2001). It must nevertheless be acknowledged that negotiations between economic actors and criminal groups often produce materially attractive outcomes for both parties, rendering the decision not to cooperate rationally less appealing (Pezzino, 1992). Doing business inherently involves weaving social relations and complex forms of cooperation and competition; accordingly, building relational capital grounded in non-opportunistic interactions - both among entrepreneurs and between firms and institutions - can act as a counterweight to predatory ties with mafias. Among the levers that can facilitate the emergence of legal networks and raise the expected payoff of non-cooperation for local operators are, first, stable and predictable institutional arrangements that mitigate the asymmetric outcomes of cooperative choices (for example, by ensuring that actors who bear substantial conversion costs obtain favorable bargaining positions in subsequent rounds); and second, the involvement of external, authoritative institutional actors that function as guarantors of trust and reputation, channeling operators toward more remunerative and secure forms of cooperation. In essence, non-cooperation rests on a shared stock of information, practices, and incentives that makes the alternative to collusion credible; the diffusion of such practices fosters an environment more conducive to innovation and economic development, but this process is slow and requires broad participation by local actors. For this reason, the strategy must be conceived as a programmatic, sustained process - not a moralizing appeal - capable of building trust and of pragmatically distinguishing degrees of compromise within the spectrum of "gray" behaviors.

Finally, although the topics of mafia presence and the housing market were treated separately in the chapters, both the empirical findings presented here and the literature (Calamunci et al., 2022) indicate a close interdependence. The table on firms under judicial administration shows that a substantial share of those firms operated in the real estate sector, corroborating the evidence reported by Transcrime (2013). Recent contributions (Calamunci et al., 2022) further point to a potential linkage between mafia presence and real estate market dynamics, yet this remains a research strand in the process of consolidation - insufficiently structured and clear to support well-founded policy prescriptions. Deepening the analysis of the connections between organized crime and real estate markets, or between mafias and the construction sector, would help clarify how organized crime shapes urban development processes and territorial transformation, particularly in areas characterized by a long history of mafia control.

To the extent permitted by the available evidence, the empirical findings presented here clearly indicate that isolated policies or simplistic analyses are inadequate to the task of promoting healthy development in territories with high levels of mafia infiltration. In particular, with respect to the dynamics of large organized crime, both overly pessimistic framings (such as those discussed in the introduction that portray crime as inevitable or mafias as globalizing) and naively optimistic narratives that proclaim the irretrievable decline of mafias are counterproductive (Sciarrone, 2002). As Amartya Sen observes, "a cognitive failure can arise as much from unreasonable optimism as from unfounded pessimism, and, strangely, the two attitudes sometimes interact." Sen goes on to note that the chronic pessimist and the incorrigible optimist may converge in the same outcome, resignation, since "the latter believes resistance unnecessary, the former believes it futile" (Sen, 2002).
From this warning follows a clear operational implication: analysis of the phenomenon must avoid such cognitive failures and be grounded in rigorous di-

agnosis, the design of coherent instruments, and the implementation of coordinated, long-term policies capable of capturing both the mutability and the resilience of criminal organizations, as well as their capacity to infiltrate licit economic circuits - including the real estate market. Only an analytical approach rooted in empirical realism and operational resolve can help break the links that tie illegality, housing exclusion, and territorial decline, thereby restoring to communities firmer prospects for development, social cohesion, and safety.

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