Organized Crime, Earthquakes and Local Public Procurement: Evidence from Italy

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Abstract

I document mafia firms' participation in public procurement contracts awarded following natural disasters. Exploiting the quasi-random assignment of municipalities to emergency relief status after earthquakes, I show that criminal firms increase their participation in public procurement auctions in emergency-designated municipalities, and particularly after emergency status is removed. Emergency status leads to a temporary increase in monitoring efforts, but a permanent positive shock to affected municipalities' reconstruction budgets. Using information on awarding procedures, I show that: after the emergency, the participation of mafia firms increases only in auctions with minimum discretion suggesting it is not the result of collusion with local administrators.

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1 Introduction

For criminal enterprises, participation in the formal economy presents many benefits – legal businesses offer the opportunity to reinvest proceeds obtained through illicit means and to extend their empires to new sectors and geographies (e.g., Becchi and Rey, 1994, Bini 1997, Gratteri 2011). Third, investments in geographic areas different from their strongholds are strategic opportunities to extend control to new territories.

Participation in public procurement is a common means of entry for organized crime into the legal economy. Procurement is often characterized by discretionary awarding mechanisms that limit competition. Criminal organizations can exploit their ties with bureaucrats and politicians or, when missing, leverage on threats and intimidations, to rig the awarding procedure (Savona 2011, Arlacchi 2007, Polo 2011) and secure higher rents from contracts. Furthermore, the large investment capacity of public administrations, and therefore the large sums at stake in public procurement contracts, make this sector an attractive opportunity (Ferraz, et al. 2015). Finally, public procurement process offers the ancillary benefit of facilitating interaction with governments and thus extend the influence to the political sphere (Barone et al., 2015, Pinotti, 2015, Di Cataldo and Mastrorocco 2018).

Despite accounts in the popular press and judicial records, there is nonetheless little systematic evidence on when and how organized crime participates in public procurement. In large part, the paucity of research on the topic may result from the difficulties of uncovering and measuring criminal firms' participation. Members of criminal syndicates participate in public auctions directly: they conceal their identities via third parties that both limit the risk of detection and obscures the illicit origins of the funds invested (Mirenda et al. 2019). Second, studying the mafia-procurement tie presents an econometric challenge: it is difficult to disentangle whether the attractiveness of public contracts or extant ties with corrupt politicians are the cause of the link.

In this paper I exploit confidential data from Italy's Anti-Mafia Directorate and exploit plausibly quasi-experimental variation in contract type and volume to study the infiltration of public contracts by mafia-linked firms. I focus on the earthquakes that hit Italy between 2008 and 2016 and on the municipalities that received emergency declarations in the aftermath. I collect data on the contracts awarded by these municipalities from Autorita‘ Nazionale Anticorruzione (ANAC), the Italian Authority supervising public procurement. For contracts with a reserve price above 150 thousand euros I observe the tax identifiers of the participants. Such information facilitates a matching between contract participants and the Anti-Mafia Database which lists the firms that were, at some point, linked to organized crime via direct (presence of mafia members in the board) or indirect ties (business ties or presence via representation of mafia-linked third persons). I may thus construct a measure of participation of organized crime at the contract level. I focus on participation as I do not always get to observe the identity on the winning firm.

Italian law recognizes a "special status" for areas that are included in a state of emergency declaration: emergency-status municipalities may put a priority on rapid recovery, and to allow for the quick restoration of safety there is more flexibility in the awarding of contracts. Funds that accompany emergency declarations are thus awarded with higher discretion in contractor selection. Monetary thresholds required for a call for tender are lifted and the legal time to award contracts is shortened. Such allowances are common in the wake of disasters (Leeson & Sobel, 2008), and it is because of this rush to spend more money with laxer enforcement that post-disaster procurement is often claimed to be corrupted. However, this narrative overlooks the fact that enforcement authorities, recognizing the increased risk of malfeasance, may step up their monitoring efforts as well (indeed, the Anti-Mafia Directorate increases its efforts in monitoring working sites of public procurement contracts).

I implement a difference in differences methodology, exploiting discontinuous changes in emergency declarations in adjacent municipalities (Cipollone and Rosolia, 2007) to identify the causal effect of emergency status on the participation of organized-crime-linked firms in public procurement. For each earthquake, the geographical perimeter of the emergency defines two groups of municipalities: those within the emergency zone (*Treatment*) and the ones just outside of it (*Control*). I examine differences between contracts in these two groups of (adjacent) municipalities during three periods: before, during and after the emergency. This comparison allows me to identify the causal effect of the state of emergency over the participation of organized crime in public procurement as adjacent municipalities are also more likely to be matched in terms of observable characteristics: limiting the risk that other confounding factors (for example ties between hit municipalities and mafia coming from previous emergency episodes) rather than the state of emergency are responsible for the effect. The identifying assumption in comparing mafia infiltration of procurement in treatment and control municipalities in these periods is that had the treated municipalities not been declared in a state of emergency, they would have experienced similar changes in the participation of organized crime as the municipalities located just outside of the emergency declaration boundary. While the geographical proximity of the municipalities and their quasi-random assignment to the emergency supports such hypothesis, I also formally test for pre-trends in the participation of organized crime into public procurement.

I find that participation of organized crime in public procurement contracts increases in municipalities that experienced the state of emergency, and that this effect appears primarily *after* the emergency declaration has been lifted (3.5 years on average). Experiencing an emergency causes an increase of 3 percent points in the probability that at least one "criminal-linked firm" (ie: a firm linked to organized crime) participates in a public procurement contract. In contrast, I find no significant effect on participation of organized crime in contracts awarded during the state of emergency. Furthermore, the increase in participation stems from new relationships between firms linked to organized crime and municipalities (*extensive margin*) rather than from repeated interactions between the two (*intensive margin*). These findings are robust to controlling for differential trends in treated and control municipalities due to different number of participants in the auctions.

The lagged response of organized crime to the state of emergency is compatible with a mechanism in which both municipalities' budgets and Anti-Mafia monitoring increase in the immediate aftermath of an earthquake. As time passes, however, reconstruction funds remain high even after the emergency declaration is lifted while monitoring effort dissipates. Criminal firms thus exploit the increased rent opportunities from reconstruction funds when the risks of detection are minimized. The data supports this interpretation: the funds spent in public works by treated municipalities are significantly higher both during and after the emergency, while also the prices municipalities are willing to pay (reservation price) increase over time. I further provide qualitative evidence that the Anti-Mafia directorate concentrates its audits during the state of emergency.

I proceed to investigate whether the increase in participation of organized crime occurs via collusive relationships between firms and local administrators (Bandiera et al. 2009) or whether criminal firms target procedures in which the active role of the administrators is minimized. I construct a simple theoretical model to guide the intuition that discretion in the awarding procedure is a necessary condition for collusion to occur. I derive the testable implication that an increase in the participation of organized crime is consistent with collusion only if it occurs in discretionary auctions.

I exploit information on discretion in the awarding procedures of procurement auctions to provide evidence against the collusion hypothesis. Local administrators enjoy two margins of discretion when awarding procurement contracts: in the awarding criterion and in the selection of the winner. Administrators can select whether to award a contract via a first-price auction or "scoring rule" (assigning points to non-price features) as well as whether to limit the number of participants ("negotiated procedure" vs open tender). Participation of criminal firms is concentrated in auctions in which both the discretion margins are minimized, arguing against the collusion hypothesis.

This study adds to three strands of literature. First I contribute to the extant body of work on organized crime by using novel data to bring evidence of one mechanism through which criminal enterprises enter the legal economy. Previous work takes the presence of organized crime as an initial condition and studies its real effects on the economy (Mirenda et al. 2019, Pinotti 2015, Di Cataldo and Mastrorocco, 2018) or the distortions it causes on the democratic process (Acemoglu et al. 2017, De Feo and De Luca, 2017, Daniele and Di Poppa 2018). My analysis contributes by documenting the "first stage" of such phenomenon: highlighting one way through which organized crime expands and enters the legal economy.

Second, my finding that participation of organized crime is concentrated in procurement auctions where discretion of the administrators is minimized contributes to the literature on procurement rules and corruption (Baltrunaite et al. 2018, Coviello et al. 2018, Auriol et al. 2016). The finding that infiltration appears not to be facilitated by the collusion of local officials follows in the spirit of the findings of Bandiera et al. (2009) and, more recently, the concurrent work of Decarolis et al. (2019). Both of these papers focus on public procurement in the Italian context and argue that inefficiency rather than corruption causes overspending, and that inefficiency itself can be a byproduct of excessive regulation aimed to shut down any risk of corruption. More broadly, my natural experiment allows to look at the effects of changes in monitoring efforts by the central authority and thus to contribute at the literature on the effect of government audits on corruption (Colonnelli and Prem, 2017, Ferraz and Finan, 2008, Olken andb Barron, 2009).

Finally, my work contributes to the scant work on natural disasters and corruption. Leeson and Sobel (2008) provide a suggestive correlation between natural disaster relief and corruption (as measured by corruption convictions) at the state-level in the U.S. Note that my findings do not imply corruption, in that taken as a whole, my analysis indicates that while reconstruction funds attract participation of criminal firms, there is no evidence that it occurs via collusion of local administrators. More generally, my work contributes to the literature on the impact of government windfalls on corruption (Brollo et al. 2013, Caselli and Michaels 2011, Vicente 2010). In particular, I shed light on the the largely unstudied question of how reconstruction funds and monitoring in response to a natural disaster may provide openings for criminal enterprises to infiltrate the legal economy, even when collusion with local administration does not occur.
The paper is organized as follows. In the next section I describes the involvement of organized crime in public procurement. Section 3 introduces the States of Emergency and the institutional background. In Section 4 I present the data and in Section 5 I describe the identification strategy. Section 6 presents the estimates of the participation of organized in public procurement. Section 7 brings evidence against the collusive behavior of the local administrators. Section 8 provides robustness checks to my main results and Section 9 concludes.

2 Organized Crime & Public Procurement

Public procurement provides both direct and indirect sources of revenue for criminal organizations, as well as opportunities for investment. Mafia firms make profits directly from the prices public administrations pay, but also indirectly by extorting winning firms.Furthermore, participation in procurement allows criminal firms to invest and “wash" the proceeds of illicit business. Finally, procurement is an opportunity for organized crime to extend its influence to the political sphere. Italian law imposes the dissolution of municipality councils in case of infiltration by the mafia; this is often the result of evidence on rigging of public procurement (Tulli, 2019).

Mafia firms may enjoy several competitive advantages over regular firms. First, they do not face credit constraints as they can count on a continuous stream of funds from illegal activities. Second, they may exploit threats and intimidation to limit competition and gain market share. Third, their political ties and corrupt linkages make it easier to rig awarding procedures. Finally, mafia firms may be more able and willing to circumvent workplace safety rules to reduce their costs (DIA, Relazione Antimafia 2009).

A factor that facilitates participation of organized crime in procurement is mafia specialization in the cement and construction industry. This has two negative consequences. It makes coercion of mafia firms more difficult, and also impacts the quality of buildings built by criminal firms (Allum in Vice, 2016). For example, some of the damages that occurred after the Aquila earthquake in 2009 were caused by the low grade used by cement criminal firms when constructing or “upgrading" some of the buildings.

Organized crime distorts the awarding process of public procurement either through illegal or legal means: using threats and violence in the first case, and participating in public procurement auctions in the second. Criminal firms may participate in procurement in at least two ways. If their size or lack of technical capacity does not allow them to bid directly, they form ties with larger firms that are more likely to win. Alternatively, if multiple mafia firms participate in an auction, they collude to bid the lowest price and to ensure that one among them wins (DIA, Relazione Antimafia 2016). In this second case, the winning firm pays a percentage to the mafia and in exchange, it obtains “protection" from extortions from other criminal groups as well as the promise of intervention if bureaucratic procedures and authorizations slow down the process.

Big events such as the Olympic Games (as in Japan), the Universal Exposition (as for the Italian Expo in 2015) or declarations of emergency following natural disasters offer an opening to enter the public procurement process. The large sums at stake make these events attractive opportunities, and in some cases participation in reconstruction may also help to build public support for criminal groups and affirm control over their territory. For example, after the 2011 earthquake in Tokyo, the Yakuza was among the first providers of relief (Reuters 2011).

The attractiveness of funds for reconstruction and the risk of participation of mafia firms in the procurement process are well known to Anti-Mafia prosecutors. The 1980 earthquake in Irpinia, Southern Italy, was the first time Italy realized the high involvement of the mafia in the aftermath of an emergency. At that time, Mafia used threats and violence toward local politicians to infiltrate procurement contracts. In more recent years, organized crime has developed more subtle ways of entering the legal economy, abandoning violence in favor of a more “invisible approach" that, on the surface, makes it resemble to a regular business (Vice, 2016). This strategy gave the mafia even wider scope to achieve its targets: a report of the European Parliament (Sondergaard 2012) found that part of the solidarity funds the EU provided for relief after the Abruzzi earthquake of 2009 was “paid to companies with direct or indirect ties to organized crime". And even in the most recent earthquake that hit Italy in 2016, Franco Roberti, head of Italian’s Anti-Mafia Directorate stated: “The risk of infiltration is always high. Post-earthquake reconstruction is a tasty morsel for criminal organizations and business interests."

3 Setting: the states of emergency

Under Italian law, a natural catastrophe is an “event that requires immediate and urgent response due to its intensity or extensiveness." The urgency and priority allows extraordinary powers to the Council of Ministers: the Prime Minister declares the “State of Emergency" without the approval of Parliament. The emergency decree includes the following information: I) the name of the commissioner in charge of supervising the operations of reconstruction, II) the amount of funds directed to the affected area, III) the duration of the Emergency and IV) the list of laws that are not enforced for the duration of the Emergency. Depending on the gravity of the disaster the commissioner overseeing the funds is either a national or a local figure: the Head of Civil Protection (Italy’s version of FEMA in the U.S.) or the Head of the Region. He is in charge of identifying the area affected by the calamity and generating the list of hit municipalities.

During the State of Emergency the law on public procurement is not fully enforced so to allow for more flexible procedures, and to set priorities on the removal of any threat to citizens’ life. Hit municipalities implement urgent procedures to restore building and infrastructure safety: immediate execution of public works and discretionary selection of contractors may substitute for a call for bids, and the time to award the contract is also shortened. The local administration is exempt from the obligation of calling an open tender and is allowed to select a contractor via direct appointment rather than via open tender procedure. To prevent these unusual practices from turning into an opportunity for malfeasance, the law imposes a cap on the value of contracts: these provisions only apply to auctions with reserve price below the cap. The cap is set at 300 thousand Euros for contracts for buildings of historical value and 200 thousand Euros for other contracts. The amount to be paid is set with an agreement between the contractor and the administration but, in case agreement cannot be reached, the administration has the power to impose a 20 % discount on the regular price adopted by the region.To balance the risk of corruption caused by higher flexibility in emergency procurement procedures, the Anticorruption Authority and the Anti-Mafia Directorate step up their monitoring efforts during the Emergency. The Anticorruption Authority ensures the presence of the prerequisites required for the implementation of the exceptional procedures allowed during the “emergency" while also checking ex-post that the selected contractors fulfill the requirements necessary to carry out the work. At the same time, the Anti-Mafia Directorate tries to ensure that auction participants are not linked to organized crime via business or family ties. For contracts above 150 thousand Euros and to participate in public procurement auctions, firms are required to provide documentation that attests that they are clear of “mafia ties." This documentation, however, while deterring infiltration of criminal firms, does not remove it completely, as organized crime may still find less visible ways to infiltrate the companies (for examples via employees rather than board members).

4 Data

I require three pieces of information to carry out my analysis: I) the identity of the municipalities in a State of Emergency, II) the list of public procurement contracts for affected municipalities as well as comparison commnities, and III) the information, for each contract, on whether or not a criminal firms participated. For each of these I draw on a different data source. I collect the list of municipalities from the decrees of the Emergency Commissioner, the list of public procurement contracts from the Italian Anticorruption Authority (ANAC) and information on criminal firms from the Anti-Mafia Investigative Directorate (DIA).

Identifying Municipalities in a State of Emergency. Seven Earthquakes hit Italy between 2008 and 2016 (Figure 1). They varied both in intensity and number of victims: the Abruzzo earthquake in 2009 was the most intense (6.6 on the Richter scale) and with the highest dead toll (309 deaths). The States of Emergency declared in the aftermath of earthquakes varied in length, from a minimum of 4.4 months (Calabria in 2012) to a maximum of 8.5 years (Emilia Romagna earthquake of 2012). Table 1 reports the list of events, their duration, and intensity.
From the documents of the Italian Agency of Civil Protection (the equivalent of FEMA in the U.S.) I recover the dates of the States of Emergency as well as the names of the Commissioners in charge of supervising the procedure. Looking at the Commissioners' decrees I manually identify the names of the municipalities included in the perimeter of the emergency: 385 municipalities were declared in a State of Emergency at least once during my period of analysis. Figure 2 shows the number of municipalities that are in a State of Emergency in each year. Given the rolling nature of the emergency declarations, municipalities may enter or exit emergency status at different point in times.

Public Procurement Contracts. Details on Public Procurement Contracts and information on the participants are from the Anticorruption Authority (ANAC). Local public administrations are required to report details on the Public Procurement auctions they award to the Anticorruption Authority. The data includes information up to the awarding phase on all the contracts for public works awarded by municipalities in the neighborhood of an earthquake between 2010 and 2017. Table 3 reports summary statistics for the public procurement contracts in my sample. Buildings and road construction are the two most common categories, covering about 70% of all contracts. The bargaining process typically lasts about two months and the winning bid has a median 20 % rebate relative to the reserve price. The procurement data also includes information on the date when each auction was opened, the criterion for the awarding of the contract (lowest price or "scoring rule") as well as the type of auction (open tender or direct negotiation). The lack of complete information on the post-award bargaining (final price of the project including renegotiation, and delay in completion) limits my analysis on the aftermath of the auction and on the quality of the

public work.
I observe the list of auction participants and their tax identifiers only for contracts with a reserve price above 150 thousand Euros and awarded after 2010. Starting from that year, firms participating in public procurement auctions with a reserve price above 150 thousand Euros had to submit their participation fee electronically. The fee is required to take part in the auction and is collected by the Anticorruption Agency. Crucially for my analysis, when submitting the payment, firms report their tax identifier.

Participation of Criminal Firms in Public Procurement I exploit confidential data from the Anti-Mafia Directorate to measure the participation of Criminal Firms in public procurement auctions. The National Anti-Mafia Database (BDNA) reports all the firms and individuals that have been found linked to organized crime and that have been targeted by an interdiction order to participate in any public procurement project. The data is used to monitor participation of criminal firms in the real economy and can only be accessed by the Anti-Mafia Directorate and the police. Linkages to organized crime can take several forms: a member of the mafia or a relative may be part of the firm's board; alternatively, members of the firm may have been found doing business with mafia representatives, or the same firm may have subcontracted business to criminal firms.
I passed the identifiers of the auctions' participants I collected from the Anticorruption Authority to the Anti-Mafia Directorate. The Anti-Mafia Directorate matched these identifiers with those of the firms reported in their database, and provided me with information on the number of participants in each auction were mafia-linked. Thus, for each public procurement contract I observe the number of participants and the fraction that were linked to the mafia. The data comes with two restrictions: I cannot link individual firms to organized crime (only the fraction of criminal-linked firms per auction), and I do not know the date when firms were linked to organized crime.

Complementary Data Sources Details on municipalities characteristics come from the Italian Census of 2001 and information on earthquakes from the National Institute of Geophysics and Vulcanology (INGV). The Census provides details on population as well as on the age of buildings and the materials used for construction (e.g., masonry buildings and reinforced concrete). The INGV supplied information on the earthquakes in my sample (epicenter, magnitude) as well as historical information on earthquakes that had hit municipalities in the past.

5 Identification Strategy and Estimating Equation

Difference-in-Differences I use a difference-in-difference methodology to identify the causal effect of the State of Emergencyon the participation of criminal firms in public procurement auctions. The exogenous timing of the disasters and the quasi-random assignment of municipalities to emergency status provides a plausible natural experiment to study the causal impact of emergency declarations on the participation of criminal firms in procurement.

I identify "treated" and "control" municipalities based on their location with respect to the border of the State of Emergency. I exploit the time dimension of the public procurement data as well as the temporary nature of the Emergency to identify differential trends between the treated and control municipalities after the emergency. A municipality is part of the *Treatment* group if it is within the perimeter of the State of Emergency, i.e. if it is listed in the decrees of the Emergency issued by the Commissioner in the aftermath of the Earthquake. A municipality is part of the *Control* group if, despite being in the proximity of the earthquake, it is not included within the Emergency perimeter. Control municipalities lie within 25 kilometers of the border of the emergency: this is the maximum distance of treated municipalities from the border of the Emergency (Table 2). For the temporal dimension of the Diff-in-Diff strategy, I exploit the timing of the State of Emergency: I compare the outcomes of contracts awarded *During* the State of the Emergency as well as *After the End* of the State of Emergency to the contracts awarded *Before* the earthquake occurred and the Emergency was declared.

Identifying Assumption To be able to interpret the diff-in-diff coefficients as the causal effects of the State of Emergency on the participation of criminal firms, the parallel trend assumption must hold. The assumption requires that, had the municipalities not been declared in a state of emergency, they would have showed similar changes over time in the participation of criminal firms in their auctions. Alternatively, if any difference in trends were to be detected, this would be entirely driven by observable characteristics that I could measure and include as controls in my specification (distance from the epicenter, seismic risk, architectural vintage of the buildings, etc.). The exogenous timing of the earthquake as well as the quasi-random assignment to the state of emergency make it plausible that the parallel trend assumption holds in my case; however I also formally test for it via an event study specification. This allows me to check whether municipalities that will be declared in a state of emergency already displayed significantly different participation of criminal firms in their public procurement auctions in the years before the event occurred.

Threats to the identifying assumption The methodology described allows me to identify the causal effect of the emergency to the extent that there is no other unobserved confounding factor that is correlated with both the assignment to the State of Emergency and the participation of criminal firms in auctions. For example, municipalities closer to the epicenter may have also experienced more earthquakes in the past, or be better at lobbying for inclusion in the state of emergency and thus already be on a trend of more infiltration by organized crime. To address this concern, as well as to address the concern that differences in trend in public procurement outcomes may stem from differences in observable characteristics of municipalities, I adopt a methodology similar to Cipollone and Rosolia (2007): I focus on the subset of municipalities (treated and control) that touch the border of the State of Emergency (Figure 3). I compare municipalities located within the emergency and adjacent to its perimeter (*Treated*) to the neighboring ones that are barely excluded from the State of Emergency (*Control*). These two groups of adjacent municipalities experienced the earthquake with similar intensity, and faced comparable damages and reconstruction needs; Their only difference should be whether or not an emergency was declared.

An additional concern is that the selection of the municipalities into the State of Emergency may not be random. Mayors with ties to organized crime may see in the State of Emergency an opportunity to bring forward the interests of criminal firms or, in case such ties were not already present, corrupt mayors may exploit the emergency as a chance to earn kickbacks by letting criminal firms participate in auctions. Such mayors may pressure the Commissioner to include them in the State of Emergency so as to increase their chances of benefitting from corruption. Reverse causality would be a risk in this case as the presence of ties to organized crime or the opportunity to build them would predict the inclusion of a municipality in the state of emergency, thus undermining the identification strategy.

I argue that this is unlikely to be a first-order concern: in the aftermath of an earthquake, the exceptional powers of the Commissioner are balanced by high scrutiny from the Central State: the Commissioner's decrees are monitored by the Prime Minister and, especially for the biggest earthquakes, the Commissioner reports to the Parliament on the status of reconstruction efforts. With such intense monitoring, it would be hard for the Commissioner to manipulate inclusion in the emergency. Furthermore, if the Commissioner were indeed manipulating assignment of emergency status, this would more likely be a concern for towns located further from the epicenter. To ensure that municipalities at the border, and for which selection into treatment may be a concern, are not the ones driving the results, I repeat my analysis on a "doughnut sample" consisting of all the municipalities within 25 km of the state of emergency (either inside or outside of it: the original sample) minus the ones touching the border of the emergency.

Sample of Treated and Control Municipalities. Table 4 reports the summary statistics for the treatment and control municipalities in the three samples described above: the full sample of municipalities that are within 25 km of the border of the Emergency (columns 1-3), the municipalities that are adjacent to the border of the emergency (columns 4-6) and the set of municipalities that are within 25 km of the border but not touching it ("Doughnut Sample").
When restricting the sample to the adjacent municipalities (Columns 3-6), the two groups are well-balanced on observable attributes. In particular, the two groups are similar in terms of Gravitational Acceleration (which proxies for the speed of propagation of the seismic wave), suggesting that municipalities on either side of the border face similar earthquake intensity and thus similar damages. Unfortunately, I am limited in my study on the use of data on the intensity (Richter

scale) of the earthquakes as these are available only for subsets of municipalities that either match with the set of treated towns (i.e. no information is available for the municipalities excluded from the state of emergency), or for locations that are very far from the earthquakes and thus do not make up a cohesive geographical subset.

To be able to interpret the coefficient of the difference in differences specification as the causal effect of the state of emergency, I must ensure that any differential trend between the treated and control municipalities in the aftermath of the earthquake is not attributable to difference in other characteristics in which the two sets of municipalities differ. To address this concern I control for time-invariant characteristics by adding municipalities fixed-effects to my specification.

In my analysis I also augment my estimating equation with interactions between the observable characteristics and time dummies (respectively *During* and *After*) the earthquake. This allows me to test whether other characteristics, rather than the state of emergency itself, cause differential trends between the two sets of municipalities. First I test for whether it is the intensity of the earthquake, rather than the state of emergency that causes the participation of criminal firms. A similar strategy allows me to address the concern that municipalities that had been hit by an earthquake in the past may have already experienced higher infiltration of criminal firms and thus have higher ability in creating a network with organized crime in the aftermath of a natural disaster. If this were the case, the difference in differences coefficient would be capturing the network ability of infiltrated municipalities rather than the effect of the emergency. I test for this alternative hypothesis by augmenting the model with interaction terms between a dummy capturing whether the municipality was hit by an earthquake in the past fifty years and time dummies.

Estimating Equation I estimate the following empirical specification on the set of public procurement contracts with a reserve price above 150 thousand Euros awarded after 2010:

$$\begin{aligned} Participation_{imet} = & \beta During_{et} \times Treat_{me} + \gamma After_{et} \times Treat_{me} \\ & + \kappa During_{et} + \lambda After_{et} + X_i + EarthQ_e + \alpha_m + y_t + \epsilon_{imet} \end{aligned} \tag{1}$$

Each observation is a public procurement contract i awarded by municipality m, in the neighborhood of emergency e in year t. The dependent variable is a dummy that takes a value of 1 if at least one participant in the auction is a firm linked to organized crime and present in the Anti-Mafia database. $Treat_{me}$ is a time-invariant indicator equal to 1 for municipalities within the perimeter of the emergency, $During_{et}$ and $After_{et}$ are dummy variables for contracts awarded during and after the emergency is closed, respectively. X_i are contract i specific characteristics (number of participants, category of procurement) and $EarthQ_e$, y_t and α_m are emergency, year of public procurement, and municipality fixed effects respectively.

The two coefficients of interest are β and γ which capture the effect of the state of emergency on the participation of criminal firms *during* and *after* the emergency, versus the baseline period *before*, when the earthquake had not yet occurred and the emergency had not yet been declared.

After estimating Equation 1 on the three samples of municipalities described above I implement also a more demanding specification: in place of comparing the mean change in the outcome variable of the treated and control municipalities, I construct matched pairs of neighbors. I match each treated municipality at the perimeter of the emergency with one in the control group with which it shares at least a portion of the geographical border. This way I create "matched-pairs" of municipalities: I compare the effect on each municipality at the border of the emergency to the direct neighbor adjacent and touching it. I finally augment my model with pair fixed-effects and weight the regression by the share of the border that the municipalities have in common.

6 The impact of the State of Emergency on the Participation of Criminal Firms in Public Procurement

Before testing the empirical specification, I plot the raw mean of the dependent variable over the three periods of analysis (*Before*, *During*, *After*) for the full set of municipalities within 25 km from the border of the emergency. Figure 6 shows that municipalities within the state of emergency display higher participation of criminal firms in public procurement auctions and that this effect is concentrated in the last period, after the state of emergency has ended. Mafia firms do not appear to target treated municipalities more during the emergency, nor do the two groups of municipalities differ in criminal firm participation prior to the earthquake.

To further probe whether this pattern plausibly has a causal interpretation (and in particular to ensure that the pattern is not driven by differential characteristics in treated and control municipalities), I run Equation 1 on the three subsamples of interest with either municipality or matched-pair fixed effects. Fixed effects allow me to control for any time-invariant difference in characteristics between the two groups. The odd columns in Table 5 report the results of this exercise while Figure 6 plots the interaction coefficients. Criminal firms increase participation in public procurement auctions by 3 percentage points after the state of emergency is over.

One concern is that the increase in participation may not driven by the state of the emergency but rather is an artifact of the nature of the data and measurement of the dependent variable. If the number of participants in auctions changes over time (e.g., because more firms see reconstruction as a profit opportunity), than the fact that the Anti-Mafia records more participants as criminal firms could merely be a "size" effect: given the larger pool of firms, it is more likely that at least one is linked to the mafia. To address this issue, in the even columns of Table 5 I augment the model with interactions between the logarithm of the number of participants and the time dummies. While noting that the number of participants may plausibly be considered a "bad control," it is nonetheless reassuring that the effect on the participation of criminal firms in the aftermath of the emergency is still positive and statistically significant even with this inclusion.

While municipality and year fixed effects control for time-invariant differences in the two sets of municipalities, a concern remains that the differential trends in the participation of criminal firms may arise from characteristics that are unbalanced between the two sets of municipalities. For example, if treated municipalities have experienced more earthquakes in the past, they may have already been vulnerable to infiltration by organized crime and thus be more likely to have ties with mafia firms today. To ensure that I am not capturing a "network effect," and that differences in their observable characteristics are not causing differential trends in the two sets of municipalities, I augment the model with interactions between municipalities' covariates and time dummies. I rely on Table 4 for the choice of characteristics. Table 6 shows that even when adding the interaction terms, the coefficient on criminal firm participation in the aftermath of the emergency is largely unaffected.

Testing for pre-trends. My causal interpretation of the difference-in-difference coefficient relies on the parallel trend assumption: were the municipalities in the treated group not included in the state of emergency, they would have followed a similar trajectory in the participation of criminal firms as the control group. I exploit the staggered nature of the earthquakes to conduct an event-study and test for whether treated municipalities displayed a differential trend before the earthquake hit. I estimate the following specification:

$$Partic_{imet} = \sum_{k=-5}^{k=5} \beta_k \mathbb{1}(Ev.Time = k) \times Treat_{me} + \sum_{k=-5}^{k=5} \gamma_k \mathbb{1}(Ev.Time = k) + \alpha_m + EarthQ_e + \epsilon_{ist} \tag{2}$$

where $\mathbb{1}(Ev.Time)$ is a dummy that takes value of one for contracts that are awarded k years from the earthquake event. The statistical significant of the coefficients β_k in the years leading to the earthquake (ie: $k < 0$) serves as a test of the parallel trend assumption. Figure 7 shows the results of this estimation. The two groups of municipalities do not appear to follow differential trends in the years before the earthquake. The slightly positive (though not statistically significant), coefficient for the year immediately preceding the event is driven entirely by seven public procurement contracts that were awarded by five municipalities (Bologna, Reggio nell'Emilia, Macerata, Rieti e Corridonia) within 12 months before the earthquake occurred and that reported participation of criminal firms. Such a positive coefficient could be a concern if, say, the Anti-Mafia Directorate had concentrated its investigative efforts in these municipalities and thus any result in the aftermath of the earthquake would be capturing Anti-Mafia enforcement effort, rather than the effect of the State of Emergency. In robustness checks I tackle the issue by running the same analysis on a subsample of municipalities that excludes these five. Furthermore, given that four out of the five municipalities causing a positive coefficients at time -1 are sizable in terms of population (they are province-city administrative units), one may be concerned that criminal firms target populous cities. In the robustness checks I also augment my specification with interaction terms between population and time dummies to address this issue.

Finally, in interpreting the event plot, it is crucial to note that the duration of the state of emergency varies across different earthquakes. For example, while two years after the Earthquake, L'Aquila was still in a State of Emergency, that was not the case for Calabria (Table 1). Therefore, the coefficient β_2 on the plot averages the *After* effect of the earthquake for Calabria with the *During* effect for L'Aquila.

Mechanism: Funds and Monitoring To summarize the results of the preceding section, emergency declarations cause an increase in criminal firms' participation in public procurement auctions of 3 percentage points, primarily after the emergency is over. There are thus two facets of emergency relief and criminal infiltration that warrant further exploration: I) mafia firms find it more profitable to enter municipalities in a state of emergency compared to adjacent ones; II) mafia firms have higher incentives to enter after the emergency versus during it. I argue that the increase in the availability of funds to municipalities in a state of emergency lies behind the first of these points, while variation in the extent of monitoring during versus after the emergency causes the lagged response in participation.
I proxy the funds available to municipalities with the sum of the reserve prices of all public work contracts (above and below 150 thousand Euros) awarded over the full period for which I have data available ($2007-2017$).Figure 8 shows the coefficients of interactions of a regression with total funds as the dependent variable. During the state of emergency, as we would expect, hit municipalities spend more in public procurement contracts compared to municipalities in the control group. Furthermore, the amount of funds they allocate to public works stays high even after the declared emergency ends. The second panel of Figure 8 shows that, over the same time period, municipalities do not change the number of contracts they are awarding by much (Table 7 reports the coefficients of the regressions). During the state of emergency, a hit municipality awards about 1 extra contract compared to its average before the earthquake. Once the emergency is over, however, the number of contracts reverts to its mean before the emergency. Columns 3 and 4 of Table 7 show that, as we would expect as a result of the preceding two findings, the average size of the contracts awarded by hit municipalities increases over the course of the emergency, and increases further for treated municipalities after the emergency is over. This holds true both in the sample of contracts above 40 thousand Euros as well as in the sample of contracts for which we have information on organized crime infiltration (above 150 thousand Euros). This pattern points toward criminal firms targeting hit municipalities for their larger availability of funds, thus higher opportunities for rent.

I exploit data from Anti-Mafia to check how authorities' monitoring effort changes over time. Police forces and Institutions are well aware of the risk of infiltration by organized crime in reconstruction projects: Anti-Mafia carries out special monitoring procedures during the emergency. Members of the Anti-Mafia physically inspect work sites related to reconstruction projects and identify all individuals and firms present, they check permits and authorizations, and look for any potential linkage to organized crime. Figure 9 shows the number of firms that have been inspected during such projects by Anti-Mafia investigators for three major earthquakes in my sample (Abruzzo 2009, Emilia Romagna 2012 and Amatrice 2016). The effort is concentrated during the State of Emergency, then fades over time.

As an alternative proxy for monitoring I exploit news on national and local broadcasts that include references to both earthquakes and organized crime for the same three major events. Specifically, from the archives of the National Public Broadcaster (RAI) and for the three earthquakes described above, I collect the news aired on national or local news broadcasts that reported both the word “earthquake," the name of the place or the date on which the earthquake occurred, and the word “mafia" or the combination of words “public procurement infiltrations."Figure 10 shows the higher frequency of news on the topic during the emergency. The qualitative evidence provided both on Anti-Mafia audits and in the media shows an increase in monitoring that criminal firms might plausibly wait to subside before participating in public procurement contracts.

Criminal Firms participation occurs via extensive rather than intensive margin The increased participation of criminal firms in public procurement contracts is compatible with two alternative mechanisms: either criminal firms enter into contracts with new municipalities (*extensive margin*), or they are participation in contracts awarded by the same set of municipalities (*intensive margin*). In the first case new ties between criminal firms and municipalities are created, while in the second relatively few new ties are created but are being exploited with greater intensity.

In order to conduct this analysis, I am limited by the fact that I do not know if a specific firm is mafia-linked – rather, the data only provide the list of firms participating in an auction, and the fraction that is linked to organized crime. I exploit the firm's tax identifiers as well as their repeated participation in auctions to compute the probability that a firm has mafia ties. I identify as “mafia firms" or “suspect firms" those with a probability above the 75^{th} percentile (0.33). I then run the main specification (Equation 1) using as dependent variable a dummy variable capturing the first time a “mafia firm" participates in a contract in a municipality.

The median (mean) firm participates in 3 (8.7) public procurement contracts, while the median (mean) number of participants in a contract is 6 (17) firms. [1]

Figure 11 shows the distribution of the probability of being a suspect criminal firm (i.e., a

[1] The algorithm I use to compute the probability that firm i is a criminal firm $Prob(Mafia\,Firm)_i$ is organized in the following steps:

1. If a firm participates in a contract with no infiltration at least once, than its probability of being a criminal firm is zero: $Prob(Mafia\,Firm)_i = 0$.
   I call a *Suspect* a firm with $Prob(Mafia\,Firm)_i > 0$.

participant with a positive probability). 1.6 percent of more than 16,000 participants are suspect firms, while one fourth of these have a probability above 33 %.
Column 2 of Table 8 shows that after the emergency suspect criminal firms are more likely to participate in public procurement contracts in municipalities they had not entered before, thus providing supporting evidence in favor of the *extensive margin* hypothesis. The coefficient for the interaction term "After the Emergency" (0.18) explains more than half of the baseline result (Column 1). Column 3 shows the effect persists even when restricting my analysis to the subsample of contracts with at least one new firm participating (clean or not). Finally, columns 4 and 5 extends the result to the full sample of municipalities. Table A1 in the Appendix confirms the robustness of the result when raising the threshold of the probability to be a "suspect firms" to 0.5, even though the coefficients are less precisely estimated.

7 Criminal Firms' participation does not occur via collusion with local politicians

In this section I aim to shed light on the mechanism underlying criminal firm participation, in particular whether it occurs through collusion with local administrators. Recall that municipalities in a state of emergency experience a positive shock to their budgets that persists beyond the duration of the state of emergency, and have higher reserve prices for the contracts they award. Concurrently, however, the Anti-Mafia increases its monitoring efforts, but only during the emergency. More funds available combined with less monitoring may increase the scope for kickbacks and malfeasance after the state of emergency has ended.

A further important consideration is that, during the emergency, local administrators enjoy greater discretion in designing the awarding process. We would expect that a local politician that intends to engage in malfeasance would prefer awarding procedures that allow for greater discretion, which provide more leeway to direct contracts to his favored firm.I exploit different margins of discretion in public procurement auctions, which provides evidence that is difficult to reconcile with the "corruption hypothesis."

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2. For each contract j, the probability of firm i being a criminal firm within that contract is:

$$PCrimF_{ij} = \frac{n.\,Suspects_j}{n.CriminalFirms_j}$$

where $n.\,Criminal\,Firms_j$ is the number of criminal firms the Anti-Mafia Authority reports in contract j.

3. In the final step I update the probability of a participant being a criminal firm:

$$Prob(Mafia\,Firm)_i = \max_j \Big(w_{ji} \times (PCrimF_{ij})\Big)$$

where w_{ji} is a weight proportional to the number of contracts a firm was found as suspect, or, $w_{ij} = \frac{n_i}{\sum_{i\ in\ j} n_i}$

7.1 Conceptual Framework: Corruption of Local Administrators

I begin by providing a conceptual framework for interpreting my results on the choice of discretion.

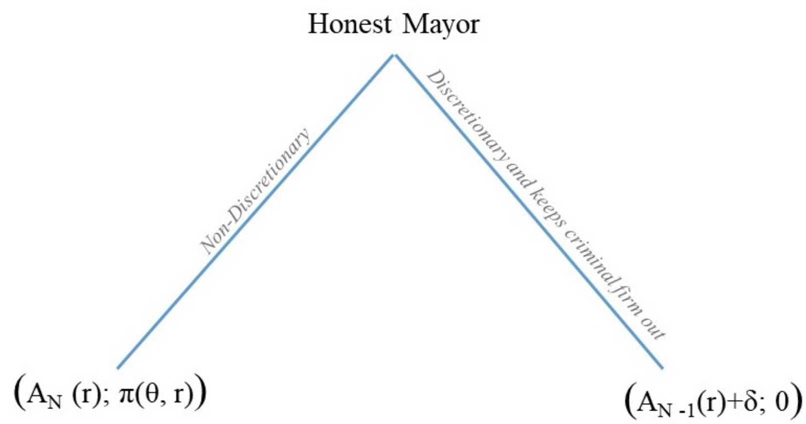
Consider a mayor who chooses whether to assign a contract via a discretionary or non-discretionary procedure. He sets a reserve price r that is the maximum price the municipality is willing to pay. Firms differ in their cost θ which is unobserved by the mayor and has a uniform distribution over $[0, 1]$. There are N potential participants in the auction: one is a criminal firm and the rest are non-criminal. A mayor may observe whether a firm is criminal or not only in the discretionary procedure.

There are two types of mayors in the economy: *honest* and *corruptible.* They differ in the way they exploit the discretionary procedure. An honest mayor exploits his discretion to keep the criminal firm out of the procurement process; the corruptible mayor, instead, can exploit discretion to elicit a bribe from the criminal firm.

The following model predicts that observing an increase in participation of criminal firms in non-discretionary auctions does not allow me to identify the mayor's *type* (i.e., honest or corrupt). However, an increase in participation of criminal firms in discretionary auction is only consistent with collusive *behavior* of corruptible mayor. This allows us to derive a test for collusive *behavior* (whether corruption actually occurred) but it does not allow to identify the *type* of the mayor: whether he is corruptible or not.

<u>HONEST MAYOR</u>

An honest mayor solves the game depicted in Game Tree 1.

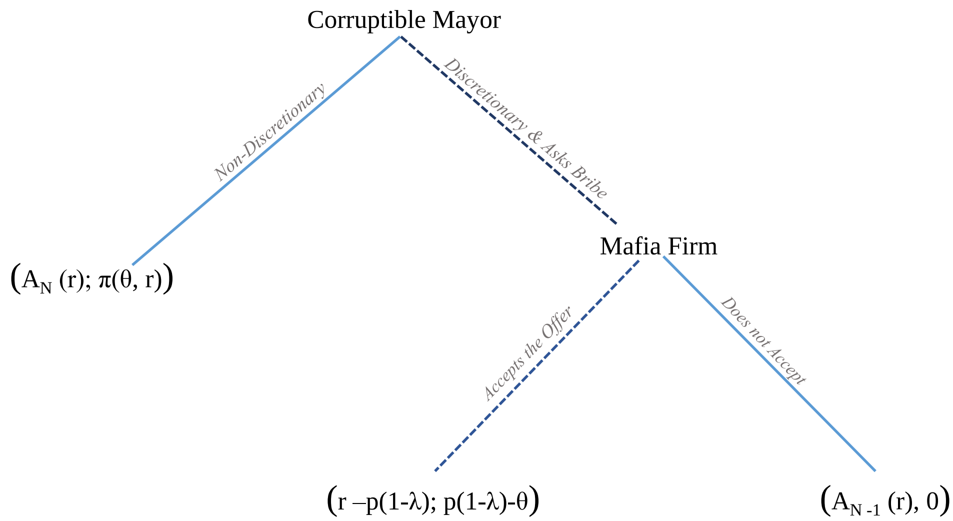


Game Tree 1: Game Tree of the Honest Mayor

At time 1 he decides whether to award a contract via a non-discretionary or discretionary procedure and sets a reserve price r. If he chooses non-discretion, he calls a first-price auction at time 2. A firm participates if it has a non-zero probability of getting a positive profit from the auction, i.e., if the reserve price is above its cost $\theta \leq r$. At time 1, the mayor's expected payoff is $A_N(r)$, the expected revenues from a first-price auction with N potential participants. Similarly, a criminal firm's expected pay-off is $\pi(\theta, r)$, a function of its own cost and of the reserve price. At time 1, if the mayor does not choose a non-discretionary auction, an honest mayor could alternatively decide to award the contract via discretionary procedure. In this case he exploits his discretion to screen firms and keep the criminal firm out of the bidding game. The payoff of an honest mayor who opts for a discretionary procedure is $A_{N-1}(r) + \delta$, where δ is a parameter capturing his taste for "honesty,"i.e., for preventing mafia firm participation, and it is distributed according to a continuous function $f(\delta)$. A criminal firm has no chance to enter the auction in this case, thus its payoff is zero. Whether an honest mayor prefers a discretionary versus non-discretionary auction depends entirely on his taste for honesty δ given that, if $\delta = 0$ he is always better off in a non-discretionary auction (Figure A1 shows the expected utility of the honest mayor with $\delta = 0$ while Figure A2 plots the bidding function of the participants).
We can therefore conclude that if the mayor is honest, the criminal firm can only enter in the public procurement auction through a non-discretionary auction.

CORRUPTIBLE MAYOR

A corruptible mayor solves the game shown in Game Tree 2. His game differs from the one of



Game Tree 2: Game Tree of the Corruptible Mayor

the honest mayor only if he decides to select a discretionary auction. In this case, he makes a "take-it-or-leave-it" offer to the criminal firm in which he offers to pay a price p in exchange for a bribe λp. The firm accepts as long as the price p covers its costs θ and the bribe λp, that is, $p(1-\lambda) \geq \theta$. Given the uniform distribution of θ, the probability that the firm accepts is exactly equal to $p(1-\lambda)$. If the criminal firm does not accept the offer, the mayor exploits his discretion to keep it out of the procurement process by running a first price auction with the remaining $N-1$ potential participants.

A corruptible mayor's expected payoff from a discretionary auction is a linear combination of the two possible outcomes of his take-it-or-leave-it offer. If the criminal firm accepts (which occurs with probability $p(1-\lambda)$), he gets $[r-p(1-\lambda)]$; if the criminal firm turns down the offer (which occurs with the complementary probability $1-p(1-\lambda)$) he gets $A_{N-1}(r)$, the outcome of a first-price auction with $N-1$ bidders. The mayor chooses the value of $p(1-\lambda)$ optimally (Figure A3). Figure 12 plots the corruptible mayor's expected revenues for the two types of awarding procedures with $N=3$ potential bidders. For values of the reserve price between the two dashed vertical lines, awarding the contract via discretionary auction is always preferable to the non-discretionary one.

Notice finally that *in Game Tree 2collusion only occurs if both the dashed branches are reached: the corruptible mayor chooses a discretionary auction and the criminal firm accepts the offer* (Figure A4 plots the probability of such event).

From the framework provided above we derive the following implications:

1. *Observing a mayor choosing a non-discretionary auction and a criminal firm participating in it is consistent with both types of mayor (honest as well as corruptible);*

2. *Observing a mayor choosing a discretionary auction and a criminal firm participating in it is consistent* ***only with*** *collusive behavior.*

7.2 Discretion & Participation of Criminal Firms

The conceptual framework implies that *discretion* is a necessary condition for collusion between mayors and firms to occur. Also, if an increase in the reserve price caused collusive behavior, then the probability of a criminal firm participating in a discretionary action must have increased.

Italian law on public procurement allows discretion on two margins: the selection of the participants (i.e., whether the municipality can limit access of participants to an auction), and the winning criterion (whether the winner is the lowest bidder or other more subjective features of the bid may be considered in the awarding phase). I exploit this information in the data to differentiate between *discretionary* and *non-discretionary* procedures and to test whether criminal firms' participation occurred via corruption.

The selection of the participants occurs either via open tender procedure (*Procedura Aperta*) or through discretionary selection (*Procedura Negoziata*). In the first case, firms are only required to submit a bid to participate in the auction and municipalities' discretion is minimized in the choice of participants. In the second case, it is the municipality that actively chooses the set of participants in the auction and award the contracts to one of them. In the extreme case of maximum discretion, the municipality awards the contract to a firm without any call for an auction (*Negoziata senza gara*).

The winning criterion may be of two types: *First Price* and *Scoring Rule*, with the second allowing more scope for discretion by the municipality. In a First Price Auction the firm that bids the highest rebate relative to the reserve price wins the contract (as long as the rebate is not unreasonably low or high). In contrast, in auctions awarded via Scoring Rule, the municipality awards points to the participants based on multiple characteristics of their bid with the aim of capturing also quality considerations (aesthetics, safety, environmental costs) of the bid. (Scoring rule auctions had been curtailed in the follow-up of a political corruption scandal that hit Italy in 1992, when it was revealed as a tool that politicians exploited to distort the awarding process and earn kickbacks from contractors.)

The conceptual framework above did not allow for a prediction on the type of the mayor: being a corruptible mayor is not a sufficient condition for collusion to happen. Even a corruptible mayor may still prefer a non-discretionary auction to a discretionary one, thus losing the opportunity of asking for a bribe, or even in the case that he chooses for a discretionary auction and asks for a

bribe, he may be turned down by the criminal firm.
This notwithstanding, the reasoning above allows to construct a test for whether collusive *behavior* occurred. Collusion occurs if a corruptible mayor opts for a discretionary auction and the criminal firm accepts his deal (i.e., the criminal firm participates in the discretionary auction).
I therefore distinguish between two types of criminal participation:

$$Prob(Criminal\ \ Firm\ Participates\ \cap\ Discretionary\ \ Auction)$$

and

$$Prob(Criminal\ \ Firm\ Participates\ \cap\ Non-Discretionary\ \ Auction)$$

In the data, an increase in the probability of the first event would only be consistent with collusion of corruptible mayors. Table 9 shows that mafia firms deliberately target auctions in which interactions with the administration as well as chances of being monitored are minimized (i.e., discretionary auctions) and I therefore reject the hypothesis of collusion.

To add further evidence, I divide public procurement contracts in four categories with increasing discretion based on the combination of the selection of the participants and the winning criterion:

I) Open Tender / First-Price Auction

II) Open Tender / Scoring Rule

III) Direct Selection / First Price

IV) Direct Selection / Scoring Rule

Figure 13 shows the change in the conditional probability of participation of a criminal firm in each of the four auction categories. Again, participation of criminal firms is concentrated in the Open Tenders and First-Price Auctions which are the auction types in which the municipality's discretion is minimized. This evidence goes against the hypothesis of collusive behavior of local administrators.

Finally in Table 10 I check whether municipalities actively changed their behavior in awarding public procurement auctions after the emergency so as to allow criminal firms to participate. Column (1) shows that municipalities did not increase the share of contracts awarded via direct selection of the winner. In column 2 I restrict the sample to the contracts with a reserve price above 200 thousand Euros, for which the law allows more discretion *only* during the state of emergency. Column 3 shows a decrease in the use of the "lowest price" criterion after the emergency, however this is not statistically significant and it still remains the prevalent criterion for the selection of the winner over the full set of contracts. This is also not a concern given that asFigure 13 shows, if anything,

criminal firm participation is concentrated in lowest price auctions.
In column (4) and (5) I check whether municipalities are exploiting their discretion in alternative ways, either inviting to the auction fewer firms than what the law requires (for many procedures the law requires a minimum number of bidders) or if they are excluding firms among the applicants (typically for excessively high or excessively low bids). None of the coefficients shows a significant change in the awarding behavior of the municipalities. Overall, the evidence suggests that municipalities do not change their behavior so to let criminal firms participate in auctions after the emergency, and that criminal firms' participation is concentrated in the least discretionary auctions, and thus there is no evidence of collusive behavior.

8 Robustness Checks

In this section I present a series of tests and variants on my main specification to probe the robustness of my results.

Pre-trends I cannot attribute a causal interpretation to the diff-in-diff coefficient if municipalities experiencing participation of mafia firms *before* the earthquake are also more likely to be included in the state of emergency. If this were the case, some reason other than the state of emergency may be causing participation of criminal firms to increase over time (for example increased enforcement of the Anti-Mafia Authority in these areas, or higher population density of these towns). As mentioned in the main analysis the positive anticipatory effect noticed in Figure 7 is driven by five municipalities: Bologna, Reggio nell'Emilia, Macerata, Rieti and Corridonia.

I therefore repeat my analysis excluding these five municipalities from my sample. Figure **??** confirms that the positive effect in the year before the earthquake is no longer present when restricted to this sample. Table 11 reports the coefficients of the difference in difference specification on this subsample, and shows that the five municipalities that experienced infiltration right before the emergency are not driving the results. Municipalities included in a state of emergency show more participation of criminal firms in public procurement auctions even when excluding those that showed an anticipatory effect.

Turning to the second alternative explanation noted above (differential population density), I add an interaction term for the log of population and the two time dummies identifying contracts awarded *during* and *after* the state of emergency. Table 12 reports the results for all municipalities (Columns 1-4) and excluding the five municipalities showing a positive coefficient the year before the earthquake (Columns 5-8). Even when controlling for trends in population, municipalities in the state of emergency display higher participation of criminal firms in public procurement auctions after the emergency is over.

Number of contracts One further potential concern is that municipalities change the number of contracts above 150 thousand Euros they award over time for reasons unrelated to the state of emergency. If this were case, the higher participation of criminal firms in the aftermath of the emergency may be a statistical artifact of the increase in contracts from treated municipalities after the state of emergency. To address this concern, in Table 13 I collapse my sample of contracts to the municipality/year/time relative to the event level. That is, each observation is now the mean of criminal firm participation in the contracts awarded by a municipality in a specific year before, during and after the state of emergency. The first two columns report the estimates for the full sample of municipalities, which are remarkably similar to the estimates shown in Table 5. Similarly, the last two columns show the estimates for the adjacent municipalities. The point estimates are still close to the ones in columns 3 and 4 of Table 5 but less precisely estimated (though the sample size is reduced by more than half).

Spatial Correlation In Table 14 I estimate my main specification (Equation 1) allowing for spatial correlation in the variance-covariance matrix of the coefficients (Conley 1999, Conley 2008). I use the median distance from the border of the state of emergency in the two sub-samples as a cutoff for the variance and covariance matrix: 10 km for all municipalities and 5 km for those adjacent to the border of the emergency. My main results remain significnat with this adjustment.

9 Conclusion

Organized crime may exploit the availability of funds, political connections, and intimidation to extend its activities beyond illicit businesses and into legal sectors of the economy. Given the hidden nature of criminal activities and thus the lack of data, it has been challenging to document whether and how such "contamination" occurs.

I use novel data on participation of organized crime in public procurement auctions in Italy to shed light on this question. I provide evidence on how states of emergency may serve as an opening for mafia firms into procurement auctions. Organized crime responds to the large sums municipalities spend in reconstruction, but only after emergency status is lifted, when the Anti-Mafia Directorate lowers its monitoring efforts. My findings are based on Italian data but are likely relevant for other contexts. For example, the media documented the participation of organized crime in disaster relief in other countries, notably in Japan after the Kobe earthquake in 1995.

The result that participation of criminal firms is concentrated in procedures with minimum discretion suggests that mafia firms do not necessarily enter the procurement process via corruption of local administrators. This is in line with judicial and police accounts of mafia enterprises choosing the least visible tactics to infiltrate in the legal economy unnoticed (DIA, Relazione Antimafia 2016).

A natural policy implication of my work may be to rethink what constitutes optimal monitoring in the wake of natural disasters, perhaps maintaining higher monitoring even after emergency status is lifted. Furthermore, the risk of infiltration is likely to extend to other events characterized by large windfalls of funds: the Olympic Games and Universal Expositions, for example, may present attractive opportunities for criminal organizations. Finally, further research is needed to better gauge the consequences of criminal infiltration, for example assessing its implications for other participating firms, the quality of public works, and to understand whether public procurement functions as a stepping stone for infiltration of organized crime in the local governance of municipalities.

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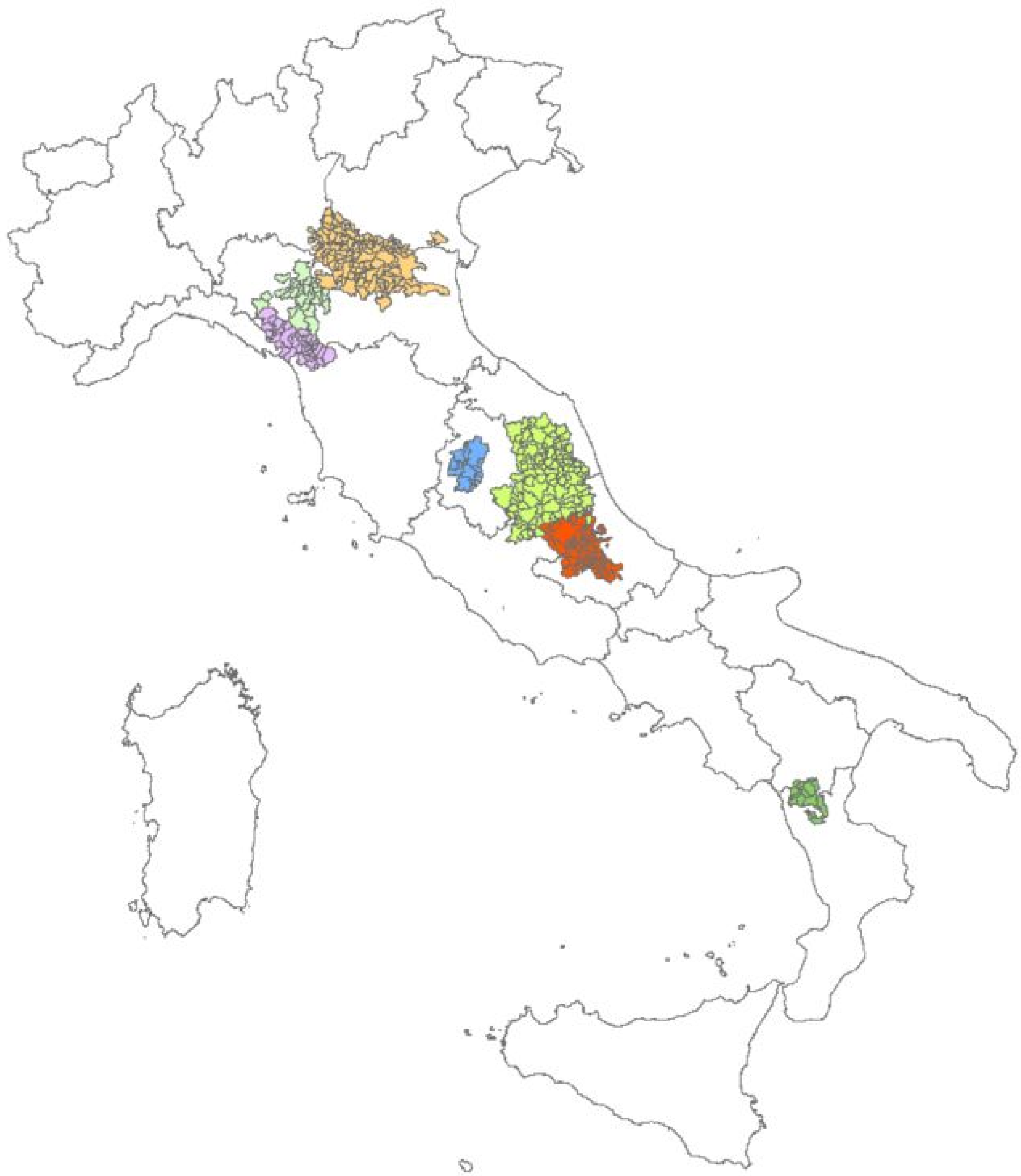

Figure 1: Earthquakes in Italy 2008-2016

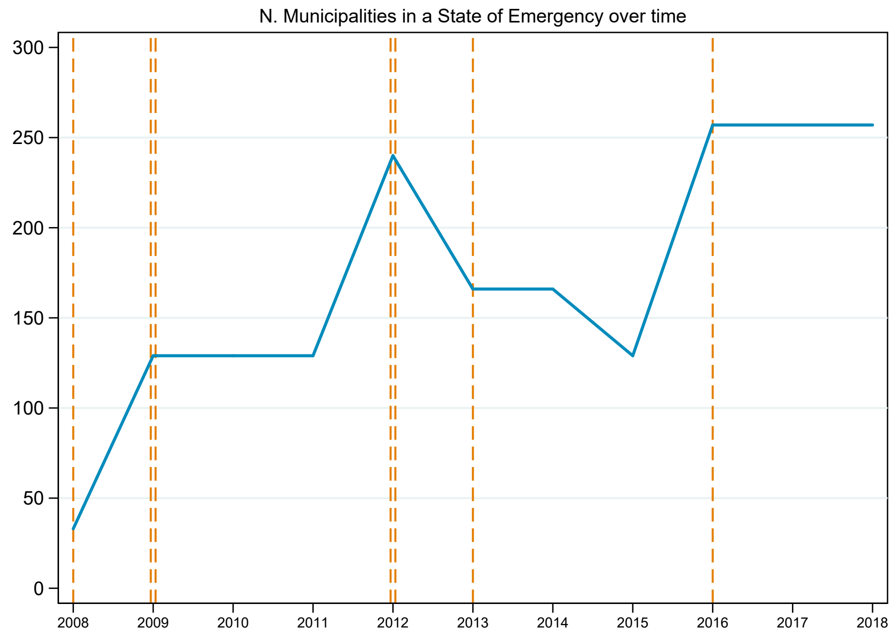

Figure 2: Number of Municipalities in a state of emergency by year over the period: 2008-2018

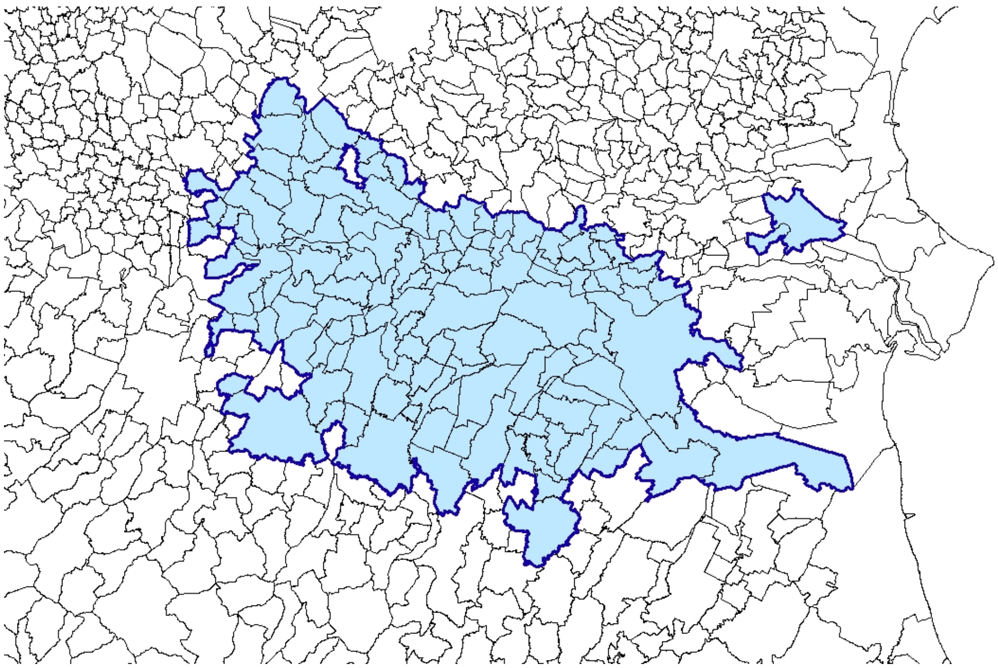

Figure 3: Municipalities included in the State of Emergency

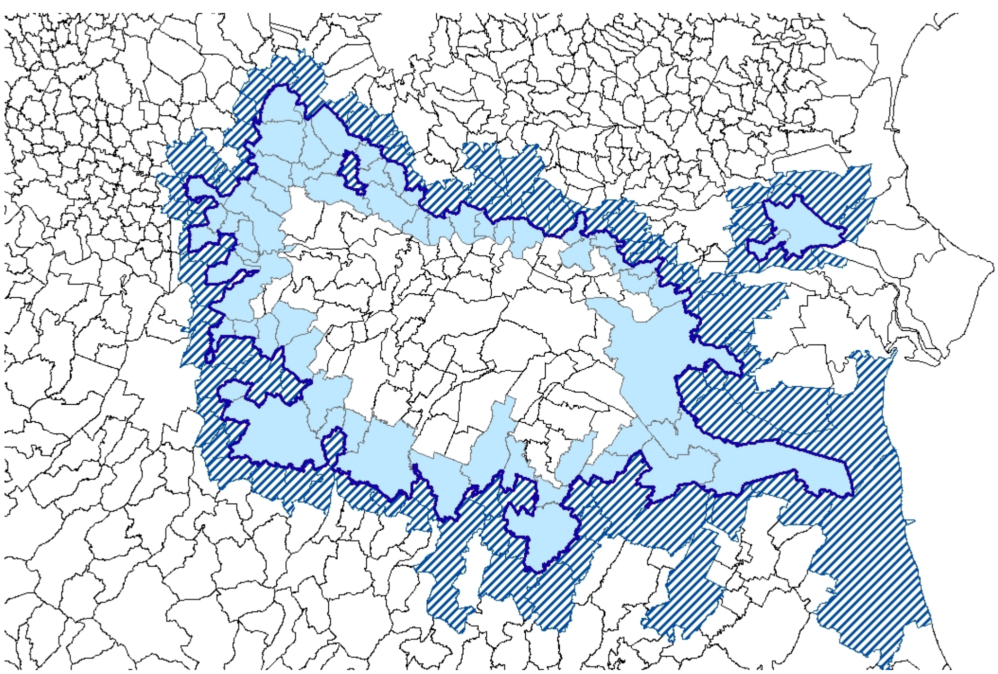

Figure 4: Identification Strategy: Municipalities adjacent to the border of the state of emergency.

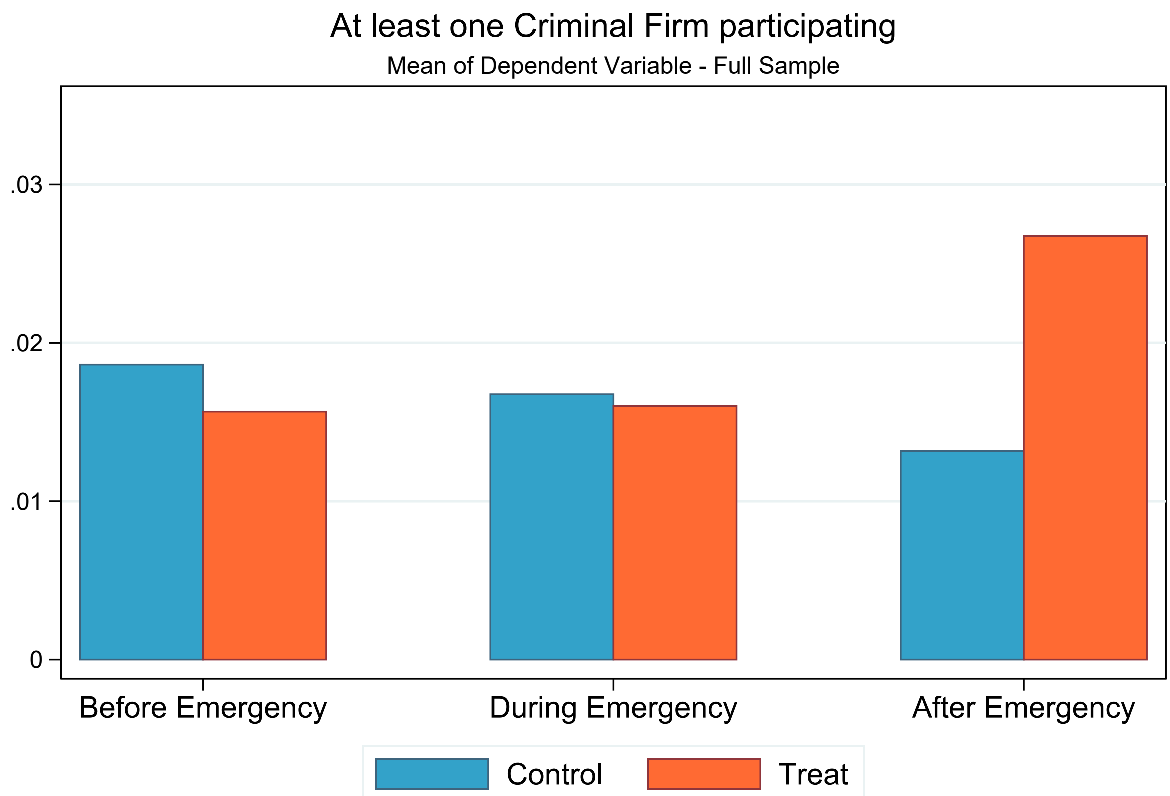

Figure 5: Raw data: Probability of at least one Criminal Firm in a contract over Time

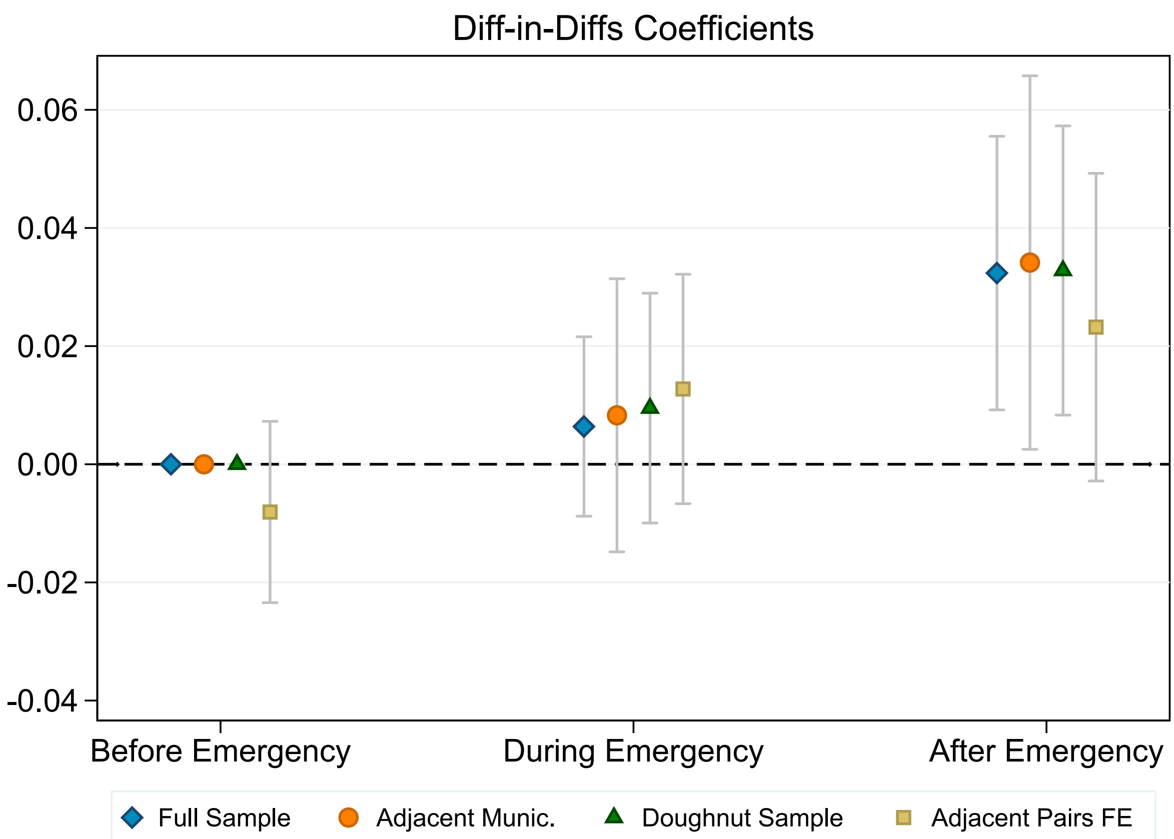

Figure 6: Interaction coefficients for the probability of at least one criminal firm participating in a public procurement contract: four alternative samples

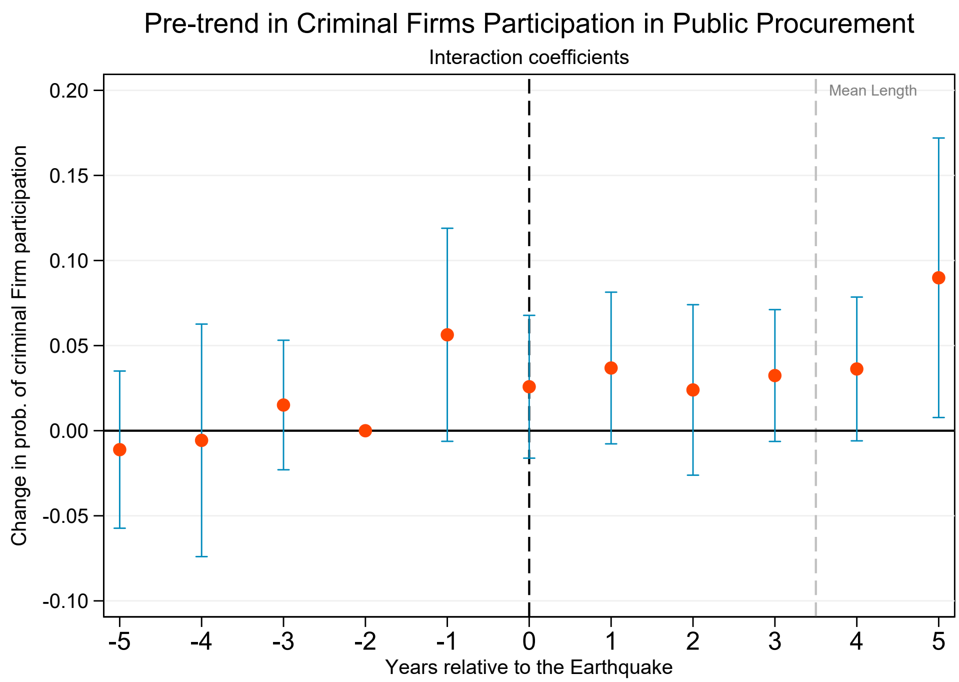

Figure 7: Pre-Trends in Criminal Firms Participation

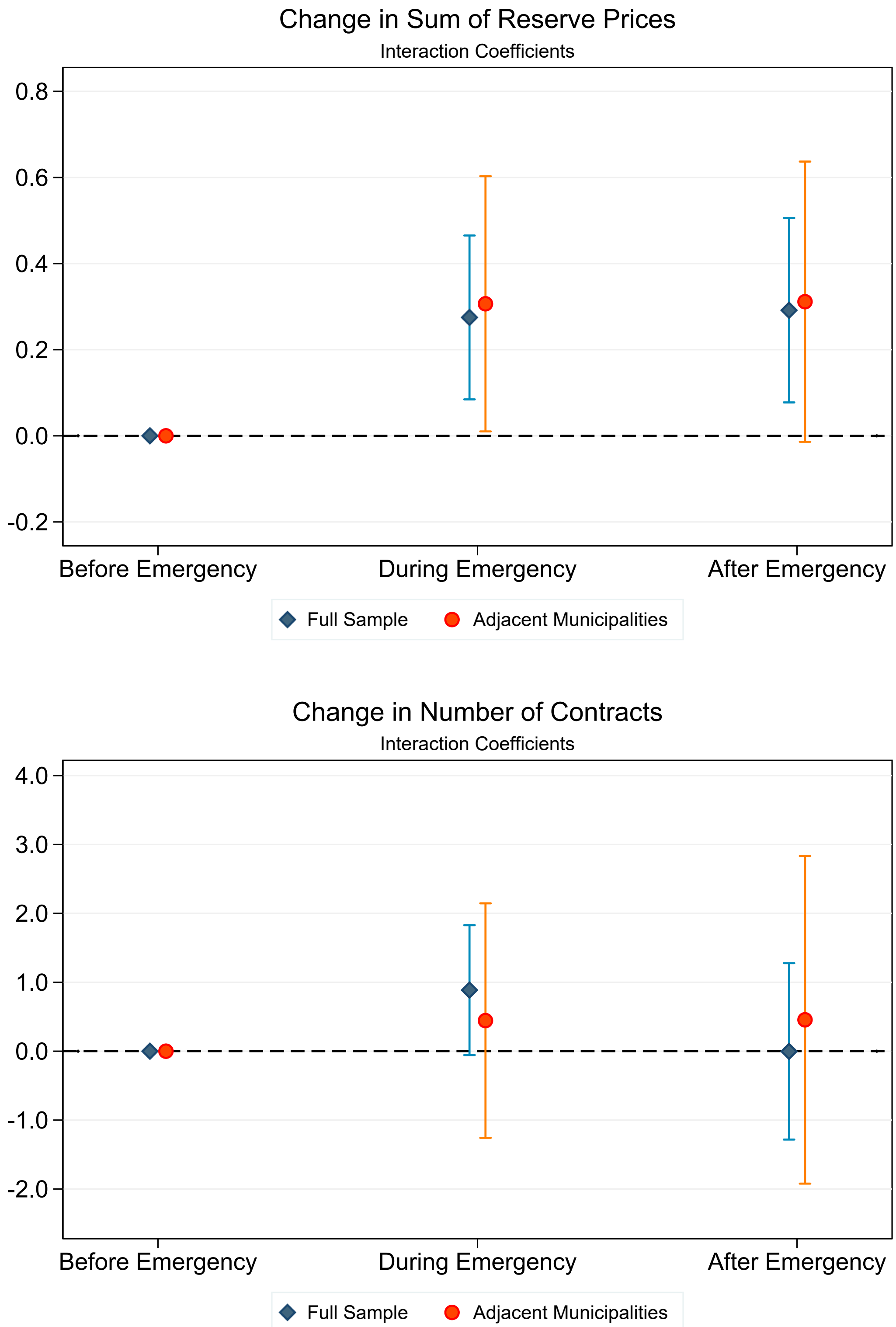

Figure 8: Changes in Available Funds and Number of Contracts within municipalities

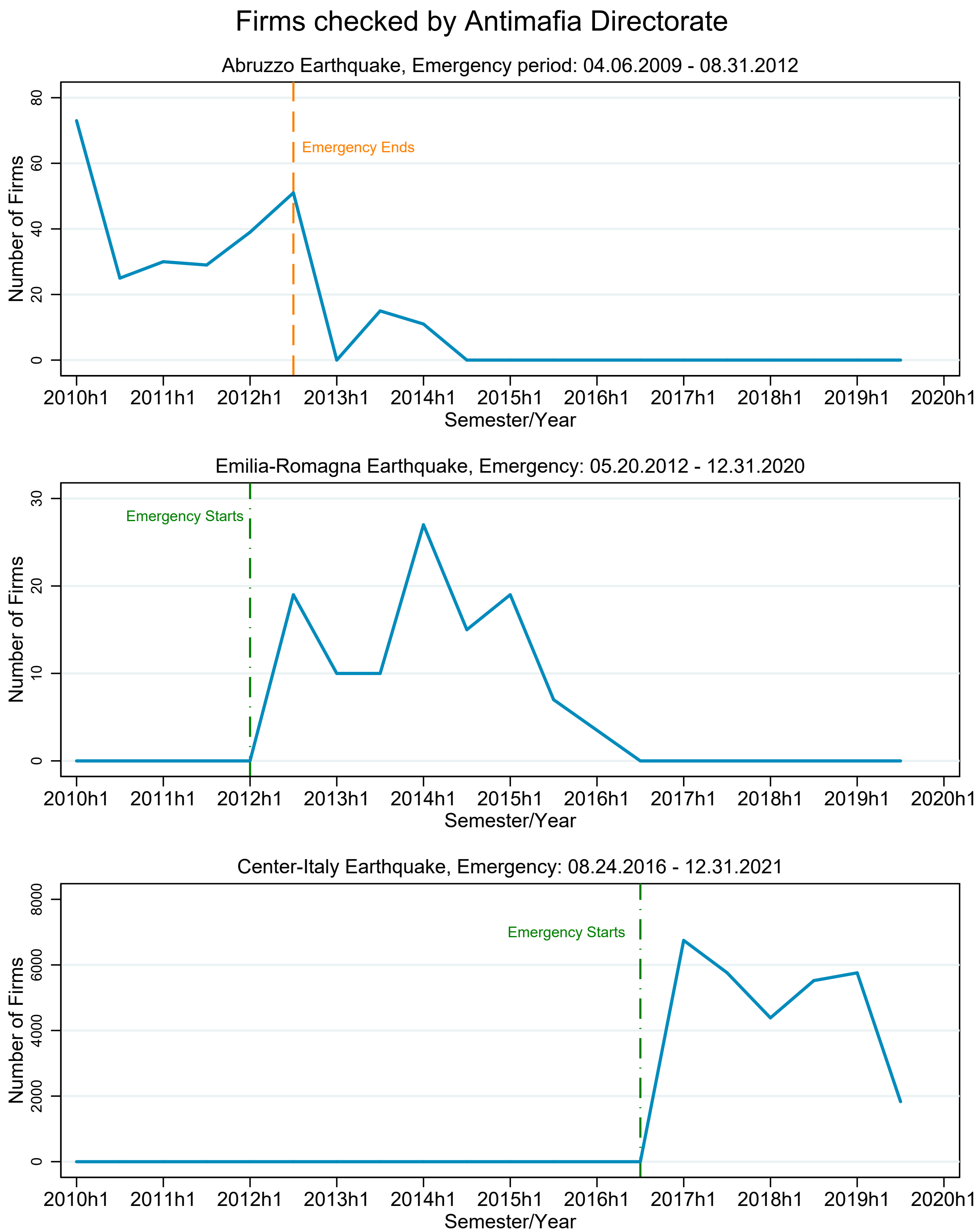

Figure 9: Firms audited by Anti-Mafia in public works sites

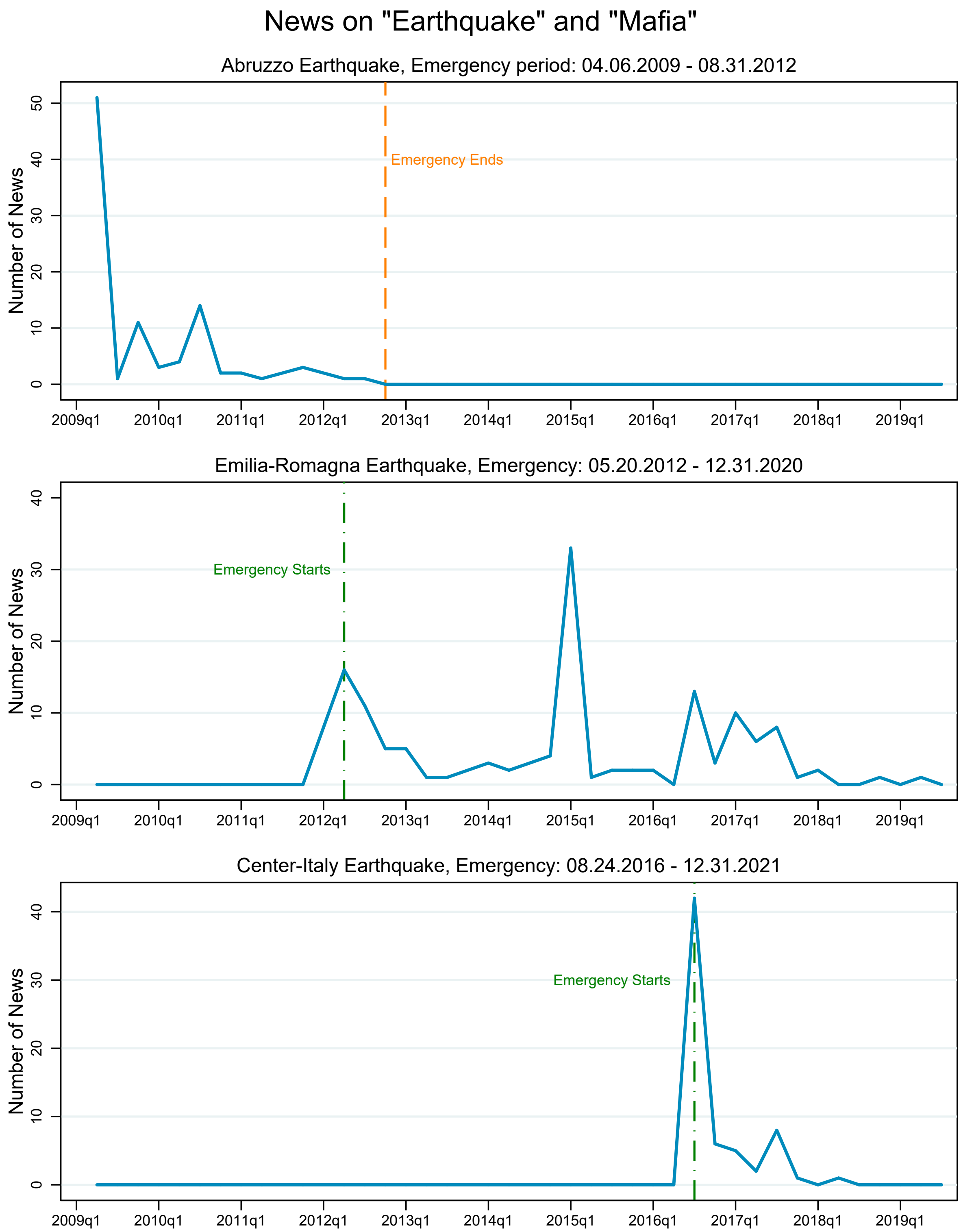

Figure 10: Local News on Earthquakes and Mafia

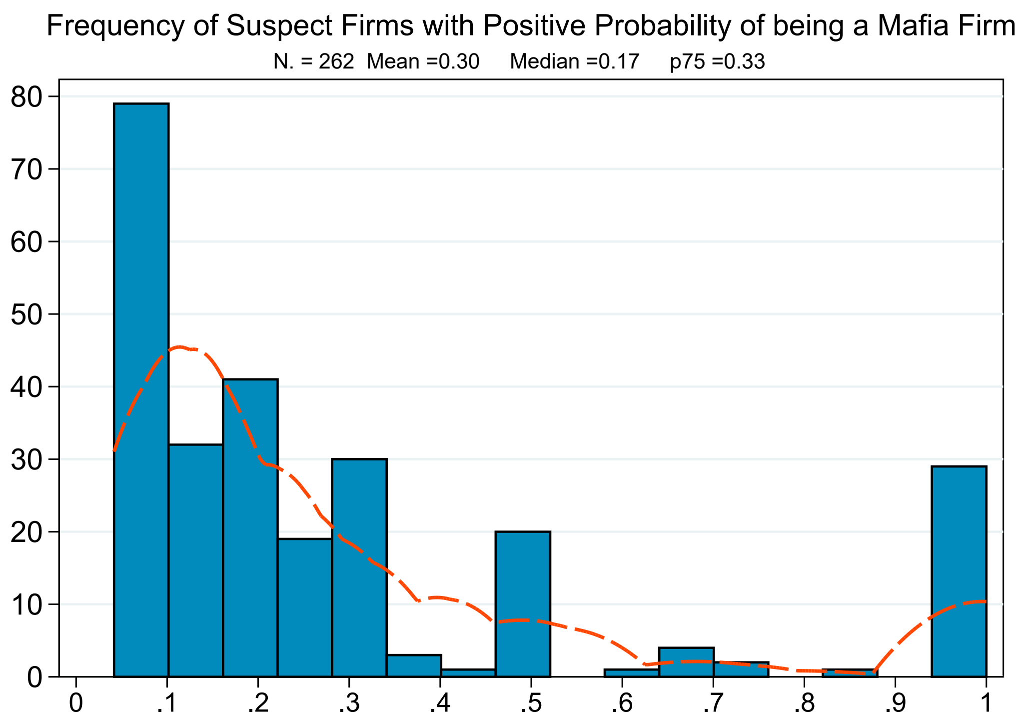

Figure 11: Frequency of Supect Firms with Positive Probability of being a Mafia Firm

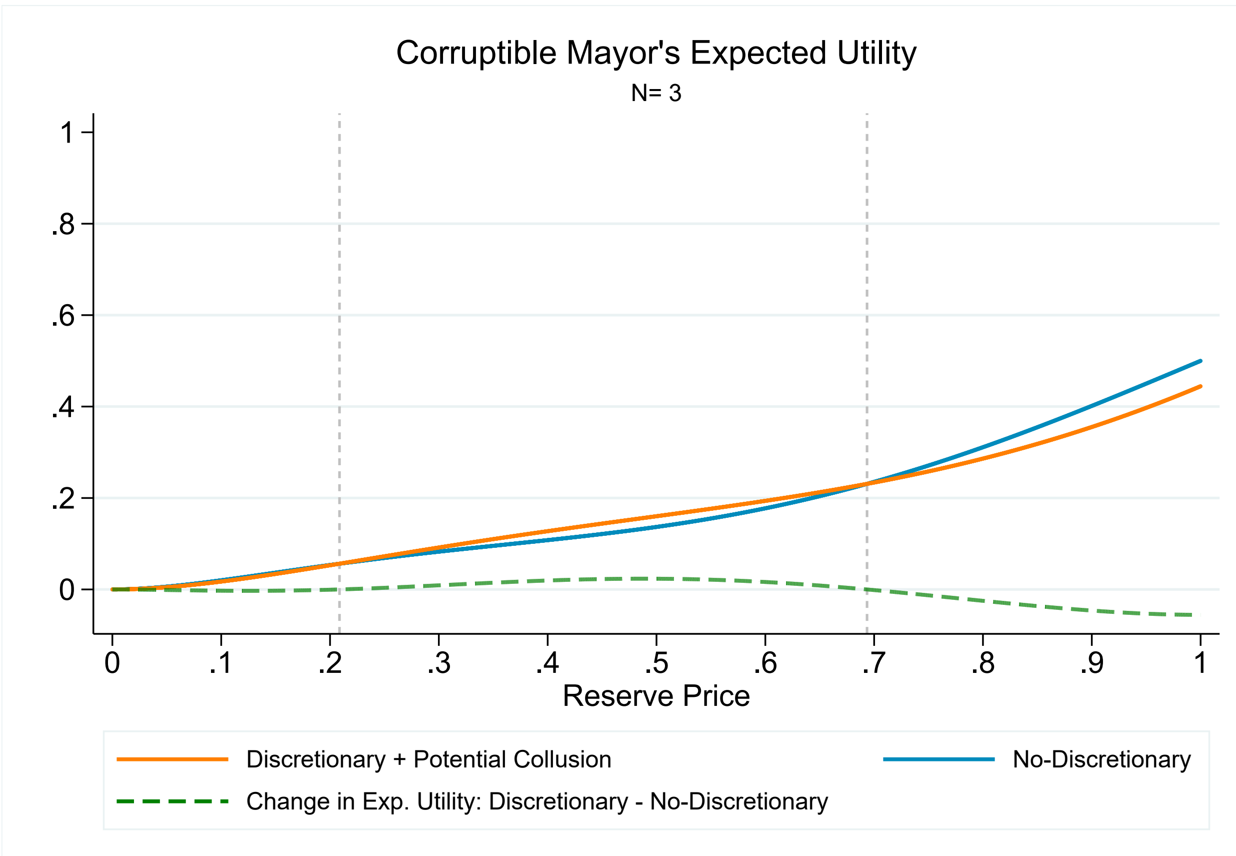

Figure 12: Expected Revenues of Corruptible Mayor in the Discretionary and Non-discretionary auction

Figure 13: Conditional Probability of Infiltration by Type of Auction

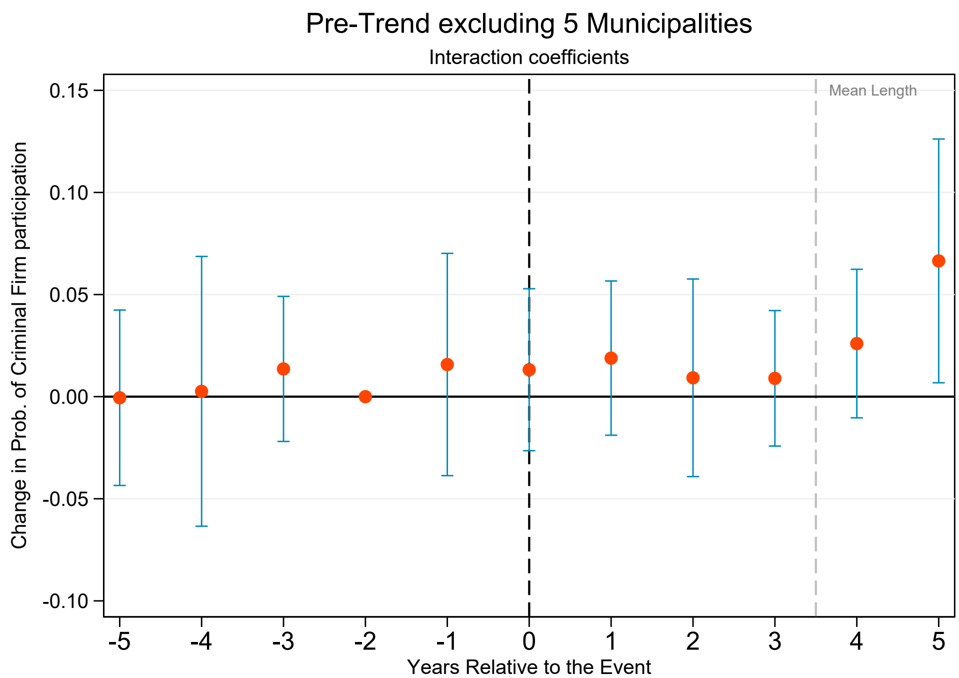

Figure 14: Pre-Trends in Criminal Firms Participation excluding 5 municipalities: Bologna, Reggio nell'Emilia, Macerata, Terni, Corridonia

Table 1: States of Emergency declared between 2008 and 2016

Date of Earthquake	*Hit Regions*	*Mean Intensity*	*Start State of Emer.*	*End State of Emer.*	*Duration State of Emer.*
23 Dec 2008	Emilia-Romagna	5.3	16 Jan 2009	31 Dec 2011	2.9 yrs
06 Apr 2009	Abruzzo	6.6	06 Apr 2009	31 Aug 2012	3.4 yrs
15 Dec 2009	Umbria	5.0	22 Dec 2009	31 Dec 2012	3.0 yrs
20 May 2012	Emilia-Romagna, Lombardia, Veneto		30 May 2012	31 Dec 2020	8.6 yrs
26 Oct 2012	Calabria, Basilicata	5.4	09 Nov 2012	17 Apr 2013	4 months
24 Aug 2016	Abruzzo, Lazio, Marche, Umbria	6.3	25 Aug 2016	31 Dec 2020	4.4 yrs

Note.-Start date of the State of Emergency is the date of the declaration of the State of Emergency from the Prime Minister. The Intensity is the mean Intensity of the Earthquake as rated from the Moment Magnitude Scale which measures the size of the event in terms of energy released.

Table 2: Summary Statistics for Municipalities in the State of Emergency

	mean	min	p50	max	sd
Class of Gravitational Acceleration [1-10]	5.70	1.00	6.00	9.00	2.25
Earthquake Intensity	5.74	3.90	5.50	11.00	1.18
Avg duration of State of Emergency (years)	3.65	0.41	3.03	6.59	2.14
Dist. from the border of the Emergency	7.43	0.36	5.56	24.81	5.76
Dist. from epicenter	30.59	0.91	28.75	81.00	15.83
Hit by an EQ between 1945-2006	0.37	0.00	0.00	1.00	0.48
Hit multiple times in 2006-2016	0.02	0.00	0.00	1.00	0.12
Population in 2005	9,282.16	98.00	3,016.00	374,425.00	28,130.64
No. Buildings	2,024.46	157.00	1,107.00	23,661.00	3,084.88
Sh. Masonry buildings	0.78	0.19	0.80	1.00	0.16
Sh. Reinforced Concrete buildings	0.12	0.00	0.09	0.70	0.11
Sh. Houses built bef 1919	0.32	0.00	0.26	0.97	0.20
N. Public Proc. Contracts	7.69	1.00	4.00	164.00	16.17
N. Public Proc. Contracts/Year	1.75	1.00	1.33	18.22	1.75
Observations	365				

Note.-Municipalities are in a State of Emergency if they have been listed in a Commissioner's decree between 2008 and 2017.

Table 3: Summary Statistics for Public Procurement Contracts

	mean	min	p50	max	sd
Reserve Price (in thsd. Euros)	491.300	150.00	284.54	40,232.23	1,031.66
Winning Rebate	0.196	0.00	0.20	0.97	0.11
Discr. Procedure	0.752	0.00	1.00	1.00	0.43
Discr. Procedure, no Auction	0.695	0.00	1.00	1.00	0.46
First Price Auction	0.834	0.00	1.00	1.00	0.37
Time to Award (months)	2.358	0.00	1.83	13.07	1.92
Construction of Buildings	0.374	0.00	0.00	1.00	0.48
Restoration of Historical Buildings	0.143	0.00	0.00	1.00	0.35
Roads, Bridges, Railways	0.359	0.00	0.00	1.00	0.48
Water, Gas, Electrical	0.124	0.00	0.00	1.00	0.33
No. Auction Participants	17.136	1.00	6.00	546.00	37.49
At least one Mafia Firm participating	0.017	0.00	0.00	1.00	0.13
% of Mafia Firms among participants	0.046	0.00	0.00	20.00	0.60
Observations	7882				

Table 4: Difference in Means between municipalities in the three groups: within 25 km of the State of the Emergency, adjacent to the emergency and within 25 km but not touching the border ("Doughnut Sample")

	ALL			**Adjacent Municipalities**			**Doughnut Sample**		
	Mean Treat	Mean Control	Diff T - C	Mean Treat	Mean Control	Diff T - C	Mean Treat	Mean Control	Diff T - C
Class of Gravitational Acceleration [1-10]	5.874	4.791	1.083***	5.614	5.410	0.205***	5.967	4.653	1.313***
	(0.073)	(0.045)	(0.086)	(0.022)	(0.023)	(0.046)	(0.111)	(0.053)	(0.124)
Avg duration of State of Emergency (years)	3.503	3.503	-0.000	3.561	3.561	0.000	3.503	3.503	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance from the border of the State of Emergency	7.369	12.307	-4.938***	3.310	2.940	0.370*	11.918	15.295	-3.377***
	(0.353)	(0.214)	(0.414)	(0.079)	(0.083)	(0.162)	(0.431)	(0.205)	(0.481)
Distance from epicenter	28.560	56.795	-28.235***	34.159	39.504	-5.344***	22.136	61.102	-38.966***
	(0.763)	(0.462)	(0.895)	(0.140)	(0.147)	(0.286)	(1.034)	(0.491)	(1.152)
Hit multiple times in 2006-2016	0.032	0.000	0.032***	0.017	0.002	0.015	0.021	0.000	0.021***
	(0.005)	(0.003)	(0.006)	(0.004)	(0.004)	(0.008)	(0.005)	(0.002)	(0.005)
Hit by an EQ between 1945-2006	0.393	0.149	0.244***	0.276	0.235	0.041*	0.494	0.119	0.375***
	(0.019)	(0.012)	(0.023)	(0.009)	(0.009)	(0.018)	(0.027)	(0.013)	(0.030)
Log(No. Buildings)	7.122	7.058	0.064	7.270	7.246	0.025	6.851	6.985	-0.134*
	(0.043)	(0.026)	(0.050)	(0.036)	(0.038)	(0.074)	(0.060)	(0.028)	(0.067)
Log(No. Residential buildings)	6.969	6.933	0.036	7.132	7.106	0.026	6.682	6.861	-0.179**
	(0.043)	(0.026)	(0.050)	(0.036)	(0.038)	(0.074)	(0.060)	(0.029)	(0.067)
Sh. Masonry buildings	0.787	0.747	0.041***	0.763	0.779	-0.017	0.816	0.738	0.079***
	(0.009)	(0.005)	(0.010)	(0.006)	(0.006)	(0.011)	(0.013)	(0.006)	(0.015)
Sh. Reinforced Concrete buildings	0.117	0.146	-0.029***	0.138	0.127	0.011	0.097	0.150	-0.054***
	(0.006)	(0.004)	(0.008)	(0.004)	(0.004)	(0.008)	(0.010)	(0.005)	(0.011)
Sh. Houses built bef 1919	0.322	0.250	0.072***	0.299	0.257	0.042**	0.353	0.249	0.104***
	(0.009)	(0.005)	(0.010)	(0.007)	(0.007)	(0.013)	(0.013)	(0.006)	(0.014)
Sh. Houses built '19-'61	0.253	0.263	-0.010	0.263	0.280	-0.017	0.240	0.259	-0.019
	(0.006)	(0.003)	(0.007)	(0.005)	(0.005)	(0.010)	(0.009)	(0.004)	(0.010)
Sh. Houses built after '62	0.425	0.487	-0.062***	0.438	0.463	-0.025*	0.407	0.493	-0.085***
	(0.008)	(0.005)	(0.009)	(0.006)	(0.006)	(0.012)	(0.012)	(0.006)	(0.013)
Log of population in 2005	8.021	8.108	-0.087	8.295	8.276	0.019	7.645	8.031	-0.386***
	(0.059)	(0.036)	(0.069)	(0.046)	(0.048)	(0.094)	(0.084)	(0.040)	(0.093)
At least one crim. Firm among the participants	0.014	0.012	0.002	0.011	0.010	0.002	0.018	0.012	0.006
	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.006)	(0.003)	(0.007)
Num. Municipalities	374	884	1,258	220	280	500	181	781	962
F-stat			181.70			10.22			114.04

Table 5: Probability of Infiltration: *DURING* the State of emergency and *AFTER* the Emergency VS BEFORE

Dep var:	***At least one Criminal Firm among the Participants to the Contract***							
	ALL		**Adjacent Municipalities**				**Doughnut Sample**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat					-0.008	-0.003		
					(0.008)	(0.008)		
During Emergency	0.002	-0.010	-0.005	-0.019	-0.008	-0.020	0.006	-0.002
	(0.008)	(0.012)	(0.015)	(0.020)	(0.014)	(0.022)	(0.008)	(0.013)
Treat*During Emergency	0.006	0.010	0.008	0.004	0.013	0.003	0.010	0.020*
	(0.008)	(0.008)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
After the End of the Emergency	-0.013	-0.015	-0.020	-0.051*	-0.008	-0.048	-0.009	0.010
	(0.012)	(0.015)	(0.023)	(0.028)	(0.025)	(0.035)	(0.013)	(0.017)
Treat*After End of Emergency	0.032***	0.030***	0.034**	0.030**	0.023*	0.024*	0.033***	0.021*
	(0.012)	(0.011)	(0.016)	(0.015)	(0.013)	(0.013)	(0.012)	(0.012)
Log(# Participants)		0.026***		0.028***		0.027***		0.025***
		(0.004)		(0.007)		(0.008)		(0.006)
Log(# Partic.) * During Emergency		0.006		0.011		0.014		0.003
		(0.006)		(0.009)		(0.010)		(0.007)
Log(# Partic.) * After end Emergency		0.005		0.023*		0.026*		-0.008
		(0.007)		(0.012)		(0.014)		(0.007)
N. Obs	8,639	8,639	3,630	3,630	4,965	4,965	4,977	4,977
R^2	0.16	0.21	0.10	0.17	0.07	0.15	0.23	0.26
Mean DV	0.017	0.017	0.020	0.020	0.021	0.021	0.016	0.016
St.Dev. DV	0.131	0.131	0.139	0.139	0.142	0.142	0.124	0.124
Munic FE	✓	✓	✓	✓			✓	✓
Adjacent Pair FE					✓	✓		
Earthquake Event	✓	✓	✓	✓	✓	✓	✓	✓
Year of Contract	✓	✓	✓	✓	✓	✓	✓	✓
Public Proc. Category	✓	✓	✓	✓	✓	✓	✓	✓

Note: Sample includes Procurement Contracts for Public Works auctioned by Municipalities after 2010 and with reserve price $\geq$ 150k. Regressions include fixed effects for: Municipalities, Year of public procurement contract, Earthquake event, Public procurement category. Columns 1-2: full sample, columns 3-4: municipalities touching the border of the emergency, columns 5-6: adjacent municipalities sample with neighboring pair fixed effecs, columns 7-8 exclude municipalities touching the border of the emergency. Standard errors clustered at the municipality level.

Table 6: Probability of Infiltration - Adjacent Municipalities: adding interaction for imbalanced characteristics between treated and control group.

	At least one Criminal Firm among the Contract Participants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
During Emergency	-0.005	-0.019	-0.005	-0.056**	-0.009	0.002	-0.010
	(0.015)	(0.020)	(0.028)	(0.023)	(0.019)	(0.016)	(0.015)
Treat*During Emergency	0.008	0.004	0.008	0.025*	0.009	0.005	0.007
	(0.012)	(0.010)	(0.012)	(0.014)	(0.012)	(0.011)	(0.012)
After the End of the Emergency	-0.020	-0.051*	-0.007	-0.036	-0.018	-0.014	-0.032
	(0.023)	(0.028)	(0.032)	(0.033)	(0.026)	(0.023)	(0.027)
Treat*After End of Emergency	0.034**	0.030**	0.035**	0.041**	0.035**	0.033**	0.032**
	(0.016)	(0.015)	(0.018)	(0.020)	(0.017)	(0.016)	(0.016)
N. Obs	3,630	3,630	3,630	3,630	3,630	3,630	3,630
R^2	0.10	0.17	0.10	0.10	0.10	0.10	0.10
Mean DV	0.020	0.020	0.020	0.020	0.020	0.020	0.020
St. Dev. DV	0.139	0.139	0.139	0.139	0.139	0.139	0.139
Log(Participants) × Time D.		✓					
Gravit. Acceleration × Time D.			✓				
Distance from Epicent. × Time D.				✓			
Distance from Emerg.Bord. × Time D.					✓		
Hit by an Earthq. '45 - '06 × Time D.						✓	
Share house built bef. 1919 × Time D.							✓

Note.-Sample of adjacent municipalities. Standard Errors Clustered at Municipality level. Regressions include Fixed effects for: Municipality, Year, Earthquake Event and Object of Contract.

Table 7: Change in Available Funds, N. Contracts and Res. Price

Data at:	**Municipality Level**		**Contract Level**	
	Log (Sum Res. Price)	Num Contr.	Log Res. Price	Log . Res. Price
	(1)	(2)	(3)	(4)
During Emergency	-0.089	0.087	-0.023	-0.139*
	(0.066)	(0.273)	(0.068)	(0.084)
Treat*During Emergency	0.154*	-0.179	0.022	0.077
	(0.083)	(0.505)	(0.073)	(0.078)
After the End of the Emergency	0.087	0.276	0.034	-0.306***
	(0.107)	(0.349)	(0.067)	(0.106)
Treat*After End of Emergency	0.252**	-0.349	0.110*	0.263**
	(0.125)	(0.684)	(0.062)	(0.112)
Observations	3,942	3,942	15,062	3,630
R^2	0.53	0.64	0.13	0.17
Mean DV	12.892	3.820	11.951	12.785
SAMPLE	$> 40k$	$> 40k$	$> 40k$	$> 150k$
Munic FE	✓	✓	✓	✓
Earthquake Event	✓	✓	✓	✓
Year of Contract	✓	✓	✓	✓
Public Proc. Category			✓	✓

Note: Sample of adjacent municipalities. Column 1: sum of reserve prices of contracts awarded by a municipality (data at the municipality level). Column 2: number of contracts awarded by a municipality (data at the municipality level). Columns 3 and 4: Log of Reserve price (data at contract level). Columns 1-3: all procurement contracts awarded after 2007 with a reserve price above 40 thousand euros. Column 4: all procurement contracts awarded after 2010 with a reserve price above 150 thousand euro. Standard errors clustered at the municipality level.

Table 8: Extensive VS Intensive Margin participation of Suspect Criminal Firm (Prob. > 75^{th} percentile)

	Crim. Firm Particip.	First Time Firm-Municipality Relationship			
	Adjac.	**Adjac.**		**Full Sample**	
	(1)	(2)	(3)	(4)	(5)
During Emergency	-0.019	-0.017	-0.024*	-0.009	-0.013
	(0.020)	(0.011)	(0.013)	(0.008)	(0.009)
Treat*During Emergency	0.004	0.001	-0.001	0.012**	0.014**
	(0.010)	(0.009)	(0.010)	(0.006)	(0.007)
After the End of the Emergency	-0.051*	-0.056**	-0.073**	-0.019	-0.025
	(0.028)	(0.025)	(0.029)	(0.013)	(0.015)
Treat*After End of Emergency	0.030**	0.025*	0.023*	0.026***	0.028***
	(0.015)	(0.013)	(0.014)	(0.008)	(0.009)
Log(# Participants)	0.028***	0.017***	0.018***	0.019***	0.021***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Log(# Partic.) * During Emergency	0.011	0.012*	0.014*	0.004	0.005
	(0.009)	(0.007)	(0.008)	(0.005)	(0.005)
Log(# Partic.) * After end Emergency	0.023*	0.026**	0.032**	0.007	0.009
	(0.012)	(0.012)	(0.013)	(0.006)	(0.007)
N. Obs	3,630	3,630	3,248	8,639	7,877
R^2	0.17	0.17	0.18	0.17	0.18
Mean DV	0.020	0.013	0.014	0.011	0.012
Sample			1^{st} Timers		1^{st} Timers

Note: Sample includes Procurement Contracts for Public Works awarded after 2010 and with a reserve price above 150 thousand Euros. Regressions include fixed effects for: year of public procurement contract, municipality, earthquake event, public procurement category. Standard errors clustered at the municipality level. Dep. Var.: Col. 1 (baseline) - Dummy equal to one if at least one criminal firm participating to the contract, Col. 2 to 5 - Dummy equal to one for the first time a suspect criminal firm (mafia firm with prob > .33) is observed participating in a municipality . Cols 3 and 5 restrict the sample to contracts where there was ever a new firm (either clean or criminal) participating.

Table 9: Probability of the joint event: Criminal Firm Participation & Discretionary Auction or Criminal Firm Participation & Non-Discretionary auction

	Mafia Part. & Discr.	Mafia Part. & Non-Dis.
	(1)	(2)
During Emergency	0.001	-0.007
	(0.006)	(0.012)
Treat*During Emergency	-0.000	0.006
	(0.003)	(0.010)
After the End of the Emergency	0.001	-0.018
	(0.011)	(0.019)
Treat*After End of Emergency	0.000	0.028**
	(0.007)	(0.012)
Observations	3,630	3,630
R^2	0.07	0.11
Mean DV	0.004	0.012
Munic FE	✓	✓
Earthquake Event	✓	✓
Year of Contract	✓	✓
Public Proc. Category	✓	✓

Note: Dependent Variable is a dummy equal to 1 in Column 1 if a mafia firm participates and the procedure is a discretionary auction. Dependent variable is a dummy equal to 1 in Column 2 if a mafia firm participates and the procedure is a non-discretionary auction. Standard errors clustered at municipality level.

Table 10: Changes in Municipalities' awarding behavior

	Discr. Proc.	Discr. Proc. Price < 200k	Award Rule: Lowest price	N. Invited < Legal N.	N. Admitt. < N. Applic'ts
	(1)	(2)	(3)	(4)	(5)
During Emergency	-0.058	-0.087	0.049	0.026	-0.010
	(0.052)	(0.090)	(0.054)	(0.024)	(0.053)
Treat*During Emergency	0.014	0.047	-0.067	-0.033	0.003
	(0.052)	(0.092)	(0.053)	(0.026)	(0.051)
After the End of the Emergency	0.007	-0.164	0.034	0.014	-0.101
	(0.069)	(0.112)	(0.077)	(0.036)	(0.075)
Treat*After End of Emergency	-0.051	0.132	-0.130	0.031	0.089
	(0.065)	(0.136)	(0.086)	(0.034)	(0.063)
Observations	3,628	764	2,740	2,336	2,775
R^2	0.32	0.50	0.38	0.20	0.19
Mean DV	0.689	0.812	0.804	0.066	0.241
Earthquake Event FE	✓	✓	✓	✓	✓
Year of Contract FE	✓	✓	✓	✓	✓
Munic FE	✓	✓	✓	✓	✓
Object of Contract FE	✓	✓	✓	✓	✓

Note.-Sample includes Procurement Contracts for Public Works auctioned by Municipalities after 2010 and with reserve price $\geq$ 150k. Standard error clustered at the municipality level.

Table 11: Probability of Infiltration: *DURING* the State of emergency and *AFTER* the Emergency vs BEFORE. Excluding 5 municipalities that showed infiltration occurring at time the months before the emergency occurred.

Dep var:	***At least one Criminal Firm among the Participants to the Contract***							
	ALL		**Adjacent Municipalities**				**Doughnut Sample**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat					-0.014*	-0.010		
					(0.007)	(0.007)		
During Emergency	0.004	-0.001	-0.002	-0.000	-0.004	0.002	0.006	-0.002
	(0.007)	(0.008)	(0.011)	(0.013)	(0.012)	(0.014)	(0.008)	(0.013)
Treat*During Emergency	0.002	0.006	0.002	-0.000	0.008	0.002	0.010	0.020*
	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)
After the End of the Emergency	-0.011	-0.018	-0.017	-0.059**	-0.007	-0.060	-0.009	0.010
	(0.010)	(0.015)	(0.018)	(0.028)	(0.022)	(0.037)	(0.013)	(0.017)
Treat*After End of Emergency	0.038***	0.035***	0.040***	0.034**	0.032**	0.030**	0.033***	0.021*
	(0.010)	(0.009)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
Log(# Participants)		0.024***		0.022***		0.021**		0.025***
		(0.004)		(0.007)		(0.008)		(0.006)
Log(# Partic.) * During Emergency		0.002		0.002		0.002		0.003
		(0.005)		(0.008)		(0.006)		(0.007)
Log(# Partic.) * After end Emergency		0.006		0.027**		0.031**		-0.008
		(0.007)		(0.012)		(0.014)		(0.007)
N. Obs	8,304	8,304	3,295	3,295	4,630	4,630	4,977	4,977
R^2	0.18	0.23	0.12	0.18	0.07	0.15	0.23	0.26
Mean DV	0.015	0.015	0.015	0.015	0.015	0.015	0.016	0.016
St.Dev. DV	0.122	0.122	0.120	0.120	0.120	0.120	0.124	0.124
Munic FE	✓	✓	✓	✓			✓	✓
Adjacent Pair FE					✓	✓		
Earthquake Event	✓	✓	✓	✓	✓	✓	✓	✓
Year of Contract	✓	✓	✓	✓	✓	✓	✓	✓
Public Proc. Category	✓	✓	✓	✓	✓	✓	✓	✓

Note: Sample includes Procurement Contracts for Public Works auctioned by Municipalities after 2010 and with reserve price $\geq$ 150k. **Sample excludes Bologna, Reggio nell'Emilia, Rieti, Corridonia, Macerata that caused a positive coefficient in Figure 7**. Regressions include fixed effects for: Municipalities, Year of public procurement contract, Earthquake event, Public procurement category. Columns 1-2: full sample, columns 3-4: municipalities touching the border of the emergency, columns 5-6: adjacent municipalities sample with neighboring pair fixed effecs, columns 7-8 exclude municipalities touching the border of the Emergency. Standard errors clustered at the municipality level.

Table 12: Probability of Infiltration: *DURING* the State of emergency and *AFTER* the Emergency VS BEFORE controlling for trends by population.

Dep var:	***At least one Criminal Firm among the Participants to the Contract***							
	All Municipalities				Excluding 5 municipalities			
	ALL		**Adjacent**		**ALL**		**Adjacent**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
During Emergency	-0.024	-0.005	-0.038	-0.028	-0.023	-0.001	-0.031	-0.012
	(0.022)	(0.024)	(0.034)	(0.034)	(0.022)	(0.023)	(0.032)	(0.026)
Treat*During Emergency	0.005	0.010	0.005	0.002	0.002	0.006	0.001	-0.001
	(0.008)	(0.008)	(0.011)	(0.010)	(0.007)	(0.007)	(0.010)	(0.009)
After the End of the Emergency	-0.036	-0.014	-0.031	0.009	-0.055*	-0.030	-0.073	-0.030
	(0.036)	(0.032)	(0.065)	(0.054)	(0.033)	(0.029)	(0.052)	(0.045)
Treat*After End of Emergency	0.032***	0.030***	0.033**	0.034**	0.038***	0.035***	0.038***	0.035**
	(0.011)	(0.010)	(0.014)	(0.014)	(0.010)	(0.009)	(0.014)	(0.014)
Log(# Participants)		0.026***		0.028***		0.024***		0.022***
		(0.004)		(0.007)		(0.004)		(0.007)
Log(# Partic.) * During Emergency		0.006		0.011		0.002		0.002
		(0.006)		(0.009)		(0.005)		(0.008)
Log(# Partic.) * After end Emergency		0.005		0.024*		0.006		0.028**
		(0.007)		(0.012)		(0.007)		(0.012)
Log(Popul. in 2005) * During Emergency	0.003	-0.001	0.003	0.001	0.003	-0.000	0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Log(Popul. in 2005) * After end Emergency	0.003	-0.000	0.001	-0.007	0.005	0.001	0.006	-0.003
	(0.003)	(0.003)	(0.006)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
N. Obs	8,639	8,639	3,630	3,630	8,304	8,304	3,295	3,295
R^2	0.16	0.21	0.10	0.17	0.18	0.23	0.12	0.18
Mean DV	0.017	0.017	0.020	0.020	0.015	0.015	0.015	0.015
St.Dev. DV	0.131	0.131	0.139	0.139	0.122	0.122	0.120	0.120

Note: Sample includes Procurement Contracts for Public Works auctioned by Municipalities after 2010 and with reserve price $\geq$ 150k. Columns 5-8 exclude Bologna, Reggio nell'Emilia, Rieti, Corridonia, Macerata from the sample. Regressions include fixed effects for: Municipality, Year of public procurement contract, Earthquake event, Public procurement category. Columns 1-2, 5-6: municipalities inside VS outside the border of the emergency, columns 3-4, 7-8: Municipalities touching the border of the emergency. Standard errors clustered at the municipality level.

Table 13: Probability of Infiltration: DURING the State of Emergency and AFTER the Emergency VS BEFORE, data collapsed at municipality/year/time relative to earthquake

At least one Criminal Firm among the Contract Participants

Sample:	**ALL**		**Adj. Municipalities**	
	(1)	(2)	(3)	(4)
During Emergency	-0.003	0.003	-0.012	-0.002
	(0.008)	(0.010)	(0.017)	(0.020)
Treat*During Emergency	0.010	0.011	0.010	0.008
	(0.009)	(0.009)	(0.017)	(0.016)
After the End of the Emergency	-0.017	-0.002	-0.031	-0.015
	(0.013)	(0.015)	(0.025)	(0.027)
Treat*After End of Emergency	0.032***	0.028***	0.034*	0.027
	(0.011)	(0.011)	(0.019)	(0.018)
Log(# Participants)		0.028***		0.031***
		(0.005)		(0.010)
Log(# Partic.) * During Emergency		-0.002		-0.002
		(0.006)		(0.013)
Log(# Partic.) * After end Emergency		-0.004		-0.001
		(0.007)		(0.014)
N. Obs	4,220	4,220	1,506	1,506
R^2	0.31	0.35	0.20	0.25
Mean DV	0.015	0.015	0.017	0.017
St.Dev. DV	0.106	0.106	0.108	0.108

Note: Each observation is the mean of the contracts awarded by a municipality in a specific year. Multiple observations within a municipality/year may occur if the event (start/end of the state of emergency) does not occur either at the beginning or the end of the year. Regressions include fixed effects for: awarding municipality, year of public procurement contract, earthquake event.

Table 14: Probability of Infiltration: DURING the State of Emergency and AFTER the Emergency vs BEFORE, Conley Standard Errors

At least one Criminal Firm among the Contract Participants						
Sample:	**ALL**			**Adjacent**		
Std. Errors:	Munic.	Conley		Munic.	Conley	
	(1)	(2)	(3)	(4)	(5)	(6)
During Emergency	0.002	0.002	-0.010	-0.005	-0.005	-0.019
	(0.008)	(0.007)	(0.011)	(0.015)	(0.013)	(0.020)
Treat*During Emergency	0.006	0.006	0.010	0.008	0.008	0.004
	(0.008)	(0.009)	(0.009)	(0.012)	(0.014)	(0.013)
After the End of the Emergency	-0.013	-0.013	-0.015	-0.020	-0.020	-0.051*
	(0.012)	(0.011)	(0.015)	(0.023)	(0.019)	(0.028)
Treat*After End of Emergency	0.032***	0.032***	0.030***	0.034**	0.034**	0.030*
	(0.012)	(0.012)	(0.011)	(0.016)	(0.017)	(0.016)
Log(# Participants)			0.026***			0.028***
			(0.004)			(0.007)
Log(# Partic.) * During Emergency			0.006			0.011
			(0.006)			(0.011)
Log(# Partic.) * After end Emergency			0.005			0.023*
			(0.007)			(0.013)
N. Obs	8,639	8,639	8,639	3,630	3,630	3,630
R^2	0.16	0.00	0.06	0.10	0.01	0.09
Mean DV	0.017	0.017	0.017	0.020	0.020	0.020
St.Dev. DV	0.131	0.131	0.131	0.139	0.139	0.139

Note: Sample includes all Procurement Contracts for Public Works auctioned by Municipalities after 2010. Regressions include fixed effects for: awarding municipality, year of public procurement contract, earthquake event, public procurement category. Columns 1-3: all municipalities within 25 km of the border of the Emergency, columns 4-6: municipalities adjacent to the border. Columns 1 and 4: baseline regression. All other columns: Conley Standard Erros with 10 km and 5 km cut-offs: median distance from border of emergency in the two samples.

Appendix

Table A1: Extensive VS Intensive Margin participation of Suspect Criminal Firm (Prob. > 0.5)

	Crim. Firm Particip.	First Time Firm-Municipality Relationship			
	Adjac.	**Adjac.**		**Full Sample**	
	(1)	(2)	(3)	(4)	(5)
During Emergency	-0.019	-0.017**	-0.023**	-0.006	-0.009
	(0.020)	(0.008)	(0.009)	(0.006)	(0.007)
Treat*During Emergency	0.004	0.000	-0.001	0.007*	0.008*
	(0.010)	(0.009)	(0.010)	(0.004)	(0.005)
After the End of the Emergency	-0.051*	-0.045**	-0.058***	-0.021**	-0.026**
	(0.028)	(0.019)	(0.022)	(0.009)	(0.011)
Treat*After End of Emergency	0.030**	0.020*	0.020	0.017**	0.018**
	(0.015)	(0.011)	(0.012)	(0.007)	(0.008)
Log(# Participants)	0.028***	0.012***	0.012***	0.012***	0.013***
	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)
Log(# Partic.) * During Emergency	0.011	0.005	0.007	-0.001	0.000
	(0.009)	(0.006)	(0.007)	(0.004)	(0.004)
Log(# Partic.) * After end Emergency	0.023*	0.012	0.016	0.004	0.005
	(0.012)	(0.009)	(0.010)	(0.005)	(0.005)
N. Obs	3,630	3,630	3,248	8,639	7,877
R^2	0.17	0.14	0.15	0.15	0.16
Mean DV	0.020	0.008	0.009	0.006	0.007
Sample			1^{st} Timers		1^{st} Timers

Note: Sample includes Procurement Contracts for Public Works awarded after 2010 and with a reserve price above 150 thousand Euros. Regressions include fixed effects for: year of public procurement contract, municipality, earthquake event, public procurement category. Standard errors clustered at the municipality level. Dep. Var.: Col. 1 - Dummy equal to one if at least one criminal firm participating to the contract, Col. 2 to 5 - Dummy equal to one for the first time a suspect criminal firm (mafia firm with prob > .50) is observed participating in a municipality . Cols 3 and 5 restrict the sample to contracts where there was ever a new firm (either clean or criminal) participating.

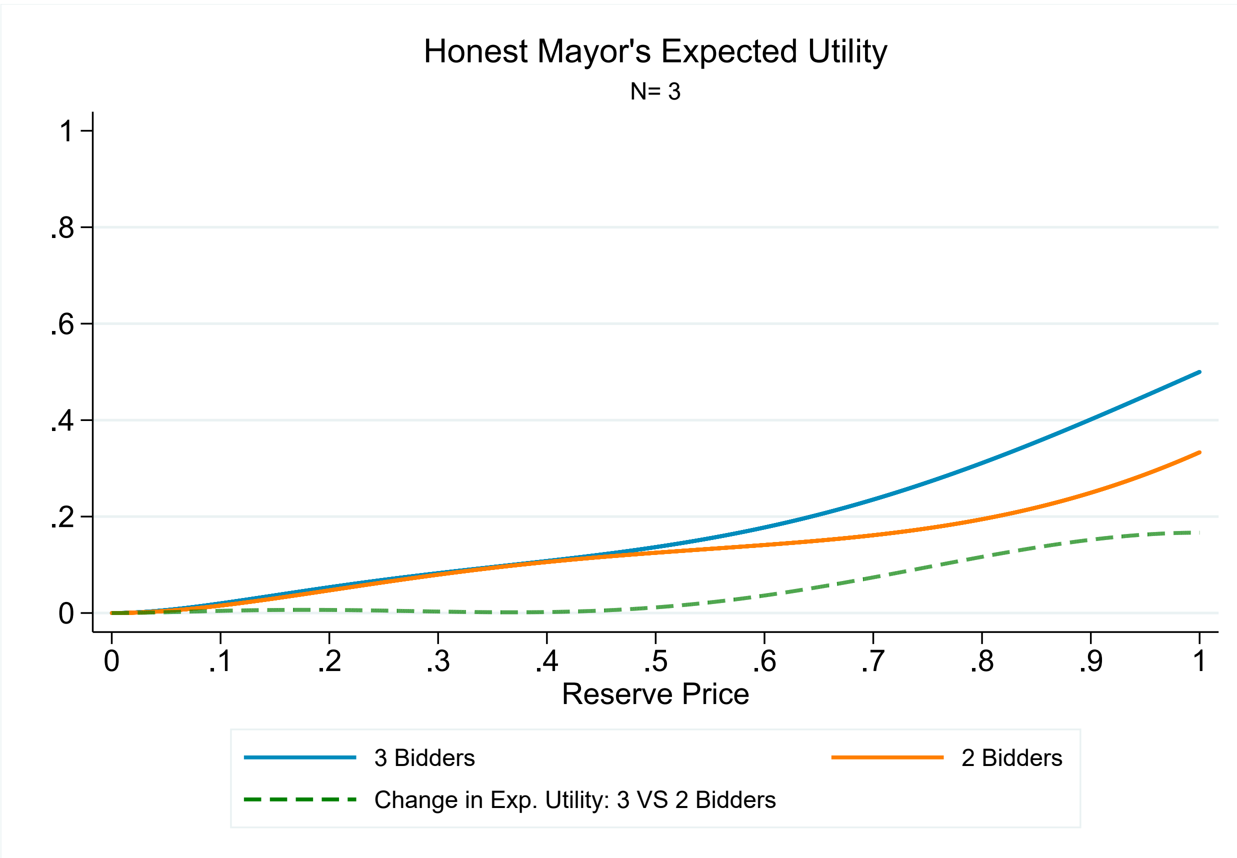

Figure A1: Expected Revenues in the Non-Discretionary auctions with 3 and 2 bidders, $\delta = 0$

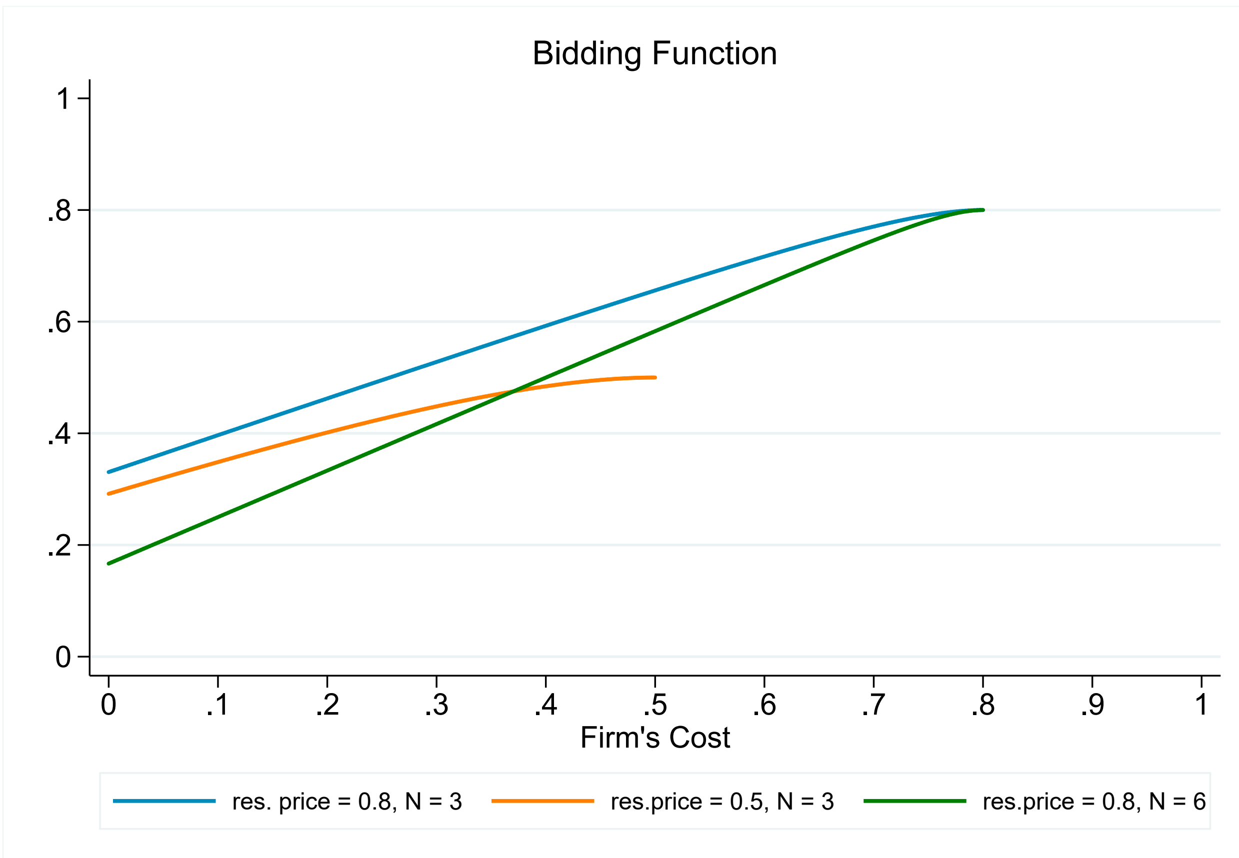

Figure A2: Bidding Function of the Firms in the First Price Auction

Figure A3: Value of the optimal offer the corruptible mayor makes to the criminal firm, but also probability that the criminal firm accepts the offer

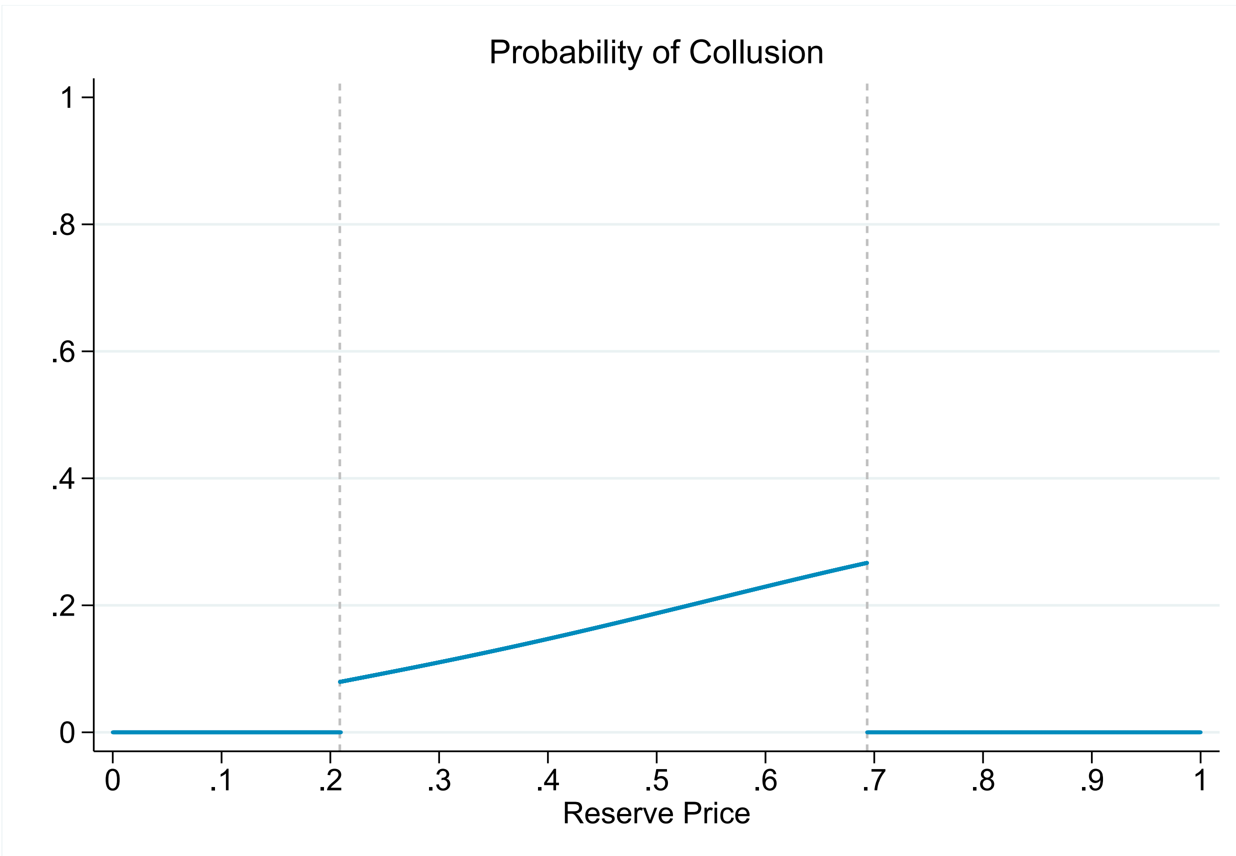

Figure A4: Probability of Collusion Occurring in a Discretionary Auction with a Corruptible Mayor