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Abstract

Infiltration of the legal economy by criminal organizations (OCGs) is potentially significant, though how pervasive remains uncertain. Beyond the volume, the motives driving infiltration are of serious policy concern. We introduce a conceptual framework to differentiate between OCGs' motives for infiltrating legal firms and validate it using new data from the Italian Financial Intelligence Unit. About 2% of Italian firms appear to have links with OCGs, with three primary motives. Firms established by OCGs are predominantly used for criminal activities (functional motive). Medium-sized firms, often infiltrated post-creation, primarily reflect a competitive motive, wherein criminal activities benefit the firm. Lastly, large, well-established firms remain separate from criminal activities and are used for pecuniary and non-pecuniary returns, such as to establish political connections (pure motive). This so far unnoticed motive accounts for a substantial share of OCGs' infiltration.

JEL-Codes: G300, L200, K400.

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1 Introduction

The United Nations estimates the proceeds from organized criminal activities at USD 2.1 trillion, or 3.6% of global GDP (UNODC, 2011). Economics logic suggests that organized crime groups (OCGs) face limits to the reinvestment of criminal profits into the criminal industry.[1] This implies that the share of the legal economy infiltrated by OCGs is potentially substantial, though how large remains to be established. Perhaps more importantly than its volume, the *motives* of infiltration are also a matter of interest as they may affect the type of policies necessary to deter organized crime. The relevance notwithstanding, empirical progress on this front has been hindered by serious challenges. Besides well-known data limitations (OCGs' activities are notoriously difficult to measure), the motives of OCGs' infiltration into the legal economy are not observable: hence, must be inferred from observable behavior. This requires a conceptual framework tailored to the available data.

This paper makes progress in providing new, more reliable evidence on the pervasiveness of organized crime groups' (OCGs) infiltration into the legal economy and, crucially, examines the motives behind such infiltration. We do so in the Italian context where leading OCGs originate and unique information is available. We develop a new conceptual framework for OCGs' infiltration of legal firms. The model delivers a rich set of testable predictions that allow us to map the firm's observable behavior to a wide range of underlying motives of infiltration. Although the conceptual framework can be applied to other countries, the endemic presence of OCGs and a sophisticated legal and institutional apparatus to fight them, make Italy an ideal setting for our analysis. In particular, we leverage the *Mappatura*, a new and highly confidential dataset assembled, and used, by the Financial Intelligence Unit of the Bank of Italy to map OCGs' investments in legal firms in Italy.[2] Over our sample period, the *Mappatura* identifies around 100,000 legal firms, approximately 2% of all Italian corporations and partnerships, as potentially connected to OCGs. Although, by its nature, we can never be certain to have a perfectly accurate map of OCGs' investments in legal firms, the *Mappatura* arguably represents

[1]For example, OCGs cannot spend significant resources on advertising to acquire new customers without increasing the risk of detection and must rely on a few trusted intermediaries to conduct their criminal business.

[2]Because of the classified nature of the underlying data, *none* of the authors had access to the list of individuals leading to the inclusion of firms in the *Mappatura* and only one author, affiliated with the Financial Intelligence Unit, had access to the firm-level data (see fn 13 for further details).

the most comprehensive attempt ever undertaken. This large sample of infiltrated firms is essential to uncover the broad set of motives identified by our conceptual framework.

Our main contribution is to uncover a previously unnoticed motive of infiltration and to show that it accounts for a sizeable share of OCGs' infiltration. Traditionally, both the legislator and the existing literature have assumed that the infiltrated firm is either used for criminal activities (e.g., to facilitate money laundering) or to benefit from criminal activities (e.g., threats to competitors to acquire market shares).[3] In both cases, the firm is directly "contaminated" by OCGs' criminal activities. Alongside these traditional motives of infiltration, our conceptual framework highlights – and the analysis of the *Mappatura* supports – a novel infiltration motive in which the legal firm is *not* directly involved in criminal activities. In this motive – which we label "pure" to distinguish it from the various "contaminated" motives – OCGs infiltrate firms to obtain financial returns or other private benefits, such as connections to politicians, which may be valuable for the OCG. As we will discuss, this new perspective on OCGs' infiltration of legal firms has important policy implications.

Section 2 presents the construction of the *Mappatura* in detail, alongside a discussion of its advantages and limitations. In a nutshell, the *Mappatura* starts with a highly confidential list of individuals who are under investigation for mafia-related crimes (or are reported in judicial documents connected, directly or indirectly, to mafia-related crimes) and have been under scrutiny by the Financial Intelligence Unit. Following the literature, we define infiltration of an OCG into a legal firm as "any case in which a natural person belonging to a criminal organization or acting on its behalf, or an already infiltrated legal person, invests financial and/or human resources to participate in the decision-making process of a legitimate business" (Transcrime, 2017, p.19). The key feature of this definition is that a person tied to an OCG plays an active role in the decision process of a legal firm. Hence, in our baseline definition, a firm is infiltrated if it has at least an owner *or* an administrator on the highly confidential list of individuals described above.[4]

[3] For example, the article 416-bis of the Italian *Codice di Procedura Penale* defines the infiltrated firm as one that benefits from the intimidation force of the criminal organization to acquire, directly or indirectly, economic benefits. The 1967 Taskforce of the President on Organized Crime (which led to the Racketeer Influenced and Corrupt Organizations (RICO) Act – the legal backbone for prosecuting organized crime in the U.S.), defines the provision of illicit goods and services as OCGs core activities, whereas when OCGs "turn to legitimate business, they terrorize, blackmail, and monopolize." (Schelling, 1971, p. 180).

[4] The accrual of financial resources is thus not a necessary condition for infiltration.

Section 3 attempts to quantify the extent of OCGs' infiltration into Italian legal firms. The *Mappatura* identifies more than 100,000 infiltrated firms over our sample period. These represent around 2% of all corporations and partnerships in Italy. The percentages in terms of private sector employment and revenues are significantly larger. Although the incidence of infiltrated firms is higher in the South, where the most important Italian OCGs originate, the majority of infiltrated firms are located in the economically more prosperous Northern regions. It is worth emphasizing that the firms included in the *Mappatura* are managed or owned by subjects of *potential* interest for anti-mafia magistrates and investigators, i.e. they cannot be deemed with certainty to be infiltrated or controlled by or linked to organized crime (a circumstance that can only be ascertained at the end of a judicial procedure). Furthermore, the infiltration of legal firms is likely not the main form of investment in legal assets by OCGs in Italy.[5] Still, these figures suggest that legal firms' infiltration by, or collusion with, OCGs is a pervasive phenomenon in Italy.

Section 4 presents our conceptual framework of the different motives behind OCGs' infiltration in legal firms. The model builds from a simple trade-off. An OCG investing in a legal firm must decide whether to contaminate the firm with illegal activities or not. For example, in what we label the *functional* motive, the OCG exploits the legal firm to conduct criminal activities (e.g., as in the case of firms used for money laundering). In what we label the *competitive* motive, instead, the OCG uses criminal activities to support the legal firm (e.g., as in the case of a construction firm that wins public procurement contracts through corruption). In both cases, the OCG benefits from directly contaminating the operations of the legal firm in its criminal activities. This benefit, however, comes at the cost of a higher risk of detection and confiscation of the legal firm. There is thus an alternative motive – which we label *pure* investment – in which the OCG keeps separate the legal firm from its illegal activities. In this case, the OCG benefits either because the legal firm provides higher financial returns and/or private benefits that the OCG leverages to support other, potentially criminal, activities in which the firm is not directly involved. For example, the OCG can use its involvement in the firm to acquire information about other potential investment opportunities or to develop relationships with politicians, administrators, etc.[6]

[5]While precise figures are unavailable, we estimate that legal firms constitute only 10-20% of the total value of assets confiscated to Organized Crime Groups (OCGs) in Italy.

[6]There is nothing pure about this motive: the individuals involved are criminals. Conceptually, the *pure* motive is distinct from money laundering, which is a crime, and thus belongs to

The model yields a rich set of predictions. First, the motives of infiltration can be distinguished in the data. Relative to a similar firm that is not infiltrated by the OCG, the scale of operation of the firm is distorted in the *functional* and *competitive* motives, but not in the *pure* investment. External sources of finance accrued at infiltration tend to be substituted with internal ones in the *pure* motive but not (necessarily) in the two other motives. Second, the model delivers a characterization of the firms in which we expect to detect the behaviors associated with the different motives: small firms are used to conduct illegal activities (*functional* motive), medium-sized firms benefit from criminal activities (*competitive* motive), the largest firms are kept separate from criminal activities (the *pure* motive).

Section 5 leverages the *Mappatura* to test the main predictions of the model and infer the relative prevalence of the different motives in the data. Firms identified in the *Mappatura* are roughly split in half between "born-infiltrated" (i.e., in which the presence of the individual tied to the OCG is detected at birth) and "born-clean" (i.e., in which the entry in the firm of the individual connected to an OCG occurs at a later date). This distinction is appealing both on conceptual and empirical grounds. On the conceptual front, the model suggests that the two types of infiltrated firms respond to different motives: "born-infiltrated" firms are smaller than "born-clean" firms, and, therefore, they are more likely to reflect the riskier *functional* or *competitive* motives relative to "born-clean" firms. Consistent with this hypothesis, born-infiltrated firms present traits that are characteristic of firms more directly connected to criminal activities: relative to born-clean firms, they are more prevalent in the home regions of the main OCGs and, more generally, in areas with weaker institutions, and are more likely to be confiscated by judicial authorities. This gives us some confidence that the distinction between born-clean and born-infiltrated firms captures different underlying motives. On the empirical front, the two groups of infiltrated firms differ in the empirical strategies available to construct a suitable control group of non-infiltrated firms. We thus organize the empirical analysis separating "born-clean" and "born-infiltrated" firms.

We consider "born-clean" firms first. Because these firms are infiltrated after birth, the infiltrated firm is observed both before and after infiltration. This allows us to compare changes in a firm's outcomes around the time of infiltration relative to a control group within a staggered DID framework. Because infil-

the *functional* motive. To the extent that the OCG invests funds in the firm, in the *pure* motive those have been cleaned at a previous stage not involving the legal firm itself.

tration occurs, by definition, at the same time as a change in at least an owner or an administrator, we compare firms that become infiltrated to those that also experience a similar change. On average, we find that infiltration of born-clean firms is not associated with significant changes in revenues and the scale of operation, but is associated with a substitution of the sources of finance away from bank loans. While new shareholders and administrators in non-infiltrated legal firms attract more bank funding, infiltration results in a significant accrual of liquidity and a reduction in funding from banks. Infiltration is preceded by a decrease in a firm's cash flows and liquidity which is absent in non-infiltrated legal firms before the entry of a new shareholder or administrator. This suggests that OCGs might target legal firms that are suffering a liquidity shortage. Once infiltration occurs, however, liquidity is so abundant that loans from banks – which are more intrusive (and possibly more expensive) – become less appealing and are discontinued or less utilized. Interpreted through the lens of the model, these results suggest that these firms predominantly respond to a *pure* investment motive. The average behavior, however, masks significant heterogeneity. In line with the model, we also find that smaller "born-clean" firms do feature an expansion in the scale of operation of the firm, consistent with a *competitive* motive.

We then turn to born-infiltrated firms. The model predicts that OCGs that want to use the legal firm to conduct illegal activities (*functional* motive) have a strong incentive to privilege this mode of infiltration, as the expected costs of confiscation are reduced by entering small. Consistent with the model, relative to newly-created legal firms born in the same province, sector, and cohort, "born-infiltrated" firms start with a larger scale of operation but have lower profitability and productivity.

Finally, Section 6 provides further results coherent with our interpretation of the evidence and discusses policy implications. Our distinction between motives for infiltration departs from the dominant idea in the literature that infiltration always brings with it criminal activities (the *functional* and *competitive* motives). Our evidence suggests that this characterization is predominant only in smaller and medium-sized firms, often directly established by the OCGs. Many infiltrated firms, however, are large and already well-established at the time infiltration takes place. In these firms, infiltration mostly reflects the *pure* motive in which the OCG is either seeking safe financial returns, or other private benefits that can be acquired by being involved in the operation of large firms. Since "born-clean" firms account for 85 percent of the total assets of infiltrated firms, this suggests that the previously undetected *pure* motive is an extremely important, if not the predominant, motive of infiltration.

The distinction also has policy implications. The optimal allocation of scarce resources to fight organized crime and the design of both monitoring and leniency programs and screening algorithms depend on the extent to which OCGs involve legal firms in criminal activities (e.g., money laundering, or corruption in public procurement) or not. But a more disturbing conclusion emerges when considering a potentially important source of benefits from infiltration – political connections. We find that infiltration is tightly associated with a firm's political connections: OCGs target politically connected firms, but also, after infiltration, the firm's political connections expand. Consistent with our model, these patterns are particularly pronounced on larger "born-clean" firms, i.e., those on which we detect the *pure* infiltration motive. This suggests that this motive hides OCGs' desire and ability to interact with the main players of the legal economy, e.g., large enterprises, politically involved persons, public administrators, and high-profile service providers (e.g., lawyers, accountants, consultants). In due time, these connections can become political power and, through lobbying (Bertrand et al., 2014, Bertrand et al., 2023), influence policymaking (e.g., anti-money-laundering and financial regulation) thus strengthening and perpetuating OCGs' grip on the economy and society at large.

Related Literature This paper contributes to our understanding of OCGs activities and relates to several strands of the literature. Organized crime is a pervasive phenomenon, particularly in low-income countries. Using cross-country survey data, (Pinotti, 2015a) finds that organized crime is a major problem in Latin America, Eastern Europe, Asia, and Western Africa. Accordingly, recent contributions have studied OCGs in a variety of contexts. For example, in Colombia, Blattman et al. (2021) document OCGs' strategies to protect rents from drug trade; in El Salvador, Melnikov et al. (2020) find that the emergence of OCGs led to a reduction in economic development while Brown et al. (2021) document how the costs of extortion from OCGs are passed through to consumer prices; in Nigeria's oil industry, Rexer (2022) finds that connections to OCGs give local producers an advantage relative to foreign companies which are exposed to violence and thefts.[7]

[7]Colonnelli and Prem (2022) and Colonnelli et al. (2022) study the effects of an anti-corruption enforcement program in Brazil on the local economy and firm-level outcomes.

Organized crime increasingly poses serious threats in advanced economies.[8] We focus on Italy, home to some of the oldest OCGs worldwide and a notable exception among higher-income countries. The main Italian OCGs are the Sicilian Mafia, the Camorra, and the 'Ndrangheta. A large literature has studied their rise in Sicily, Calabria, and Campania during the nineteenth century (Gambetta, 1996, Lupo, 2009, Bandiera, 2003, Buonanno et al., 2015, Dimico et al., 2017, and Ciccarelli et al., 2023); their expansion to other Italian regions during the 1960 (Varese, 2006) and to other countries (Transcrime, 2015). The literature has documented large negative effects of these OCGs on the socio-economic (e.g., Acemoglu et al., 2020) and political (e.g., Alesina et al., 2019) development of the country. For example, within a synthetic-control approach, Pinotti (2015b) finds that the presence of OCGs lowered regional GDP per capita by 16%. More recently, Fenizia and Saggio (2023) finds that the dismissal of city councils infiltrated by organized crime increases employment, the number of firms, and industrial real estate prices, particularly in sectors dominated by OCGs and in municipalities where fewer incumbents are re-elected. Exploiting the same policy, Slutzky and Zeume (2023) find that the enforcement action increases competition.

Our paper is more directly related to the – primarily empirical – literature that studies OCGs' infiltration of legal firms. Our first contribution is conceptual. Although several papers have extended the canonical Beckerian model of crime to account for different aspects of criminal organizations (e.g., Buchanan, 1973, Backhaus, 1979, Fiorentini and Peltzman, 1997, and Dixit, 2004), we are not aware of formal models of OCGs' motives to infiltrate legal firms. The criminology literature has developed taxonomies of infiltrated firms (see, e.g., Arlacchi, 2010, Parbonetti, 2021). These taxonomies, however, are not suited to our purpose. First, we need a set of testable hypotheses to infer the motive of infiltration from observed behavior. More importantly, the existing taxonomies are developed studying legal firms involved in criminal investigations and therefore *assume* that the legal firm is necessarily involved in criminal activities. In contrast, our conceptual framework and empirical evidence highlight that this is not necessarily the case.

On the empirical front, Le Moglie and Sorrenti (2022) compare provinces with high versus low presence of OCGs before and after the 2008 financial cri-

[8]For instance, the (Transcrime, 2017) report studies infiltration of legal firms in five European Countries (the UK, the Netherlands, Italy, Sweden and Slovenia) using 2,380 references to OCG infiltration from a variety of open sources (such as academic studies, law enforcement operations and reports, newspaper articles).

sis and find that provinces with less presence of OCGs have been subject to a lower drop in the number of new firms, suggesting that OCGs helped firms overcome the reduction in the availability of credit. Daniele and Dipoppa (2022) documents the strategic behavior of firms participating in public procurement projects to elude screenings to detect mafia-connected firms. Calamunci and Drago (2020) find that the assignment of infiltrated firms to judicial investigations has a positive spillover on competing firms suggesting a large burden imposed by infiltrated firms on other firms.

The most closely related paper to ours is Mirenda et al. (2022). They study the effect of 'Ndrangheta infiltration on firms' performance in the North and Centre of Italy. They propose a creative approach in which infiltration is based on whether the firm's owners and/or directors have family names associated with OCGs and come from the same municipality of origin. Focusing on "born-clean" firms to implement a DID framework, they find that 'Ndrangheta infiltration generates a significant rise in firms' revenues and a deterioration of the firm's financial position and exit. They argue that the findings are consistent with what we label *functional* motive: the OCG's predatory behavior uses infiltration predominantly for money laundering and/or rent extraction. Our analysis points to a different conclusion and has different policy implications. Besides leveraging a novel (and more comprehensive) data source – the *Mappatura*, we differ from Mirenda et al. (2022) in several important ways. We model – and find evidence consistent with – a wider set of motives for infiltration. Alongside the *functional* motive (which we primarily detect on born-infiltrated firms), we also find evidence for a *competitive* and a novel *pure* motive on "born-clean" firms. We thus show that restricting attention to "born-clean" firms to conduct a DID analysis may be misleading, as these firms do not provide a representative picture of OCGs' infiltration motives. Furthermore, when studying "born-clean" firms within a DID framework, we explicitly control for the fact that an infiltration mechanically induces a change among managers/shareholders of the firm. This correction reverses Mirenda et al. (2022) conclusions, even when using their infiltration definition and data. In sum, considering a wider set of outcomes to test the theory and a different empirical strategy, we paint a different picture of OCGs' infiltration in the Italian legal economy, with radically different policy implications.

2 Background and Data

This section first provides background information on Italy's main OCGs (Section 2.1) and then describes the *Mappatura* (Section 2.2).[9]

2.1 OCGs in Italy

Italy provides a natural context to study OCGs' infiltration in the legal economy. First, Italy has a pervasive presence of autochthonous OCGs. The main OCGs in Italy are the Sicilian Mafia, the Camorra, and the 'Ndrangheta. Originating from their respective regions (Sicily, Campania, and Calabria, all in the South of Italy), these criminal organizations have expanded into other regions in the traditionally richer Northern part of the country, as well as abroad. They dominate illicit activities but also infiltrate the legal economy, posing a significant challenge to law enforcement and governance (DNA, 2020). Second, as a result of this widespread influence, Italy has developed a comprehensive regulatory framework aimed at countering OCGs.

The Sicilian Mafia, whose origins can be traced back to the 19th century (see Gambetta, 1996 and Lupo, 2009), is perhaps the most widely known, at least in part because of its historical connections to OCGs in the U.S. (see, e.g., Mastrobuoni and Patacchini, 2012 and Mastrobuoni, 2015). The Sicilian Mafia's organizational structure is characterized by a centralized hierarchy where a central committee controls multiple criminal families and enterprises. This structure has made it easier to fight against the organization and it is now generally believed that the influence of the Sicilian Mafia has somewhat been reduced.[10] In contrast to the Sicilian Mafia, the Camorra, is characterized by smaller clans often in fierce competition with each other (DNA, 2020).

The 'Ndrangheta – which also originated in the 19th century in the southern region of Calabria but then expanded nationwide and abroad (Varese, 2006, Ciconte, 2008) – is organized around tightly closed family-based clans. In contrast to what was generally believed, recent investigations have demonstrated that the 'Ndrangheta does have a centralized committee that, among other things, coordinates the activities of the different clans, helps form alliances to under-

[9] Additional data sources are described in Appendix A.

[10] A landmark trial, the so-called Maxiprocesso, resulted in the conviction of numerous Mafia members and gave a significant blow to the organization. This period reached a tragic climax with the assassinations of two prominent anti-Mafia judges, Giovanni Falcone and Paolo Borsellino, in 1992, and subsequent terrorist attacks.

take large-scale illegal activities, and settles disputes. The family-based structure and the secrecy of the highest layer of the organization (itself unknown to lower-level members) have made it difficult to counter 'Ndrangheta as effectively as the other two organizations. Notwithstanding notable law enforcement efforts and successes in recent years, the 'Ndrangheta is amongst the richest and most powerful OCGs at the global level (Europol, 2013). According to Transcrime (2015), its revenues from illicit activities in 2010 amounted to over 3.5 billion euro, nearly twice as much as those of the Sicilian Mafia. Of these revenues, only a quarter are estimated to be produced in the organization's region of origin, in contrast to the two-thirds estimated for the Sicilian Mafia and the Neapolitan Camorra. Although we cannot distinguish the infiltration of legal firms by the different OCGs, it is thus likely that the majority of the infiltration in the *Mappatura* are tied to the 'Ndrangheta.

2.2 The *Mappatura* of OCGs Infiltration in the Legal Economy

The Creation of the *Mappatura* Studying OCGs' infiltration into the legal economy is generally difficult due to the paucity of data. This project leverages the *Mappatura* – a novel database assembled by UIF, the Financial Intelligence Unit of the Bank of Italy. UIF, established in 2007, is responsible for combating money laundering and terrorist financing and has complete operational and administrative autonomy. To help UIF perform its tasks, the law establishes disclosure requirements on financial intermediaries, supervisory authorities, administrative bodies, and professional associations.

To carry out its duties, UIF collects data on financial flows and information mainly through the suspicious transaction reports (STRs) transmitted by financial intermediaries, professionals, and other operators. STRs provide the most comprehensive information available on transactions that are potentially linked to criminal activities (in 2022 alone, UIF received 155,426 STRs UIF, 2022). This large amount of information is then screened by UIF to reduce false positives, analyzed, and transmitted to investigative bodies.

The construction of the *Mappatura* – UIF's most systematic effort to map OCGs infiltration in the Italian legal economy and arguably the most comprehensive attempt undertaken worldwide to date – involves two steps.

Step 1 All physical persons identified in STRs are searched for in the most comprehensive judicial and investigative records available on OCGs. This process produces a highly confidential list of individuals that are potentially implicated in OCGs activities. The most important source – accounting for around 90% of the individuals on the list – is if the individual appears as being of interest to the *DNA* – the Antimafia National Directorate (*Direzione Nazionale Antimafia*).[11] The *DNA* was established in 1991 with the explicit goal of coordinating *all*, but also of giving impulse to new, investigations that relate to OCGs in Italy. The list of individuals that are of interest to the *DNA*, therefore, arguably includes *any* individual that Italian investigative bodies and judicial authorities consider of potential interest in investigating OCGs' activities. Importantly, the list does not include only individuals who have already been put on trial, but also individuals for whom investigations are ongoing, as well as individuals who are simply "on the radar" of investigative forces.

The comprehensiveness of this data source is crucial to gain an accurate picture of the phenomenon under consideration for two reasons. First, belonging to an OCG is a crime on its own in Italy (article 416-bis of the penal code). However, in practice, it is difficult to prove affiliation to a secret criminal organization. Many "Mafiosi" are therefore investigated, brought to court, and convicted for crimes other than 416-bis. Second, numerous investigations have highlighted how individuals who assist OCGs in infiltrating the legal economy are *not* members of the OCGs—the so-called *zona grigia* (grey area). The DNA list includes these individuals as well. The DNA list is extremely confidential and, to the best of our knowledge, has not been used for research before.

Step 2 Following the literature, we define infiltration of an OCG into a legal firm as "any case in which a natural person belonging to a criminal organization or acting on its behalf, or an already infiltrated legal person, invests financial and/or human resources to participate in the decision-making process of a legitimate business" (Transcrime, 2017, p.19). The key feature of this definition is that a person tied to an OCG plays an active role in the decision process of a legal firm. Hence, in our baseline definition, a firm is infiltrated if it has at least an owner *or* an administrator among the individuals identified in Step 1. Using their unique social security identifier, we match individuals on the list with the owners, directors, and auditors for the universe of Italian legal firms extracted from the Infocamere database of the Italian Chamber of Commerce. A

[11] The two other sources are: *a)* individuals mentioned in the press (searched through the World-Check database) for being arrested or investigated for involvement with OCGs, and *b)* individuals for whom UIF received information requests on OCG-related matters from judicial authorities, Italian investigative authorities, or foreign Financial Intelligence Units.

firm is then classified as infiltrated by an OCG when at least one of its owners, directors, or auditors, belongs to the list obtained in Step 1. The firm's date of infiltration is the first year in which such a match occurs (and can, of course, coincide with the year of creation of the firm).[12,13]

The *Mappatura* in Perspective Since the *Mappatura* has not been previously used, it is important to compare it with existing data used to study OCGs' infiltration of legal firms in Italy.

The *Mappatura* identifies about 106,000 infiltrated firms. This casts a much wider net than previously done in the literature. The current frontier in the field is the creative approach pioneered by Mirenda et al. (2022). Focusing on 'Ndrangheta infiltration in the Central and Northern Italy, they define infiltration as the presence of an owner or a director that carries the family name and place of birth typically associated with 'Ndrangheta families obtained from Dalla-Chiesa et al. (2014) report for the Antimafia Parliamentary Commission. This approach yields a final sample of about 9,000 infiltrated firms.

Calamunci and Drago (2020), Fabrizi and Parbonetti (2021), and Bianchi et al. (2022) pursue a different approach that arguably minimizes the likelihood of false positives. They study firms identified as infiltrated by OCGs according to investigative records. This approach, however, comes at the expense of a limited sample size of 450, 645, and 1,840 firms, respectively.[14] Other useful benchmarks are the registry of confiscated firms, which – at the last stage of the confiscation process – consists of around 3,000 firms, and that of firms that are blacklisted for participation in public procurement, which consists of about 2,800 firms over the years 2016-2022. These two lists partially overlap and are not publicly available, to the best of our knowledge.

[12]Note that, in this definition, the accrual of financial resources is thus not a necessary condition for infiltration. Conversely, a firm under the grip of an OCG through usury or extortion is also not infiltrated according to the definition, unless the OCGs participates in the decision-making process of the firm.

[13]Because of the extreme confidentiality of the underlying data, *none* of the authors had access to the list of individuals identified in Step 1. The matching of that list with Infocamere data (Step 2) was performed by separate (and highly restricted) staff at the Italian Financial Intelligence Unit (UIF) with access to the data. The identifier of the identified *firms* (but not of the *individuals* on the list) was then shared with one of the UIF-affiliated authors of this paper. This author then performed the regressions and empirical analyses. The other authors never had access to the data, including at the firm level.

[14]Decarolis et al. (2020) match a confidential dataset from AISI (Italy's domestic intelligence and security agency) that identifies individuals suspected of various crimes to firm-level records, without the ability to separate OCG involvement from other crimes.

Limitations of the *Mappatura* The *Mappatura* is not without limitations. First, the comprehensiveness of the data inevitably implies that some false positives might be included in the list. The primary information from DNA, however, comes with a risk indicator articulated in five levels. Based on extensive conversations with people acquainted with the DNA data, including UIF analysts, the *Mappatura* omits individuals with a score equal to 1 who may include, e.g., acquaintances of mafia members, people informed of the facts being investigated, etc. This drastically alleviates the issue of false positives.[15,16]

Despite its unprecedented coverage, the *Mappatura* certainly suffers from false negatives. By definition, it misses individuals that do not generate any STRs. Due to confidentiality reasons, we do not know how many individuals are on the DNA list and thus the extent of false negatives. Furthermore, our methodology, which identifies infiltrated firms through the presence of owners, administrators, or auditors, naturally misses cases of infiltration in which none of these roles in the firm is involved.

3 How Pervasive is OCGs' Infiltration of Legal Firms?

This Section describes firms in the *Mappatura* and provides novel evidence on how pervasive is OCGs' infiltration of legal firms

Infiltrated Firms and Overall Incidence The *Mappatura* identifies 106,122 infiltrated firms over our sample period (2005-2020). This number corresponds approximately to 2% of all corporations and partnerships in the economy. The percentages are significantly larger in terms of employment and revenues. It is worth emphasizing that the definition of infiltration in the *Mappatura* does *not* imply that infiltrated firms are necessarily controlled by OCGs. It does imply, however, that an individual allegedly connected to an OCG has a prominent role in the firm. Thus, these figures reveal that legal firms' infiltration by, or collusion with, OCGs is a pervasive phenomenon in Italy.

[15] Results are robust to further excluding firms identified with a risk score equal to 2 and firms for which the score is not available. In principle, another potential source of false positives is individuals under investigation who end up 'clean' at the end of the investigation itself; accurate data on this are lacking.

[16] The original mapping developed at UIF also included firms flagged in STRs that are potentially related to organized crime networks. Such links may be deemed less certain and, furthermore, the timing of infiltration cannot be estimated. Therefore, these firms have not been included in this paper.

Table 1: Difference in firm characteristics by infiltration status

	Mappatura, all (1)	Full economy (2)	*Mappatura* dummy coefficient (3)	*Mappatura,* born infiltrated (4)	*Mappatura,* born clean (5)
All *Mappatura* firms					
Year of birth	2002.7	2000.6	1.23***	2008.2	1997.1
No. employees	16.3	2.9	13.68***	5.4	27.8
=1 if corporation	0.717	0.517	0.15***	0.686	0.749
=1 if partnership	0.175	0.407	-0.17***	0.211	0.137
No. directors	2.1	1.6	0.52***	1.9	2.4
No. owners	3.0	2.5	0.52***	2.5	3.6
No. auditors	4.7	4.3	0.50***	4.1	5.0
Number of firms	106,122	5,224,062		54,187	51,935
***Mappatura* firms in Cerved**					
Assets (IHS)	6.9	6.0	0.97***	6.3	7.3
Revenues (IHS)	6.7	5.9	0.82***	6.3	7.0
Payroll (IHS)	5.3	4.8	0.68***	4.9	5.7
Number of firms	64,388	2,079,674		31,157	33,231

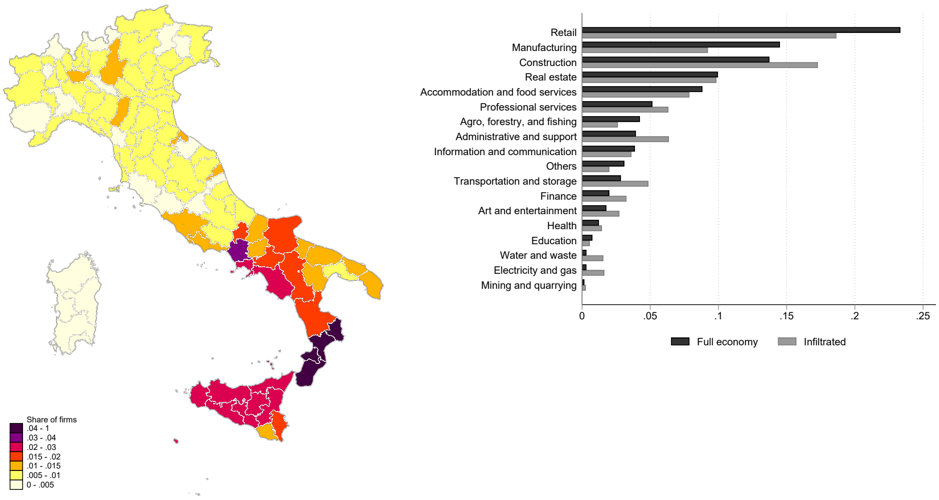
Notes: The unit of observation is a firm for all statistics on the table. Column (1): average characteristics of *Mappatura* firms. Column (2): average characteristics of all firms in the economy (Infocamere). Column (3): each row reports the parameter estimate and significance of a firm-level regression including province-by-sector fixed effects, where the independent variable is a dummy equal one if a firm appears in *Mappatura* and the outcome variable is the one corresponding to each row. Column (4): average characteristics of the subset of *Mappatura* firms that are born infiltrated. Column (5): average characteristics of the subset of *Mappatura* firms that are born clean. Cerved variables appear in inverse hyperbolic sine form. *** p<0.01, ** p<0.05, * p<0.1.

Table 1 reports basic descriptive statistics illustrating the differences between infiltrated firms and other firms in the economy. Column 1 reports average characteristics for infiltrated firms and column 2 does so for the whole economy. Column 3 reports estimates from regressions where the explanatory variable is an indicator equal to 1 for firms that are infiltrated, and where we control for province-by-sector fixed effects. Relative to the rest of the economy, infiltrated firms are younger, larger, and more likely to be corporations. These patterns hold unconditionally as well as controlling for province-sector fixed effects.

Geographic Distribution Figure 1 Panel A reports a map of the incidence of *Mappatura* firms across Italian provinces. Unsurprisingly, we observe a higher incidence in the home regions of the main OCGs in the South of Italy. The highest incidence is found in certain provinces in Calabria – home of the *'ndrangheta*

Figure 1: Geographic and sector-level distribution of infiltration

(a) Geographic distribution **(b)** Distribution by sector



Notes: These figures present the geographic and sector-level distribution of all firms potentially connected to organized crime, identified in the *Mappatura*. In Panel A, we present the total number of infiltrated firms over the average number of firms in the province. In Panel B, we present the share of infiltrated firms by sector over the total number of infiltrated firms and the average across years of the number of firms by sector over the total number of firms in the economy.

– with a peak in Reggio Calabria.[17] Nevertheless, the majority of firms in the *Mappatura* (around two-thirds) are located in the more prosperous regions in the Center-North of Italy. Table A3, Panel A in the Appendix explores how the incidence of such firms correlates with the institutional development of Italian provinces. The incidence of firms potentially connected to organized crime is higher in provinces with lower income per capita (consistent with evidence, cited above, that OCGs originated in less developed regions but also stifled economic development), lower degrees of social capital (measured by blood donation and trust) and slower courts (both consistent with hypothesis in the literature (see, e.g., Gambetta, 1996), and a higher share of the population with family names from the regions of origins of Italian OCGs (a proxy that presumably correlates with OCGs ability to control the territory). Interestingly, when we include all variables at once (Column 7), the correlation with income per capita becomes positive. This is consistent with the idea that, once we control for the ”supply” of OCGs (through proxies for social capital and territory of origins), income per capita captures ”demand” – i.e., business opportunities for OCGs.

[17]Other provinces with substantial infiltration are Vibo Valentia, Catanzaro, and Crotone in Calabria; Caserta, Napoli, and Salerno in Campania; and most of those in Sicily.

Sectoral Distribution Figure 1 Panel B reports a bar chart with the sectoral distribution of firms in the *Mappatura*, relative to the sectoral distribution of all firms in the economy. Unlike the stark geographic divide, OCGs' infiltration is quite balanced across sectors. We confirm the previous literature view that certain sectors, particularly those that deal with public administration, are particularly vulnerable to infiltration: there are disproportionately high shares of *Mappatura* firms in "Construction," "Transportation and storage," "Water and waste," and "Electricity and gas."[18] At the same time, the Figure illustrates how the wide net of the *Mappatura* recovers a distribution of infiltration across sectors that is broadly representative of the nationwide economic structure. This suggests that while traditional sectors in which OCGs can deploy their criminal expertise are certainly relevant, they are far from being the sole, and perhaps the main, destination of OCGs' infiltration into the legal economy. This observation motivates our conceptual framework in the next Section.

4 Conceptual Framework

This Section turns to our second key question: "What are the motives of infiltration?" The *Mappatura* enables a quantitative analysis that covers a large sample of firms whose underlying motives of infiltration are unobservable and must be inferred from the data. To do so, we introduce a new taxonomy of motives and a conceptual framework that allows us to infer the motives of infiltration from the observable behavior of infiltrated firms.

4.1 Motives of Infiltration

Reasons to invest in legal firms The illegal activities of OCGs – i.e., their core business – generate large amounts of liquidity. Several considerations suggest that such liquidity cannot be exclusively reinvested in illegal activities. For example, the risk of confiscation tampers returns from illegal activities: a basic risk-diversification argument suggests allocating some of the revenues into safer – from the point of view of the threat of enforcement – assets. Furthermore, OCGs cannot advertise their illegal products, which sets a limit to their customer base. Additionally, they must rely on a limited set of trusted counterparts in the illegal economy: while the threat of violence can relax enforcement

[18] Among more disaggregated sectoral splits, the sector with the higher presence of OCGs is "Waste collection, treatment, and disposal," with 11.5% of infiltrated firms.

constraints, it is not a perfect substitute for trust since the use of violence attracts the attention of enforcement bodies. Finally, the consumption of the fruits of the illegal business also requires access to legal means of payment other than cash.

In sum, the optimal "portfolio management" of a large OCG requires the investment of at least part of the profits generated by illegal activities in legal assets. Of course, infiltration of legal firms is not the only legal asset class in which OCGs can invest their money. Although estimates are difficult to come by, our calculations from official records suggest that legal firms account for only 10-20% of the value of all assets confiscated to OCGs in Italy, most of them being real estate. But this may be just a reflection of the fact that while the value of real estate may be insensitive to confiscation, that of a business may collapse following confiscation.[19] This begs the question of why OCGs would invest resources in legal firms.

Infiltration Motives in the Literature This question has been extensively covered in the criminal and policy literature. Starting from the detailed analysis of samples of infiltrated firms identified in judicial investigations, the literature (see, e.g., Arlacchi, 2010, Commissione Antimafia, 2018, De Simoni, 2022) has developed several taxonomies. For example, Parbonetti (2021) – possibly the most comprehensive analysis to date – distinguishes between *supporting* firms (i.e., firms that are empty shells used to mask illegal activities), *cartiere* firms (i.e., "paper mills" that specialize in false invoicing), and *star* firms (i.e., larger firms that display superior economic performance due to the exploitation of their close connection with OCGs). These classifications provide a useful taxonomy of infiltration motives from the perspective of investigative bodies and are consonant with the legal definition of the infiltrated firm (see footnote 3).

What the analysts' taxonomy and the criminal code definition have in common is the idea that somehow OCGs involve the legal firm in their criminal activities. For example, in what we label the *competitive* motive, they might leverage their criminal expertise to benefit the firm. Alternatively, in what we label the *functional* motive, they might use the legal firm in support of criminal activities, e.g., in the case of money laundering. We call legal firms infiltrated with these motives "contaminated", meaning that the OCG "contaminates" – and presumably distorts – the legal activity of the infiltrated firm with criminal activity or criminal methods.

[19] Furthermore, it might be harder to confiscate infiltrated firms, particularly if infiltration occurs through board members rather than ownership of equity shares.

However, involving the firm in criminal activities increases the risk of detection. It is thus conceivable that OCGs may want to infiltrate legal firms purely as an investment vehicle that generates safer (albeit smaller) pecuniary returns, or other non-pecuniary benefits that cannot be obtained through criminal activities or by investing in other legal assets. For example, OCGs can obtain relatively high and safe returns if they have access to ″private equity″ like investment opportunities. Furthermore, being involved in the operation of a firm, even (or, perhaps, especially) if it is not ″contaminated″ by criminal activities, opens the door to connections to other firms, public administration, politicians, etc., fostering the relational capital of the OCG. These connections can be useful to identify further opportunities – both legal (like for any other entrepreneur), and illegal. We label this new and previously underappreciated bundle of motives ″pure″ – with the understanding that there is nothing pure about it, since ultimately infiltration happens by, or on behalf of, OCGs. In our terminology, ″pure″ simply reflects the idea that the legal firm itself is not ″contaminated″ with criminal activities.

The goal of our analysis is to infer the underlying motives of infiltration from the economic behavior of a large sample of infiltrated firms identified in the *Mappatura*. We therefore put forward a parsimonious conceptual framework that encompasses both the ″contaminated″ and the ″pure″ motives. The infiltration of OCGs into legal firms is a complex phenomenon and, inevitably, our conceptual framework entails a degree of simplification and is not meant to directly assist investigative efforts.[20] At the same time, our approach maps testable predictions to different motives of infiltration thereby enabling a quantification of their relative prevalence in the *Mappatura*, overcoming the limitations of studies based on smaller, selected, samples from judicial investigations.

4.2 Set-Up

Benchmark As a benchmark, consider the investment of a firm in the legal economy. The entrepreneur has access to an investment opportunity that re-

[20]Money laundering – which we include in the *contaminated*, rather than in the *pure* motive – provides a case in point. As an example, consider a legal firm in which a seemingly legitimate entrepreneur invests. The entrepreneur, who operates on behalf of individuals tied to OCGs, might have the availability of funds to invest that *originally* come from illegal activities, but that have *already* been laundered. If the firm is not directly used to launder the money (e.g., through false invoicing or other means) we would label this infiltration as *pure*, even though a careful investigation might be able to link the investment to transfers of funds that can ultimately be traced back to money laundering activity.

turns output $y = \theta f(k)$, where θ is the entrepreneur's talent, k is the capital invested in the firm, and $f(k)$ is an increasing and strictly concave function. More broadly, capital k could be interpreted as a bundle of inputs that include assets, labor, and materials that all need to be financed. We will thus sometimes refer to k as the scale of operation of the firm. Critically, k, and associated sales y and monetary profits Π are observable in the data.

The entrepreneur has no funds and borrows from a competitive banking sector at an interest rate of $1 + r$. The entrepreneur solves

$$\max_{k} \quad \Pi(k) = \theta f(k) - (1 + r)k \tag{1}$$

This problem yields a unique solution, k^*, implicitly defined by the first order condition $\theta f'(k^*) = (1 + r)$. Denote with Π^* the profits at k^*.

OCG's involvement in the legal firm We now consider infiltration by an OCG. The OCG faces a fundamental choice: whether to involve the firm in its criminal activities or not. On the one hand, involving the firm in criminal activities benefits the OCG in potentially many ways. On the other hand, it increases the risk that the firm is confiscated. If there were no benefits unless the firm is involved in criminal activities, then in equilibrium all infiltration would be of the *contaminated* type. To capture the idea that OCGs may want to infiltrate legal firms without directly involving them in criminal activities, we assume that the OCG has an unlimited supply of funds that yield a pecuniary return $(1 + i) < (1 + r)$. The assumption captures the idea that the OCG has abundant, possibly idle, liquidity to invest, introduces a pecuniary motive for infiltration, and allows us to derive additional predictions on how infiltration changes the sources of finance of the firm.

The OCG invests $k_m \geq 0$ in the infiltrated firm and the latter borrows k_b from the competitive banks at interest rate $(1 + r)$. Given our definition of infiltration, we do not distinguish whether k_m comes in the form of equity or debt. Furthermore, we focus on how infiltration changes the firm's *demand* for bank finance and assume that banks do not adjust their *supply* of funds to the firm in response.[21] Like before, denote the scale of operation of the infiltrated firm with $k = k_m + k_b$.

The OCG chooses the type of infiltration and the scale of the firm and of its investment in it solving

[21] We study banks' responses to infiltration in a separate project.

$$
\begin{aligned}
max_{k,k_m,\mathbf{I}^c,\mathbf{I}^f} \quad & V^m(k, k_m, \mathbf{I}^c, \mathbf{I}^f) = \\
& = ((1+\lambda\mathbf{I}^c)\theta f(k) - (1+r)k + (r-i)k_m)(1-\rho(\mathbf{I}, k_m, k^*)) + \mathbf{I}^f \gamma C(k), \\
s.t. \quad & k_m \leq k; \mathbf{I}^c, \mathbf{I}^f \in \{0,1\}, \mathbf{I}^c + \mathbf{I}^f \leq 1.
\end{aligned} \tag{2}
$$

Relative to the benchmark case, the problem of the OCG differs along several dimensions: the comparison between the objective functions in (1) and (2) reveals the different motives of infiltration.

First, the OCG chooses indicator functions $\mathbf{I}^c$ and $\mathbf{I}^f$ that capture whether the firm is directly involved with the OCG's criminal activities or not. $\mathbf{I}^c$ captures a *competitive* motive – the OCG's criminal activities enhance the firm's performance by λ. For example, a firm that acquires larger market shares through the intimidation of rivals or wins more public procurement contracts through the corruption of public officials. $\mathbf{I}^f$, instead, captures a *functional* motive – the OCG distorts the operation of the firm, i.e., the choice of k, away from profit maximization to support criminal activities that yield payoff (k). For example, firms that are used to produce false invoicing to facilitate money laundering or firms that hire workers over the profit-maximizing level to acquire consensus in, and control over, a certain territory belong to this typology. The *contaminated* motive thus emerges when the solution to the program in (2) yields $\mathbf{I} = \max\{\mathbf{I}^c, \mathbf{I}^f\} = 1$.[22] In contrast, the *pure* motive emerges when the solution entails $\mathbf{I} = 0$ and the firm is kept separate from the OCG's criminal activities.

Second, infiltration introduces a risk of confiscation $\rho(\mathbf{I}, k_m, k^*) \in (0, 1)$.

Assumptions

1 $\partial\rho(1, k_m, k^*)/\partial z \geq 0$ *for* $z = k_m, k^*$;

2(a) $\rho(1, k_m, k^*) > \rho(0, k_m, k^*)$ *for all* $k_m, k^* \geq 0$,

2(b) $\partial\rho(1, k_m, k^*)/\partial z > \partial\rho(0, k_m, k^*)/\partial z$ *for all* $z \geq 0, z = k_m, k^*$

Assumption 1 states that the risk of confiscation is increasing in k^* and k_m: the larger the firm and the larger the OCG's investment in the firm, the more likely that the firm ends up under the investigative radar.[23] Assumption 2(a)

[22] For simplicity, we assume that the firm is involved in either of the two motives, but not both contemporaneously, i.e., $\mathbf{I}^c + \mathbf{I}^f \leq 1$.

[23] The assumption that the risk of confiscation depends on the undistorted scale of the firm, k^*, rather than the scale chosen by the OCG, k, captures the intuition that larger firms are under more scrutiny without overly complicating the algebra. One rationale is that, by regulation, they must disclose more information

states that, for all levels of k^* and k_m, the risk of confiscation is higher in the *contaminated* motive than in the *pure* motive. Assumption 2(b) states that the scale of the firm and the OCG's involvement increases the likelihood of detection more when the firm is a *contaminated* than when it is *pure*. These assumptions appear natural: for example, an OCG is more likely to attract attention when it threatens a competitor, or it wins a public contract rigging a procurement auction, relative to when it simply provides cheaper finance to an entrepreneur.

Finally, the OCG's funds, k_m, lowers the cost of capital of the firm by $(r - i)k_m$. This happens in both the *contaminated* and *pure* motive. The OCG invests $k_m > 0$ only if $r > i$. If that was not the case, the *pure* motive would never arise in the model, since k_m increases the risk of detection.[24]

4.3 Distinguishing Infiltration Motives in the Data

The *contaminated* and *pure* investment motives can be distinguished in the data considering both the scale of operation, k, and the sources of finance, k_m relative to k_b, of the firm.

Operational Scale In an interior solution, the first-order condition is

$$(1 + \lambda \mathbf{I}^c)\theta f'(k) + \frac{\mathbf{I}^f \gamma C'(k)}{(1 - \rho(\mathbf{I}, k_m, k^*))} = (1 + r). \tag{3}$$

Relative to non-infiltrated firms, the operating scale of the firm k, expands in the *contaminated* infiltration ($\mathbf{I} = 1$) but not in the *pure* motive ($\mathbf{I} = 0$). *Competitive* infiltration, $\mathbf{I}^c = 1$, increases the returns from investing in the firm. *Functional* infiltration, $\mathbf{I}^f = 1$, also increases the scale of the firm relative to the benchmark if $C'(k) > 0$ – a natural assumption. For example, false invoicing is associated with an artificial boost in revenues $f(k)$ and thus k.[25] Similarly, a firm that hires workers to increase social consensus and control increases k relative to k^*. In contrast, in an interior solution in which the firm still borrows $k_b > 0$ from banks, k does not expand in the *pure* infiltration.

[24]The *pure* motive could still arise when $r < i$ if infiltration – even if disconnected from criminal activities – also generates non-pecuniary benefits for the OCG. These non-pecuniary benefits, while hard to observe, may be important in practice. For simplicity, the baseline model focuses on the pecuniary motive. A more general formulation would let r be the sum of a pecuniary, r_p, and non-pecuniary component, r_n. If $r_p > i$, our analysis remains unchanged. Section 6 discusses sources of, and evidence for, non-pecuniary benefits in the *pure* motive.

[25]In the typical firm used for false invoicing the increase in revenues $f(k)$ is accompanied either by a corresponding increase in costs (to avoid the higher tax burden) or by an increase in debts towards the tax authorities before the sudden bankruptcy of the firm.

Implication 1 *Contaminated infiltration increases firm's scale of operation k and revenues y, pure infiltration does not.*

Within *contaminated* infiltration, the *competitive* and *functional* motives can be distinguished in the data: profits, $\Pi^m = ((1 + \lambda \mathbf{I}^c)\theta f(k) - (1 + r)k + (r - i)k_m)$, increase in the *competitive* motive and decrease in the *functional* motive.

Sources of Finance The two motives of infiltration also differ in the sources of finance employed by the firm. The first order condition w.r.t. k_m,

$$\Pi^m \frac{\rho'(\mathbf{I}, k_m, k^*)}{(1 - \rho(\mathbf{I}, k_m, k^*))} = r - i, \tag{4}$$

highlights the key trade-off: funds from the OCG, k_m, yield a marginal benefit $r - i$; but increase the risk of detection. As noted above, in the *pure* motive, the scale of the firm k does not change – this motive is thus characterized by a *substitution* of market sources of finance k_b with funds from the OCG. *Pure* infiltration takes advantage of the lower cost of capital supplied by the OCG to substitute more expensive sources of finance for the firm. If the OCG's source of finance wasn't cheaper, there wouldn't be a reason to invest to begin with. *Pure* infiltration targets firms that experience difficulties in accessing bank finance (higher r in the model).[26]

The *contaminated* investment has more nuanced implications. While the scale of the firm k increases, funds from the OCG increase the risk of detection more than in the *pure* motive. That is, $\frac{\rho'(1,k_m)}{(1-\rho(1,k_m))} > \frac{\rho'(0,k_m)}{(1-\rho(0,k_m))}$ (from Assumption 2a). Holding constant Π^m, and thus firm's scale, this implies a lower OCG's investment k_m in the *contaminated* infiltration relative to *pure*. If $\mathbf{I} = 1$ increases the marginal effect of k_m on the risk of detection enough, then the *contaminated* firm exclusively relies on external sources of finance ($k_m \to 0$), as the marginal gains from cheaper finance, $(r - i)$, do not compensate for the increased risk of detection. In summary, *pure* infiltration implies the substitution of external sources of finance with internal ones. Conversely, the *contaminated* infiltration does not necessitate this substitution and might result in the opposite effect.[27]

[26] We focus on an interior solution because the corner case in which $k_b = 0$ is not so relevant in practice, at least for large firms for which the *pure* motive is most likely, as we will describe shortly. The corner case is more likely to be relevant for credit-rationed firms that have multiple sources of capital if the OCG's investment can substitute the most expensive source of finance. The OCG, however, might not be able to substitute the most expensive sources of finance, such as long-term loans. Furthermore, the OCG also cares about the degree of monitoring associated with the source of finance: all else equal, it will substitute sources of finance, notably bank loans, that bring more scrutiny to the firm.

[27] These observations are in line with accounts based on investigative records. *Cartiere* – firms

Implication 2 *Pure infiltration substitutes external sources of finance with internal ones, contaminated infiltration less so, if at all.*

4.4 Infiltration Motives and Firm's Size

When does the OCG prefer one motive over the other? That is, for which parameters does the solution to the program in (2) involve $\mathbf{I} = 1$ as opposed to $\mathbf{I} = 0$? Since the motives are unobservable, answering this question is necessary to derive testable predictions. In general, it is difficult to provide a complete characterization of comparative statics for discrete choices (Athey et al., 1998). The model, however, provides intuitive guidance.

Figure 2 illustrates the OCG's motive of investment as a function of managerial talent θ, focusing on an interior solution in which all three motives – *functional*, *competition* and *pure* – can arise. Since the scale of operation, k, monotonically increases in θ, the figure characterizes the infiltration motive as a function of the firm's size. All else equal, the *contaminated* motives have a higher risk of detection relative to the *pure* (Assumption 2). The *contaminated* motives are thus more likely when the value of the confiscated firm is not too large, i.e., for low values of θ (and thus smaller scale k and revenues y). Large firms are too valuable and, instead, the *pure* motive is chosen. Between the two *contaminated* motives, however, the benefits of the *competitive* motive $(1 + \lambda)$ are complementary in θ, while those of the *functional* motive (captured by γ) are not. A clear ranking emerges:

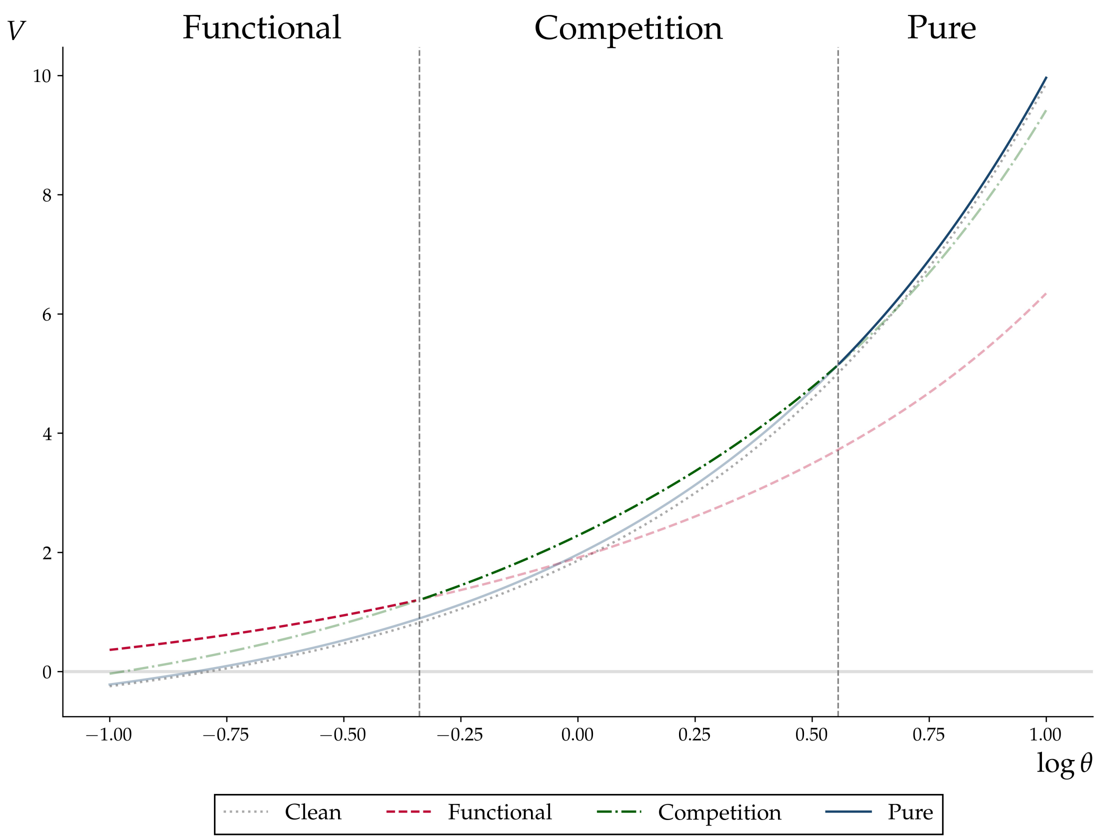
Implication 3 *The functional motive is chosen for small firms, the competitive motive for medium-sized ones, the pure motive for the largest firms.*

5 Motives of Infiltration: Evidence

This Section leverages the *Mappatura* to infer the relative prevalence of the different infiltration motives. To derive testable predictions, Section 5.1 introduces a distinction between "born-infiltrated" and "born-clean" firms. "Born-infiltrated" firms are smaller than "born-clean" firms, and, therefore, Implication 3 suggests that they are more likely to reflect the riskier *contaminated* motives relative to "born-clean" firms. We document patterns in geographic

that issue false invoices – typically accumulate large volumes of debts with the tax authority before shutting down; infiltrated *competitive* firms attract more external finance because of their superior performance (Parbonetti, 2021).

Figure 2: Firm's Size and Infiltration Motives (Comparative Statics)



Notes: The above shows the value of infiltration for the OCG under the optimal choice of k_m and k for each strategy, with theta varied by two orders of magnitude. The functional forms used are as follows: $f(k) = \frac{k^{\epsilon}}{\epsilon}$; $C(k) = \frac{k^{\gamma}}{\gamma}$; $\rho(I, k_m, k^*) = (1 - I)\rho_1(k_m) + I\rho_2(k_m)\rho_2(k^*)$ where each ρ_i is a logistic function with supremum L_i, growth rate g_i, and midpoint ξ_i. The parameters used are as follows: $\lambda = \frac{1}{2}$; $r = 0.15$; $i = 0.025$; $\epsilon = \frac{1}{4}$; $\gamma = \frac{1}{5}$; $L_1 = \frac{1}{10}$; $g_1 = 2$; $\xi_1 = e$; $L_2 = \frac{3}{\sqrt{10}}$; $g_2 = \frac{5}{4}$; $\xi_2 = 0$. We further assume market entry incurs fixed cost $F = 1$.

diffusion and risk of confiscation consistent with this hypothesis. We then explore Implications 1 and 2 separately on the two groups of firms, since they differ in the empirical strategies available to construct a suitable comparison group of non-infiltrated firms. Section 5.2 examines ″born-clean″ firms, Section 5.3 ″born-infiltrated″ ones. The *Mappatura* strongly supports the implications of the model, with the behavior associated with *contaminated* motives detected on ″born-infiltrated″ and smaller ″born-clean″ firms, and behavior associated with the *pure* motive on larger, ″born-clean″ firms.

5.1 Prediction 1: *Born-Infiltrated* versus *Born-Clean* firms

The *Mappatura* points to the presence of an important distinction between two main types of infiltration: 51% of all infiltrated firms are "born-infiltrated" (i.e., the presence of the individual tied to the OCG is detected when the firm is established) and 49% are "born-clean" (i.e., the entry in the firm of the individual connected to an OCG occurs at a later date). Table 1 shows that "born-infiltrated" firms are significantly smaller than "born-clean": they have fewer employees, assets invested, and revenues. Implication 3 then yields

Prediction 1 *Relative to Born-clean firms, Born-infiltrated are more likely to reflect a contaminated motive than the pure motive. Born-infiltrated firms thus (a) are at a higher risk of detection (higher $\rho(\mathbf{I}, k_m, k^*)$), and (b) are more prevalent in OCGs' home regions (higher γ and λ)* .[28]

Table 2 confirms prediction 1(a): *born-infiltrated* firms have a higher likelihood of being confiscated. We obtain data on all firms confiscated to OCGs by judiciary authorities in Italy. Columns (1) and (2) show that firms in the *Mappatura* are around 30 times more likely to have been confiscated relative to firms that are never infiltrated. Among firms in *Mappatura*, Columns (3) and (4) show that *born-infiltrated* firms are almost twice more likely to have been confiscated than *born-clean* firms.

Appendix Figure A1 confirms prediction 1(b). The *contaminated* motives are more likely when the benefit of combining the investment with the OCG's criminal expertise is large, i.e., when λ or γ are high. This is presumably the case in the OCGs' regions of origin, where they can exert a higher degree of socio-economic control. The Figure reports the share of firms that are *born infiltrated* over the total number of infiltrated firms. While we observe significant variation across all of Italy, there is a clear over-representation of born-infiltrated firms in the regions of origin in the South of Italy (Appendix Table A1 confirms this in a regression framework). Appendix Table A3, Panel B also finds that the share of born-infiltrated firms is higher in provinces with a lower institutional development (lower economic activity, lower trust, slower courts, higher prevalence of family names from the regions of origins of Italian OCGs).

[28] In our static framework, born-clean and born-infiltrated firms are equivalent. Conditional on the motives of infiltration (and on θ), the two modes of infiltration yield the same solution for k and k_m. To see why, consider a born-clean firm set-up by an entrepreneur. Upon infiltration, the OCG maximizes $V^m(k, k_m) - T$, s.t. the entrepreneur's participation constraint, $T \geq \Pi^*$. This yields the same solution of the born-infiltrated firm in (2). We therefore exploit the difference in firm's size between the two modes of infiltration to derive testable predictions. Footnote 38 sketches a micro-foundation that is consistent with our model and with the evidence.

Table 2: Born-Infiltrated vs. Born-Clean: Confiscation Risk

	(1)	(2)	(3)	(4)	(5)	(6)
		All firms			Within infiltrated	
Born-Infiltrated	0.013***	0.012***	0.012***	0.003**	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Born-Clean	0.013***	0.009***	0.009***			
	(0.001)	(0.001)	(0.001)			
Observations	5,175,704	1,169,379	1,169,379	80,586	28,340	28,340
R-squared	0.036	0.040	0.040	0.191	0.195	0.195
YOB × Province × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Infiltrated at birth firms	50689	22356	22356	43254	18430	18430
Infiltrated after	48770	12015	12015	37332	9910	9910
Mean dep var	0.0007	0.0007	0.0007	0.0162	0.0133	0.0133
p-value diff. in coefficients	0.998	0.0221	0.0228			

Notes: This table presents the difference in seized probability based on whether the firm was born infiltrated or infiltrated after birth. Columns 1 and 4 use the universe of firms from infocamere, while the rest of the columns use only firms that we observe in the CERVED dataset. All regressions include year of birth by industry (2-digit) by province of birth fixed effects. The list of controls are total assets, total revenue, and total number of works, all of them measured at birth. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021), pp. 46-47). Robust standard errors clustered at province of birth-year of birth level are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

These patterns give us confidence that the distinction between born-clean and born-infiltrated firms captures different underlying motives. We now separately verify on the two samples Implications 1 and 2.

5.2 Prediction 2: Infiltration Motives in *Born-clean* Firms

Because born-clean firms are relatively large, the model implies that these firms predominantly reflect the *pure* motive. Implications 1 and 2 then yield:

Prediction 2(a)-(b) *Born-clean firms mainly reflect the pure motive. Infiltration is associated (a) with no significant change in the firm's sales y and scale of operation k, and (b) with substitution of the sources of finance away from bank loans (lower k_b/k).*

5.2.1 Empirical Approach

Born-clean firms are, by definition, observed both before and after infiltration in the data. To test the prediction, we thus compare infiltrated firms' outcomes around the date of infiltration relative to a suitably constructed comparison group of non-infiltrated firms within a difference-in-differences framework. A firm's *date of infiltration* is defined as the year in which an OCG-linked individual first joined the firm either as an owner, director, or auditor. As such, an empirical issue arises by which, *by definition*, infiltration of born-clean firms coincides with changes in the firm's ownership and management, which are likely to arise during special circumstances of a firm's life and could be associated with large changes in firm performance and operations (Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007).

To deal with this issue, we propose an empirical approach that compares infiltrated firms to non-infiltrated firms that *also* experience an inflow of a new owner/director/auditor. That is, we first define an *inflow event* as the year in which a new owner/director/auditor joins the firm. In the case of several such occurrences during our sample period, we denote as the focal *inflow event* the one in which the greatest number of new owners/directors/auditors joined the firm, and, in case of ties, we select the earliest year. We then explicitly account for such *inflow events* within the DID framework.

Of course, our approach is not intended to identify the "causal" effect of infiltration on the firm. By definition, infiltration involves an individual with links to OCGs, while other *inflow events* do not. Because of this, the type of firms in which infiltration occurs are likely facing different circumstances.[29] For example, OCGs could target firms facing particular liquidity or borrowing shocks, which would prevent interpreting post-infiltration dynamics as treatment effects of infiltration. Conditional on those shocks, infiltrated firms will also differ in their owners' (unobservable) willingness to do business with OCGs. To a large extent, however, our model speaks to such pre-trends themselves, as well as dynamics in firm outcomes after the infiltration. With these caveats in mind, the intuitive approach we follow leads to pretty clear results and radically different conclusions with regard to OCGs' motives of infiltration.

Estimating Equations We are ultimately interested in the evolution of relevant firm outcomes following infiltration vis-a-vis the evolution following a non-criminal inflow. With this goal, we estimate the following regression:

$$y_{ipst} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta_1 \times \text{Post I}_{it} + \beta_2 \times \text{Post INF}_{it} + \epsilon_{ipst}, \tag{5}$$

where i, p, s, and t stand for firm, province, sector, and year. The dummy variable Post I_{it} takes value one after firm i has experienced the inflow event,

[29]Table A4 reports average differences among the group of infiltrated firms, firms that experience an inflow event, and all other firms and finds differences among these groups.

regardless of whether it involved individuals tied to OCGs or not. The dummy variable Post INF_{it}, instead, takes value one after firm i is infiltrated. Our key parameter of interest is β_2 which captures the differential change in outcome y after an infiltration compared to the differential change for those firms that experienced a non-criminal inflow event. That is, β_1 captures the change in outcomes following a non-criminal inflow event while the equivalent effect for an infiltration event is given by $\beta_1 + \beta_2$.

We include three sets of fixed effects: α_i are firm-level fixed effects that absorb any observed or unobserved heterogeneity across firms that is constant over time, α_{st} are sector-year fixed effects that absorb any sector-level (39 2-digits sectors) heterogeneity that changes over time, and α_{pt} are province-year fixed effects that capture any province-level (107 provinces) time-varying heterogeneity. Finally, ϵ_{ipst} is an error term that we clustered at the firm level to allow for arbitrary correlation of the errors across time within a firm.

We also investigate the dynamics of firm outcomes before and after non-criminal inflow and infiltration by estimating an event study specifications:

$$y_{ipst} = \alpha_i^k + \alpha_{st}^k + \alpha_{pt}^k + \sum_{j \in \{-5,\ldots,-2,0,\ldots,5\}} \gamma_j^k \cdot D_{i,t-j}^k + \epsilon_{ipst}^k, \tag{6}$$

for $k \in \{I, INF\}$, where I stands for an inflow event unrelated to OCGs and INF stands for infiltration. $D_{i,t-j}^I$ is a dummy variable equal to one if firm i experienced a non-criminal inflow event $t-j$ periods ago. $D_{i,t-j}^{INF}$ is a dummy variable equal to one if firm i experienced an infiltration event $t-j$ periods ago. We estimate the dynamic effects γ_j^I in a sample of firms that includes (i) firms that never experience any sort of inflow, and (ii) firms that experience a non-criminal inflow event. Instead, we estimate the dynamic effects γ_j^{INF} in a sample of firms that includes (i) firms that never experience any sort of inflow, and (ii) firms that experience an infiltration event. Our coefficients of interest, the difference $\gamma_j^{INF} - \gamma_j^I$, describe changes in outcomes around infiltration relative to a clean inflow event.[30]

5.2.2 Empirical Results

Prediction 2(a): Operational Outcomes Figure 3 illustrates the dynamics of firm operational outcomes around infiltration and other inflows. The left panels report estimates for γ_j^{INF} and γ_j^I from equation (6), while the right panels report

[30] We discuss several robustness checks in Section 5.2.3.

the difference between the two, $\gamma_j^{INF} - \gamma_j^I$ (i.e., the net change associated with infiltration relative to a non-criminal inflow event).

Figure 3 appears to suggest that infiltration raises the operating scale of the firm. However, we see that the dynamics around a non-criminal inflow event are very similar to those related to an infiltration event. As such, the net change associated with infiltration (after accounting for the inflow event itself) is indistinguishable from zero. These zero estimates are similar across various measures of operational outcomes, including revenues, employment, payroll, and intermediate inputs.

Table 3, columns 1-4, reports estimates from the static specification in equation (5). In line with the evidence from Figure 3, changes in operational outcomes associated with inflows are large (estimated β_1 range in 0.11–0.23), while changes specifically associated with infiltration (β_2) are small and close to zero.

The results indicate that infiltration of *born-clean* firms is not associated with changes in the operational aspects of the firm, relative to those observed in any firm that experiences an inflow of new owners or managers. This is potentially consistent with the *pure* motive which, indeed, the model suggests should be particularly prevalent among these firms. To confirm this prediction, however, we need to consider the financial position of the firm, since the *pure* motive implies the entry of additional, and cheaper, sources of finance into the firm. Unlike the operational outcomes, we are going to find significant changes in those outcomes.

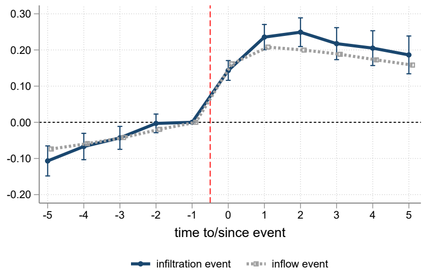
Prediction 2(b): Sources of Finance Figure 4 illustrates the dynamics of firm financial position around infiltration and other inflows. As before, the left panels report estimates for γ_j^{INF} and γ_j^I from equation (6), while the right panels report the difference between the two. Columns 5-8 of Table 3 report the corresponding estimates from the static specification in equation (5).

Consistent with prediction 2(b), a stark difference emerges. The first two rows of Figure 4 show that relative to regular inflow events, infiltration is associated with a substitution away from bank lending. We rely on detailed loan-level data from the credit registry of the Bank of Italy. We find that infiltrated firms borrow less capital from banks, which is in stark contrast with the strong increase in bank debt reliance for firms who experience a non-criminal inflow. This is true for the extensive and intensive margins (first and second rows in Figure 4, respectively).

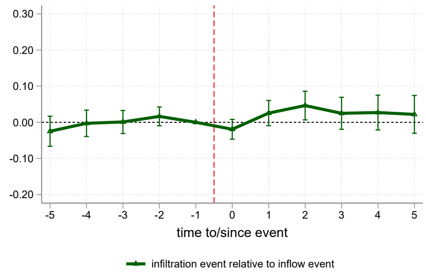
The decline in bank loans upon infiltration deserves a more careful discus-

Figure 3: Infiltration, Revenues, and Operational Outcomes

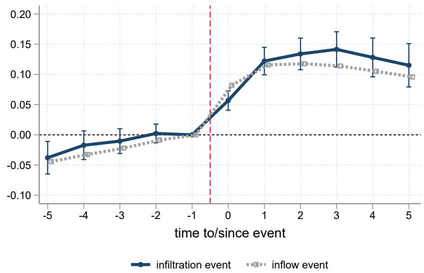
(a) Revenue: infiltration vs. inflow



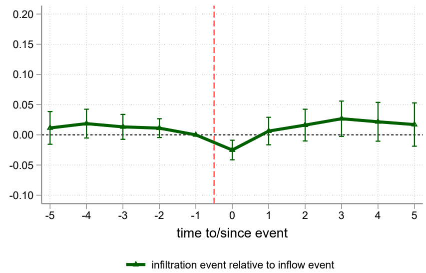
(b) Revenue: Δ infiltration and inflow



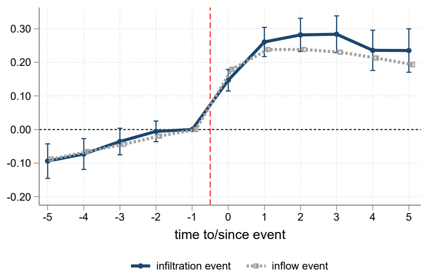
(c) Number of employees: infiltration vs. inflow



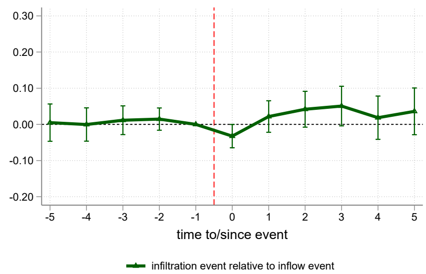
(d) Number of employees: Δ infiltration and inflow



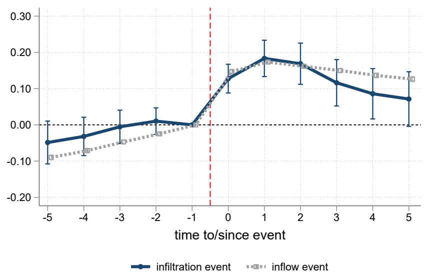
(e) Payroll: infiltration vs. inflow



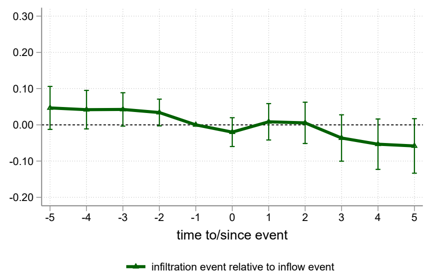
(f) Payroll: Δ infiltration and inflow



(g) Intermediate inputs: infiltration vs. inflow



(h) Intermediate inputs: Δ infiltration and inflow



Notes: Left panels: Point estimates and 95% confidence intervals for parameters γ_j^{INF} and γ_j^{NC} from equation (6). Right panel: Difference between γ_j^{INF} and γ_j^{NC} estimates. The infiltrated firms sample includes born-clean firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. The specification includes sector-year and province-year fixed effects. All outcome variables are in the inverse hyperbolic sine form. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021), pp. 46-47).

Table 3: Infiltration of Born-Clean Firms

	(1)	(2)	(3)	(4)
Panel A: Operational outcomes				
Dep. variable	Revenues	No. Employees	Payroll	Inputs
Post Infiltration	0.014	-0.006	0.006	-0.041*
	(0.016)	(0.010)	(0.020)	(0.022)
Post Any Inflow	0.203***	0.112***	0.234***	0.180***
	(0.002)	(0.001)	(0.002)	(0.002)
No. observations	9,758,931	9,758,931	9,758,931	9,758,931
No. firms	1,555,154	1,555,154	1,555,154	1,555,154
No. infiltrated firms	17,708	17,708	17,708	17,708
No. inflow event firms	828,022	828,022	828,022	828,022
Panel B: Financial outcomes				
Dep. variable	=1 any bank loans	Bank loans if >0	Receivables	Cash
Post Infiltration	-0.040***	-0.206***	0.112***	-0.010
	(0.004)	(0.059)	(0.015)	(0.018)
Post Any Inflow	0.028***	0.151***	0.162***	0.070***
	(0.001)	(0.007)	(0.002)	(0.002)
No. observations	9,758,931	5,217,909	9,758,931	9,758,931
No. firms	1,555,154	829,942	1,555,154	1,555,154
No. infiltrated firms	17,708	10,231	17,708	17,708
No. inflow event firms	828,022	492,759	828,022	828,022

Notes: This table presents the point estimates from equation (5). The sample excludes born-infiltrated firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. All columns include sector-year and province-year fixed effects. All outcome variables are in inverse hyperbolic sine form except for the dummy variable `=1 any bank loans`. Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

sion. In principle, the reduction in bank lending to infiltrated firms could stem from a *demand* or from a *supply* channel. The *demand* channel is the one emphasized by our conceptual framework: the firm no longer needs to borrow funds from the bank due to the increased sources of finance brought in by the OCG.[31] On the *supply* side, however, the bank might decide to further reduce lending to a firm that they perceive to have been infiltrated or involved in dodgy deals.[32] Since, as we show below, OCGs seem to target firms that experience liquidity problems, the reduction in the supply of funds might indeed accelerate a previous pre-trend in which the supply of funds to the firm is drying up.

The *supply* channel, however, is unlikely to account for the entire reduction

[31]It is worth noting that, in practice, the *demand* channel likely masks a further motive. Through suspicious transactions reports (STRs), banks are the backbone of the financial crime enforcement system. The infiltrated firms might thus prefer to shy away from interactions with banks to limit scrutiny, rather than saving on the costs of capital. This argument, which is particularly plausible among larger firms with good access to capital markets, justifies our focus on the interior solution of the model.

[32]The bank's response is *a priori* ambiguous as the bank might also become more willing to lend to a firm whose financial position has improved due to the entry of new sources of funds.

in bank borrowing. The third row of Figure 4 and column (7) of Table 3 reveal that infiltrated firms increase their commercial credit following infiltration—i.e., they become net suppliers of working capital for other firms in their supply chain. While the supply of funds from banks might have partially dried up, the overall sources of finance available to the firm have expanded.

Consequently, the liquidity position of the firm should improve. The entry of new owners with large amounts of cash to be invested, or of administrators with links to potential financiers, should be associated with an increase in the liquidity of the firm. The last row in Figure 4 supports this prediction, as illustrated by the trend reversal and jump in cash holdings around the time of infiltration. Interestingly, the static difference-in-difference specification in Column 8 of Table 3 misses this effect (it is indeed negative, but not statistically different from zero). This happens because infiltrated firms display a negative pre-trend relative to the control group of firms who experience a non-criminal inflow, consistent with OCGs targeting, or being accepted by, firms that are experiencing (potentially temporary) liquidity problems. Combined with the earlier results on operational outcomes, these findings indicate that OCGs target firms who are likely in *financial* but not in *economic* distress.

Predictions 2(c): Heterogeneity Among Born-Clean Firms Taken together, the results so far support the predictions of the model: born-clean firms predominantly reflect a *pure* motive. To the extent that born-clean firms reflect a mix of motives, however, the model suggests:

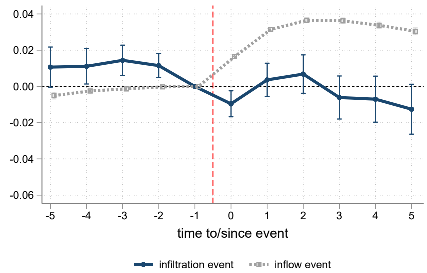
Prediction 2(c) *Within born-clean firms, smaller firms reflect a contaminated motive: the firm's revenues y and scale of operation k increase.*

Table 4 supports this prediction. Among *born clean* firms, the higher risk of detection associated with infiltration of the contaminating type is relatively less costly for small and young firms. The dynamics of infiltration for these firms, therefore, should reveal a contaminating motive, rather than a pure investment one. Indeed, Table 4 columns 1 to 4 find support for this further set of predictions. While we find that non-criminal inflows have a stronger effect on smaller and younger firms, we find that these heterogeneous effects are (strongly statistically significant) larger for firms that experience an infiltration.[33]

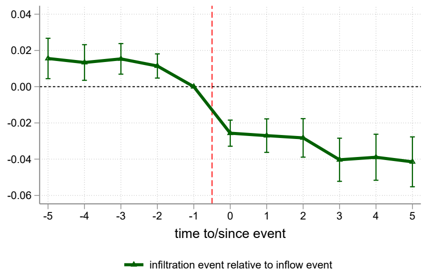
[33]Consistently with the model, (unreported) results find similar results for firms infiltrated at a younger age.

Figure 4: Infiltration and Financial Position

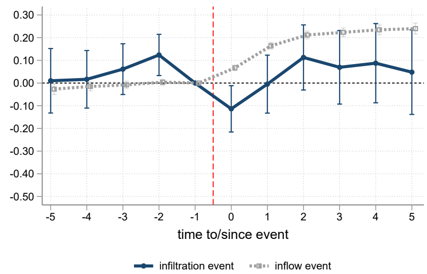
(a) Bank loans, ext. margin: inf. vs. inflow



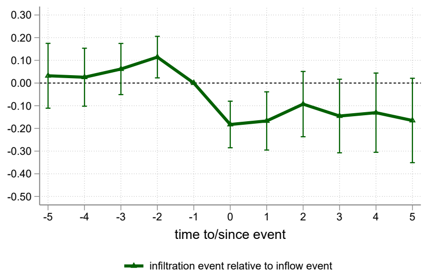
(b) Bank loans, ext. margin: Δ inf. and inflow



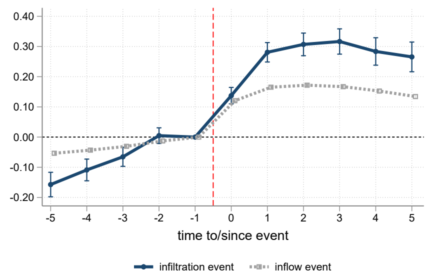
(c) Bank loans, int. margin: inf. vs. inflow



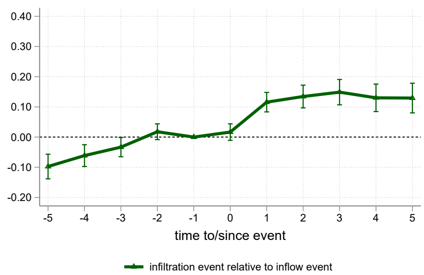
(d) Bank loans, int. margin: Δ inf. and inflow



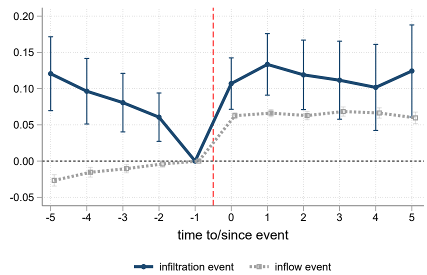
(e) Receivables: inf. vs. inflow



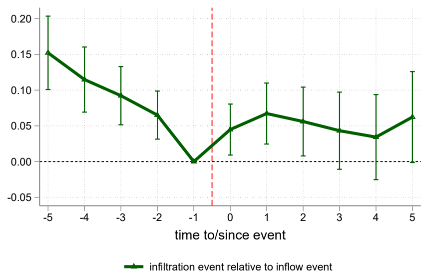
(f) Receivables: Δ inf. and inflow



(g) Cash holdings: inf. vs. inflow



(h) Cash holdings: Δ inf. and inflow



Notes: Left panels: Point estimates and 95% confidence intervals for parameters γ_j^{INF} and γ_j^{NC} from equation (6). Right panel: Difference between γ_j^{INF} and γ_j^{NC} estimates. The infiltrated firms sample includes born-clean firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. The specification includes sector-year and province-year fixed effects. All outcome variables are in the inverse hyperbolic sine form except for the first row, which is a dummy variable. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021) pp. 46-47).

Table 4: Heterogeneous effects in operational outcomes by firm size

Dep. variable	Revenue (1)	No. Employees (2)	Payroll (3)	Inputs (4)
Post Infiltration × Small	0.208***	0.007	0.045	0.187***
	(0.031)	(0.022)	(0.039)	(0.045)
Post Infiltration	-0.060***	0.018	0.035	-0.086**
	(0.023)	(0.017)	(0.028)	(0.035)
Post Any Inflow × Small	0.273***	0.157***	0.313***	0.366***
	(0.003)	(0.003)	(0.005)	(0.006)
Post Any Inflow	-0.006**	-0.008***	-0.007*	-0.101***
	(0.003)	(0.002)	(0.004)	(0.005)
Observations	9,758,931	9,758,931	9,758,931	9,758,931
Mean dep variable	6.371	1.435	3.617	4.184
Number of infiltrated	17708	17708	17708	17708
Number of inflow firms	828022	828022	828022	828022

Notes: This table presents the point estimates from equation (5). The sample excludes firms born infiltrated. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. *Small* takes value one for firms with whose assets are less than 2m Euro one year before the infiltration or inflow event. All columns include sector-year and province-year fixed effects. Outcome variable is revenues in inverse hyperbolic sine form. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021), pp. 46-47). Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

5.2.3 Robustness and Comparison with Mirenda et al. (2022)

Appendix B presents a robustness analysis along three dimensions. First, the two-way fixed effects model has certain limitations.[34] We estimate a stacked-panel model in which we compare infiltrated firms to firms that experience an inflow in the same year, as in Cengiz et al. (2019). We also estimate the static model in Wooldridge (2021) that retains the staggered adoption dimension of our panel. Second, we explore the robustness to several changes in our definition of infiltration. Finally, we confirm the robustness of our results to various sample restriction decisions.

Our analysis of *born-clean* firms' infiltration parallels Mirenda et al. (2022). Since we find radically different results from theirs, it is important to understand where the differences arise. In principle, the difference could arise from

[34]In the presence of heterogeneous treatment effects, the two-way fixed-effects (TWFE) model suffers from "bad" comparisons if later treated units are used as a control for early treated units. In our context, the number of never-treated units (i.e., firms that did not experience either an infiltration or an inflow event) is substantially larger and this is not a major concern. Following De Chaisemartin and d'Haultfoeuille (2020), the share of the estimates with negative weights (i.e., coming from these "bad" comparisons) are very small (0% for infiltration and 6% for other inflow events).

i) a different empirical proxy for infiltration (i.e., our reliance on the *Mappatura* rather than family surnames associated with OCGs in Italy), or *ii*) a different sample (as our sample includes all of Italy while Mirenda et al. (2022) focus on investments in the North); or *iii*) our comparison to other firms that also experience an inflow event. Appendix Figure A2 and Table A2 show that the latter is the key driver of the difference. Focusing on revenues (the main outcome shared by the two analyses) we show that introducing our correction in Mirenda et al. (2022)'s infiltration proxy and sample recovers our null result.

5.3 Prediction 3: Infiltration Motives in *Born-Infiltrated* Firms

Testable Predictions for Born-Infiltrated Because born-infiltrated firms are relatively small, the model implies that these firms predominantly reflect the *contaminated* motive. Implications 1, 2 and 3 yield:

Prediction 3(a)-(b) *Infiltration on Born-infiltrated firms predominantly reflects a contaminated motive and is thus associated with 3(a) a higher scale of operation (higher k) at birth, 3(b) lower performance and worse selection (lower θ) in the case of functional investment ($\mathbf{I}^f = 1$) relative to the competition investment ($\mathbf{I}^f = 1$).*

While prediction 3(a) immediately follows from implications 1, 2 and 3, prediction 3b requires an explanation. Within the *contaminated* motive, the *competitive* motive is associated with an increase in firm performance, while the *functional* motive with a decrease (holding constant θ, k is distorted away from its profit-maximizing level since the OCG also cares about the criminal payoff $\gamma C(k_m)$. This suggests that relative to a non-contaminated firm in the same market, the infiltrated firms of the *functional* type survive even with low productivity θ, provided it is sufficiently well-selected on γ. While not formally modeled, this selection argument naturally emerges in an industry equilibrium extension that models entry and survival along the lines of Melitz (2003).

Empirical Approach Unlike born-clean firms, born-infiltrated firms are, by definition, not observed before infiltration. The difference-in-difference framework is thus not feasible.[35] Studying these firms is however important for two reasons. First, these firms account for about half of all infiltrated firms in our sample and for 7.2% of all assets invested in newly created firms in the typical year. Second, and crucially, the patterns of these firms can help us shed light

[35]Note that, indeed, Mirenda et al. (2022) omit these firms from the analysis.

on the motive of infiltration, as this might be different than for the rest of the infiltrated firms.

To test the predictions, we compare *born infiltrated* firms to firms established in the same year, province, and sector. This comparison will necessarily bundle both the effect of infiltration on the firm as well as how infiltration alters the process of entrepreneurial selection. To investigate selection, we borrow our empirical specification from Banerjee and Munshi (2004) study of capital misallocation in India, in which a group of "insiders" entrepreneurs has better access to capital than a group of "outsiders". In their framework, insider firms are run by negatively selected managers – as they do not need to be as good as the financially constrained "outsiders" to survive. While initially larger, these firms display lower productivity and profitability at birth and over time. The analogy with infiltrated firms of the *functional* type is perfectly fitting.

Borrowing from Banerjee and Munshi (2004), we estimate:

$$y_{it} = \beta_1 \times BI_i + \beta_2 \times BI_i \times Age_{it} + \alpha_{psb} + \alpha_t + \epsilon_{itpsb} \tag{7}$$

where i, t, p, s, b stand for firm, year, province, sector, and cohort. BI_i is a dummy that takes value equal one if firm i was born-infiltrated, while Age_i is the age of i in year t. α_{psb} are year of birth by province of birth by industry fixed effects, while α_t are year fixed effects.[36]

Empirical Results Table 5 reports the results. We find a strong validation of the model's prediction. Across the same operational outcomes we explored above – revenues, employment, payroll, and inputs –we show that *born infiltrated* firms are born larger than firms born in the same year-province-sector.[37] Moreover, as shown in row 1 of Table 5, we observe a deteriorating trend for *born infiltrated* firms, as they become both smaller on several dimensions over their life-cycle. These findings are in line with the negative managerial selection implied by the model. Appendix Table A5 finds that total assets increase over time, while the probability of having positive profits decreases.

[36] Note that the linear effects of Age_i cannot be separately identified from cohort and year effects and is thus absorbed in the specification.

[37] For consistency, we include all firms that appear in the CERVED dataset without imposing a positive revenue restriction. If we exclude observations with revenue $= 0$, then the negative selection appears even stronger.

Table 5: Born-Infiltrated Firms at Birth and Over Time

	(1)	(2)	(3)	(4)
Panel A: Operational outcomes				
Dep. variable:	Revenue	No. Employees	Payroll	Inputs
Born infiltrated × Age	-0.014**	-0.008***	-0.024***	-0.031***
	(0.005)	(0.002)	(0.004)	(0.005)
Born infiltrated	0.165***	0.156***	0.199***	0.228***
	(0.022)	(0.009)	(0.018)	(0.020)
Panel B: Financial outcomes				
Dep. variable:	=1 any bank loans	Bank loans if >0	Receivables	Cash
Born infiltrated × Age	-0.001	0.020**	0.034***	-0.005
	(0.001)	(0.005)	(0.004)	(0.004)
Born infiltrated	0.020***	0.704***	0.627***	0.257***
	(0.003)	(0.028)	(0.018)	(0.014)
Observations	6,126,878	6,126,878	6,126,878	6,126,878
Infiltrated firms	22455	22455	22455	22455
Mean dep var (Panel A)	4.848	0.985	2.629	3.215
Mean dep var (Panel B)	0.338	4.274	4.243	3.123
YOB × Province × Industry FE	Yes	Yes	Yes	Yes

Notes: Infiltrated at birth is a dummy that takes the value one if the firm was born infiltrated. Age is a continues variable that measure the age of the firm in every year. The sample includes all firms in the CERVED dataset. All regressions include year of birth by province of birth by 2-digit industry fixed effects, and year fixed effects. Outcome variable is revenues in inverse hyperbolic sine form, except for column 1 Panel B which is a dummy. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021), pp. 46-47). Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

6 Discussion and Policy Implications

6.1 The non-pecuniary benefits of Infiltration

The evidence so far supports our distinction between the *contaminated* and *pure* infiltration motives. This distinction departs from the dominant idea in the literature that infiltration always brings with it criminal activities. The evidence suggests that this characterization applies well to smaller and medium-sized firms, often directly established by the OCGs. Many infiltrated firms, however, are already large and well-established at the time infiltration takes place. The behavior of these firms is in line with the implications of what we have labeled the *pure* motive, in which the infiltrated legal firm remains disconnected from criminal activities. ”Born-clean” firms, which are more likely to reflect this *pure* motive, account for 85% percent of the total assets of infiltrated firms. This suggests that this previously undetected *pure* motive is an extremely important, if not the predominant, motive of infiltration.

For simplicity, the model has assumed that the benefit of *pure* infiltration is pecuniary: the OCG earns a higher financial return from investing in the legal firm liquidity that is hard to reinvest in the criminal business and financially costly and risky to hoard. As already mentioned, alongside the financial returns, *pure* infiltration is likely motivated by non-pecuniary benefits as well. Crucially, these private benefits are distinct from those in the *functional* motive. In the *functional* motive, the OCG benefits from the crimes the firm is involved with. In contrast, in the *pure* motive, the OCG seeks private benefits that (*i*) are disconnected from criminal activity, and (*ii*) can only be acquired by being involved in the operation of large firms. For example, the OCG might use the firm to expand its "relational capital", establishing relationships with important actors in the legal economy, such as other firms, industry associations, public administration, politicians, etc.

Two considerations hint at this possibility. First, the majority of infiltration occurs through administrators rather than owners. This suggests that "private equity" like investments in which the OCG seeks higher financial returns might not be the sole benefit of *pure* infiltration. Second, and as noted above, the substitution of external sources of funds for internal ones is a characteristic mark of *pure* infiltration. *Pure* infiltration happens predominantly in larger firms, that tend to have relatively good access to finance. The substitution of bank loans for internal funds might thus be driven, not so much by the lower cost of the funds provided by the OGC, but by other considerations (see footnote 26). A complementary hypothesis is thus that the *pure* motive is also driven by OCG's desire to expand its "relational capital" in the legal economy. Being actively present in the legal economy through their unsuspected and talented representatives can be the way OCGs accumulate this valuable relational capital.

Two pieces of evidence lend some support to this hypothesis. While the benefits entailed by such "relational capital" are unobservable, we can test whether infiltration itself is associated with the accumulation of "relational capital". Table A6 in the Appendix explores the connections of board members to other firms. OCGs infiltrate firms whose board members have significantly more connections to other firms. This correlation holds across firms, conditional on several firm and individual controls. It is conceivable that the more connected the board members of infiltrated firms are to other firms, the greater the accrual of information to the OCG about potential investment opportunities in other businesses – a non-pecuniary benefit of the infiltration.

Furthermore, within firms, individuals connected to OCGs sit on more boards than other board members of the same infiltrated firm. On average, every individual tied to OGCs sits on 4 to 5 boards. The average board member of infiltrated firms, however, sits on an average of two boards. This is consistent with the *pure* motive for two reasons: first, because *pure* infiltration needs individuals (e.g., high-level professionals, managers, consultants) that are competent, look clean, and are tied to and can be trusted by the OCG. These individuals are in scarce supply and end up being deployed across several infiltrated firms.[38] Second, because the build-up of ”relational capital” requires a direct personal involvement. It is worth stressing that, consistent with our definition in Section 2.1, this type of infiltration might introduce managerial capital linked to the OCG without necessarily involving the accrual of financial resources.

Table 6 considers political connections and lends further support to the hypothesis that *pure* infiltration might conceal, at least in part, a desire to expand the OCG’s ”relational capital” in the legal economy. We match owners and administrators of firms with elected politicians. Column (1) finds that relative to clean inflow events, infiltration-targeted firms are more likely to have a politician on their boards. Column (2) shows that this relationship is stronger when infiltration happens on larger firms – those that are more likely to reflect the *pure* motive.[39] Turning to dynamics post-infiltration, Column (3) finds that infiltration is associated with an increase in the likelihood that the firm is politically connected, over the change estimated for a clean inflow event. In this case, however, the relationship is not stronger for larger firms (Column 4).

In sum, the *pure* motive might respond to OCGs’ desire (and ability) to interact with the main players of the legal economy, e.g., large enterprises, politically involved persons, public administrators, and high-profile service providers (e.g., lawyers, accountants, consultants). This hypothesis was con-

[38]For example, investing large sums of money without using (the threat of) violence – as in the *pure* motive – requires trusted, and respectable, intermediaries. These intermediaries are a scarce resource for OCGs and, therefore, the OCG cannot easily split large sums to be invested into many small firms. The *pure* motive thus appears in larger firms. In contrast, the *contaminated* motives hinge on criminal activities (e.g., the threat of violence, corruption) for which there are economies of scale (once a person has been used to threaten violence or corrupt, (s)he might just as well do so across many transactions). The *contaminated* motive can thus appear in many small firms. This logic also suggests a micro-foundation for the distinction between the infiltration of born-clean and born-infiltrated firms. If there are increasing returns to scale in criminal activities, a ”clean” entrepreneur might have a higher cost of contaminating the firm with criminal activities than the OCG. This provides a rationale for why ”born-infiltrated” firms are more likely to be of the *contaminated* type.

[39]Born-infiltrated firms also have more political connections (unreported results).

Table 6: Infiltration and political connections

Dep. variable:	Political connection			
	(1)	(2)	(3)	(4)
Infiltrated	0.027***	0.028***		
	(0.002)	(0.002)		
Infiltrated × Assets		0.013***		
		(0.002)		
Post Infiltration			0.025***	0.021***
			(0.003)	(0.006)
Post Any Inflow			0.011***	0.013***
			(0.000)	(0.001)
Post Infiltration × Small				0.006
				(0.007)
Post Any Inflow × Small				-0.002***
				(0.001)
Observations	1,020,779	1,020,779	9,758,931	9,758,931
Mean dep variable	0.078	0.078	0.073	0.073
Number of infiltrated	22735	22735	17708	17708

Notes: This table presents the relationship between infiltration and political connections. The dependent variable is a dummy that takes the value one if a firm has an elected politicians either as owners or administrators. Columns 1 and 2 present the correlation between being infiltrated and the prevalence of political connections in the firm. In this sample, we compare infiltrated firms to firms that suffer an inflow-event in the year prior to the event. Controls in columns 1 and 2 include total revenue, total assets, cash, as well as industry and year of event fixed effects. In column 2, we interact Infiltrated with demeaned total assets before the event. Columns 3 and 4 present the point estimates from equation (5). The sample excludes firms born infiltrated. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. Controls in columns 3 and 4 include sector-year and province-year fixed effects. Outcome variable is revenues in inverse hyperbolic sine form. Infiltrated firms are taken from a Mapping of firms potentially connected to organized crime developed at UIF (UIF (2021), pp. 46-47). Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

firmed to the research team by some of the prosecutors and investigators who are most familiar with the latest trends in OCGs' activities, particularly in the case of 'Ndrangheta – the OCG likely accounting for the majority of infiltrated firms in the *Mappatura* (see above).

6.2 Policy Implications and conclusions

The distinction between the *contaminated* motives and the *pure* motive has important policy implications, both at the operational and the strategic levels in the fight against criminal organizations.

First, if most infiltration is directly connected to criminal activities, then deploying scarce investigative resources directly to counter-crime will also be effective in detecting infiltration and curbing OCGs' returns from their investments. If, instead, as our results suggest, the majority of infiltration capital flows (of both apparently respectable human capital as well as already-laundered financial assets) are disconnected from the underlying criminal activity, there is a significant risk that these flows remain undetected and continue to multiply investment opportunities for OCGs. This risk is further compounded by the increased ramifications of their connections. To the extent that our results challenge the status quo perception in the literature and among policymakers, they suggest a potential misallocation of scarce investigative resources: the marginal investigative officer should be deployed to analyze financial transactions and investigate connections rather than other forms of criminal activities. Unlike the financial transactions of the *contaminated* motive – which have a high risk of detection, being directly conducted by (or linked to) firms that actively engage in illegal activities, the financial operations connected to the *pure* motive and the investments to build relational capital are 'hidden' and have a much lower risk of detection, being far from any illegal conduct. The fight against the *pure* motive requires a significant strengthening of the financial analysis know-how of investigative agencies and prosecutors and the development of skills needed to identify professionals at risk of collusion with OCGs.

Second, and within the anti-money laundering apparatus, the design of monitoring systems, leniency programs, and screening algorithms, depends on the extent to which OCGs involve legal firms in criminal activities (e.g., money laundering, or corruption in public procurement) or not. On the monitoring front, the evidence calls for a significant upgrade of the collaboration provided by specific categories of reporting agents – such as auditing firms and consultants – who are typically closer, by the nature of their function, to the firm's economic and financial developments and changes in governance. An important avenue for future work is to understand the role of these individuals in facilitating *pure* infiltration. A key distinction between the *contaminated* and the *pure* infiltration is that in the former there likely is a victim (e.g., the competitor who was threatened or who lost the public procurement contract because of corruption), in the latter, there isn't (by definition, the entrepreneur is willing to accept the 'pact with the devil' and benefit from the OCG's cheaper finance and relational capital). Leniency programs for financial crimes connected to OCGs might thus have to be strengthened, with appropriate incentives, to fight infiltration of the *pure* motive. Furthermore, our evidence provides insights that are relevant for the design and optimization of algorithms used to detect infiltrated firms (see, e.g., Cariello et al., 2024 for an operational contribution). These algorithms are increasingly used by public investigative agencies as well as private entities (e.g., banks) to monitor transactions, detect suspicious operations, and be compliant with anti-money laundering regulations.

Finally, a more disturbing conclusion emerges when considering a potentially important source of benefits from *pure* infiltration – political connections. Our results suggest that the *pure* infiltration might significantly increase the economic power of OCGs, as they present themselves with a totally clean and faultless image. They can thus interact freely and develop connections with the main economic players (managers of large enterprises, high-profile consultants, public officers making decisions on tenders, and politicians). In this regard, our findings are consistent with the alarms raised in recent years by the Italian intelligence and security agencies (see, e.g., DIS (2019)), for which our paper provides the first rigorous and comprehensive evidence. This accumulation of "relational capital" can have far-reaching consequences. Given the well-known influence of economic lobbies on the legislative process in modern democracies (see, e.g., Bertrand et al., 2014, Bertrand et al., 2023), this economic power can become, over time, political power: i.e., OCGs can ultimately affect the law-making process (e.g., the production of anti-money laundering and financial regulation) thus strengthening and perpetuating their grip on the economy and society.

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A Additional Data Sources

We merge the *Mappatura* dataset with several different administrative data, namely the complete register of owners, administrators, and auditors of all legal firms, firms' operations and balance sheets, credit registry loan-level data, and employment records.

Data on firm composition: owners, directors, and auditors. We observe the identity of owners, directors, and auditors of the universe of firms in Italy using the Infocamere database from the Italian Chamber of Commerce. For each individual, we observe both name and social security identifier, which allow for direct matching with the *Mappatura*. The Infocamere database also provides information on firm location, sector, and years of entry and exit.

Balance sheet and income statement data. We use balance sheet and income statement panel data on the universe of Italian non-financial corporations from Cerved, a standard dataset used in firm-level analyses of Italian firms (Mirenda et al., 2022).[1] The dataset includes operational and financial outcomes such as revenues, payroll, intermediate inputs, assets, liquidity, credit, and debt.

Credit registry. We access loan-level records for all firm-bank credit relationships in Italy through the confidential credit registry database managed by the Bank of Italy.[2]

Social Security aggregates. We use a firm-level panel dataset aggregated from Social Security records (INPS) to study employment counts and average salary at the firm level. Employment and average salary are disaggregated for different worker categories (e.g., managers, white-collar workers, blue-collar workers).

Politicians. We obtain data on elected politicians from the Ministry of the Interior. The dataset includes municipal, provincial, and regional-level politicians and national congress members from 1993 to 2023. To merge politicians to owners and administrators, we construct the national identifier of the politicians (codice fiscale) based on their demographic characteristics (i.e., full name, age, place of birth). The final dataset includes 567,205 politicians with a national identifier.

[1]Firms that are not covered by this data are sole proprietorships or unincorporated partnerships.

[2]We do not observe loans below Euro 75,000 Euro pre-2009 and loans below Euro 30,000 post-2009. See Bofondi et al. (2018) for more details.

B Robustness exercises

In this appendix section, we discuss the robustness of our results to three main empirical decisions. First, we discuss the robustness to the empirical design employed in the paper, second, we discuss the robustness to the definition of infiltration, and finally to sample restrictions.

B.1 Empirical design

Our main specification for the "born-clean" analysis relies on a two-way fixed-effects model (TWFE). As discussed in footnote 34, in the presence of heterogeneous treatment effects, the TWFE model suffers from "bad" comparisons if later treated units are used as a control for early treated units, thus biasing the estimated parameter from the TWFE model. In our context, the number of never-treated units (i.e., firms that did not experience either an infiltration or an inflow event) is substantially larger and this is not a major concern. Following De Chaisemartin and d'Haultfoeuille (2020), the share of the estimates with negative weights (i.e., coming from these "bad" comparisons) are very small (0% for infiltration and 6% for other inflow events). In any case, we perform two robustness exercises for this model.

First, we estimate a stacked-panel regression as in Cengiz et al. (2019). To do this, we create a panel around each cohort that was infiltrated and compare it with the cohort of firms that receive an inflow event. Thus, in this model, we are always comparing infiltrated firms to firms that experienced an inflow event in the same year. In Figure A4 and Table A7, we present the results that are aligned with the main results presented under the TWFE model.

Second, we estimate a static model in the staggered difference-in-difference framework that is robust to the presence of heterogeneous treatment effects. In particular, we estimate the model suggested by Wooldridge (2021). Note that in our context we have two types of firms that are experiencing a staggered change and we are interested in the difference between both. Therefore, what we do is to estimate the coefficient for each group and then test for the difference between both. In Table A8, we present the results which shows the robustness of our conclusions to implementing this alternative estimation method.

B.2 Measure of infiltration

Our analysis relies on the novel and comprehensive data from *Mappatura*. However, there have been other measures used in previous papers to define business-mafia relations. In Tables A9 and A10, we present the robustness of our results to these different measures. In column 1, we present the results for our baseline specification. In column 2, we extend our measure based on *Mappatura*, but we follow a similar strategy as in Mirenda et al. (2022) where we also call infiltrated a firm where the owners of a company faced an infiltration in another firm that they owned. In column 3, we present the measure of infiltration based on surnames by Mirenda et al. (2022). In columns 4 and 5, we present the union of these measures where, in column 4, we use *Mappatura* as in column 1, while, in column 5, we use the extended measure of *Mappatura* as in column 2. Finally, in column 6, to further reduce concerns about false positives, we drop from the sample infiltrated firms that have an risk score equal to 2 (see Section 2.2 for details on the score). Overall, we find our results to be robust to different definitions of infiltration.

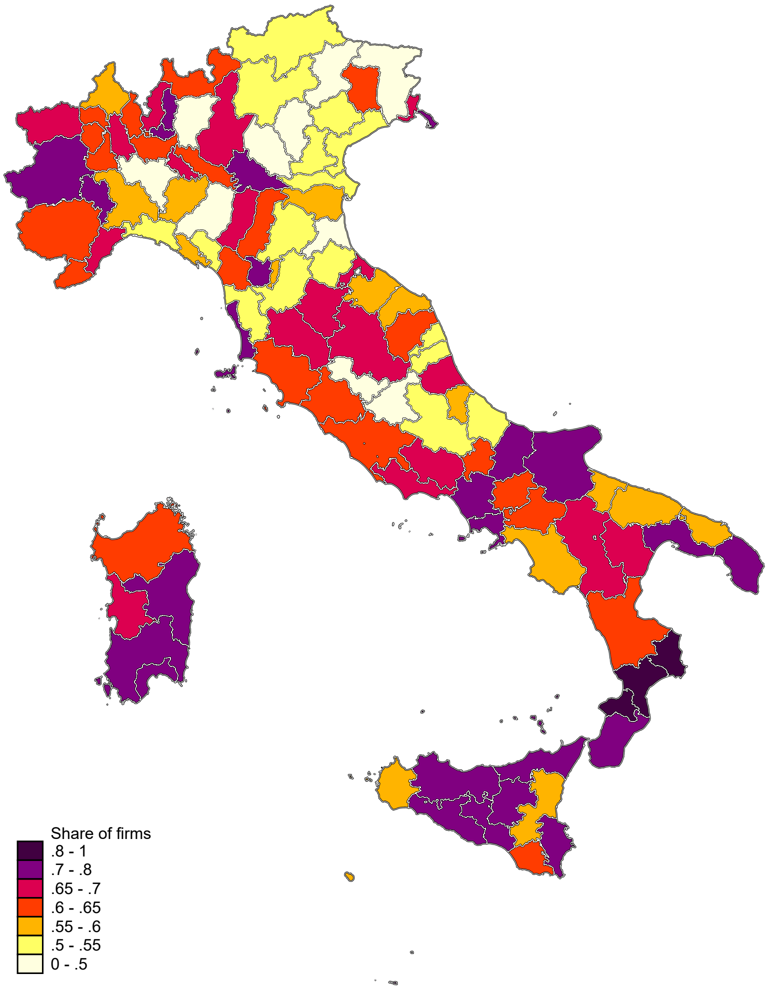
B.3 Sample restriction

There are two main decisions in terms of sample restrictions that we made in our analysis. The first is that we keep firms with positive revenues for the "born-clean" analysis as in Mirenda et al. (2022). The second is that we estimate the model using the entire country, as opposed to excluding the southern region as in Mirenda et al. (2022). Table A11 presents the robustness to both decisions.

C Additional Empirical Results

Figure A1: Geographic distribution of infiltration by type

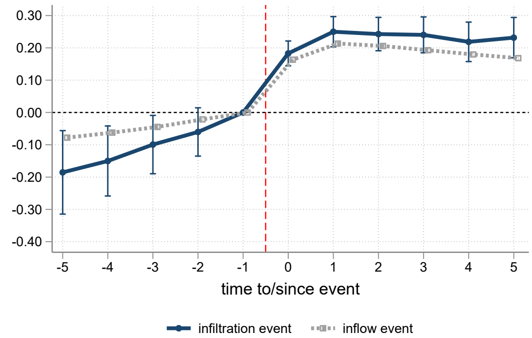
(a) Born infiltrated over any infiltration



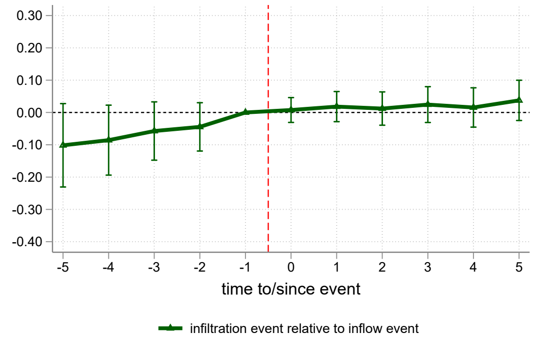
Notes: These figures present the geographic distribution of firms potentially connected to organized crime, identified in the *Mappatura*. We present the distribution of the share of infiltrated firms at birth over all infiltrated firms in the province.

Figure A2: Infiltration and Revenues, Mirenda et al. (2022) infiltration definition

(a) Infiltration event vs. inflow event



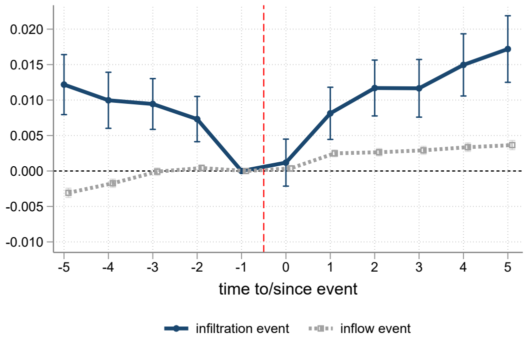
(b) Δ infiltration and inflow



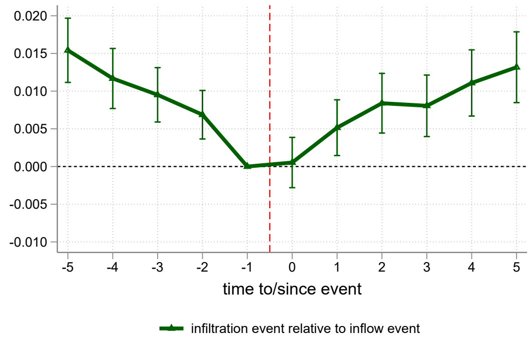
Notes: These figures present the point estimates and confidence intervals at the 95% level from equation (**??**). The sample excludes firms born infiltrated. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. The specification includes sector-year and province-year fixed effects. Revenues is in the inverse hyperbolic sine form.

Figure A3: Infiltration and Profitability

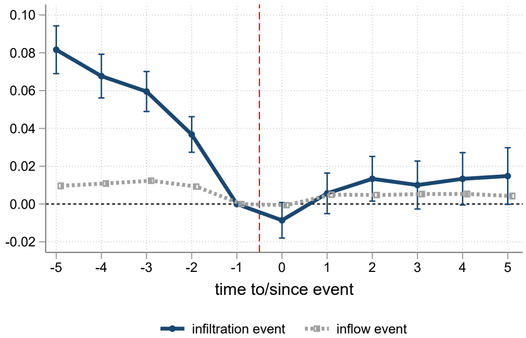
(a) ROA: infiltration vs. inflow



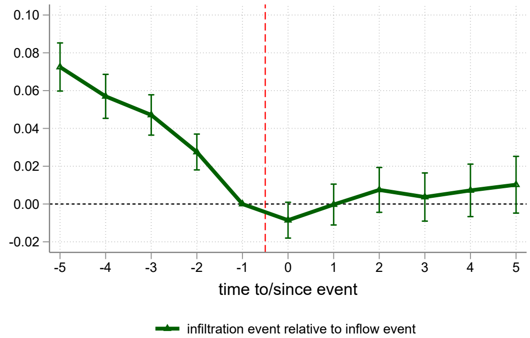
(b) ROA: Δ infiltration and inflow



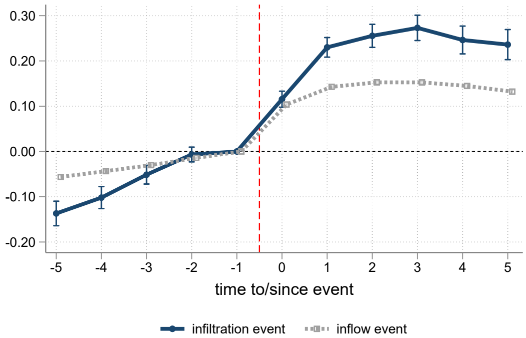
(c) Profits > 0: infiltration vs. inflow



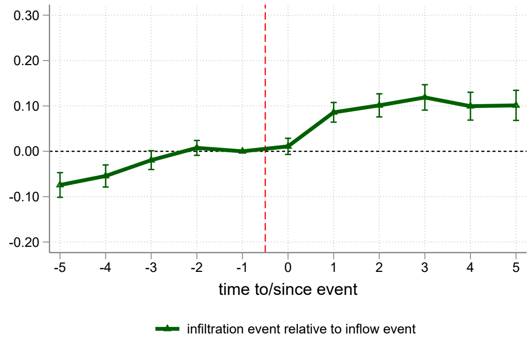
(d) Profits > 0: Δ infiltration and inflow



(e) Assets: infiltration vs. inflow



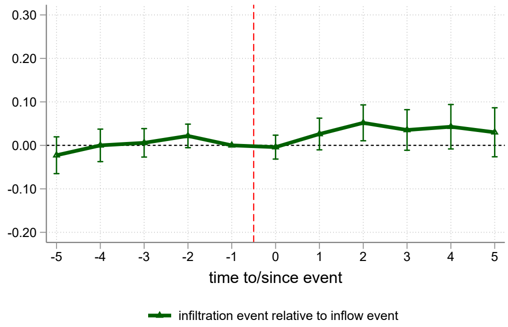
(f) Assets: Δ infiltration and inflow



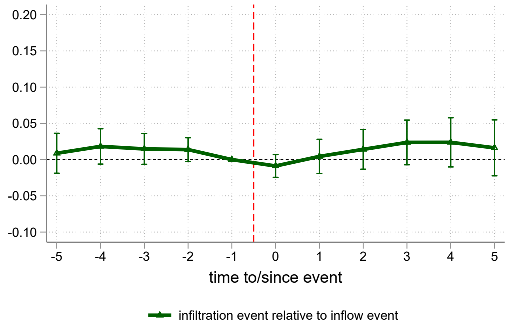
Notes: Left panels: Point estimates and 95% confidence intervals for parameters γ_j^{INF} and γ_j^{NC} from equation (6). Right panel: Difference between γ_j^{INF} and γ_j^{NC} estimates. The infiltrated firms sample includes born-clean firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. The specification includes sector-year and province-year fixed effects. All outcome variables are in the inverse hyperbolic sine form.

Figure A4: Dynamic specification stacked panel

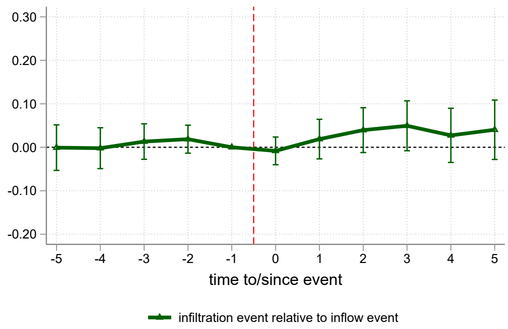
(a) Revenue



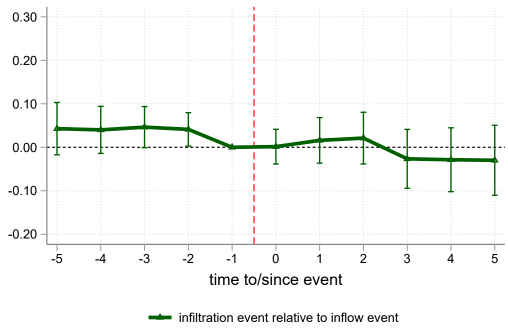
(b) No. Employees



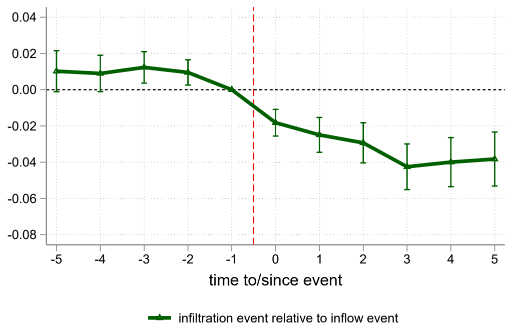
(c) Payroll



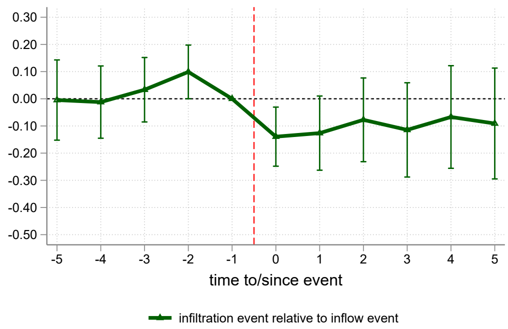
(d) Inputs



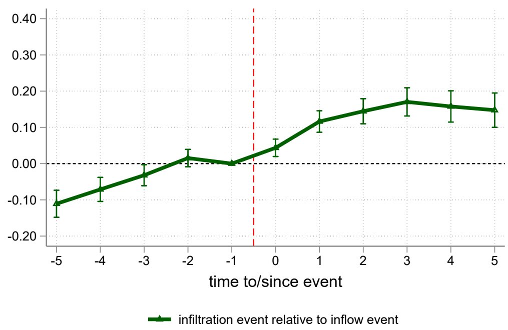
(e) Bank loans, extensive margin



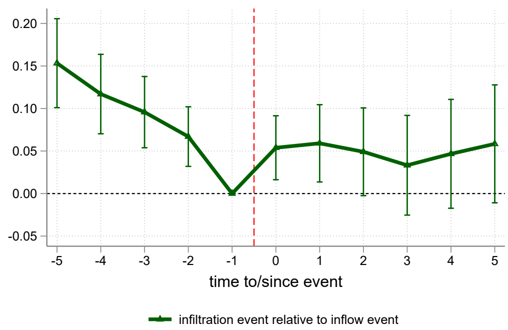
(f) Bank loans, intensive margin



(g) Receivables



(h) Cash holdings



Notes: This figure presents the point estimates and 95% confidence intervals for parameters from an stacked panel specification. The sample includes infiltrated firms and firms that experience an inflow event. The specification includes firm, year-cohort, sector-year-cohort and province-year-cohort fixed effects. All outcome variables are in the inverse hyperbolic sine, form except for panel e which is a dummy.

Table A1: Geographic distribution by type of infiltration

	Infiltrated over all firms (1)	Born infiltrated over all firms (2)	Born clean over all firms (3)	Born infiltrated over infiltrated firms (4)
Home region	0.021***	0.004***	0.017***	0.098***
	(0.003)	(0.001)	(0.003)	(0.023)
Observations	107	107	107	107
R-squared	0.579	0.528	0.544	0.145
Mean dep variable	0.0112	0.00369	0.00754	0.626

Notes: This table presents the relationship between infiltration by type and mafia regions. The dependent variable in column 1 (2/3) is the total number of infiltrated (born infiltrated/born clean) firms over the average number of firms in the province, while in column 4, is the share of born infiltrated over all infiltrated firms. *Home region* takes a value one if the firm is located in the provinces of Sicily, Calabria, or Campania. All regressions include year fixed effects. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Comparison with Mirenda et al. (2022)

	(1)	(2)	(3)	(4)	(5)
	Infiltration: Mirenda et al. (2022)			Infiltration: *Mappatura*	
	Published version	Own construction	Baseline specification	Mirenda et al. (2022) specification	Baseline specification
Post Infiltration	0.237***	0.175***	0.031	0.205***	0.031
	(0.024)	(0.024)	(0.019)	(0.019)	
Post Any Inflow			0.209***		0.206***
			(0.002)		(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
No. observations	6,124,827	9,025,675	7,318,815	8,989,456	7,297,491
No. firms		1154559	1138921	1149005	1133700
No. infiltrated firms		4297	4297	11404	11404
No. inflow firms		-	617104	-	618774

Notes: This table presents the comparison of point estimates between the infiltration definition and research design of Mirenda et al. (2022), and infiltration as defined by *Mappatura* and our research design. In all columns, the estimation sample excludes firms from the South, and include sector-year and province-year fixed effects. The dependent variable is revenue in inverse hyperbolic sine form. In column 1, we report the published estimate from Mirenda et al. (2022). Column 2 shows our results when using their research design and the surnames provided in their replication files. Column 3 estimates equation (5) based on surname-related infiltration. Column 4 uses the *Mappatura* data to identify infiltration, but follows the research design of Mirenda et al. (2022). Column 5 presents our baseline estimates from equation (5). Standard errors clustered at the firm level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A3: Infiltration and regional characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	Share of infiltrated firms						
GDP per capita	-0.008***						0.002**
	(0.002)						(0.001)
Financial development		0.002					0.001
		(0.002)					(0.001)
OCGs family names			0.011***				0.016***
			(0.002)				(0.003)
Length court cases				0.010***			0.005**
				(0.003)			(0.002)
Blood donation					-0.006***		0.001
					(0.002)		(0.002)
Trust						-0.008***	0.004
						(0.001)	(0.003)
Mean dep var	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208
Panel B	Share of born infiltrated firms						
GDP pc	-0.007*						0.006
	(0.004)						(0.007)
Financial development I		0.006					0.005
		(0.005)					(0.004)
OCGs family names			0.026**				0.014**
			(0.013)				(0.007)
Length court cases				0.015***			0.012*
				(0.005)			(0.006)
Blood donation					-0.005		0.002
					(0.003)		(0.004)
Trust						-0.011**	0.002
						(0.004)	(0.008)
Observations	105	105	86	104	102	105	102
Mean dep var	0.318	0.318	0.318	0.318	0.318	0.318	0.318

Notes: This table presents the correlation between the extent of infiltration and province-level characteristics. In Panel A, the dependent variable is constructed as the number of infiltrated firms alive in each year in a province over the total firms in that province and then we take the average across years. In panel B, the dependent variable is constructed as the number of born infiltrated firms alive in each year in a province over the total number of infiltrated firms in that province and then we take the average across years. *GDP per capita* is the provincial GDP per capita that we average across years. *Financial development* is defined as the variation across firms in the cost at which they can borrow (Guiso et al., 2013). We construct the share of *OCGs family names* by computing the share of people with each last name in mafia home regions (Sicilia, Campania or Calabria), then we keep in each region the top-100 last names. Then, we construct the share of people in non-mafia regions that have any of these last names. The source for the presence of last names is `http://www.gens.info/lib/cog/istruzioni.html`. *Length court cases* is defined as the average length of court cases. *Blood donation* is measured as the incidence of blood donation (Guiso et al., 2004). *Trust* is defined as the average trust on others across different cohorts (Guiso et al., 2004). Robust standard errors are presented in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Infiltrated firms, Inflow-event firms, and never-inflow firms: Average attributes

	Infiltrated (1)	Inflow event (2)	Never-inflow (3)
Panel A. Geographic location			
North	0.405	0.510	0.485
Center	0.249	0.251	0.251
South	0.346	0.239	0.265
Sicily	0.077	0.050	0.053
Calabria	0.035	0.016	0.018
Campania	0.157	0.079	0.088
Panel B. Firm characteristics			
Year of birth	1999.99	1998.76	2003.65
No. employees	29.08	12.03	4.41
(log) Revenues	6.40	5.91	5.35
No. managers	2.30	2.01	1.53
No. owners	3.40	2.91	2.26
Fraction ownership born in Sicily	0.06	0.04	0.06
Fraction ownership born in Calabria	0.04	0.02	0.02
Fraction ownership born in Campania	0.13	0.07	0.09
Panel C. Sectoral composition			
Agriculture, forestry, fishing	0.018	0.024	0.014
Mining, quarrying	0.004	0.002	0.001
Manufacturing	0.132	0.163	0.153
Electricity, gas, etc.	0.013	0.006	0.003
Water, waste, etc.	0.018	0.006	0.003
Construction	0.152	0.135	0.167
Wholesale & retail trade	0.183	0.201	0.236
Transportation & storage	0.064	0.040	0.030
Accommodation & food services	0.057	0.056	0.062
Information & communication	0.047	0.052	0.048
Finance & insurance	0.008	0.009	0.008
Real estate	0.096	0.117	0.107
Professional business services	0.065	0.068	0.067
Administrative & support	0.071	0.053	0.047
Education	0.007	0.011	0.008
Health	0.032	0.028	0.014
Arts, entertainment, recreation	0.024	0.018	0.016
Others	0.012	0.013	0.015
Number of observations	73,906	2,937,713	4,746,342
Number of firms	18,317	786,121	862,226

Notes: Cerved sample, observations with non-zero revenues. Excludes firms born infiltrated. Column (1): firm-year observations for years prior to infiltration. Column (2): firm-year observations for years prior to inflow event. Column (3): firm-year observations for all sample years.

Table A5: Born infiltrated and profitability

Dep. variable:	(1) Total assets	(2) Exit	(3) Profits >0	(4) Profits/assets
Born infiltrated × Age	0.028***	-0.000	-0.005***	-0.000
	(0.003)	(0.000)	(0.001)	(0.000)
Born infiltrated	0.672***	-0.000**	-0.041***	-0.027***
	(0.016)	(0.000)	(0.003)	(0.001)
Observations	6,126,878	6,126,878	5,600,019	5,591,073
YOB × Province × Industry FE	Yes	Yes	Yes	Yes
Infiltrated firms	22455	22455	20993	20966
Mean dep var	5.875	0.0002	0.697	0.0587

Notes: Born infiltrated is a dummy that takes the value one if the firm was born infiltrated. Age is a continues variable that measure the age of the firm in every year. The sample includes all firms in the CERVED dataset. All regressions include year of birth by province of birth by 2-digit industry fixed effects, and year fixed effects. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: Distinct firm links: difference between those with and without some link to infiltrated firms

	Firm links per person			Infiltrated-firm links per person		
	(1)	(2)	(3)	(4)	(5)	(6)
=1 if any link to infiltrated firm	5.119***	5.143***	5.003***	1.796***	1.799***	1.798***
	(0.020)	(0.020)	(0.020)	(0.004)	(0.004)	(0.004)
Person controls	No	Yes	Yes	No	Yes	Yes
Firm controls	No	No	Yes	No	No	Yes
Mean outcome variable	1.91	1.91	1.91	0.09	0.09	0.09
No. observations	8,317,898	8,212,008	8,064,011	8,317,898	8,212,008	8,064,011

Notes: Estimates and standard errors of β from the following regression, estimated among the person-level dataset of all Infocamere owners, administrators, and auditors (pooled across years):

$$y_i = \beta \times 1\{\text{Any Link to Infiltrated Firm}\}_i + X_i'\gamma_1 + F_i'\gamma_2 + \varepsilon_i,$$

where i indexes people, y_i is either the number of distinct firm links (columns (1)–(3)) or the number of distinct infiltrated-firm links (columns (4)–(6)), X_i are person-level characteristics (average age over observed years, average age squared, province-of-birth fixed effects, gender, foreign-born dummy), and F_i are the average firm characteristics of the firms to which person i has links to (average firm age, average number of employees, share of firms that are "societá di capitale"). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Robustness: Stacked panel regressions

Dep variable:	Revenue	No. Employees	Payroll	Inputs	=1 any bank loans	Bank loans if >0	Receivables	Cash
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Infiltrated × Post	0.020	-0.002	0.014	-0.027	-0.034***	-0.138**	0.132***	-0.009
	(0.015)	(0.010)	(0.019)	(0.022)	(0.004)	(0.059)	(0.013)	(0.018)
Observations	5,382,559	5,382,559	5,382,559	5,382,559	5,382,559	3,100,642	5,224,886	5,382,559
R-squared	0.847	0.904	0.876	0.870	0.732	0.702	0.870	0.693
YOB × Province × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms	789795	789795	789795	789795	789795	475124	776959	789795
Infiltrated firms	16788	16788	16788	16788	16788	9831	16533	16788
Mean dep var	6.663	1.622	3.954	4.354	0.524	11.95	5.723	3.724

Notes: This table presents the point estimates from an stacked panel regression. We construct the sample by creating a panel of -5 and +5 years after the treatment event for each cohort of infiltrated firms and firms that experience an inflow event. The sample excludes born-infiltrated firms. $PostInfiltrated$ takes the value one after a firm i is infiltrated, while $Post$ takes the value one after the infiltration or experiece an inflow event. All columns include firm, year-cohort, sector-year-cohort and province-year-cohort fixed effects. All outcome variables are in inverse hyperbolic sine form except for column 5 which is a dummy. Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A8: Robustness: Wooldridge (2021)

Dep variable:	Revenue	No. Employees	Payroll	Inputs	=1 any bank loans	Bank loans if >0	Receivables	Cash
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Infiltration								
Post Infiltration	0.272***	0.144***	0.303***	0.227***	0.005	0.120**	0.367***	0.075***
	(0.015)	(0.011)	(0.020)	(0.023)	(0.004)	(0.060)	(0.015)	(0.018)
Panel B: Non-Infiltration inflow								
Post Non-Infiltration inflow	0.213***	0.121***	0.246***	0.205***	0.035***	0.203***	0.180***	0.071***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.008)	(0.002)	(0.002)
Panel C: Difference								
Difference	0.059	0.023	0.057	0.022	-0.030	-0.083	0.187	0.004
p-value difference	0.000	0.038	0.004	0.342	0.000	0.170	0.000	0.826

Notes: In this table, we present the estimated parameter of interest using the method suggested by Wooldridge (2021) for staggered difference-in-differences. In Panel A, we compare infiltrated to firms that never experience an inflow event, while in Panel B, we compare firms that experience an inflow event to firms that never experience an infiltration. In Panel C, we take the difference of the coefficients and compute the p-value of the difference. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A9: Robustness: Infiltration definition, operational outcomes

Panel A: Revenues

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	0.031	-0.038***	0.031	0.028*	-0.031***	0.030
	(0.019)	(0.009)	(0.024)	(0.016)	(0.009)	(0.020)
Post Any Inflow	0.206***	0.204***	0.209***	0.206***	0.204***	0.206***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF ∪ MMR	Ext. UIF ∪ MMR	UIF sidna ≥ 3

Panel B: No. Employees

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	0.010	-0.008	-0.002	0.005	-0.007	0.007
	(0.013)	(0.006)	(0.016)	(0.011)	(0.006)	(0.014)
Post Any Inflow	0.114***	0.111***	0.116***	0.113***	0.111***	0.114***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF ∪ MMR	Ext. UIF ∪ MMR	UIF sidna ≥ 3

Panel C: Payroll

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	0.038	-0.031**	0.023	0.031	-0.026**	0.032
	(0.025)	(0.013)	(0.032)	(0.020)	(0.012)	(0.026)
Post Any Inflow	0.236***	0.233***	0.240***	0.236***	0.232***	0.236***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF ∪ MMR	Ext. UIF ∪ MMR	UIF sidna ≥ 3

Panel D: Inputs

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	-0.027	-0.125***	-0.052	-0.037	-0.118***	-0.032
	(0.028)	(0.014)	(0.035)	(0.023)	(0.013)	(0.030)
Post Any Inflow	0.181***	0.183***	0.184***	0.181***	0.183***	0.181***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF ∪ MMR	Ext. UIF ∪ MMR	UIF sidna ≥ 3

Notes: Point estimates from equation (5) using different measures of infiltration. Column (1), UIF, uses the *Mappatura* definition excluding firms from the South (for comparability with remaining definitions); column (2), Ext. UIF, extends *Mappatura* applying the owners-of-owners procedure (also excluding South); column (3), MMR, uses the infiltration definition of Mirenda et al. (2022); column (4) uses the union of UIF and MMR; column (5) uses the union of Ext. UIF and MMR; column (6) uses *Mappatura* but excludes firms with the lowest risk factor (Sidna=2). The sample excludes born-infiltrated firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. All columns include sector-year and province-year fixed effects. All outcome variables are in inverse hyperbolic sine form. Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A10: Robustness: Infiltration definition, financial outcomes

Panel A: =1 any bank loans

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	-0.033***	-0.024***	0.001	-0.024***	-0.023***	-0.035***
	(0.005)	(0.003)	(0.007)	(0.004)	(0.002)	(0.005)
Post Any Inflow	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF $\cup$ MMR	Ext. UIF $\cup$ MMR	UIF sidna ≥ 3

Panel B: Receivables

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	0.124***	0.024***	0.050**	0.099***	0.027***	0.125***
	(0.018)	(0.009)	(0.024)	(0.015)	(0.009)	(0.019)
Post Any Inflow	0.163***	0.160***	0.166***	0.162***	0.160***	0.163***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF $\cup$ MMR	Ext. UIF $\cup$ MMR	UIF sidna ≥ 3

Panel C: Cash

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	0.006	-0.015	-0.016	-0.001	-0.014	0.008
	(0.023)	(0.012)	(0.030)	(0.019)	(0.012)	(0.024)
Post Any Inflow	0.071***	0.069***	0.071***	0.071***	0.069***	0.071***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	7,297,491	7,177,676	7,318,815	7,278,594	7,159,988	7,292,605
No. firms	1,133,700	1,112,625	1,138,921	1,130,820	1,109,966	1,132,801
No. infiltrated firms	11,404	32,179	4,297	15,366	35,482	10,505
No. inflow event firms	618,774	582,656	629,800	613,736	578,439	618,774
Infiltration definition	UIF	Ext. UIF	MMR	UIF $\cup$ MMR	Ext. UIF $\cup$ MMR	UIF sidna ≥ 3

Panel D: Bank loans if > 0

	(1)	(2)	(3)	(4)	(5)	(6)
Post Infiltration	-0.162**	-0.137***	0.055	-0.113*	-0.122***	-0.158**
	(0.072)	(0.033)	(0.091)	(0.058)	(0.031)	(0.074)
Post Any Inflow	0.169***	0.170***	0.170***	0.169***	0.170***	0.169***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	4,201,483	4,129,329	4,211,868	4,192,281	4,120,888	4,198,565
No. firms	654,680	641,556	657,151	653,265	640,290	654,118
No. infiltrated firms	6,950	22,227	2,846	9,582	24,366	6,388
No. inflow event firms	393,124	367,675	399,345	389,975	365,128	393,124
Infiltration definition	UIF	Ext. UIF	MMR	UIF $\cup$ MMR	Ext. UIF $\cup$ MMR	UIF sidna ≥ 3

Notes: Point estimates from equation (5) using different measures of infiltration. Column (1), UIF, uses the *Mappatura* definition excluding firms from the South (for comparability with remaining definitions); column (2), Ext. UIF, extends *Mappatura* applying the owners-of-owners procedure (also excluding South); column (3), MMR, uses the infiltration definition of Mirenda et al. (2022); column (4) uses the union of UIF and MMR; column (5) uses the union of Ext. UIF and MMR; column (6) uses *Mappatura* but excludes firms with the lowest risk factor (Sidna=2). The sample excludes born-infiltrated firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. All columns include sector-year and province-year fixed effects. All outcome variables are in inverse hyperbolic sine form except for the dummy variable `=1 any bank loans`. Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table A11: Robustness: Sample restrictions

Dep variable:	Revenue	No. Employees	Payroll	Inputs	=1 any bank loans	Bank loans if >0	Receivables	Cash
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Exclude 0 revenue restriction								
Post Infiltration	0.026	-0.010	0.003	-0.010	-0.039***	-0.267***	0.205***	0.007
	(0.026)	(0.010)	(0.020)	(0.023)	(0.004)	(0.059)	(0.018)	(0.016)
Post Any Inflow	0.472***	0.148***	0.344***	0.329***	0.041***	0.195***	0.325***	0.141***
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.007)	(0.002)	(0.002)
Observations	11,840,215	11,840,215	11,840,215	11,840,215	11,840,215	5,651,835	11,840,215	11,840,215
Mean dep variable	5.284	1.192	3.016	3.537	0.435	11.69	4.787	3.308
Number of infiltrated	20331	20331	20331	20331	20331	10945	20331	20331
Number of inflow firms	925027	925027	925027	925027	925027	516173	925027	925027
Panel B: Exclude firms in the South								
Post Infiltration	0.031	0.010	0.038	-0.027	-0.033***	-0.162**	0.124***	0.006
	(0.019)	(0.013)	(0.025)	(0.028)	(0.005)	(0.072)	(0.018)	(0.023)
Post Any Inflow	0.206***	0.114***	0.236***	0.181***	0.030***	0.169***	0.163***	0.071***
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.008)	(0.002)	(0.003)
Observations	7,297,491	7,297,491	7,297,491	7,297,491	7,297,491	4,201,483	7,297,491	7,297,491
Mean dep variable	6.467	1.428	3.583	4.147	0.526	11.80	5.307	3.607
Number of infiltrated	11404	11404	11404	11404	11404	6950	11404	11404
Number of inflow firms	618774	618774	618774	618774	618774	393124	618774	618774

Notes: This table presents the point estimates from equation (5). In panel A, we keep observations with 0 revenue, while in panel B, we exclude firms located in the South. The sample excludes born-infiltrated firms. For all treated firms (either infiltrated or inflow-event firms), we include observations from -5 and +5 years after the treatment event. Post Infiltration$_{it}$ takes the value one after a firm i is infiltrated, while Post Any Inflow$_{it}$ takes the value one after firm i is infiltrated or experiences a non-criminal inflow event. All columns include sector-year and province-year fixed effects. All outcome variables are in inverse hyperbolic sine form. Standard errors clustered at the firm level. * p<0.1, ** p<0.05, *** p<0.01.