A Loan You Can't Refuse: Credit Rationing and Organized Crime Infiltration of Distressed Firms*

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October 29, 2025

Abstract

We show that credit constraints significantly increase the risk that firms are infiltrated by organized crime, defined as the covert involvement of criminal organizations in corporate decision-making. Using confidential data on criminal investigations, credit ratings, and loan histories for the universe of Italian firms, we find that a downgrade to substandard credit status reduces credit availability by 30% over five years and increases the probability of infiltration by 5%, relative to comparable firms. A local randomization design comparing firms just above and below the downgrade threshold confirms this result. The effect is pervasive across sectors and regions, but particularly strong in real estate, where the probability of infiltration rises by 10% following a downgrade. Infiltrated firms also display higher survival rates than other downgraded firms, despite similar declines in employment and revenues. These findings suggest that organized crime can serve as a financial backstop – sustaining non-viable businesses and potentially redirecting their strategies to serve criminal interests.

Keywords: Organized crime, Firms, Bank Credit
JEL codes: G32, K42, L25, O17

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*We are deeply grateful to Francesco Drago, Sergio Galletta, Thomas Le Barbanchon, Giovanni Mastrobuoni, Filippo Palomba, Zach Porreca, Juan Vargas, and seminar participants at the 8th Workshop on the Economics of Organized Crime 2024, 15th Petralia Workshop, World Bank and AL CAPONE Conference on the Finances of Organized Crime 2024, Brazilian Econometric Society 2024, FIBRE Workshop at Bocconi University 2025, Texas Economics of Crime Workshop 2025, and 16th Transatlantic Workshop on the Economics of Crime 2025. We gratefully acknowledge financial support from the Italian Ministry of University and Research under the PRIN 2020 grant for the project *The Dark Side of the Money: Causes and Consequences of Organized Crime and Corruption (DARKSIDE)*. This project uses highly confidential data from the *Mappatura*. Developed at UIF, the *Mappatura* identifies "firms potentially connected to organized crime" (UIF, 2021, pp. 46–47). For simplicity, this paper refers to such firms as "infiltrated". The views expressed in this paper are those of the authors and do not involve the responsibility of UIF or the Bank of Italy. The usual disclaimers apply.

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1 Introduction

Modern criminal organizations increasingly resemble diversified business conglomerates, operating across both illegal and legal markets. According to Europol (2021), over 80% of criminal networks active in the European Union use legitimate firms to integrate illicit proceeds into the financial system and to reinvest them in profitable legal activities. In addition, criminal organizations may use legitimate firms to cultivate political connections, capture public funds or subsidies, and enhance the organization's social legitimacy and influence within local communities (see, e.g., Barone and Narciso, 2015; Fenizia and Saggio, 2024; Arellano-Bover et al., 2024).

But how do criminal organizations acquire control over firms? Traditionally, they have relied on a dual strategy of money and threats—*plata o plomo*, "silver or lead"—to exert influence over economic and political actors (see, e.g., Gambetta, 1993; Dal Bó et al., 2006; Daniele and Dipoppa, 2017; Alesina et al., 2019; How Choon et al., 2024). However, advances in enforcement technologies and policing strategies have raised the costs of using violence (Lessing, 2017). In addition, violent tactics may provoke public backlash and lead citizens to "rally around the flag," thereby strengthening support for law enforcement (Campedelli et al., 2023). For these reasons, the vast financial resources at the disposal of criminal organizations may now represent a more effective instrument of influence – especially toward actors with urgent liquidity needs.

In this paper, we examine whether Italian firms facing tighter credit market conditions are more likely to be *infiltrated* by criminal organizations, defined as criminal groups participating in firms' decision-making processes (Transcrime, 2017). This definition is operationalized in the *Mappatura*, a highly confidential database on Italian firms developed by the Financial Intelligence Unit of the Bank of Italy (UIF) which leverages data received by the Italian Antimafia Directorate, which classifies a firm as "infiltrated" if (at least) one of its owners or executives is involved in anti-mafia investigations, in addition to being reported to UIF in connection to some suspicious transaction. Based on this definition, the *Mappatura* flags over 100,000 firms, or over 2% of all Italian firms during the period 2001-2020, thus providing the most comprehensive measure of organized crime presence in the Italian economy – and, arguably, one of the most reliable indicators of organized crime infiltration globally.

Using these data, we provide the first causal evidence that financial distress – driven, in turn, by a downgrade in firms' credit ratings – substantially increases the risk of mafia infiltration. To this end, we combine the *Mappatura* with firm-level credit histories and loan-level data covering the universe of Italian firms between 2001 and 2020. Our main analysis uses a difference-in-differences design, comparing firms downgraded to the "substandard" risk category in a given year to a control group of firms that were not downgraded that year but share an identical credit rating history in prior years. To further bolster the credibility of our identification strategy, we exploit the fact that banks' assignment of firms to different risk categories partly depends on whether a credit score falls above or below a specific cutoff. This score is computed by an external agency (CERVED) using a confidential algorithm based on the firm's past balance sheets. Importantly, neither the value of the score nor the algorithm is disclosed to the firm. These institutional features create an ideal setting for a regression discontinuity design, in which firms near the cutoff are effectively quasi-randomly assigned to the substandard risk category. Since the score increments in discrete steps of 0.01, we implement a local randomization approach, selecting the largest range of score values within which pre-treatment covariates remain balanced (Cattaneo et al., 2015, 2024).

As expected, firms downgraded to the substandard category experience a sharp decline in credit access. In particular, outstanding bank credit declines by about 7 percent on average over the following years, and the cumulated effect after five years amounts to over 30 percent. This pattern is consistent with banks responding to heightened perceived credit risk by tightening lending conditions—curtailing both the renewal of existing loans and the extension of new credit. Simultaneously, we observe a significant increase in the probability of infiltration. The effect grows over time, reaching +0.1 percentage points – or a 4.8% increase over the baseline infiltration rate – five years after the downgrade. Notably, these estimates are virtually identical when employing the difference-in-differences and regression discontinuity designs, respectively.

These findings are consistent with criminal organizations serving as an alternative source of finance for firms excluded from legal credit markets. When banks withdraw lending, criminal groups may step in, offering unregulated financial support – potentially along with other illicit services – to firms in distress. In line with this interpretation, downgraded firms that become infiltrated are significantly more likely to survive than downgraded firms that are not infiltrated despite displaying a similar decline in employment and other measures of operational activity after the downgrade.

Taken together, these findings suggest that the financial support offered by organized crime may help credit-constrained firms survive episodes of distress – but at the cost of keeping otherwise non-viable businesses afloat. These "zombie firms" may gradually shift away from the objective of profit maximization typical of market-driven enterprises, and instead serve the strategic interests of the criminal organizations that sustain them.[1] Consistent with this interpretation, we estimate larger increases in infiltration of firms operating in the real estate sector, which offers greater opportunities for money laundering and reinvestment (see, e.g., Unger and Ferwerda, 2011). The effect is also more pronounced among larger firms, which provide better platforms for establishing political connections (Arellano-Bover et al., 2024). The stronger effect among larger firms implies that the number of workers employed in infiltrated firms rises by about 10% after a credit downgrade—roughly twice the increase observed in the probability of infiltration (5%).

Our findings are consistent with extensive judicial evidence from recent years documenting the ties between criminal organizations and Italian firms, particularly in Northern Italy.

[1]The term "zombie firms" refers more generally to businesses with deteriorating fundamentals and persistent problems meeting their interest payments (Adalet McGowan et al., 2018). Results available upon request show that, even in our context, the credit downgrade increases the probability of arrears in loans payments. These firms would exit in competitive markets but, instead, can survive due to external sources of finance provided under distorted incentives – for instance, as part of a financial rescue plan backed by the government during a systemic crisis. For other examples of zombie firms, see Caballero et al. (2008) on Japan's lost decade; Acharya et al. (2020) on zombie lending in Europe; and Schivardi et al. (2020) on the Italian case.

Among these cases, the trajectory of Perego Strade S.r.l., exposed by the maxi-investigation *Infinito*, is especially revealing. Founded in 1991 as a family business in Lombardy, Perego had become a leading player in demolitions, earth-moving, and waste management – sectors long attractive to organized crime – with more than 125 employees and over 60 active work-sites by 2008. That same year, however, the firm entered a severe liquidity crisis, fueled both by the global credit crunch and by poor managerial decisions. A subsequent capital increase created Perego General Contractor, with 51 percent of shares formally retained by the original owners and 49 percent held through two fiduciary companies that in reality concealed the participation of prominent members of the 'Ndrangheta, the powerful Calabrian mafia. The group quickly established control, resorting to intimidation and even physical assaults against managers and employees. In the months that followed, Perego became a vehicle for mafia operations, bidding directly for large public contracts — thus circumventing anti-mafia rules that exclude criminal organizations from procurement — and engaging in illegal waste disposal. These activities triggered multiple judicial proceedings and ultimately led to the conviction of the original owner, Ivano Perego, to 12 years for mafia association and to the compulsory liquidation of the firm.[2]

This case—like many others—vividly illustrates the role of liquidity constraints in facilitating the infiltration of legitimate firms by organized crime and the severe consequences such infiltration can have on corporate strategies and market dynamics. Our empirical analysis moves beyond judicial evidence and anecdotal accounts in two key ways. First, we exploit unique data covering the universe of Italian firms, which allows us to systematically document the prevalence of these dynamics across the economy and their heterogeneity by sector, region, and firm size. Second, we address the endogeneity of bank credit by leveraging plausibly exogenous variation in firms' assignment to risk categories, which generates quasi-random differences in access to credit.

Our results have important policy implications. Money laundering enables criminal or-

[2]The Perego case is extensively documented in official sources, including Italian Parliamentary Commission on Illegal Waste (2012) and Court of Milan (2012), and has been analyzed by Alessandri (2017).

ganizations to integrate their proceeds into the legal economy while concealing their illicit origin. Without this process, criminals would be unable to safely access or enjoy their wealth, effectively losing any incentive to engage in large-scale criminal enterprise in the first place. At the same time, this very need to engage with the formal economy makes organized crime partially observable through firm-level financial and ownership data. As such, the growing availability of administrative and financial datasets – coupled with advances in data analytics – offers enforcement authorities a powerful opportunity to detect and disrupt criminal networks through financial surveillance (see, e.g. Cariello et al., 2024; Ambrosini et al., 2024).

Our paper contributes to a growing literature examining the complex and often symbiotic relationship between organized crime and the legal economy. A well-established view now holds that modern criminal organizations are not confined to predatory behavior or the provision of illicit goods and services (such as drugs or human smuggling), but extensively interact with the official economy and other formal institutions. Indeed, the seminal work of Gambetta (1993) traces the origins of the Sicilian Mafia to its function as a provider of property rights' protection in a context of weak state institutions after the Italian unification. A number of empirical studies support this historical account. Buonanno et al. (2015), Dimico et al. (2017), and Acemoglu et al. (2020) exploit variation in local demand for protection across Sicilian municipalities to document how institutional fragility fostered the rise of organized crime. In a more recent historical context, Dipoppa (2024) examines the post-war construction boom in Northern Italy, showing that criminal organizations acted as intermediaries between construction firms and southern migrant laborers, enabling firms to circumvent labor regulations, reduce tax liabilities, and cut operational costs.

The increasing availability of firm-level data has further advanced our understanding of how organized crime interacts with legal businesses. Arellano-Bover et al. (2024) develop a conceptual framework outlining three main motives behind mafia infiltration of firms: (i) to facilitate illicit activities, such as money laundering; (ii) to enhance a firm's competitiveness in legal markets through illegal means (e.g., intimidation or bribery); and (iii) to invest criminal proceeds to obtain financial returns or networking opportunities with key players in the economy, including politicians. Using the same measure of infiltration as in the present paper – constructed from suspicious transaction reports and investigative records – they examine how these motives map into patterns of infiltration by firm size and sector, and into post-infiltration firm dynamics. They find on average no substantial changes in operational outcomes such as revenues, employment, labor costs, or intermediate inputs. However, infiltrated firms reduce their reliance on external bank credit and increase internal liquidity, consistent with a money-laundering motive. Mirenda et al. (2022) reach partly different conclusions using an alternative infiltration measure based on whether a firm's owners or directors share surnames and places of origin with known members of the 'Ndrangheta. They find that infiltration is associated with increases in revenues, labor costs, and input use, alongside a deterioration in financial health, pointing to a more extractive or rent-seeking form of infiltration. Arellano-Bover et al. (2024) attribute these differences in the findings of the two papers to both the use of distinct infiltration measures and differences in identification strategies – most notably, the fact that they control for changes in firm management unrelated to infiltration, whereas Mirenda et al. (2022) do not. Since this factor appears to influence estimated effects, in our analysis we assess the sensitivity of our results to controlling for board turnover unrelated to infiltration episodes.

We contribute to this literature by studying an important determinant of infiltration – namely, financial distress – using rich firm-level data on credit scores, bank loans, and infiltration by organized crime. In doing so, we are closest to Castelluccio and Rizzica (2023), who show that the economic shock induced by the COVID-19 pandemic heightened the risk of infiltration. However, their analysis studies the overall effect of an exceptional macroeconomic shock and considers finance only indirectly – through heterogeneity by access to government-guaranteed loans – while we focus directly on the role of credit constraints in normal times. Moreover, unlike Castelluccio and Rizzica (2023), who measure infiltration based on the surname and birthplace of firm owners and executives (as in Mirenda et al., 2022), we rely on the suspicious transaction reports matched with individuals flagged by the Antimafia Directorate based on unique tax identifiers. As argued in Arellano-Bover et al. (2024), this approach significantly reduces the likelihood of both false positives and false negatives relative to name- and birthplace-based proxies.

While credit constraints have been widely shown to harm firm growth, productivity, and employment (Aghion et al., 2010; Manova, 2013; Banerjee and Duflo, 2014; Cingano et al., 2016), we highlight a novel mechanism through which they can impact the real economy: strengthening the foothold of criminal organizations. Our comparison of downgraded firms that are infiltrated with those that are not suggests that organized crime may allow the former to survive – despite comparable declines in employment and operational performance – potentially undermining fair competition. This result aligns with the aggregate-level evidence from Le Moglie and Sorrenti (2022), who show that, after the 2007 financial crisis, business creation was more resilient in Italian provinces with higher mafia presence. It is also consistent with recent work showing that judicial confiscation of infiltrated firms leads to gains in market competitiveness and productivity (Calamunci and Drago, 2020; Slutzky and Zeume, 2024; Ambrosini et al., 2024), and with broader evidence on the negative economic effects of organized crime (Pinotti, 2015; Fenizia and Saggio, 2024; Daniele and Dipoppa, 2023).[3]

The paper is structured as follows. The next section describes the institutional setting and the data. The empirical strategy and results are presented in Sections 3 and 4, respectively. Finally, Section 5 concludes.

[3]Bonaccorsi di Patti (2009) focuses specifically on the relationship between organized crime and access to credit – rather than aggregate outcomes – finding a negative association. At the firm level, Calamunci et al. (2021) show that companies confiscated from the mafia and placed under judicial administration experience a contraction in bank credit and a higher likelihood of being credit rationed. Our analysis examines the reverse causal channel: the effect of credit rationing on the probability of infiltration.

2 Institutional framework and data

2.1 Italian criminal organizations and the legal economy

Italy is home to three of the oldest and most powerful criminal organizations in the world: the Mafia, the 'Ndrangheta, and the Camorra. These groups originated over 150 years ago in the southern regions of Sicily, Calabria, and Campania, respectively, but their influence has since expanded across the entire country. The strategies underlying this expansion, however, have varied significantly across regions.

In Southern Italy, criminal organizations have remained rooted in traditional activities such as smuggling and racketeering – operations frequently accompanied by the pervasive use of violence. This reliance on violence has had substantial economic consequences, including a sharp decline in private investment and overall economic activity (Pinotti, 2015). By contrast, their expansion into Central and Northern Italy has been far more discreet. Starting in the 1960s and 1970s, Southern criminal groups followed internal migration routes, targeting southern workers with labor racketeering schemes (Dipoppa, 2024). In the decades that followed, their focus shifted toward more lucrative ventures, such as kidnappings for ransom and drug trafficking (Mirenda et al., 2022).

The wealthier regions of Central and Northern Italy offered criminal organizations not only more profitable illicit markets but also greater opportunities within the legal economy. Regions such as Lombardy, Piedmont, Veneto, and Emilia-Romagna – with their dynamic and diversified production structures – provided a fertile ground for investments in legitimate businesses.

These investments channel billions of euros in illicit proceeds into the legal financial system, in what is commonly referred to as "money laundering." Criminal groups often establish or acquire legal firms, often using shell companies and/or figureheads, to issue invoices for fictitious transactions. These schemes can scale up significantly when infiltrated firms collude with others to accept false invoices, thereby reducing their tax liabilities. The fictitious profits generated by such operations allow the ultimate beneficiaries of criminal activities to increase their personal consumption and asset accumulation.

Importantly, such money laundering operations require criminal organizations to gain control of legitimate firms operating in the legal economy – that is, to "infiltrate" them. Beyond concealing the origin of illicit funds, managing or owning legal firms can yield organized crime two other types of advantages. First, criminal revenues can be boosted when infiltrated firms expand their business by intimidating competitors, acquiring public funds thorough corruption, or other illegal means. Further, investments in legitimate firms - even if the latter are not involved in (or supported by) any criminal activity - can yield economic returns, social and political connections, and ultimately help criminals extend their influence across legal and illegal domains.

Between 2015 and 2020, Italian authorities seized assets worth €12 billion from criminal organizations (Il Sole 24 Ore, 2023). However, these seizures likely represent only the tip of the iceberg in terms of the total share of the economy controlled by organized crime. Estimating the full extent of these investments is particularly difficult given the increasing complexity and interconnectedness of modern economies, which offer criminal groups a wide array of tools to obscure the origins of their funds. A recent estimate places money laundering in Italy at 1.5–2% of GDP, which should be seen as a lower-bound figure (Giammatteo, 2025). These illicit financial flows pose a serious challenge to law enforcement and policymakers, as they are seamlessly integrated into the legal economy, often indistinguishable from legitimate economic activities and patterns of wealth allocation.

To address this threat, the Financial Intelligence Unit of the Bank of Italy (*Unità di Informazione Finanziaria*, hereafter UIF) has developed a confidential database that maps organized crime infiltration in Italian firms. Established in 2007, UIF is responsible for combating money laundering and terrorist financing. As part of its institutional mandate, UIF receives all Suspicious Transaction Reports (STRs) filed by financial intermediaries and designated professionals across Italy. In 2022 alone, UIF received over 155,000 STRs. These reports are subjected to rigorous analysis to minimize false positives before being forwarded to investigative authorities (UIF, 2021).

In recent years, UIF has integrated the Suspicious Transaction Reports (STRs) with two additional data sources – namely, investigative records on suspected members of criminal organizations and firm-level ownership and management registries – to construct a confidential database known as the *Mappatura* ("mapping"). This dataset offers a detailed account of Italian firms allegedly infiltrated by organized crime and provides one of the most comprehensive measures to date of criminal organization presence in the legal economy.

The *Mappatura* was built in two stages. First, individuals flagged in STRs were cross-referenced with records from the Antimafia National Directorate (DNA), to identify those considered "of interest" in investigations of criminal organizations. The DNA data include not only formally affiliated members of such groups, but also individuals suspected of collusion. Moreover, the registry covers not only those who have been investigated or convicted, but also suspects. The resulting list thus comprises individuals flagged for suspicious transactions who are also under suspicion, investigation, or conviction for ties to organized crime.

In the second step, these individuals were matched, using unique social security identifiers, with the owners, directors, and auditors of all Italian firms. Whenever a match is identified, the firm is classified as "infiltrated" from that year onward, with infiltration treated as an absorbing state. This assumption helps minimize false negatives, such as cases in which the flagged individual exits the firm but it remains connected to organized crime through other undisclosed ties.

Naturally, some degree of underreporting or misclassification is unavoidable. For instance, firms linked to organized crime through informal arrangements or external associates – rather than through listed owners or executives – would not be detected, resulting in false negatives. These limitations are common to most measures of organized crime, and indeed to crime statistics more broadly.

Nevertheless, the *Mappatura* offers several clear advantages over previously used indicators. First, it provides a consistent and comparable measure of infiltration across the universe of Italian firms over an extended time period and over the different mafia groups. Second, the inclusion of suspects – as opposed to formally investigated or convicted individuals only – reduces the likelihood of false negatives. Third, it captures the timing of infiltration, allowing for meaningful variation over time in the outcome variable – similar to Mirenda et al. (2022) but unlike, for example, Decarolis et al. (2024).

Data. The *Mappatura* covers all limited liability and joint stock companies operating in Italy since 2000. Comprehensive data on these companies are obtained from CERVED. Established in 1973 as the electronic version of the firm registry of the Veneto region, CERVED has grown into a centralized repository for firm registries at the national level, including detailed records on companies' owners, directors, and auditors. The *Mappatura* classifies a firm as infiltrated in a given year if at least one of these key stakeholders is suspected, under investigation, or convicted for ties to criminal organizations.[4]

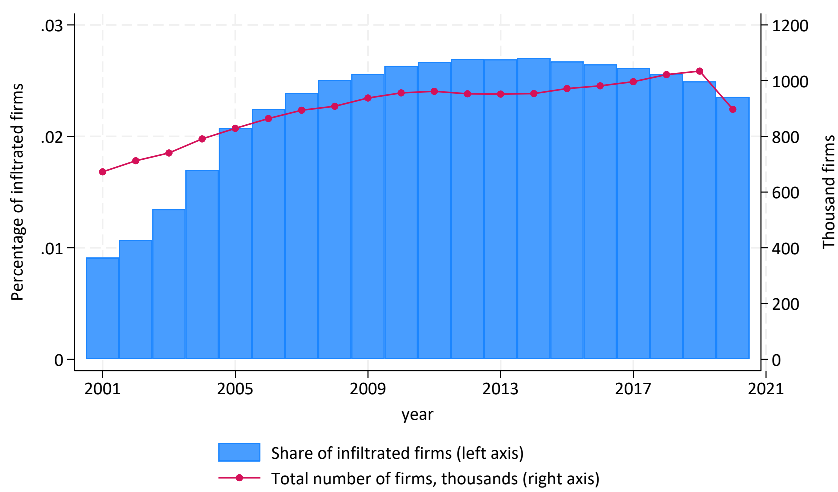
Our database covers the period 2001–2020 and includes 2.3 million companies, of which 61,186 (2.6%) are classified as infiltrated at some point during the sample period. Figure 1 displays the annual number of firms in the sample (right axis) and the corresponding share identified as infiltrated (left axis). The number of firms grows steadily from 672,000 in 2001 to over 1 million in 2019, before falling below 900,000 in 2020 due to the COVID-19 pandemic. The share of infiltrated firms rises from less than 1% in 2001 to a peak of 2.7% in 2014, then declines slightly to 2.4% by 2020. This pattern may reflect both actual trends in organized crime infiltration and, most likely, variation in its detection over time. In particular, infiltration cases may be detected only with a delay as new information emerges, which could explain the decline observed in the final years of the sample. Both the difference-in-differences and regression discontinuity designs used in our empirical analysis account for

[4] Given the sensitive nature of information related to past criminal records and ongoing investigations, individual-level data on owners and directors were never disclosed to the authors. Only a firm-level indicator of infiltration was made available to one UIF-affiliated author, who independently conducted the empirical analysis. The other authors did not have access to any part of the data.

these period-specific factors affecting all firms in the same year, including reporting trends, so the latter would not bias comparisons of infiltration rates between downgraded and non-downgraded.

Figure 2 compares the sectoral distribution of infiltrated firms to that of all firms operating in Italy. Infiltrated firms are overrepresented in the construction and services sectors, while they are comparatively underrepresented in manufacturing. This pattern is consistent with prior evidence on the sectoral composition of mafia-affiliated firms (Calamunci et al., 2022).

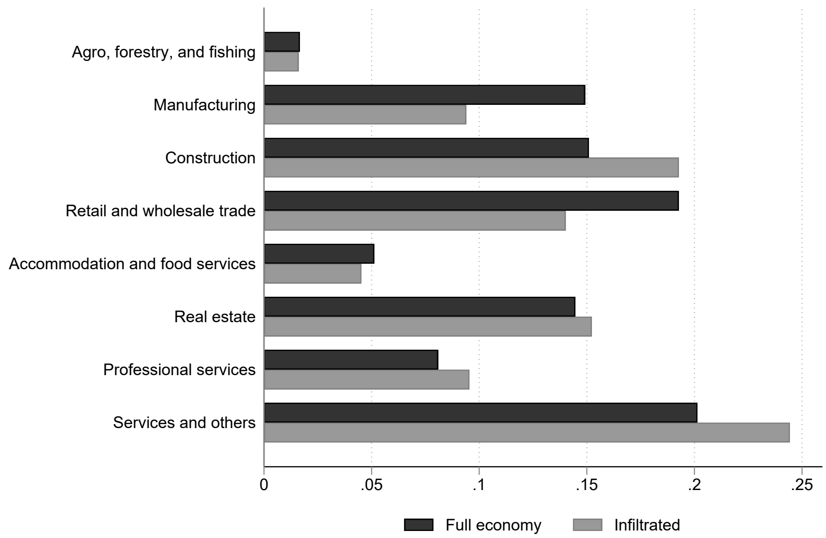
Figure 1: Total sample and share of infiltrated firms



Notes: This figure shows the total number of firms in our sample (right vertical axis, in thousands) and the share of infiltrated firms (left vertical axis) for each year in the sample period.

Figure 3 displays the geographical distribution of infiltrated firms across provinces, both as a share of total firms (Panel a) and in absolute numbers (Panel b). While infiltrated firms represent a larger share of firms in Southern regions historically more affected by organized crime, such as – namely Calabria, Campania, and Sicily – in absolute numbers they are widespread across the country; unsurprisingly, they are especially concentrated in the most populous provinces, including Milan, Rome, and Naples.

Figure 2: Distribution of infiltrated and total firms across sectors



Notes: This figure compares the sectoral distribution of all Italian firms (black bars) with that of infiltrated firms (grey bars).

As a preliminary step to our main analysis of the impact of credit rationing on firm-level infiltration, Figure 4a plots the relationship between credit market frictions and the share of firms infiltrated by organized crime across Italian provinces. Following Guiso et al. (2013), credit market frictions at the local level are measured by the log of the excess interest rate spread, defined as the difference between average loan and deposit rates in the province relative to the most financially developed province, averaged over the period 1990–1997. This spread serves as an inverse measure of access to credit or, equivalently, a measure of credit constraints faced by firms in each province.

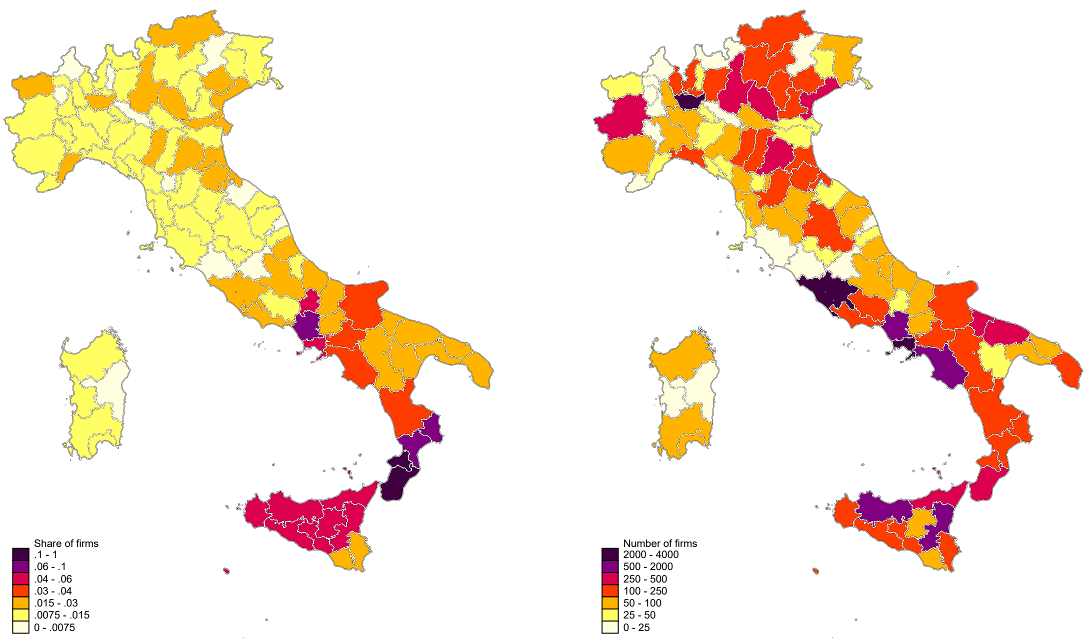
The graph reveals that infiltrated firms are more prevalent in provinces with less developed credit markets, as indicated by higher interest rate spreads. However, this relationship may reflect a number of confounding factors. For example, provinces with weaker credit markets are typically poorer, and Figure 4b shows that the share of infiltrated firms tends to decline with average GDP per capita across provinces. Interestingly, the relationship becomes positive in the upper tail of the income distribution, generating a slightly U-shaped pattern. This is consistent with the notion that the wealthiest areas – such as Milan – typically attract organized crime investment for laundering and re-investment purposes.

While these aggregate patterns are suggestive, they do not permit strong conclusions about the causal effect of credit access – or any other factor – on organized crime infiltration. To overcome this limitation, we merge the *Mappatura* with rich firm-level data on access to credit, including information on bank loans and credit ratings.

Figure 3: Number and share of Infiltrated Firms across Provinces

(a) Share of Infiltrated Firms

(b) Number of Infiltrated Firms

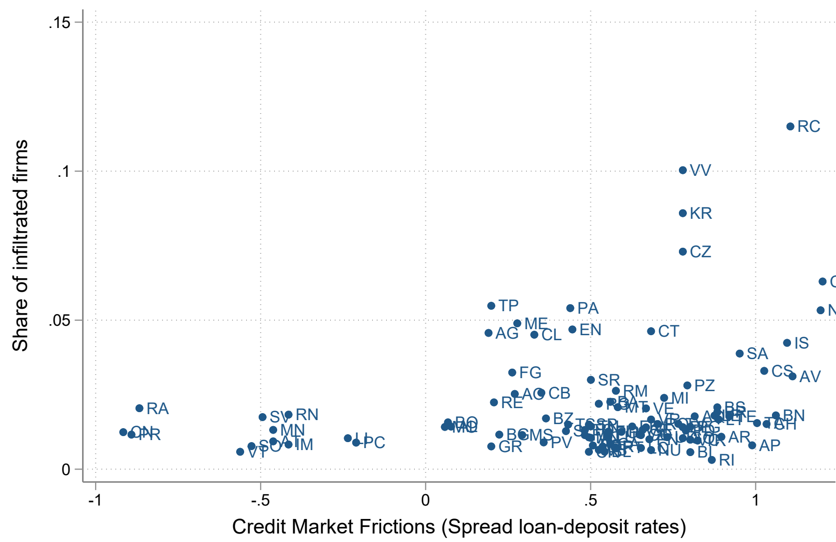


2.2 Credit Score and Loans

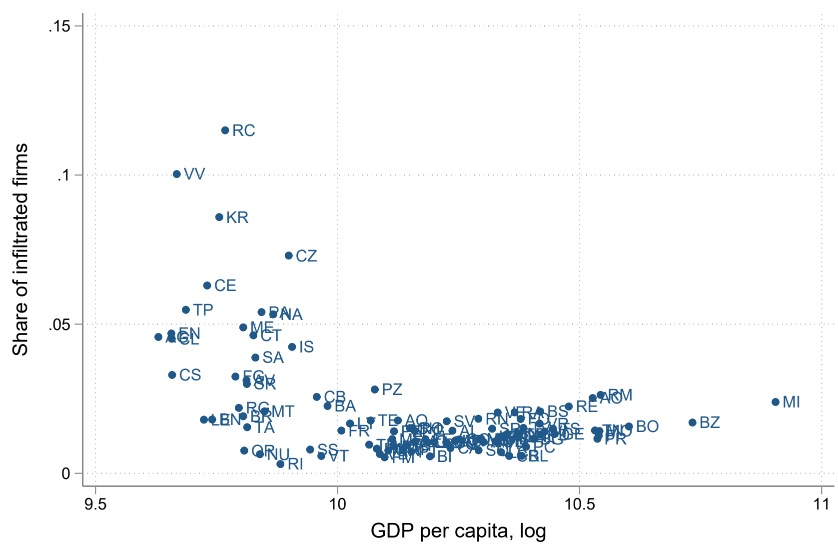
Italian firms have traditionally relied heavily on bank loans as their primary source of financing, in contrast to more market-based systems in advanced economies such as the United States, the United Kingdom, and France, where equity and bond markets play a larger role (D'Auria et al., 1999). This reliance reflects the structure of the Italian economy: as of 2022, 96% of firms were micro-enterprises with fewer than 10 employees, and 99.9% qualified as

Figure 4: Relationship between the Share of Infiltrated Firms, Provincial GDP, and Credit Market Frictions across Provinces

(a) Share of Infiltrated Firms and Credit Market Frictions



(b) Share of Infiltrated Firms and Province GDP



Notes: GDP per capita data across provinces are based on Eurostat data. Credit market frictions are measured by the excess spread between loan and deposit rates, computed as an average between years 1990 and 1997 (Guiso et al., 2013). The share of infiltrated firms across provinces is based on our calculations.

small and medium-sized enterprises (SMEs) with fewer than 250 employees (ISTAT, 2024).[5]

Due to their small size and limited financial transparency, these firms often lack direct access to capital markets, making them highly dependent on bank loans for liquidity. At the same time, assessing the creditworthiness of small firms is challenging for banks, as public information is scarce and financial statements are often less detailed or standardized. To address this, Italian banks rely heavily on standardized credit risk indicators based on firms' balance sheets and other metrics of solvency and liquidity. Firms classified as "substandard" face higher borrowing costs and reduced access to credit, and may be excluded from the credit market altogether.

The main credit scoring system used by Italian banks is provided by CERVED, which collects and analyzes financial statements to produce a proprietary credit score summarizing a firm's financial health (see, e.g., Panetta et al., 2009; Rodano et al., 2016; Schivardi et al., 2020). Following the approach originally proposed by Altman (1968), the score is computed as a Z-index combining several financial ratios – such as EBIT margins and asset turnover – to predict the likelihood of financial distress. Firms are assigned to the "substandard" risk category when their score exceeds a predetermined cutoff.

Previous studies confirm the central role of the CERVED rating in lending decisions of Italian banks. For example, Rodano et al. (2018) show that access to credit varies dramatically between risk categories – performing firms receive more credit and pay lower interest rates than substandard firms – while it remains relatively flat within each category. Importantly, the CERVED score is based entirely on historical balance sheet data, and neither the algorithm nor the cutoffs used to assign risk categories are disclosed to firms or banks. These institutional features generate plausibly exogenous variation in credit access for firms near the cutoff, which we leverage to estimate the causal effect of credit constraints on the likelihood of organized crime infiltration.

[5] In Italy, only 24% of workers are employed in large firms (those with over 250 employees), the second-lowest share in the European Union after Greece. By comparison, the figure is 48% in France and 42% in Germany. Source: Eurostat.

Data. Being part of the Bank of Italy, UIF has access to the credit risk ratings produced by CERVED, along with the underlying scores that determine these ratings. Each firm is assigned a discrete rating between 1 and 9 in a given year, where scores from 1 to 4 indicate "low risk," 5 to 6 indicate "medium risk," and a score of 7 or above classifies the firm as "substandard." Figure 5 displays the distribution of yearly ratings across all firms in our sample for the period 2001–2020 (solid bars).

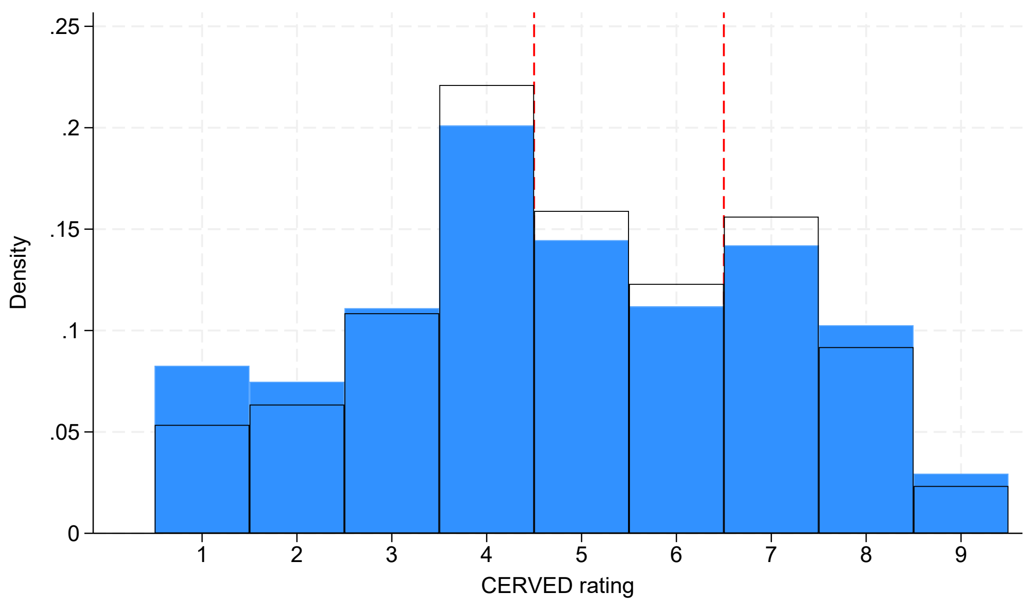
In our empirical analysis, we focus on the consequences of being downgraded to substandard status (i.e., when the rating increases to 7 or above), as this represents the most critical threshold in terms of access to credit (Rodano et al., 2018). For this reason, we restrict our attention to firms that, in at least one year in our sample, were rated at the margin between "low" and "medium" risk (ratings 4 and 5) or between "medium risk" and "substandard" (ratings 6 and 7) – 60% of all observations, or 72.5% of all firms in our data. Due to significant longitudinal variation in ratings, the yearly distribution of ratings within this subsample, shown in hollow bars in Figure 5, closely resembles that of the full sample, with a slight over-representation of ratings between 4 and 7 (66%, compared to 60% in the full sample). Crucially, UIF has also access to the underlying continuous risk score used to assign the rating. This score allows us to implement a regression discontinuity design by comparing firms scoring just above and just below the threshold for substandard classification, under the assumption of quasi-random assignment near the cutoff.

Finally, UIF has access to data from the *Centrale dei Rischi*, the national credit registry, which covers the universe of bank-firm relationships. The registry includes all loans exceeding €30,000 since 2009, and all loans above €75,000 prior to that year. We use these data to document changes in credit access following a downgrade to substandard status.

3 Empirical strategy

We estimate the dynamic effect of financial distress on organized crime infiltration using both a stacked Difference-in-Differences (DiD) design and a Local Randomization design near a

Figure 5: Distribution of Credit Scores



Notes: The graph shows the distribution of yearly ratings across all firms in our sample over the period 2001-2020 (in solid bars), and the rating distribution across firms that were assigned a rating between 4 and 7 in at least one year (in hollow bars).

Regression Discontinuity cutoff (LR-RD). In both frameworks, we compare the probability of infiltration between firms downgraded to a substandard rating in a given year – thereby facing restricted access to bank credit in the subsequent period – and a control group of firms that were not downgraded in the same year.

To isolate the causal effect of financial distress, the DiD design matches downgraded and non-downgraded firms on their prior rating history and other observable firm characteristics. The LR-RD design further sharpens identification by restricting the comparison to firms with credit scores just above and just below the cutoff for substandard classification. For these firms, the downgrade can be plausibly considered exogenous.

3.1 Stacked Difference-in-Differences

We identify as treated all firms that are downgraded to substandard – meaning that their risk rating increased from 6 or lower to 7 or higher – in any year t between 2006 and 2015. Since our panel spans 2001–2020, we can estimate dynamic treatment effects for up to five years following the downgrade, as well as placebo effects for up to five years prior. Let $Treat_{i,t} = 1$ for each treated firm i downgraded in year t.

Each treated firm is matched to a control firm that (i) is not downgraded to substandard in the same year, (ii) shares the same rating history in the previous five years, and (iii) belongs to the same macro-region, sector (7 ATECO 1-digit sections plus a residual category), and firm-size category (4 employee-size bins plus a missing category). We set $Treat_{i,t} = 0$ for matched control firms.[6]

About half of the 1.6 million firms observed between 2006 and 2015 display a risk rating above 7 in at least one year. We exclude firms with ratings above 7 throughout the entire period ("always treated"), leaving 478,225 firms that exhibit some variation in treatment status. Of these, 370,995 are successfully matched to a control, yielding a matching rate of

[6] When a treated firm matches with multiple control firms, we randomly select one. If there are more treated than available control firms, we allow reuse of controls across treated units.

78%.

Table 1 presents descriptive statistics for both the original and the matched samples, along with standardized differences. The matched sample closely resembles the original sample of firms in terms of observable characteristics. While differences in means are often statistically significant – unsurprising given the large sample size – they are quantitatively small. In particular, all standardized differences fall below the 0.25 threshold commonly used to indicate substantial imbalance (Imbens and Rubin, 2015). In addition, Appendix Table A1 shows that the treated and control groups are balanced in terms of several variables not used for the matching –variables used for matching are balanced by construction – such as assets, revenues, and labor costs (among others).

We assign to each control firm the same event time t_0 as its matched treated counterpart and estimate the following event-study specification:

$$Y_{i,t+j} = \sum_{j=-5}^{5} \beta_j (Treat_{i,t} \times Time_{t+j}) + \sum_{j=-5}^{5} \gamma_j Time_{t+j} + \delta Treat_{i,t} + \alpha_i + \epsilon_{i,t+j}, \qquad (1)$$

where $Y_{i,t+j}$ is an indicator for whether firm i is infiltrated in year $t + j$; $Treat_{i,t}$ denotes treatment status in year t; $Time_{t+j}$ is a year-specific dummy; α_i is a firm fixed effect; and $\epsilon_{i,t+j}$ is the error term.[7]

When estimating the impact of the downgrade on infiltration, we treat the latter as an absorbing state – i.e., $Y = 1$ in all periods after infiltration. This assumption reflects the idea that infiltration marks a structural shift in the firm's operations and objectives, which may persist even after the individual(s) linked to organized crime leave the firm. This conservative choice mitigates the risk of false negatives – namely, mis-classifying as non-infiltrated a firm that is (still) infiltrated.

Our primary coefficients of interest are the β_j's. The year prior to the downgrade, $t -$

[7] We will estimate the same equation to document the relevance of the CERVED risk rating for the firm's access to credit, thus replacing the infiltration with the log change in bank credit to firm i between year $t + j - 1$ and $t + j$ as the main dependent variable, $Y_{i,t+j}$.

Table 1: Comparison Between the Full and Matched Samples

	(1) Original Sample	(2) Matched	(3) Difference	(4) p-value	(5) Std. Diff.
Rating	5.131	5.461	-0.330	0.000	-0.208
	(0.001)	(0.002)			
North	0.476	0.485	-0.009	0.000	-0.017
	(0.000)	(0.001)			
Center	0.258	0.261	-0.003	0.000	-0.008
	(0.000)	(0.001)			
South	0.266	0.254	0.012	0.000	0.027
	(0.000)	(0.001)			
Less than 10 emp.	0.871	0.849	0.022	0.000	0.063
	(0.000)	(0.000)			
Between 10 and 49 emp.	0.108	0.134	-0.026	0.000	-0.080
	(0.000)	(0.000)			
Between 50 and 249 emp.	0.019	0.016	0.002	0.000	0.018
	(0.000)	(0.000)			
More than 250 emp.	0.003	0.001	0.002	0.000	0.038
	(0.000)	(0.000)			
Agriculture	0.015	0.008	0.007	0.000	0.071
	(0.000)	(0.000)			
Manufacturing	0.136	0.132	0.004	0.000	0.012
	(0.000)	(0.000)			
Construction	0.159	0.173	-0.014	0.000	-0.038
	(0.000)	(0.000)			
Wholesale and Retail Trade	0.202	0.207	-0.004	0.000	-0.011
	(0.000)	(0.001)			
Accomodation and Food	0.060	0.046	0.014	0.000	0.061
	(0.000)	(0.000)			
Real Estate Activities	0.131	0.137	-0.006	0.000	-0.017
	(0.000)	(0.000)			
Professional Serivices	0.085	0.084	0.001	0.005	0.004
	(0.000)	(0.000)			
Other sectors	0.211	0.213	-0.002	0.001	-0.005
	(0.000)	(0.001)			
Number of observations	1,511,283	576,287	2,087,570		

Note: This table shows the means and standardized differences for key variables between the full original sample and the matched sample. The last column reports the standardized difference between group means.

1, serves as the reference category (i.e., $\beta_{-1} = 0$). Coefficients β_0 to β_5 capture post-treatment effects on infiltration, while β_{-5} to β_{-2} help assess the plausibility of the parallel trends assumption. Importantly, this stacked DiD approach avoids the pitfalls of traditional staggered DiD estimators, which may assign negative weights to some treated units in the presence of heterogeneous treatment effects (see, e.g., De Chaisemartin and d'Haultfoeuille, 2020; Borusyak et al., 2024).

We also replicate the analysis on a subsample of firms that were not previously infiltrated—so that, by construction, $\beta_j = 0 \ \forall j < 0$. This sample restriction is intended to limit the risk that results are driven by reverse causality, whereby past infiltration influences subsequent credit downgrades.[8]

Importantly, credit constraints may simultaneously influence both the risk of infiltration and a firm's probability of survival—indeed, firms may resort to organized crime precisely as a strategy to weather financial distress following a credit downgrade. If infiltration improves survival, the estimated effect of credit constraints on infiltration could be upwardly biased due to selective attrition: non-infiltrated firms may exit the sample earlier, while infiltrated firms remain observable for longer. To mitigate this concern, our preferred specification extends the sample through $t + 5$ for all firms by imputing the infiltration status of those that exit based on their last observed value.[9]

To further investigate how mafia infiltration may mediate the effects of credit downgrades on long-term firm outcomes, we compare survival rates and other performance indicators between downgraded firms that are infiltrated and those that are not. While this comparison is not causal, it offers valuable insights into the consequences of organized crime infiltration for firm dynamics and market functioning.

Finally, alongside the event-study specification, we estimate the average effect over the

[8]The Regression Discontinuity approach presented in the next section offers an alternative solution to this issue.

[9]We also report estimates based on the original (i.e., non-extended) sample. As expected, those estimates are larger in magnitude so, in order to be conservative, our preferred estimates are those relying on the extended sample.

full post-downgrade period using the following equation:

$$Y_{i,t+j} = \beta_j(Treat_{i,t} \times Post_{t+j}) + \gamma Post_{t+j} + \delta Treat_{i,t} + \alpha_i + \epsilon_{i,t+j}, \qquad (2)$$

where $Post_{t+j} = 1$ for all years after the firm is downgraded to substandard status, and other variables are as previously defined.

3.2 Local Randomization near the Regression Discontinuity cutoff

To further mitigate endogeneity concerns, we assess the robustness of our findings by restricting the sample to downgraded and non-downgraded firms with risk scores just above and just below the cutoff determining substandard classification. CERVED applies sector-specific thresholds to map the underlying risk score into a categorical rating. Sectors include manufacturing, commerce, construction, services, transportation and utilities, and agriculture. For each firm i in sector k and year t, we compute a standardized score $S_{i,t} = S^*_{i,t} - C^k_t$, where $S^*_{i,t}$ is the original (non-standardized) score and C^k_t is the sector- and year-specific cutoff above which a firm is downgraded. Thus, firm i is classified as "substandard" if $S_{i,t} > 0$.

Identification in this RD design relies on the assumption that firms within a sufficiently narrow window around the cutoff are quasi-randomly assigned to either side (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). This assumption is particularly plausible in our context: as discussed in Section (2.2), the score is based solely on historical balance sheet data, and neither the algorithm nor the cutoff rules are disclosed outside of CERVED.

Turning to estimation, the conventional approach in RD settings employs local linear or polynomial regression within an MSE-optimal bandwidth around the cutoff (Imbens and Kalyanaraman, 2012; Calonico et al., 2014, 2020). However, in our setting, the running variable $S_{i,t}$ is discrete, progressing in steps of 0.01. In such cases, Cattaneo et al. (2015) recommend using Local Randomization inference rather than local polynomial estimation, as the former provides exact p-values and more reliable confidence intervals, particularly when working with small samples near the cutoff (see also Cattaneo et al., 2024).

Following Cattaneo et al. (2015), we select the largest symmetric bandwidth around the cutoff within which set of pre-treatment covariates are balanced between treated and control groups, and then conduct permutation tests within this window. In our case, the set of pre-treatment covariates includes the past values of the dependent variable (i.e., infiltration history). Including additional covariates alters neither the selected bandwidth nor the estimation results.

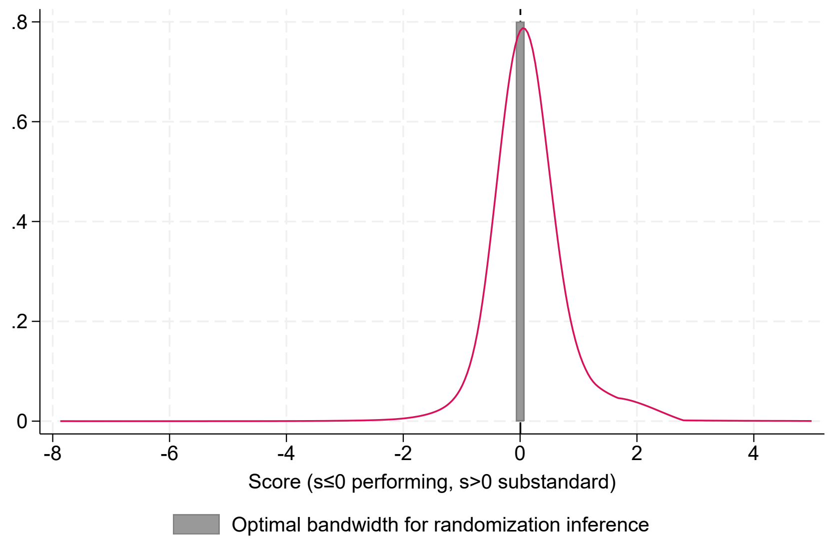
The selection algorithm yields $[-0.07, 0.08]$ as the optimal bandwith for $S_{i,t}$. Panel (a) of Figure 6 plots the distribution of $S_{i,t}$ along with the optimal bandwidth. The distribution ranges approximately between -8 and 5, with long tails on both sides. In fact, 99% of observations fall between -1.63 and 2.24, and 95% between -0.91 and 1.78.

Panel (b) zooms in on the density of $S_{i,t}$ within the optimal bandwidth. Consistent with the identifying assumption of quasi-random assignment near the threshold, the density appears balanced on either side. Firms with $S_{i,t} \in [0.01, 0.08]$ are downgraded, while those with $S_{i,t} \in [-0.07, 0.00]$ are not. Following Cattaneo et al. (2015), we treat these two groups as in a randomized experiment and use randomization inference to compute exact p-values. This approach is preferable to standard asymptotic methods, especially given the relatively small sample size within the selected bandwidth (just over 200,000 firm-year observations, compared to nearly 2 million in the full sample). We also present robustness checks controlling for sector-year fixed effects.

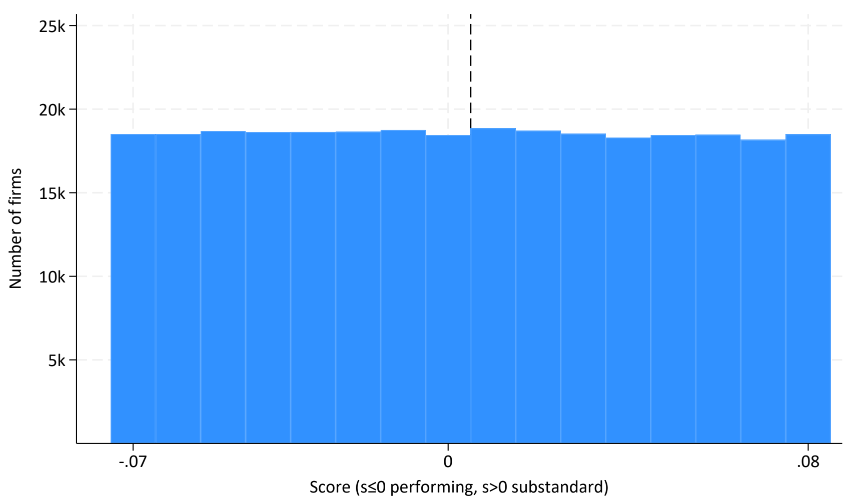
Using this framework, we compare the probability of infiltration between downgraded and non-downgraded firms at different horizons relative to the downgrade (from $t - 5$ to $t + 5$).

Figure 6: Distribution of the CERVED risk score (the running variable in the LR-RD design)

(a) Density of the CERVED score



(b) Density of the score within the bandwidth



Notes: Panel (a) plots the distribution of the CERVED risk score and the optimal bandwidth employed in the LR-RD analysis, selected using the approach of Cattaneo et al. (2015). Panel (b) plots the density of the risk score within the selected bandwidth.

4 Results

4.1 Difference-in-differences estimates

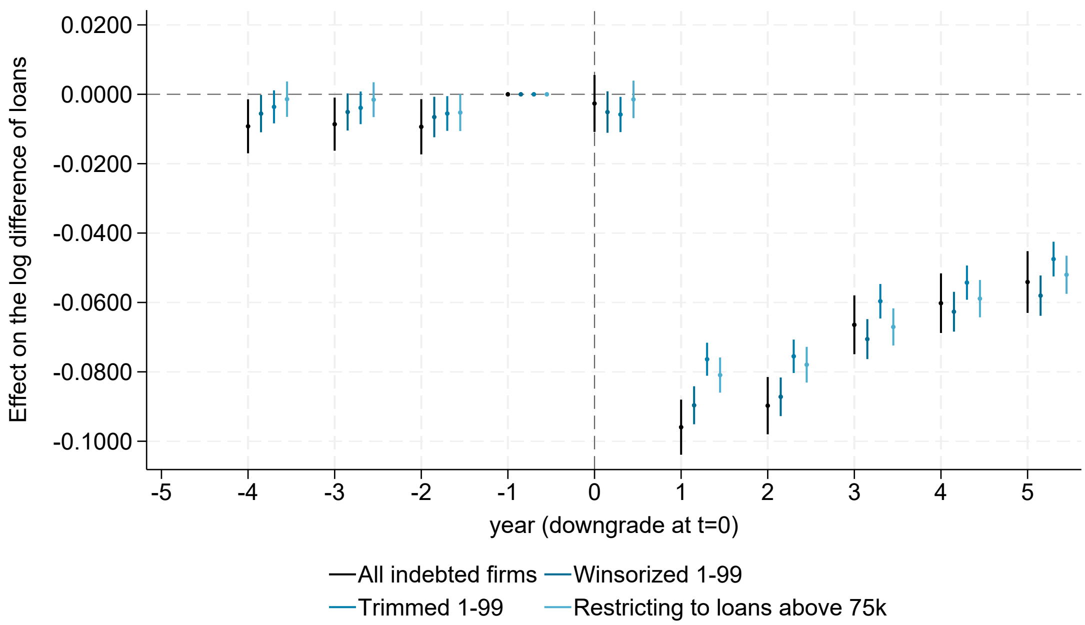
We preliminarily show that being downgraded (i.e., receiving a CERVED risk rating of 7 or above) reduces a firm's access to credit. To this end, Figure 7 plots the dynamic treatment effects of the downgrade on the log-change in the firm's outstanding bank credit between years $t-4$ and $t+5$, estimated from the event-study specification in equation (1).[10] In addition, Table 2 reports, in the top panel, the average effect over the post-downgrade period (estimated from equation (2)) and, in the bottom panel, the effect at $t+1$ – that is, immediately after the downgrade.

Given the substantial variation in loan size, we show that results are robust to winsorizing or trimming the data at the 1st and 99th percentiles. Moreover, since the national credit registry (*Centrale dei Rischi*) covers all loans above €30,000 only from 2009 onward (while covering loans above €75,000 before 2009, as discussed in Section 2.2), we also replicate the analysis restricting the sample to loans above €75,000 to ensure comparability over time.

The evidence in Figure 7 shows that a CERVED downgrade reduces a firm's outstanding bank credit by about 7 percent on average over the following years; the cumulated effect after five years amounts to over 30 percent. This finding is consistent with banks reacting to increased perceived credit risk by tightening lending conditions, limiting both the renewal of existing loans and the issuance of new credit.

[10] All our data are available for each firm between $t-5$ and $t+5$, where t is the year of the credit downgrade, so we can compute the log-change in bank credit starting from year $t-4$ onward. When estimating the effect of the downgrade on the probability of infiltration, we can also include year $t-5$.

Figure 7: The effect of the credit downgrade on bank credit, event study



Notes: The figure reports the yearly estimates of the percentage change in outstanding bank loans from equation (1) from t-4 to t+5. The year before the downgrade t-1 serves as the reference category. The estimates are based on firms receiving loans and we report the results: i) on the original sample; ii) winsorizing the dependent variable at 1%; iii) trimming the dependent variable at 1%; iv) considering outstanding loans above €75,000. The bars indicate 95% confidence intervals. Table 2 reports estimates of the average treatment effects for the same samples. Standard errors are clustered at the firm level.

Table 2: The effect of the credit downgrade on bank credit, average treatment effect and dynamic effects at $t + 1$.

	(1) All indebted firms	(2) Winsorized 1 - 99	(3) Trimmed 1 - 99	(4) Above 75k euros
	Panel A. Average effect after the downgrade			
Treat x Post	-0.0681***	-0.0687***	-0.0584***	-0.0649***
	(0.0020)	(0.0012)	(0.0011)	(0.0012)
Mean DV at t-1	.0107	-.0080	-.0100	.0025
	Panel B. Dynamic effect in t+1			
Treat x Event Time (t+1)	-0.0960***	-0.0896***	-0.0764***	-0.0809***
	(0.0041)	(0.0028)	(0.0024)	(0.0026)
Mean DV at t-1	.0107	-.0080	-.0100	.0025
N. Obs	3,653,946	3,653,946	3,579,693	3,110,906

Note: The table reports the estimates on access to credit from equation (2) in the top panel, and the effect at $t + 1$ estimated from (1) in the bottom panel. The estimates are based on firms receiving loans and we report the results i) on the original sample; ii) winsorizing the dependent variable at 1%; iii) trimming the dependent variable at 1%; iv) considering outstanding loans above €75,000. Figure 7 reports the event study estimates graphically. Standard errors are clustered at the firm level. *** p< .01, ** p< .05, * p< .1.

Turning to our main outcome of interest, Figure 8 plots the dynamic treatment effect of the downgrade on the probability of mafia infiltration for five different specifications of the sample. For each of these specifications, Table 3 reports the average effect over the 5-year period after treatment (Panel A) and in year $t + 5$ (Panel B), along with relative effects over the baseline (bottom of each panel).

As explained Section 3, our preferred specification "extends" the sample to include firms that exit the dataset (due to closure or other reasons), in order to avoid that endogenous differences in survival probability between infiltrated and non-infiltrated firms bias upward the estimated effect of the downgrade. According to this specification, the downgrade increases the probability of infiltration by 0.11 percentage points in the post-treatment period, or +4.8% over the mean probability of infiltration in the estimation sample (2.3%).

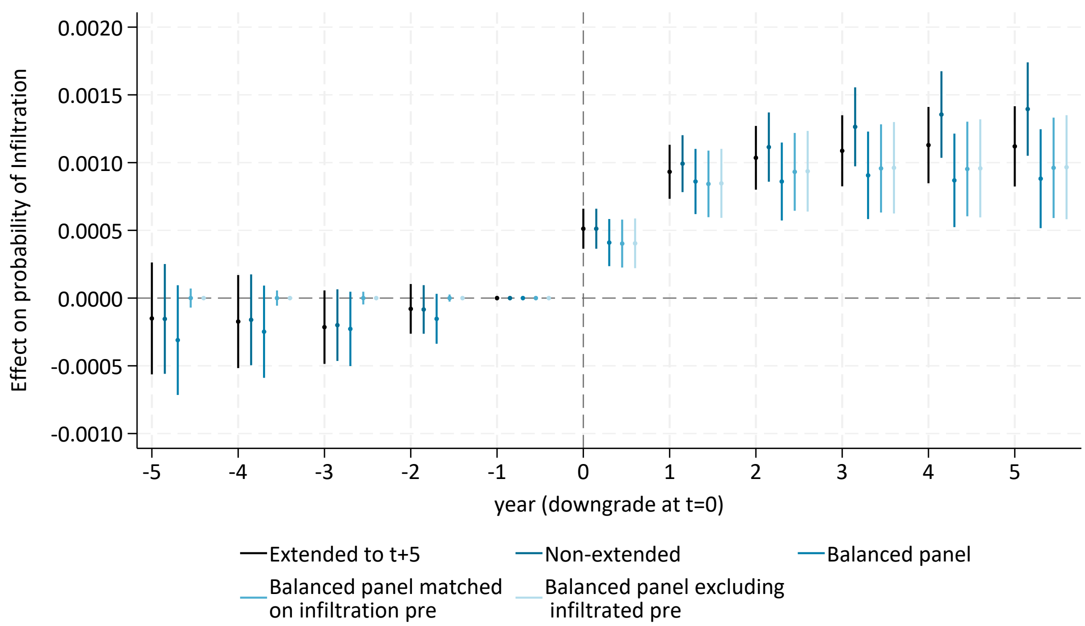
The estimated effect of the downgrade is very robust across all the specifications in Figure 8 and Table 3. Specification (2) is based on the "non-extended" sample, which does not prolonge the series for firms exiting the data. In line with our conjecture, the effect estimated on this alternative sample is larger than in our preferred specification (+6.1% over the baseline, as opposed to +4.8%). The main results are also confirmed when we restrict the analysis to a fully balanced panel of firms that are present in the dataset on all periods between $t-5$ and $t+5$ (specification 3). Therefore, our results seem very robust when using different approaches for dealing with attrition.

The last two specifications presented in Figure 8 and Table 3 address a different type of concern, namely reverse causality from mafia infiltration to credit downgrade. To this purpose, in specification (4) we match control firms on prior history of infiltration, while in specification (5) we exclude altogether firms that were ever infiltrated before $t = 0$. The estimated effects of the downgrade remain very similar to the main specification, i.e. about +0.1 percentage point increase 5 years since the downgrade. Notice that, for both specifications (4) and (5), pre-treatment coefficients are mechanically equal to zero. Importantly, even in specifications (1)-(3), in which we do not match treated and controls on pre-treatment outcomes, there is no evidence of differential trends in the years before the downgrade.

Of course, matching on prior credit history (as we do in all specifications) and possibly on past infiltration history (as we do in specifications 4 and 5) does not fully address concerns about reverse causality or, more generally, the endogeneity of credit downgrade. The RD estimates presented in the next Section 4.2 present a more convincing approach for addressing such concerns.

Before moving to the RD results, we replicate the Difference-in-Differences analysis restricting the sample to the first episode in which firms receive a rating of 7 or higher. In the total sample, ratings may oscillate above and below 7 over time, meaning that the same firm may appear as treated and control, respectively, at different points in time. In this context, the average effect estimated by the Difference-in-Differences specification may average heterogeneous treatment effects with negative weights (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Borusyak et al., 2024). Restricting the sample to first downgrade episodes avoids this problem. The effects estimated on this restricted sample, reported in Figure Figure A1, are very similar to those estimated on the total sample.

Figure 8: The effect of the credit downgrade on organized crime infiltration, event study



Notes: The figure reports the yearly estimates on mafia infiltration from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. Firms are matched on macroregion, sector, dimension category and rating history. The estimates show the effects on: i) the sample extended to year t + 5; ii) the original non-extended sample; iii) the balanced panel between t-5 and t+5; iv) the balanced panel between t-5 and t+5 in which firms have been matched also on infiltration history before time 0; v) the balanced panel where we excluded firms infiltrated before time 0. Table 3 reports estimates of the average treatment effects for the same samples. Standard errors are clustered at the firm level.

Table 3: The effect of the credit downgrade on organized crime infiltration, average treatment effect and dynamic effects at $t + 5$.

Sample	(1) Extended to t+5	(2) Non extended	(3) Balanced Panel	(4) Balanced panel, matched pre	(5) Balanced panel excluding inf.
	Panel A. Average effect after the downgrade				
Treat x Post	0.0011***	0.0010***	0.0010***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Mean DV at t-1	.0222	.0222	.0224	.00474	0
% change	4.85	4.60	4.40	17.74	.
	Panel B. Dynamic effect in t+5				
Treat x Event Time (t+5)	0.0011***	0.0014***	0.0009***	0.0010***	0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean DV at t-1	.0222	.0222	.0224	.00474	0
% change	5.05	6.29	3.93	20.27	.
N. Obs	8,378,472	7,467,136	5,317,730	5,194,552	5,169,912

Note: The table reports the estimates on mafia infiltration from equation (2) in the top panel, and the effect at $t + 5$ in the bottom panel. Each column report the estimates on a slightly different sample, respectively: column (1) on the sample extended to year t + 5; column (2) on the original non-extended sample; column (3) the balanced panel between t-5 and t+5; column (4) on the balanced panel between t-5 and t+5 in which firms have been matched also on infiltration history before time 0; column (5) on the balanced panel where we excluded firms infiltrated before time 0. Figure 8 shows the yearly effects graphically. Standard errors are clustered at the firm level. *** $p < .01$, ** $p < .05$, * $p < .1$.

4.2 Regression Discontinuity estimates

The DiD approach presented above assumes that non-downgraded firms that are identical in terms of prior credit history and other characteristics provide a valid counterfactual for downgraded firms in the absence of the downgrade – or, put differently, the downgrade is as good as randomly assigned within this subsample of firms. While the absence of differential pre-trends in Figure 8 is consistent with such assumption, we cannot in principle rule out the possibility the infiltration itself may affect the risk of credit downgrade or that both variables may depend on other omitted (time-varying) factors.

To alleviate such concerns, we compare downgraded and non-downgraded firms with risk scores just above and just below the cutoff that determines the downgrade. Indeed, quasi-random assignment to the downgrade seems particularly plausible when comparing firms within a narrow bandwidth of the cutoff. To further corroborate this hypothesis, we test for the continuity at the cutoff of other outcomes measured in the year before. Table A3 shows that there are no statistically detectable changes at the cut-off for the log change in revenues, purchases, cashflow, labor costs, and number of employees the year before.

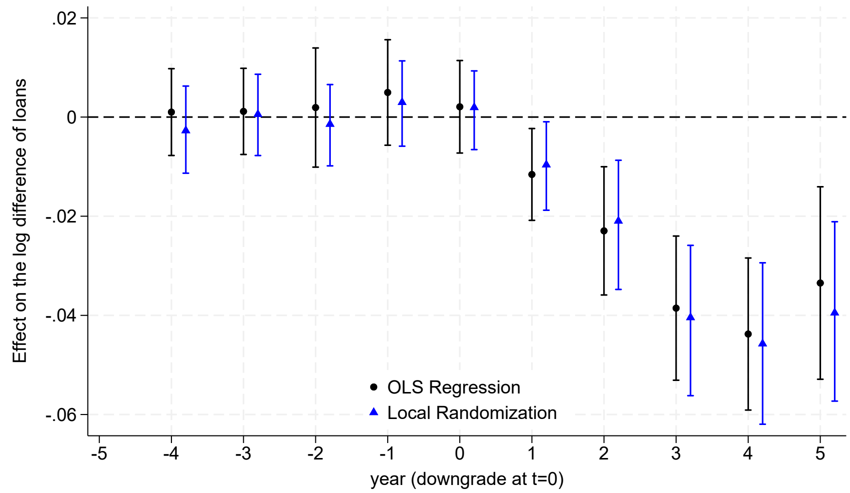
Figure 9 shows the effects of a downgrade on bank credit and the probability of infiltration, respectively, at each year before and after the downgrade. The coefficients and confidence intervals are estimated using local randomization inference within the optimal RD bandwidth selected by according to the criterion of Cattaneo et al. (2015) – as described in Section 3.2. For comparison, we also run OLS regressions within the optimal bandwidth, clustering standard errors by sector-year. The estimates confirm that downgraded firms (just above the cutoff) suffer a reduction in the availability of bank credit over the following years and, simultaneously, an increase in the probability of infiltration. At the same time, no effect is detected on either of the two variables in the period prior to the downgrade.[11] The results are virtually identical when using local randomization or OLS regressions within the RD bandwidth.

Most importantly, the magnitude of the effect is essentially identical when using the DiD and RD approaches: becoming a subprime firm increases the probability of infiltration by 0.1 percentage points. For this reason, we will leverage the Difference-in-Differences on full sample for conducting the heterogeneity analysis, so we do not have to worry about slicing the sample too thin.

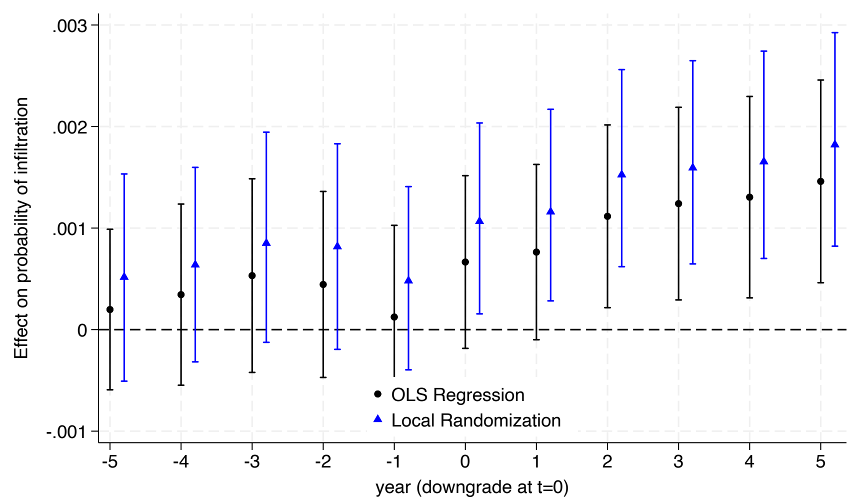
[11] Relatedly, no other firm characteristic displays significant discontinuities prior to the downgrade (see Appendix Table A3)

Figure 9: The effect of the credit downgrade on bank credit and organized crime infiltration, LR-RD estimates

(a) The effect on bank credit



(b) The effect on organized crime infiltration

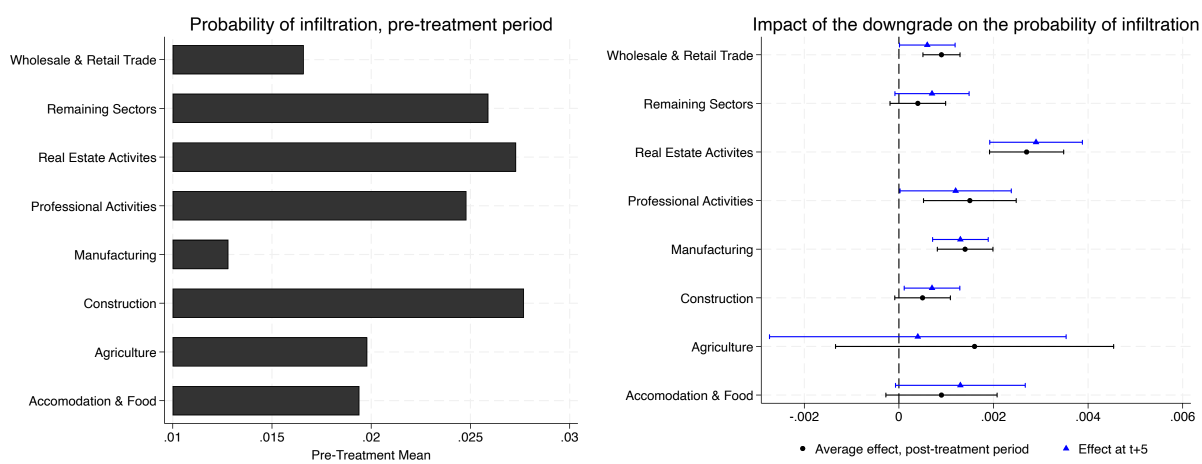


Notes: This figure shows the effect of the downgrade on bank credit (Panel a) and on the probability of infiltration (Panel b) comparing downgraded and non-downgraded firms with risk scores just above and just below the cutoff that determines the downgrade. The plots shows estimated effects in each year before and after the downgrade (and associated 95% confidence intervals) obtained by selecting the optimal RD bandwidth according to the criterion of Cattaneo et al. (2015) and running both local randomization inference and standard OLS regressions within the optimal bandwidth (additional details in Section 3.2). Standard errors are clustered at the firm level.

4.3 Heterogeneity and Robustness

In Figures 10 and 11 we investigate how dynamic treatment effects vary across sectors, geographical areas in Italy, and firm size categories, respectively. Starting with the first dimension, we consider the seven sections of the ATECO 2007 Classification of Economic Activity: Agriculture, Manufacturing, Constructions, Wholesale and Retail Trade, Accommodation and Food Services, Real Estate Activities, Professional Activities, and a residual category. The left graph of Figure 10 shows the baseline probability of infiltration in each sector (i.e., at $t-1$), while the right panel of the same figure shows both the average effect of the downgrade across firms within the same sector. In particular, the right graph plots both the effect at $t+5$ and the average effect over the entire period after the downgrade – as estimated, respectively, from equations (1) and (2).[12]

Figure 10: The effect of the credit downgrade on organized crime infiltration, heterogeneity by sector



Notes: The figure on the left shows the mean of the probability of infiltration for each sector, prior to the treatment period. The figure on the right reports the estimates for the coefficient on mafia infiltration from equation (2) in black, and the effect at t + 5 in blue panel, together with their corresponding confidence intervals. The estimates are reported for different economic sectors. Standard errors are clustered at the firm level.

Interestingly, the real estate sector exhibits both the highest baseline rate of organized crime infiltration and the largest increase following a credit downgrade. Over a five-year

[12] The estimated coefficients are reported in Appendix Table A2.

period, the probability of infiltration rises by 0.27 percentage points — equivalent to a 10% increase relative to the baseline infiltration rate in year $t-1$ (2.7%). This prominence of the real estate sector is consistent with extensive qualitative evidence highlighting its appeal to criminal organizations as a main vehicle for money-laundering. Indeed, real estate transactions typically involve large, illiquid assets with flexible pricing, creating ample opportunities for laundering illicit profits on a large scale through fictitious sales and purchases (for a review, see Sclafani and Lavorgna, 2020).[13]

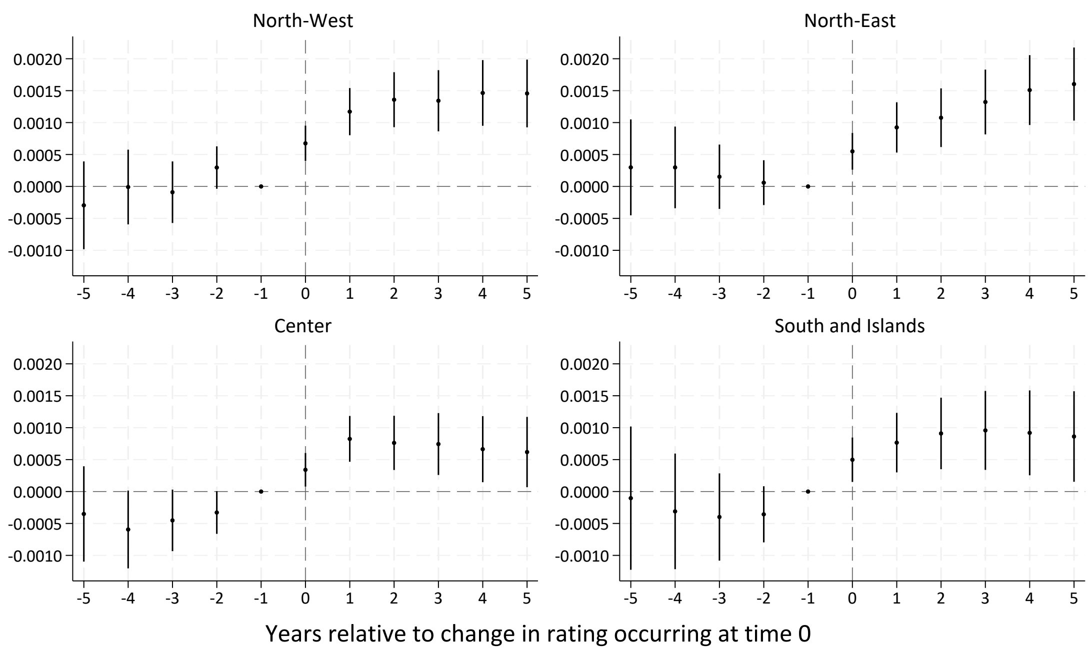
In Figure 11 we turn to the heterogeneity of the effect across different macro-regions. The impact of a credit downgrade is higher in the North, though the difference with other areas is not statistically significant. Figure 12 displays, instead, the heterogeneity in the effect by firm size. The increase in infiltration probability is most pronounced among larger firms (those with 50 or more employees). These firms may offer more scalable platforms for laundering illicit proceeds and may be particularly valuable for securing political connections or non-economic returns such as social legitimacy and prestige. The stronger effect among larger firms also means that the workforce employed in infiltrated firms increases by more than the probability of infiltration after downgrade – 10% and 5%, respectively.[14]

We next explore how the estimated effect varies under progressively stricter definitions of infiltration. The DNA classifies individuals involved in anti-mafia investigations using a risk index ranging from 1 (lowest) to 5 (highest), reflecting both the strength and credibility of the connection to the criminal organization. Following Arellano-Bover et al. (2024), we classify firms associated with individuals rated at level 1 as non-infiltrated, to reduce the risk of false positives—since these cases often involve peripheral figures or mere acquaintances of targets under investigation. In our baseline analysis, we therefore consider as infiltrated only firms linked to individuals with a risk score of 2 or higher.

[13]As shown in Figure 10, a similarly high baseline level of organized crime infiltration is observed in the construction sector, although the post-downgrade increase is more modest. This is consistent with the close relationship between construction and real estate: while construction is concerned with the physical building of structures, real estate involves the development, ownership, and commercialization of land and property.

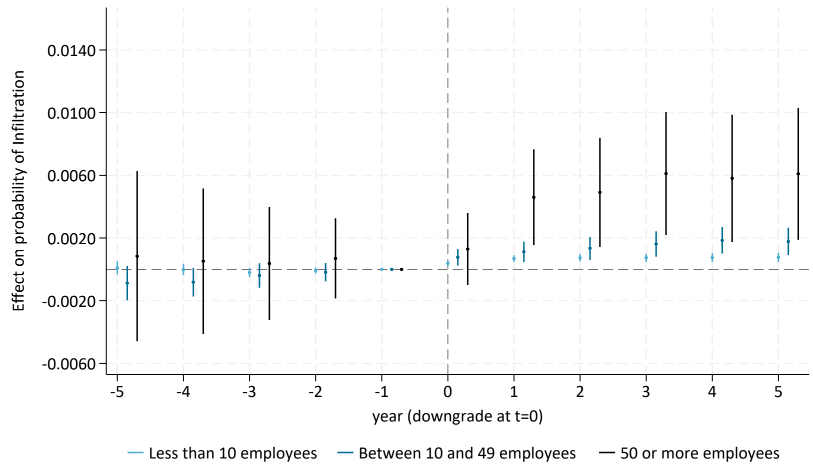
[14]These results are not reported for brevity but are available upon request.

Figure 11: The effect of the credit downgrade on organized crime infiltration, heterogeneity by macro-region



Notes: The figure reports the yearly estimates on mafia infiltration from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. Each panel report estimates for a different macro-region. The bars indicate 95% confidence intervals. Standard errors are clustered at the firm level.

Figure 12: The effect of the credit downgrade on organized crime infiltration, heterogeneity by firm size

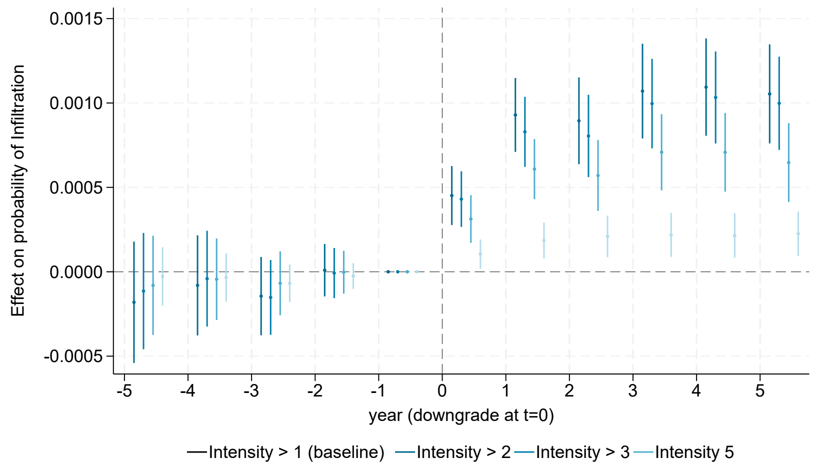


Notes: The figure reports the yearly estimates on mafia infiltration from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. Different markers refer to different dimensional classes: respectively below 10 employees, between 10 and 49 employees, 50 or more employees. The bars indicate 95% confidence intervals. Standard errors are clustered at the firm level.

In Figure 13, we replicate the analysis using increasingly stringent thresholds: scores of 3 or higher, 4 or higher, and finally only 5. In each case, firms associated to individuals scoring below the threshold are coded as non-infiltrated. The estimated effect remains statistically significant across these alternative definitions, though smaller in magnitude as the definition becomes narrower, reflecting a higher risk of false negatives – that is, mis-classifying some truly infiltrated firms as non-infiltrated.

One potential concern is that our analysis may be capturing general changes in firm control rather than actual mafia infiltration – an issued discussed also by Arellano-Bover et al. (2024). Financially distressed firms, for instance, may naturally experience a higher likelihood of board turnover. Figure A2 shows that firms experiencing a downgrade are more likely to undergo changes in their board composition. However, this pattern declines over time, in contrast to the trend observed for infiltration in Figure 8. In any event, Figure 14 replicates our main analysis while controlling for periods during which firms experience

Figure 13: The effect of the credit downgrade on organized crime infiltration, heterogeneity by intensity of infiltration



Notes: The figure reports the yearly estimates on mafia infiltration from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. Higher values of mafia intensity imply stricter definitions of mafia infiltration. Standard errors are clustered at the firm level.

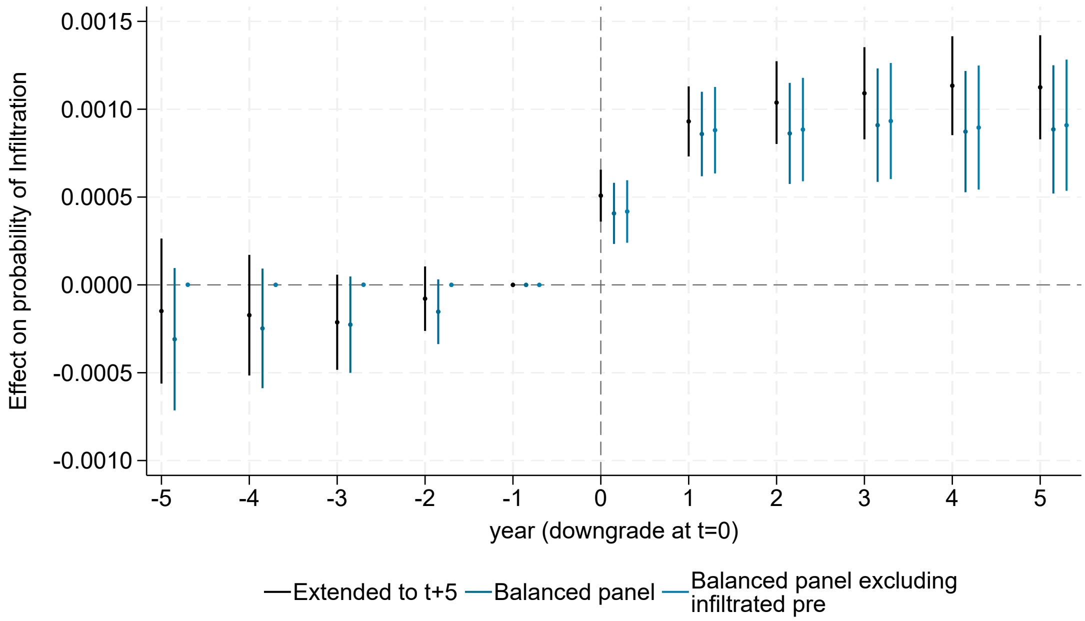
changes in board membership. The results remain robust under this specification.

4.4 Credit Downgrade, Mafia Infiltration, and Firm Outcomes

Finally, we examine long-term outcomes for firms that were and were not infiltrated by organized crime following a credit downgrade. Specifically, we estimate equation (1) for several key firm-level outcomes – namely, survival probability, number of employees, labor costs, profits, and net worth – separately for infiltrated and non-infiltrated firms.

Figure 15 highlights a stark divergence in survival trajectories. While both groups experience a decline in survival probability after the downgrade, the drop is substantially larger for non-infiltrated firms – approximately 15 percentage points after five years, compared to 10 percentage points for infiltrated firms (i.e., a 50% difference). These patterns strongly suggest that the presence of organized crime in the firm may provide a financial buffer that mitigates the adverse effects of the credit downgrade on firm survival.

Figure 14: The effect of the credit downgrade on organized crime infiltration, controlling for changes in the board of the firm.

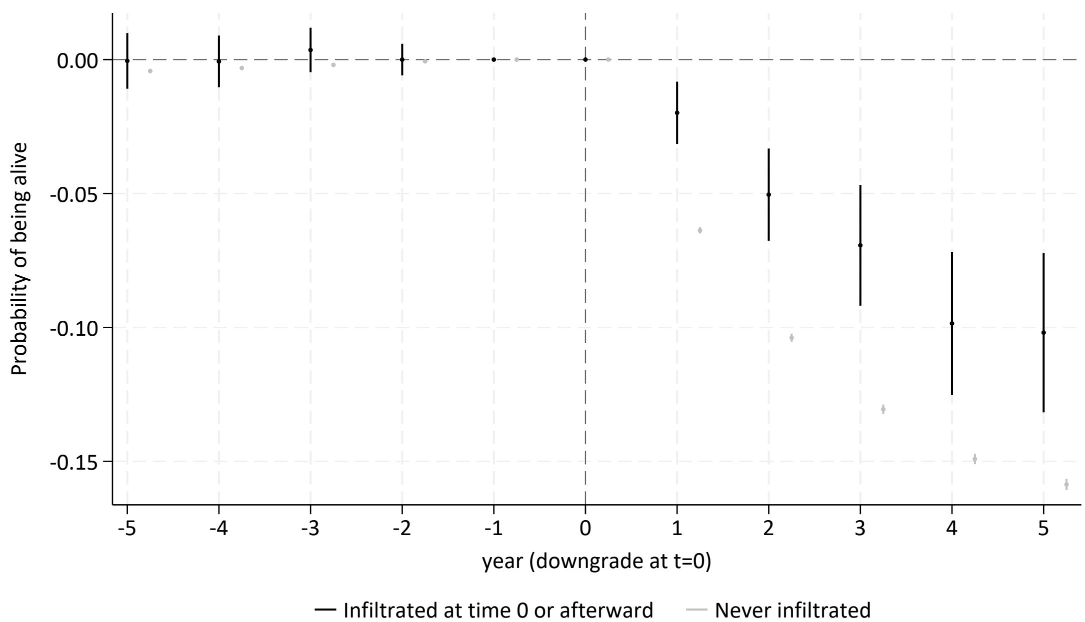


Notes: The figure reports the yearly estimates on mafia infiltration from equation (1) between t-5 and t+5 including a dummy controlling for major changes in the board composition. The year before the downgrade t-1 serves as the reference category. The estimates are reported controlling for whether the firm undergoes a changed in board membership. Standard errors are clustered at the firm level.

However, this resilience does not appear to reflect superior firm fundamentals. Figure 16 shows that infiltrated and non-infiltrated firms display similar declines in other performance metrics, such as employment, labor costs, profits, and net worth. This disconnect suggests that while infiltration may improve short-term survival, it does not translate into improved operational outcomes.

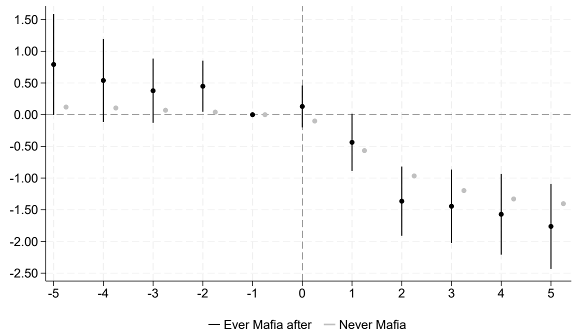
Taken together, these findings support the interpretation that criminal organizations offer a financial lifeline to credit-constrained firms. These firm-level results align with aggregate patterns documented by Le Moglie and Sorrenti (2022), who show that provinces with a strong organized crime presence experienced smaller declines in business formation after the 2007 financial crisis.

Figure 15: Survival probability after the credit downgrade, infiltrated vs. non-infiltrated firms

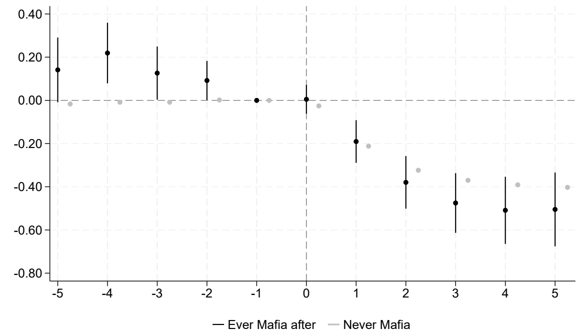


Notes: The figure reports the yearly estimates on survival probability from equation (1) between t-5 and t+5 separately for firms that were never infiltrated (gray markers) and firms that were infiltrated at some point in time between 0 and t+5 (black markers). The year before the downgrade t-1 serves as the reference category. The bars indicate 95% confidence intervals. Standard errors are clustered at the firm level.

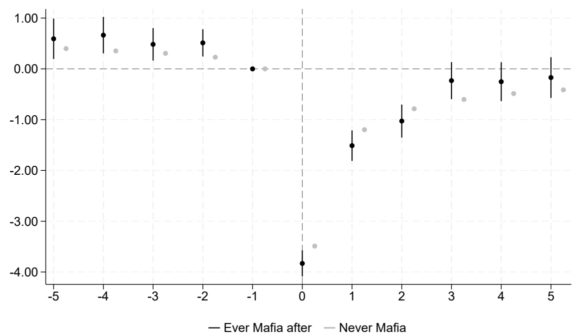
Figure 16: Firm outcomes after the credit downgrade, infiltrated vs. non-infiltrated firms



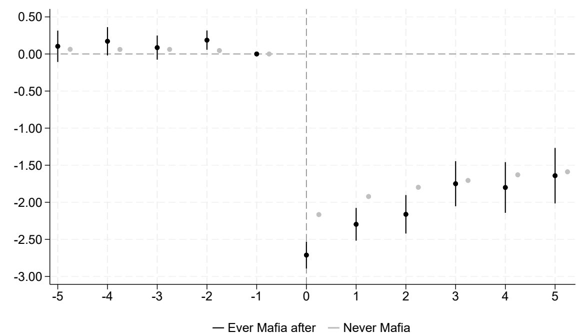
(a) Number of workers



(b) Labor costs



(c) Profits



(d) Equity

Notes: The figure reports the estimates from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. The bars indicate 95% confidence intervals. Each panel report estimates for a different outcome. Panel (a) displays the total number of employees at the firm level, based on administrative records from the Italian Social Security Institute (*Istituto Nazionale di Previdenza Sociale*, INPS). To reduce the influence of outliers, the variable is winsorized and trimmed at the 1st and 99th percentiles. Panels (b), (c), and (d) use data from CERVED Group, which compiles financial statements of firms legally required to submit them. Panel (b) presents the evolution of the logarithm of labor costs, calculated as the sum of wages, social security contributions, and pension fund payments. Panel (c) shows the inverse hyperbolic sine (IHS) transformation of firm profits, defined as revenues minus costs. Panel (d) reports the IHS of equity, measured as the sum of nominal capital and all budget reserves. Given profits and equity may show negative values, we use the inverse hyperbolic sine transformation in panel (c) and (d). Standard errors clustered at the firm level.

However, the poor performance of infiltrated firms – virtually indistinguishable from that of non-infiltrated firms that ultimately exit the market – raises concerns about distorted market dynamics. Their continued survival points to a zombie lending mechanism in which subprime firms remain active not due to improved fundamentals but because of external financial support from criminal organizations, potentially crowding out more efficient competitors. This financial support may, in turn, reflect an underlying quid pro quo, with infiltrated firms offering criminal groups a foothold in the legal economy or access to strategic influence.

5 Conclusions

This paper sheds new light on the conditions that facilitate the infiltration of organized crime into the legal economy, a phenomenon with profound economic and institutional implications. While the presence of criminal organizations in legitimate markets is a long-standing concern, we provide novel, causal evidence on the importance of financial distress – driven, in turn, by credit rationing – as a specific determinant of firm infiltration.

Our analysis combines unique firm-level data on mafia infiltration with comprehensive administrative data on firms' credit ratings, balance sheets, and borrowing activity. This dataset allows us to track the timing and intensity of infiltration with unprecedented precision. To identify the causal effect of financial distress on mafia infiltration, we leverage both a difference-in-differences approach, matching downgraded firms with otherwise identical controls, and a regression discontinuity design based on the confidential credit score that determines access to bank loans.

Across both empirical strategies, our findings are strikingly consistent. Firms downgraded to a substandard credit rating experience a persistent decline in bank loans and, subsequently, a significantly higher likelihood of mafia infiltration. The effect amounts to +5% on average, and up to 10% in real estate – a sector traditionally considered as very vulnerable to organized crime infiltration. Importantly, infiltrated firms show higher survival rates following the downgrade, though without corresponding gains in employment or productivity, suggesting that organized crime serves as a financial lifeline at the cost of distorting market selection.

These findings carry important policy implications. In periods of economic hardship, when traditional credit channels tighten, financially distressed firms may become easy targets for criminal groups seeking to launder money and expand their influence. Preventing such infiltration requires more than criminal enforcement – it calls for strengthening financial transparency, enhancing credit access for high-risk but viable firms, and equipping financial regulators with the tools and data needed to detect suspicious patterns early. Ultimately, curbing the spread of organized crime into the legal economy is critical to safeguarding competition, preserving institutional integrity, and ensuring that market survival is driven by performance – as opposed to the availability of illicit capital.

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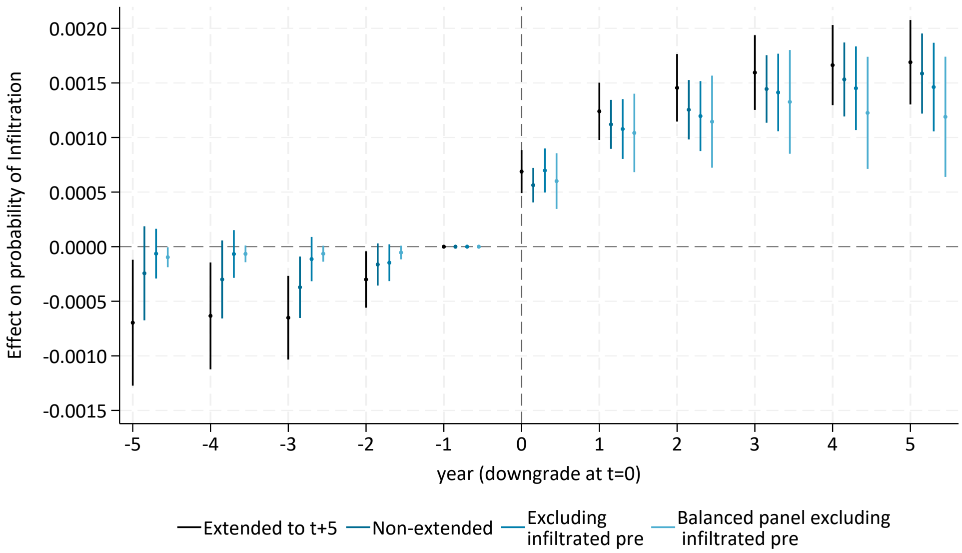
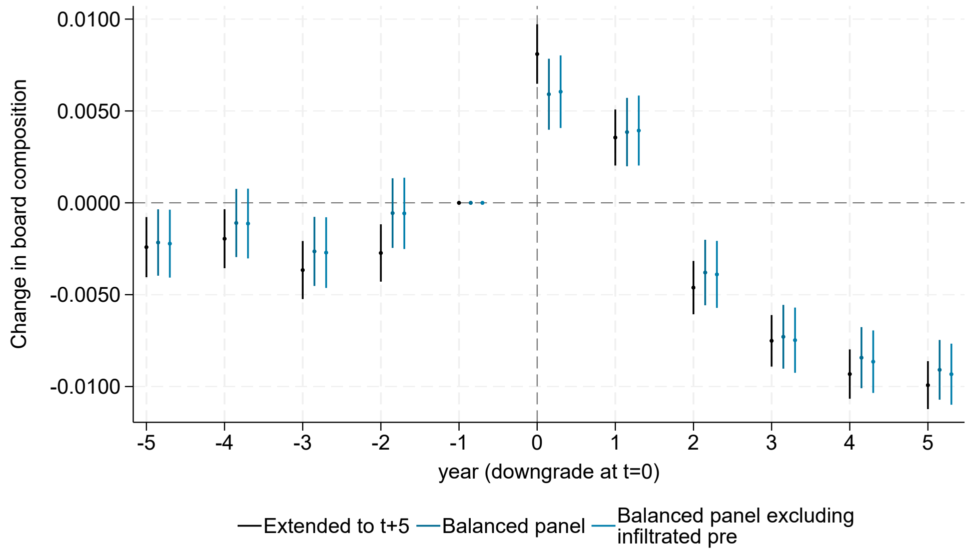
Online Appendix

Figure A1: Probability of mafia infiltration following an increase of the credit score to 7 or above restricting the sample to firm whose rating increases to 7 or above in year 0 for the first time.



Notes: The figure reports the yearly estimates on the probability of mafia infiltration from equation (1) between t-5 and t+5. We restrict the analysis to firms whose rating was never 7 or above before time 0. The estimates show the effects on: i) the sample extended to year t + 5; ii) the original non-extended sample; iii) the extended sample excluded firms infiltrated before time 0; iv) the balanced panel between t-5 and t+5 where we excluded firms infiltrated before time 0. The year before the downgrade t-1 serves as the reference category. The bars indicate 95% confidence intervals. Standard errors are clustered at the firm level.

Figure A2: Probability of observing a change in the board composition around a worsening of the credit rating.



Notes: The figure reports the yearly estimates on the probability of observing a change in the board composition from equation (1) between t-5 and t+5. The year before the downgrade t-1 serves as the reference category. The bars indicate 95% confidence intervals. Standard errors are clustered at the firm level.

Table A1: Means, differences and standardized differences between the treated and control firms

	(1) Control group		(2) Treated group			(1)-(2)	(1)-(2)	(1)-(2)
	N	Mean/(SE)	N	Mean/(SE)	N	Difference	P-value	Std. Difference
Log of assets	419912	6.147	419615	5.996	839527	0.150	0.000	0.093
		(0.002)		(0.003)				
Log of revenues	419912	5.481	419615	5.397	839527	0.084	0.000	0.038
		(0.003)		(0.003)				
Log of number of employees	425877	1.073	425877	1.073	851754	0.000	0.989	0.000
		(0.002)		(0.002)				
IHS of net income	419912	1.204	419615	0.685	839527	0.520	0.000	0.181
		(0.004)		(0.004)				
IHS of net equity	419912	4.709	419615	4.414	839527	0.295	0.000	0.178
		(0.003)		(0.003)				
IHS of purchases	419912	4.240	419615	4.202	839527	0.037	0.000	0.012
		(0.005)		(0.005)				
IHS of labor costs	419912	3.433	419615	3.448	839527	-0.016	0.008	-0.006
		(0.004)		(0.004)				

Note: This table shows the means and standardized differences for key variables between the treated and control firms measures the year before the change in rating. The last column reports the standardized difference between group means.

Table A2: Effect of a worsening of the credit score on the probability of infiltration. Analysis by sector.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector:	Agriculture	Manufacturing	Constructions	Wholesale & Retail Trade	Accommodation & Food	Real Estate Activities	Professional Activities	Remaining Sectors
				Panel A. Average Treatment Effect				
Treat x Post	0.0016	0.0014***	0.0005	0.0009***	0.0009	0.0027***	0.0015**	0.0004
	(0.0015)	(0.0003)	(0.0003)	(0.0002)	(0.0006)	(0.0004)	(0.0005)	(0.0003)
Mean DV at t-1	.0198	.0128	.0277	.0166	.0194	.0273	.0248	.0259
% change	7.99	10.76	1.76	5.28	4.42	9.80	6.03	1.49
				Panel B. Dynamic effect at t + 5				
Treat x Event Time (t+5)	0.0004	0.0013***	0.0007*	0.0006*	0.0013	0.0029***	0.0012*	0.0007
	(0.0016)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0005)	(0.0006)	(0.0004)
Mean DV at t-1	.0198	.0128	.0277	.0166	.0194	.0273	.0248	.0259
% change	1.83	9.95	2.59	3.67	6.70	10.66	4.66	2.84
N. Obs	51,400	1,181,034	1,441,306	1,803,698	363,764	1,101,354	650,364	1,784,582

Note: The table reports the estimates on mafia infiltration from equation (2) in the top panel, and the dynamic effect at $t+5$ estimated form (1) in the bottom panel. The estimates are reported separetely for different economic sectors. *** $p < .01$, ** $p < .05$, * $p < .1$. Standard errors are clustered at the firm level.

Table A3: Delta Log Change in variables other than the rating at time t-1.

Variable:	(1) Δ Log Revenues	(2) Δ Log Purchases	(3) Δ Log Cashflow	(4) Δ Log Labor Costs	(5) Δ Log Employees
Above 7	-0.006	0.005	0.004	-0.003	-0.001
	(0.004)	(0.004)	(0.005)	(0.003)	(0.002)
N. Obs	248,696	221,229	222,746	200,682	197,799
R^2	0.02	0.02	0.00	0.01	0.01
Mean DV	0.059	0.021	-0.019	0.091	0.052

Note: The table presents regression discontinuity estimates obtained using the local randomization approach for various outcome variables in the period preceding the change in rating. Following Cattaneo et al. (2015), we restrict the sample to observations with score values within the bandwidth selected for the main outcome reported in the paper (i.e., [0.07, 0.08]). The outcome variables represent changes in the logarithm of the following: (1) revenues, defined as annual turnover from sales of goods and services; (2) purchases of goods and raw materials; (3) cash holdings, including cash, bank deposits, and short-term credit; (4) labor costs, including wages, social security contributions, and pension fund payments; and (5) number of employees. *** p¡0.01, ** p¡0.05, * p¡0.1. Standard errors are clustered at the firm level.