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The Effects of Local Demand and Supply Restrictions on Markup

Antonio Acconcia[*] and Elisa Scarinzi[†]

Abstract
We investigate the causal effects on markup of a contraction in demand and supply. For differentiated manufacturing products, transport and business services, markups shrink severely following a contraction in demand whereas they amplify after a contraction in supply. In either case the effect is short-lived. For local firms operating in retail, wholesale, restaurant, and accommodation, a supply contraction determines a boost in markups that lasts a few years; a demand contraction instead drives down the labor costs without affecting the markups. We also find heterogeneous effects among firms caused by the supply shock, as firms with the lowest markups already tend to increase more the markup while highest markup firms mainly gain in terms of market shares. Overall, after a deep shock like the Covid-19 one our findings suggest significant labor market adjustment in sectors with substitutable workers and enhanced output market concentration.

JEL classification: E30, D22, D40.

Keywords: Demand/Supply Contraction, Markup, Local Competition, Labor Market, Demand Reallocation.

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1 Introduction

Markup adjustments should provide information on how demand and supply shocks are transmitted to the real economy (i.e. Woodford, 2011; Broer et al., 2020). However, it is difficult to identify causal relationships using aggregate data because changes in aggregate markup are usually the outcome of more than one source of variability (Nekarda and Ramey, 2020). A contraction in demand should lower the markup for firms with market power but would have little effect in a highly competitive environment, where firms have less control over the prices they can charge. A reduction in supply determined by a lower number of firms should encourage higher markups for the firms that remain in the market due to the reallocation of demand. Since net business formation tends to be procyclical, it is difficult to ascertain the empirical relevance of these theoretical predictions.[1]

In this paper, we present a contribution to the strand of literature on the firm-level markup dynamics by relying on natural experiments. The implications of Italian legislation provide us with quasi-random sources of demand and supply contractions that we exploit within a unified empirical framework of analysis. The exogeneity of the demand/supply shocks allows to avoid the typical concern of similar investigations. The use of firm-level data allows us to compare the response to the shocks across sectors arguably characterized by different degree of local competition. This turns out to be relevant in order to understand the transmission mechanism explaining the markup variability.

Supply shocks are determined by an Italian law which in order to reduce mafia economic power enables the inheritances of otherwise innocent persons, who may have some mafia connection (i.e. relatives of mafiosi or front men), to be seized. If the inheritance consists of a firm, the seizure implies the shut-down of production, at least temporarily, similar to the shock assumed in theoretical models as the one by Bilbiie et al. (2019) and investigated empirically by Bils (1987) and Broda and Weinstein (2010), among others. Thus, information about municipalities and sectors affected by such shocks allows investigation of the effect of an unanticipated drop in supply within a given local market. Demand shocks come from episodes of compulsory administration after city-council dis-

[1]Cournot competition drives an inverse relationship between markup and the number of firms and a positive relationship between markup and demand (Galí and Zilibotti, 1995; Bertoletti and Etro, 2016). Monopolistically competitive markets are exploited by Galí (1995), Jaimovich (2007), Jaimovich and Floetotto (2008) and Bilbiie et al. (2012), among others. In this framework the degree of substitutability among varieties generates the negative link between the markup and the number of firms. See also Boar and Midrigan (2019).

missals, due to mafia infiltration. These episodes were exploited by Acconcia et al. (2014a) to estimate the size of the public spending multiplier at the local level. The present study relies on their work to shed light on the markup adjustment in response to a contraction in demand.

The focus on firm-level reactions to demand and supply shocks has implications for both price and quantity dynamics, and for policy. Price adjustments induced by changes in the economic environment should act as a regional rebalancing mechanism in response to an idiosyncratic local shock (e.g. Corsetti et al., 2020). The way local prices respond to demand changes determines the efficacy of fiscal policy in countering area-specific recessionary shocks (Moretti, 2010; Shoag, 2013; Acconcia et al., 2014a; Nakamura and Steinsson, 2014; Chodorow-Reich, 2019; Corbi et al., 2019). Evidence on the effects of contractions improves our understanding of deep recessions like the one determined by the Covid-19 pandemic (Baqaee and Farhi, 2020a), and of the role of stabilization policy (Ravn and Sterk, 2020).

In view of the economic sectors concerned by the identified shocks, we mainly provide evidence for two groups of firms for which the relevance of local competition is plainly different. These firms are involved in: (i) retailing, wholesaling, accommodation and foods, whose geographically relevant market is quite narrow with respect to the entire economy; (ii) business services, manufacturing goods and transportation services. Moreover, since the possibility to set a price above the marginal cost depends on the firm price elasticity of demand, we also distinguish between differentiated and standardized products.

Markups are difficult to measure because they would require challenging information on marginal costs or econometric estimate of output elasticity of a variable input. In either case, issues could be raised to the resulting measures (Syverson, 2019; De Loecker et al., 2020; Autor et al., 2020; Bond et al., 2020). In this paper, we use the so called accounting approach which is based on directly observable data under the assumption of equality between average variable cost and marginal cost. The same approach has been recently used by Antràs et al. (2017), among others, to investigate the responses of U.S. firms to trade shocks.[2] In particular, we use data for a large sample of Italian firms and

[2] De Loecker et al. (2020) posit cost minimization by producers and obtain the markup as the wedge between a variable input's expenditure share in revenue and that input's output elasticity. They show that markups in U.S. have increased on average from 21% in 1980 to 61% in 2014. The distribution of markups has become, however, more skewed with a fat upper tail while the median of the distribution has remained unchanged. For the same period, average profit rates have increased from 1% of sales to 8%. By relying on both

measure the markup in terms of profit margin scaled by total revenue. Average variable cost does not of course generally equal marginal cost; however, this is not a major concern in our analysis. Conditional on firm-level fixed effect, the accounting measure allows to correctly assess the markup adjustment as long as the yearly variation in scale elasticity is not correlated with the occurrence of the investigated shocks. As is discussed below, the sources of our demand and supply shocks imply that the exogeneity requirement is indeed true.

In line with standard theoretical predictions, we find that the markups on differentiated products reduce in municipalities and provinces suffering a contraction in demand, and increase with episodes of firm exit from the market. In contrast, neither firm exit nor reduction in demand has any effect on the markup of standardized manufacturing goods, tradable across the board, and thus subject to strong external competition. The exit shock amplifies somewhat the markups on retail, wholesale, accommodation and food. For these horizontally differentiated local services, the drop in demand has instead negligible effects on markups mainly because of the downward adjustment of the wage bill. Some heterogeneity characterizes the response to the reallocation of demand resulting from a supply contraction: firms with the lowest markups already increase more the markups while highest markup firms mainly gain in terms of market shares. This latter evidence recalls those in Autor et al. (2020) and De Loecker et al. (2020).

Taken together, our findings for sectors highlight the role of demand elasticity and competition in determining the response of markup, while those by type of shock confirm that conflicting conclusions regarding the cyclicality of markup may be achieved without identifying the two sources of variability. The reduction of markups in response to a contraction in demand supports the hypothesis that idiosyncratic local shocks can be an important driver of price changes (Nakamura and Steinsson, 2008). The unresponsiveness of markups of firms which arguably face strong competition in the product market is in line with results in Bertola et al. (2012). The opposite response to demand and supply shock is consistent with the evidence on the inflationary supply shifts and deflationary demand shifts during the Covid-19 recession (Balleer et al., 2020). Evidence on labor costs of firms competing locally and arguably employing lower skilled substitutable workers

the accounting approach and the cost minimization approach, Autor et al. (2020) provide strong evidence suggesting that the concomitant increase in aggregate markups and decline in the labor share are triggered by a reallocation of market share towards 'superstar firms' with both low labor shares and high markups. With direct measures of capital costs, Barkai (2020) clearly shows that the declining shares of both labor and capital are offset by a large increase in the share of pure profits.

points to the prompt downward adjustment of the wage bill after a contraction in final demand or in the number of incumbent firms. A related evidence is reported by Jäger and Heining (2019), who show that unexpected worker deaths raise the remaining workers' wages. Finally, the heterogeneous effects of the two shocks among firms would suggest more output market concentration after the Covid-19 recession.

Identification of the relevant effects builds on narrative, statistical evidence, and the availability of firm-level panel data. The quasi-randomness of the exit shock rests on the fact that the police investigation leading to the shutdown of a firm is completely unrelated to how the firm operates. The type of evidence that typically results in a firm seizure is related to the owner's other tasks and activities, or the activities of people connected to the firm's front man. Firms can be seized also because the historical flow of income of the owner or front man is too low to justify ownership of the assets. In either case, it follows that a seized firm cannot be described as a 'mafia firm' in the conventional understanding of mafia: when seized the firm was operating legally. As a related point, we would note also that whether people connected to the mafia tend to buy relatively more profitable firms does not affect our main evidence since our sample does not include seized firms.[3] Seizure episodes are used only to identify the municipality, sector, and year of shutdown of production. Moreover, reliance on panel data avoids concerns that our sample might be affected by self selection due to the entrepreneur choosing to start a company in a particular location either to avoid a mafia environment or to operate within it. However, we provide formal statistical evidence that there is no systematic link between seizures and local economic activity. In particular, we document that (i) the average markup in our sample is insignificantly different from the average markup of the seized firms—before being seized; (ii) before seizure episodes, the average markup in our sample was neither exceptionally low not exceptionally high. Finally, we refer to Acconcia et al. (2014a) for arguments and statistical evidence regarding the quasi-randomness of city-council dismissals and related public spending drops.[4]

Our evidence related to demand-side shocks adds to work on markup variations over the business cycle which originated with Rotemberg and Woodford (1992). Models based on sticky prices (e.g., Galí et al., 2007; Woodford, 2011) usually imply countercyclical vari-

[3] The potential concern would apply only if either the average performance in sectors involved or not involved in episodes of seizure are compared, or seized firms are compared with not-seized firms.

[4] Since current data on public actions, similar to those used by Acconcia et al. (2014a) are not available, identification of the demand shock in the present paper rests on their discussion and clear evidence. Thus, our analysis is inspired by the reduced form of their empirical model.

ations, a prediction supported by Galeotti and Schiantarelli (1998), among others but rejected recently by Anderson et al. (2020) and Nekarda and Ramey (2020). Our results are in line with the more recent findings.

Evidence on the effects of the exit shock is related to the stream of work on markups and the level of competition. The results based on traditional approaches that use measures of concentration can be misleading because of the endogeneity of these measures (Syverson, 2019). To the extent that a concomitant increase in both markup and concentration is accompanied by an efficiency gain, we cannot infer a causal effect of reduced competition (Autor et al., 2020; Bessen, 2017; De Loecker et al., 2020). How concentration is measured also matters for interpretation of the results (Hall, 2018).[5] Our approach is more similar to those approaches that exploit exogenous events and instrumental variables. De Loecker et al. (2016) find an incomplete cost pass-through to prices as the immediate consequence of the India's trade liberalization episode which lowered the marginal costs; hence, as a result of the higher markups producers benefited relative to consumers. For the United States, Gutiérrez and Philippon (2017a) argue that the decreased competition determined by higher regulation explains much of the recent increase in markups and slow-down in investment.[6] Corsetti et al. (2018) show a higher level of pricing-to-market for highly differentiated goods, that is, those for which the cross-market substitution of quantity by firms is very low. Our results provide further evidence that in local markets markups vary with the firms' market power.

There is wide-ranging debate and a large literature on Italian criminal organizations which originated with Gambetta (1993), who provides an analysis of the economic and political role of the Sicilian Mafia. Since Acconcia et al. (2014a,b), several empirical papers have exploited anti-mafia legislation to study its deterrent effect.[7] Recently, Alfano et al.

[5]Assessing whether markups depend on the number of firms and the competition is relevant also for welfare analysis. Monopolistic competition and product variety imply that market and planner equilibria are equivalent only under Dixit-Stiglitz preferences and constant markup (Bilbiie et al., 2012). The benchmark calibration in Edmond et al. (2019) suggests that if all markup distortions were eliminated the representative consumer would gain 6.6 % in consumption-equivalent terms. Boar and Midrigan (2019) show that households might benefit from policies that remove the distortions due to markup dispersion even though they lead to higher markups and concentration.

[6]Mantovani et al. (2017) show that an active antitrust intervention contributed to the drop in online hotel prices.

[7]For instance, Daniele and Geys (2015) provide an assessment of the law allowing city-council dismissals while Di Cataldo and Mastrorocco (2019) use this law to study the impact of mafia infiltration within local governments. Fenizia and Saggio (2020) point out a strikingly large beneficial effect of city council dismissal on employment—about twice the 2020 Italian unemployment rate—in the long run, that is nine years after the dismissal. Providing insight for this remarkable and captivating evidence is not, however, straightforward

(2019) used information on confiscated firms which following the trials were allocated to other uses; they found an inverse correlation between the number of these firms and regional unemployment. Relying on evidence for Sicily, Ferrante et al. (2019) argue that the seizure policy could be useful to fight criminal organizations and could lead to higher levels of market competition. Similarly, Slutzky and Zeume (2020) suggest that anti-mafia enforcement actions increase competition for public procurement contracts.

The rest of the article is organized as follows. Section 2 provides institutional details on the laws targeting mafia connections. Section 3 presents the empirical model and Section 4 discusses the main results. Sections 5 presents results of alternative specifications of the empirical model. Section 6 concludes.

2 Institutional Setting

We introduce our key explanatory variables by providing background information on the way the Italian law deals with mafia-related crime. As a result of the rising incidence of organized crime in the Italian economy, in 1982 the Italian legislator issued the so-called *Rognoni-La Torre* Law which explicitly targeted mafia-type organizations.[8] In particular, Article 1 subsection 7 allows compulsory expropriation of the heritage of people found guilty of direct or indirect involvement in the activities of a mafia group: All assets of the person sentenced that were used to commit the offense or are the direct or indirect outcome of mafia activity must be confiscated. A few years later, D.L. No. 306, dated June 8, 1992—and then Art. 24 of D.L. No. 519 Anti-mafia Penal Code, dated September 6, 2011—clarified that any individual found guilty of mafia activity must prove the legal origin of his assets to avoid them being confiscated. In reality, the assets of *suspected* mobsters are usually seized by the courts for preliminary investigation long before sentencing and determination of any confiscation of assets.[9]

since they do not find change in worker composition as well as individuals or firms transitioning from the informal to the formal sector.

[8]Having been first presented to Parliament in 1980 by the Sicilian leader of the Italian Communist Party, Pio La Torre, the law was not issued until September 13, 1982, following the murders of La Torre on April 30, 1982, and the Prefect of Palermo, Carlo Alberto dalla Chiesa, on September 3, 1982. Two articles—416-bis and 416-ter—were added to the penal code after the law had been published.

[9]Specifically, an asset is confiscated if: (i) it is at the disposal of the convicted individual, though owned by a frontman; (ii) its value is at odds with the financial status of the convicted individual; (iii) it is the product or tool of an illegal activity; (iv) the convicted individual cannot prove right to the property. A confiscated asset might be returned to the convicted individual if the related judgment is withdrawn as the result of new facts

There have been many episodes of pre-emptive seizure and confiscation targeting companies. Although such companies operate in the market legally, they become subject to seizure either because they are owned by or at the disposal of an individual related to a mafia clan. This applies in particular to firms owned by relatives of *mafiosi* or their front men. If the pre-emptive order relates to a company, then it is supplemented by the appointment of a commissioner whose main tasks include writing a detailed report on the firm's activity and future business prospect (D.L. No. 230, June 14, 1989). If the report is approved by the court, the company is handed over to the commissioner. However this can take a minimum of six months from seizure which reduces the chance of the firm being reintegrated into the economic fabric in the short run. In any case, the commissioner's responsibilities are confined to general administration and do not allow the firm to be rented or sold. The commissioner remains in charge of the company until confiscation or seizure is revoked. In the case of confiscation, the firm becomes part of the state heritage and the commissioner is replaced by the Italian agency (hereafter ANBSC) responsible for the administration of all assets confiscated from the mafia.

The case study of the 'Suvignano estate' farmhouse in Tuscany is a clear example of the lengthy process from seizure to business recovery. The compulsory administration started with the pre-emptive seizure order issued by Giovanni Falcone in 1993; confiscation happened only in 2007. The entire process ended in 2018 when the asset was granted to the region of Tuscany.

Episodes of seizure and confiscation involving companies imply an abrupt and unexpected halt to their economic activity. We exploit these types of episodes to identify the municipalities affected by a shock that determines a contraction in supply and reduced market competition, similar to the case of an exogenous change to the cyclical pattern of firm market exit. We argue that the quasi-randomness of the shock rests on the fact that the patrimonial pre-emptive measures emerge suddenly in the course of the ongoing police investigation and target companies conducting legal business in a legal manner. There are no self selection concerns due to potential correlation between the shock of interest and the state of the local competition. At the same time, anticipations of such measures are unlikely to play a significant role on the local economic activity.

The rise in mafia infiltration of public administrations throughout the 1980s caused tougher anti-mafia measures. According to a 1991 law (D.L. No. 164, May 31, 1991) that is

that imply that the conviction was based on false premises; however, this is a rare occurrence. The conditions of the seizure order are the same as the conditions related to confiscation.

still in place, central government has the right to remove elected local officials from their posts on the production of evidence that their decisions were influenced by the mafia.[10] In the case of a city council being fired, central government will appoint three non-elected, external commissioners, who will be responsible for governing the municipality for a period of up to 18 months. Acconcia et al. (2014a) show that, in the case of dismissal of a municipal government based on evidence of mafia infiltration, the first year of compulsory administration is associated with a sharp contraction in public spending. During the period 1986–1999, the average contraction in spending determined by the appointment of external commissioners amounted to about half a percentage point of the provincial level value added, comparable to the change in the fiscal variables in some leading empirical analyses of multipliers. In particular, the extensive documentation relative to the municipality of Pompei, whose city council was dismissed on September 11, 2001, reveals that the spending cuts affected a range of budget chapters, such as purchase of mechanical equipment, maintenance of public parks and gardens, extraordinary street maintenance and extraordinary maintenance of the water and sewage systems.

Reports from the *Commissione Parlamentare d'Inchiesta* to the Italian parliament suggest that incriminating evidence leading to city-council dismissals often emerges randomly during police investigations.[11] The absence of a systematic link between episodes of dismissal and local economic activity allowed Acconcia et al. (2014a) to use such episodes as an instrument to identify unexpected variations in province-level public spending. Since similar data on spending are not available after the 1990s, in what follows we use information on dismissals to estimate an empirical model similar to the reduced form equation in Acconcia et al. (2014a). The main advantage of this approach is that it allows us to exploit firm-level data with information on dismissals at the municipality level, and to estimate a unique model which combines both demand (council dismissals) and supply (seizure of firms) shocks.

[10] The city-council dismissal legislation was introduced after the mafia-related murder in Taurianova, a very small Italian municipality.

[11] Dismissals typically follow (i) investigations of crimes by local administrators or politicians (not necessarily linked to their official functions); (ii) investigations of extortion, illegal trade in weapons and drugs, and mafia wars for the control of local territory; (iii) investigations prompted by whistleblowers, providing information on crimes typically unrelated to mafia infiltration in public administration; (iv) investigations prompted by the resignation of a city mayor or a city council member, suggesting mafia pressure; (v) vote-buying (Commissione Parlamentare d'Inchiesta 2005).

3 Data and Empirical Strategy

To identify a supply shock, we refer to (i) the year when the firm's economic activity stopped because of the seizure order; (ii) the municipality in which the seized company's headquarters was located; (iii) the firm's economic sector of operation before seizure.[12] Hence, the Municipality×Sector×Year indicator, S, identifies the pool of firms potentially affected by the competition shock, that is, those firms that were operating in the same sector and municipality as the seized company and which remain in the market after the seizure. Also, to study the effects of the demand shocks we consider the interaction Municipality×Year×Semester identifying each episode of compulsory administration. If the official decree determining the compulsory administration is published in the first semester of the year, the demand shock is labelled D.[13]

Our period of investigations covers the years 2008-2018 and includes 107 cases of city councils being put under compulsory administration for mafia infiltration, relative to 97 municipalities, and 1,829 cases of seized firms distributed over 424 municipalities (see Table 1). However, since we rely on yearly data and since multiple instances of seizure can affect the same municipality in the same year, we exploit 1,072 Municipality×Sector×Year 'treated' cases to estimate the effects of a supply shock. Figure 1 shows municipalities affected by at least one episode of seizure or compulsory administration during 2008-2018. While episodes of city-council dismissals are almost totally confined to the four regions in the south of Italy which are characterized by the historical presence of mafia, episodes of seizure and confiscation of firms are spread across the whole country. This mainly reflects the money laundering strategy of various mafia clans which increasingly tend to invest their profits across the legal sectors of richer areas of the country.

The *direct* effect of compulsory administration should be detectable at the municipal level for manufacturing and related services, transportation and warehousing, professional and business services since the presence of commissioners cuts the demand for these products.[14] These sectors are characterized by a number of seizure episodes, and thus are affected by supply shocks, too. However, in either case the markups are likely to vary noticeably only if the firms enjoy market power since otherwise the output price would be very close to the marginal cost. Therefore, we provide evidence relative to the

[12] Of course, data protection regulation does not allow us to identify those firms.

[13] Notice that the size of the yearly drop in public spending may depend on the proximity of the dismissal date to the end of the calendar year. We do not have information on semester of seizure orders.

[14] Other economic sectors may be affected by any indirect (or general equilibrium) effect.

group of industries described above which we call Manufacturing-Business-Services, and those in these industries' subgroups which likely produce standardized and differentiated goods.

Before their seizure, around half of the subsequently seized firms were operating in service industries supplying local goods that is, retailing, wholesaling, accommodation and food services (hereafter Distribution-Food). The local dimension of the shock implies that its effect should not extend far beyond the seized firm. In fact, if the seized firm's geographical market is local, then all firms potentially affected by the shock will be located proximate to the seized firm. Therefore, we can use this group of firms to assess the effect of a lower level of competition due to a contraction in supply.[15]

As recalled by De Loecker et al. (2020), there exist three distinct approaches to measure the markup of a firm: the accounting approach that relies on directly observable factor shares and margins of profits; the demand approach that exploits the first-order condition associated with optimal pricing; the production approach that requires an explicit treatment of the production function and assumes cost minimization of variable input of production. We rely on the accounting approach which has been recently implemented by Antràs et al. (2017), Karabarbounis and Neiman (2019), and Autor et al. (2020), and previously by Broda and Weinstein (2006), among others. This approach is useful because it does not require econometric estimation of production function or demand function as prerequisite for measuring the markup. In particular, we use balance-sheet data for a large sample of firms operating in Italy to get a proxy for the difference between price and marginal cost, expressed as a percentage of the price, that is earnings before interest, taxes, depreciation and amortization, scaled by total revenue (multiplied by 100). While the general validity of this proxy rests on the equality between marginal cost and average variable cost, it is reliable for assessing the response of markup to our identified demand and supply shocks as long as the yearly changes in the scale elasticity, if any, are not correlated with the occurrence of the shocks. Since both shocks are based on implications of police investigation unrelated to the local business cycle and the firm performance, this requirement is plainly satisfied. Moreover, for the vast majority of firms supplying local services, usually characterized by fixed costs being a relatively small share of the total cost of production, the accounting profit rate is also reliable for measuring the level of markup.

The source of our sample is AIDA database supplied by Bureau van Dijk. In par-

[15] Although we do not have detailed information on the specific economic activity of the seized firms, we have information on the industry group—defined by the ANBSC— in which they operated before shutdown.

ticular, to estimate the firm-level specification we consider a restricted sample based on municipalities and sectors characterized by episodes of council dismissals and seizures and an enlarged sample which also includes municipalities adjacent to the treated ones. In either case, all firms for which we have information on total revenue and profitability during 2008-2018 are included. The stability of results between the two samples should provide support to our identifying strategy. To account for spatial spillovers we broaden even more the sample by taking into account all Italian municipalities. The restricted sample contains 90,454 firms while the more comprehensive one 145,423 firms. Given the sources of our two shocks, the groups of firms investigated are the Distribution-Food and the Manufacturing-Business-Services; the rest of the sample is mainly considered for comparison. Table 2 shows that one-fourth of the total sample consists of firms operating in the Manufacturing-Business-Services sector and that about one-third consists of Distribution-Food firms. Table 3 shows that the distribution of firms by dimension in our sample mirrors that of the population of Italian firms, which is characterized by a very large number of small firms.

Table 4 shows that the average markup is 7.6 percentage points for the whole sample and 7.4 for the Manufacturing-Business-Services sector; the medians are about 6 and 6.6 percentage points, respectively. Distribution-Food shows lower values. The huge difference between the revenue means and medians for the whole sample and the two subsamples is consistent with the fact that most Italian firms are very small sized. Figure 2 shows the downward trend in the average markup by year during the sample period, going from 8.2 to 7.2 percentage points. These values are similar to those reported in De Loecker et al. (2020) for the United States during the same period.

Table 5 reports the results of mean-difference tests which compare the firms in our sample with seized firms for which we have data. In the case of this latter group, average values refer to the years before the seizure orders. In terms of markup, we find no statistically significant differences if we consider all firms or only the firms in our subsets. This suggests that the seized firms are quite similar to those in our main sample in terms of profitability and avoids any suspicion that our results are driven by outperforming seized firms.[16]

The baseline empirical model to assess the response of markup to the demand and

[16]In the appendix, we report more information regarding our sample of firms.

supply shocks is:

$$\Pi_{i,m,g,t} = \beta S_{m,g,t} + \gamma D_{m,t} + \delta_i + \lambda_t + \varepsilon_{i,m,g,t} \tag{1}$$

where $\Pi_{i,m,g,t}$ is the markup (or total revenue) of firm i, located in municipality m, operating in sector g, during year t; $S_{m,g,t}$ is a binary treatment variable which takes the value of one if the Municipality×Sector×Year indicator identifies at least one episode of shutdown of production in municipality m, sector g, year t and zero otherwise; $D_{m,t}$ is a binary treatment variable for the municipality which in the first semester of year t entered compulsory administration status because of mafia infiltration in the city council; γ_i and λ_t are, respectively, firm-specific and time-specific fixed effects; $\varepsilon_{i,m,g,t}$ is an error term. We usually consider an extended version of the baseline specification allowing for lagged $S_{m,g,t}$ and lagged $D2_{m,t}$—the latter identifying municipalities that went into compulsory administration in any month during year t—to capture the delayed effects of the shocks.

Conditional on the controls, the Ordinary Least Square (OLS) estimator of β and γ can be interpreted as the difference in means of Π between the treated and untreated observations. If the error term is independent of S, then the parameter β identifies the causal average effect of softening the competition; similarly, if it is independent of D then γ identifies the causal average effect of a negative demand shock. Conventional inferences can be misleading in the case of serially correlated outcomes; we therefore base our inferences on standard errors robust to serial correlation at firm level (Bertrand et al., 2004).

Our empirical framework is characterized by staggered treatment timing with more than one episode of type-S treatment affecting a number of municipalities. In such situation, Goodman-Bacon (2021) shows that if treatment effects are heterogeneous then the OLS estimate of β could be sensible to the number of sample periods a given unit is in the treatment status. In fact, when already-treated units act as controls, changes in their treatment effects over time get subtracted from the single-coefficient estimate of the Difference-in-Differences effect.[17] To take into account this potential concern, we extend the sample with never-treated municipalities adjacent to the treated ones so to increase the number of control units.[18] Moreover, we also use a two-stage estimator where unit and period

[17]When the empirical model exploits variation across groups of units that receive treatment at different times, Goodman-Bacon's analysis shows that the OLS estimate of the treatment effect in a standard two-way fixed-effects regression is a weighted average of all possible two-by-two Difference-in-Differences estimators in the panel data. Already treated units serve as controls in some of these estimators. See also Callaway and Sant'Anna (2020) and Baker et al. (2021), among others, for the issue of staggered treatment timing.

[18]The presence of a large never-treated group reduces the potential for negative weights attached to the treated group (Jakiela, 2021).

fixed effects are determined in the first stage with the sample of untreated observations (Gardner, 2021). Finally, we investigate the possibility of heterogeneous treatment effects.

4 Empirical Evidence

Before discussing our main results, we provide some evidence based on pooling all economic sectors. Table 6 shows that our two shocks have opposite effects on revenue: as expected, the exit shock increases revenue while the demand shock depresses it (see the column 1). Adding lags and the interaction term only marginally changes these effects and their standard errors (see column 2). The coefficients of the lagged variables have the same sign as the corresponding impact coefficients and are statistically different from zero. However, while those related to the episodes of compulsory administration are virtually the same, suggesting a persistent negative effect of the demand shock, the value of the coefficient of lagged S is half that of the coefficient of S. The interaction coefficient is insignificantly different from zero, thus the effect is not magnified by the two shocks occurring simultaneously. Finally, in column 3 we take account of the staggered treatment by using the two-stage estimator with the enlarged sample. All point estimates are virtually the same and remain statistically significant. We consider that these results support our predictions. The increase in revenue is consistent with the idea that the S shock captures the demand shift in favor of firms that remain in the market. The fall in revenue after a city-council dismissal is in line with major cuts in public spending determined by the compulsory administration (Acconcia et al., 2014a).

Table 7 presents the results for markup. We estimate a strongly significant positive effect of the exit shock whatever the specification and estimation method adopted. By pooling all sectors together, we do not instead find a significant effect of the demand shock; anyway, we notice that the point estimate is negative as expected.[19]

4.1 Markup Adjustment at Local Level

Table 8 presents our basic evidence by sector. The column 'Core Sectors' reports results from pooling the two main groups of firms: estimates are qualitatively very similar to

[19]The results not reported here show that the firm's market share (by sales revenue) is affected positively by the S shock but is unresponsive to the D shock. Hence, a shock which increases the firm's revenues and market shares also enhances their profitability. Market share is computed considering the total revenues of all the sample firms operating in the same province$\times$industry.

those for the entire economy, that is, the supply shock has a positive effect on revenue and markup while the demand shock depresses the revenue with no noticeable effect on markup. However, the estimated coefficients and *t*-statistics increase; in particular, we note a positive and sizable change in the markup as a result of the exit shock which results in a rise in profitability of 0.4 percentage points, that is about 8 percent of the 2018 country mean. Moreover, it is confirmed that after one year the effect on revenue of both shocks persists while the effect of the exit shock on markup almost disappears. The interaction term suggests that when the shocks occur contemporaneously we observe no additional effect.

The rest of Table 8 reports the separate results for Manufacturing-Business-Services and Distribution-Food. The main difference with respect to the aggregate results is related to the demand shock: we estimate a statistically significant strong reduction in the average markup for the Manufacturing-Business-Services sector; the point estimate suggests lower markups by 0.814 percentage points, that is more than 10 percent of the country mean and median. In contrast, we estimate an insignificantly different from zero impact for Distribution-Food, the group of firms involved in stronger competition at local level. Finally, we find that—relative to the sample average—the supply shock has similar impact on markup across all sectors, and that all the coefficients of the revenue equation related to the demand shock are negative while those related to the supply shock are positive.

Arguably, the variations in markup could be associated to variations in the firm price elasticity of demand which is determined by the level of competition and the market elasticity of demand. Very high elasticities, as in the limiting case of perfect competition, imply that in equilibrium the price should be as close as possible to the marginal cost, preventing a reduction in the output price (and in the markup) without a corresponding reduction in the production cost. In this case, customers will be unlikely to budge much over the product price.

A primary benefit of differentiation is that it can make firm-level demand more inelastic, allowing firms to deviate from the cost-pricing rule. Therefore, while in principle increments in the markup are not constrained at least in the short run, a downward adjustment can apply only to differentiated products. To investigate this in our empirical model, we adapt the strategy in Giannetti et al. (2011) to split the Manufacturing-Business-Services sectors according to the types of goods produced, standardized or differentiated. Table 9 shows that if the firm supplies differentiated goods markups are affected by both of the shocks. The point estimates imply markups of about 8 percent higher for incumbent firms that benefit from the exit shock and of about 19 percent lower if affected by the drop in demand. Results reported in Table 10 for the enlarged sample and the two-stage estimator are virtually the same.

Taken together, the above evidence would suggest that: (i) when demand drops, markups adjust downward for firms with market power, otherwise they remain constant; (ii) a reduction in the number of firms, determining a reallocation of demand, pushes up markups, as predicted by imperfect competition models (e.g. the Cournot oligopoly): firms that benefit from the reallocation of demand find it profitable to set higher output prices.[20]

4.1.1 Evidence on Production Cost

Demand restrictions significantly reduce the revenue of firms horizontally differentiated and competing locally, without any effect on their markups. The coefficient capturing the impact effect of the demand shock on markup is estimated positive and insignificantly different from zero. One explanation is of course the downward stickiness of input and output prices. A different explanation, consistent with the decrease in revenue, is that both input and output prices drop in a way that prevents a relevant change in the markup. Table 11 provides evidence in that respect. When the total variable cost is the outcome variable of the empirical specification, it follows a strong negative effect of the demand restriction for the Distribution-Food. We do not find instead a similar result for Manufacturing-Business-Services, as the relevant coefficient is estimated insignificantly different from zero.

Workers of firms operating in the distribution sector as well as those of restaurants and hotels can be quite substitutable. Therefore, the strong competition of the local labor market implies that these firms are able to pass through to labor costs the depressive effect of the reduction in demand in such a way that the markup is preserved. When the empirical specification is estimated with the labor cost share replacing the total variable cost, we find again a strong negative effect of the demand shock only for the Distribution-Food. The relevant coefficient for Manufacturing-Business-Services is estimated positive, though only marginally statistically significant.

[20] The main evidence for the rest of economy comes from the financial sector where we estimate higher markups in the case of the demand shock, a result that mirrors the evidence on countercyclical margins on loans in the banking sector (for instance, Olivero, 2010; Cuciniello and Signoretti, 2015).

These results support the theoretical conjecture that, in sectors characterized by a low degree of vertical differentiation and homogeneous human capital of the workforce, a drop in the final demand causes a reduction in the revenue of the firms which in turn prompts a downward adjustment of the wage bill without any effect on the price-cost margin. When firms instead compete retaining market power thanks to product differentiation and skilled workforce, the drop in demand severely depresses the markup but not the wage bill. Actually, in this case the labor share increases.[21]

Table 12, first row, also makes more transparent what happens after a supply restriction. The spike in the markup we documented above comes with a reduction of the labor share, crosswise among sectors, without any effect on the level of the wage bill—the latter result is not reported. Hence, the reallocation of the final demand due to the sudden exit of the seized firms pushes upward the markups of the other firms that remain on the market, given that the increased labor supply prevents any concomitant upward wage pressure.[22]

4.2 Assessment of the Identification Assumption

The assumption for identification is that demand and supply contractions are exogenous conditional on the covariates included in the model. Potential threats to identification arise in case of differential trends—firms treated in a given period would not have followed the same trend of untreated firms if, counterfactually, no contraction in supply or demand had occurred—or differential shocks that affect markups and also the timing of the contraction shocks. For instance, our main estimates could be biased toward zero if demand contractions occur together with positive (differential) shocks to the firms, while supply contractions occur at time of profit drops. Since the markup can be observed for both treated and untreated firms before and after years of the shocks, the possibility of differential trends affecting our results can be evaluated by investigating the evolution of markup around the period of demand or supply contractions. Furthermore, when pre-event trends are parallel, potential differential shocks would have to be sudden in onset

[21] In principle, an *increase* in the production cost driven by the demand contraction could explain the rise in markup, even when the output prices remain constant. However, we discard this possibility that we consider quite unrealistic.

[22] Together with the trend in markups, much recent research also documents a decline in labor share (e.g., Karabarbounis and Neiman, 2013). As noted by De Loecker et al. (2020), profit maximization by individual firms implies that the labor share is inversely proportional to the markup. Our evidence is consistent with this prediction.

and also associated with council dismissals in case of markup fall, and with firm seizures in case of markup spike. This implies that at least some potential threats to identification are less compelling, as the timing of council dismissals and seizures are the quasi-random outcomes of secret police investigations.

To check the relevance of pre-event trends, we now provide a graphical evaluation of markup dynamics based on tools developed by Freyaldenhoven et al. (2021), given the following panel model:

$$\Pi_{i,t} = \delta_i + \lambda_t + q_{i,t}\,\psi + \sum_{s=-G}^{S} \gamma_s\, Z_{i,t-s} + \varepsilon_{i,t} \tag{2}$$

where $Z_{i,t}$ is either $S_{m,g,t}$ or the sum of $D_{m,t}$ and the lag of $D2_{m,t}$. The term $\sum_{s=-G}^{S} \gamma_s\, Z_{i,t-s}$ implies leads and lags around the time of the shocks to assess about the presence of trends before the shock and to capture delayed effects of the shock. The model also contains firm fixed effect, δ_i, calendar year fixed effect, λ_t, and a vector of further controls $q_{i,t}$ including the variable $S_{m,g,t}$ or $D_{m,t}$ and $D2_{m,t}$, depending on which shock we are investigating, and region$\times$industry trends to take into account potential local trends in markups. The coefficients of interest, γ_s, are normalized to 0 in $s = -1$, that is one year before the demand or supply contraction; hence, the assumption of no differential trends can be investigated by assessing whether $\gamma_s = 0$ for $s < -1$. Moreover, we also check whether the entire dynamic effects of a shock has been correctly contemplated by testing the null hypothesis that dynamics level off after S periods (Freyaldenhoven et al., 2021).

Multiple S-type shocks occur over different years in a number of municipalities and sectors, not allowing to label pre-event and post-event years unambiguously. Thus, we drop firms involved in such instances from the sample and use four leads to test for pre-event trends and up to seven lags. Each event-study plot will report estimates of the cumulative effects $\sum_{s=-4}^{k} \gamma_s$ at different horizons k.

Figure 3 refers to the event of a demand shock while Figure 4 to that of a supply shock.[23] Whatever shock considered, we do not find evidence of pre-event differential trends affecting treated units: Each pre-event coefficient is estimated insignificantly different from zero, thus supporting the causal interpretation of our results.

Regarding the effect of a shock, for Manufacturing-Business-Services firms it is confirmed the quite strong decline in markup caused by the demand contraction, whose effect

[23]The sample used is the enlarged one; however, similar evidence emerges with the restricted sample.

goes away after two years consistent with the duration of the council dismissal and the evidence reported in Acconcia et al. (2014a). Moreover, it is also confirmed the unresponsiveness of markup to a demand shock for Distribution-Food firms. A supply contraction tends to push up the markup. However, while the contraction determines a short lasting effect among the Manufacturing-Business-Services firms, it causes a gradual and persistent impact in the Distribution-Food sector.[24] Thus, the main message of the present analysis is that firms competing in a local environment benefit for quite much time of an event forcing firms to close or reduce their operations, while firms competing in a more global environment may benefit only for a while of such an event.

4.3 Heterogeneity of Markup Response

Recent studies have revealed the remarkable changes in the distributions of markups and market shares over the last decades. De Loecker et al. (2020) show that from 1980 onward the distribution of markups in the United States has become more skewed with a fat upper tail: The rise in the unweighted average markup is nearly exclusively attributable to markup increments for the firms with the highest markups already. At the same time, the substantial reallocation over time of market shares to high-markup firms drive the strong rise in revenue-weighted markups (Baqaee and Farhi, 2020b; De Loecker et al., 2020) and the emergence of the so-called superstar firms (Autor et al., 2020).[25]

Table 13 shows that markups increase heterogeneously in response to our reallocation shock. We extended the baseline empirical specification with the interaction between the lagged markup and the S dummy. The coefficient of the interaction term is estimated negative and with quite high precision: Markups increase more among firms with the lowest markups already—that is, in the year before the supply shock. In particular, when evaluated at the first quartile of the markup distribution, estimates imply that the reallocation shock determines higher markups by about 0.65 and 0.37 percentage points for Differentiated and Distribution-Food, respectively. The corresponding increments evaluated at the third quartile of the markup distribution are 0.42 and 0.17, respectively (see Figure 5). Qualitatively similar results hold if we interact the S dummy with the size of

[24]Notice that the bulk of the estimated effect for Distribution-Food is not related to average values of markups for treated units below those of untreated ones. A spike in markups after the supply-shock also emerges without controlling for firm-specific fixed effects.

[25]Two potential explanations for the rise of the superstar firms are that they reflect a reduction of competition due to a weakening of antitrust enforcement (Gutiérrez and Philippon, 2017b, 2018), or the market outcome of greater competition (Autor et al., 2020).

the firms, measured using the value of total assets. Therefore, our evidence suggests that less competition mainly affects the markup of smaller firms applying lower markups.[26]

Since markups adjust heterogeneously, one might expect that firms' revenues should move accordingly. To shed light on this possibility, we estimate the following empirical model

$$Revenue_{i,t} = \phi(S_{m,g,t} \times Markup_{i,t}) + \beta S_{m,g,t} + \gamma D_{m,t} + \psi Markup_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

where ϕ—attached to the interaction between $Markup$ and S—is the coefficient of interest. The sign of this coefficient provides guidance on the correlation between revenue and markup around their respective means, when they increase because of the reallocation shock.

Table 14 presents our results. As expected, the baseline correlation between revenue and markup, captured by the coefficient ψ, is estimated positive in either regression and significantly different from zero at the 5 percent level in case of Differentiated. For this group of firms, the coefficient ϕ is, instead, estimated negative and statistically significant, implying that higher increments—more than the average—of markup are associated with lower increments of revenue. Given the heterogeneous adjustment of markups, it follows that firms with higher (lower) markups react to the reallocation shock by raising relatively less (more) the markup which, in turn, implies larger (smaller) increments of revenues. Therefore, our evidence suggests a tendency of higher markup firms selling differentiated goods to increase their market shares after an increase in demand.[27]

We close our investigation about the reallocation shock by looking at the role of the number of firms in the market. A pretty standard economic argument suggests that the effect of this shock should reduce with the increase in the number of firms, as more firms imply greater competition. However, while theoretically clear, an empirical assessment of this relationship is questionable because it rests on the way the relevant market is determined. That said, we simply refer to the municipality to identify the relevant market

[26] The coefficient attached to the interaction between the dummy D and the lagged markup is estimated negative for each of the three samples considered. However, it is statistically different from zero—at the 10 percent significance level—only for the full sample (results not reported).

[27] For the sake of completeness, we also allowed for the interaction between markup and the demand shock, though the latter determines homogeneous effects on markup. The attached coefficient is indeed estimated insignificantly different from zero.

geographically.[28] Moreover, to proxy the degree of competition we use the number of firms in our sample or the total number of active firms in 2017, as recorded by ISTAT, in either case divided by the size of the municipality area. Results of the interaction between the proxy for competition and the dummy S are reported in Table 15 and Table 16. We find that the effect of the reallocation shock reduces with the density of firms in the market; it is quite precisely estimated for the Distribution-Food, that is the sector indeed characterized by local competition.

4.4 Aggregation and Cross-border Effects

To identify the effects of our shocks as accurately as possible, we estimated the regression model at the firm level and often restricted the sample to municipalities characterized by episodes of council dismissals and/or seizures. However, this does not allow us to capture potential spillovers across municipalities or sectors.

Spending variations in one municipality can affect economic activity in neighboring municipalities, through different channels. On the one hand, some of the contraction in demand in one municipality, generated by the compulsory administration, might be targeted at firms located in nearby areas, thereby driving down economic activity both within and outside the municipality suffering the spending cut. Moreover, the indirect effect of this contraction translates into lower levels of household spending, and may depress economic activity in other sectors than the sector targeted by the drop in public spending. On the other hand, it is possible that the reduction in local economic activity in the municipality under compulsory administration will translate into increased economic activity in nearby areas because the production factors relocate. In the case of this second type of spillover, the economic activity of two nearby areas would show a negative correlation. If these types of spillovers were empirically relevant, our estimates would miss part of the effects of spending innovation in a province.

The above evidence is based on the assumption that the land area of a municipality is a good proxy for the geographical market of the seized firm, an assumption which would appear quite realistic in the case of retailing, accommodation, restaurants and cafeterias. We now check for whether our estimates miss part of the supply shock due to the effect

[28] In particular, when the regression model is estimated with the entire sample of firms we identify the local market with the Municipality, while when the regression model is estimated restricting to Manufacturing-Business-Services or Distribution-Food firms, we identify it by means of the variable Municipality×Sector.

of the reduction in the number of firms which are felt across the borders of the municipal territory.

To analyze the cross-border effects, we consider the enlarged sample that includes municipalities adjacent to those directly associated with the shocks and aggregate *treated* and adjacent municipalities that belong to the same province by averaging the outcome variables and the main regressors across firms for any province×year. This accounts for the possibility that the effect of a local shock also reflects complementarity (as a result of demand leakages) or substitutability (as a result of high spatial mobility of the factors of production) across adjacent municipalities. Notice that, in doing so, we take account of the occurrence of multiple shocks in the same province. For comparison with previous results, we standardize the main regressors to the range 0-1.

The main evidence comes from the demand shock. The drop in revenue due to the contraction in demand is larger than before, supporting the conjecture that because of demand leakages and cumulative shocks the previous estimates fail to capture the overall effect of the contraction in demand. Accordingly, the drop in markup is now detectable even with the sample including the entire economy. Pooling Manufacture-Business-Services and Distribution-Food results in a drop in the markup of 0.94 percentage points which is about 11% of the sample average. The province-level effect of the exit shock is comparable to the previous municipality level estimate, as a result mainly of the large number of industries involved in seizure episodes. Figure 6 (based on the entire economy) summarizes the main evidence and suggests that a 10% reduction in revenue due to a demand shock is associated with roughly 4.5% reduction in the price; an equivalent increase in revenue due to a supply shock is associated with higher price by about 4.5%. If we consider the core sectors these figures become 6%.

To complete the analysis, in Table 18 we present the results for an extended sample that includes all the remaining Italian municipalities, and, as before, aggregating the firm data at the province level. The response of the markup to the supply shock is virtually the same as that estimated previously—that is, for the treated and adjacent municipalities—but the response to the demand shock is even stronger which is consistent with the presence of cross-border effects from the demand shock.

A simple back of the envelope calculation suggests that the province-level estimates are consistent with the public spending local multiplier estimated by Acconcia et al. (2014a) for a different period. The average contraction in spending in their group of provinces characterized by compulsory administrations amounted to about half a percentage point of the provincial value added. Under the assumption that the drop in profitability is a useful proxy for the drop in value added, then the estimate we obtained for the entire economy would suggest a value for the local multiplier of $0.63/0.46 = 1.35$. This value becomes 1.91 if estimates with all municipalities are considered.

5 Conclusions

Assessing the explanation for the movements in prices and profit margins over the business cycle is challenging mainly because these movements are usually the result of more than one driving force. In particular, during periods of economic slack markups may be affected by the direct effect of the drop in spending through the price elasticity of demand and also by the indirect effect determined by changes in the degree of competition due to the exit of firms. The empirical strategy adopted in this paper to investigate on these two effects exploits a panel data set of Italian firms and a quasi-experimental framework, in the vein of recent empirical contributions in macroeconomics (Fuchs-Schündeln and Hassan, 2016).

We point out to the possibility of price reduction as a consequence of a drop in demand (Nakamura and Steinsson, 2008) and thus to pro-cyclical movements of markups along the business cycle, in line with results by Stroebel and Vavra (2019), Anderson et al. (2020), and Nekarda and Ramey (2020). The estimated size of the markup reduction is statistically and economically significant mainly for manufacturing and business services differentiated products. It is quite negligible for distribution, hotels, and restaurants because of the reduction in the wage bill.

The shutdown of production due to firm seizures and the resulting reallocation of demand determines higher markups and higher revenues for differentiated products and for services supplied to the local market. In particular, firms with the lowest markups already increase more the markups while highest markup firms mainly gain in terms of market shares. The latter evidence is consistent with the rise of superstar firms as documented by Autor et al. (2020).

When episodes of seizures and council dismissals occur at the same time, how firms react to the changed environment is less clear. The main implication would be that during a downturn—when spending drops and companies go out of business—markups might exhibit drops or spikes depending which effect prevails. We can assume that this would apply also during an economic boom. Ultimately, only the well identified conditional cyclicality of the markup is useful to evaluate alternative business cycle models.

The focus on the local dimension of demand and supply variations implies that idiosyncratic shocks can at least in part explain the inflation differentials among areas of a country. The point estimates of the effects on revenues and markups suggest that such shocks have real effects, too.

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Appendices

A Definitions of Variables and Sources of Data

Sources of data:

- Agenzia Nazionale per l'Amministrazione e la Destinazione dei Beni Sequestrati e Confiscati alla criminalità organizzata (ANBSC)
- Ministero dell'Interno
- Analisi informatizzata delle aziende di capitale italiane (AIDA), Bureau van Dijk Electronic Publishing
- Istituto Nazionale di Statistica (ISTAT)

Main variables:

- *Markup* is earnings before interest, tax, depreciation and amortization—that is, the sum of Operating Income, Amortizations, Depreciations, and Write-downs—scaled by Revenue, times 100. The numerator and the denominator are measured at current prices. Source: AIDA.
- *Revenue* is total revenues due to sales of goods, services, and other revenues. It is measured in thousands of euros at current prices. Source: AIDA.
- D is a binary treatment variable identifying the demand shock. Any entry is determined by the Municipality$\times$Year$\times$Semester indicator whose value equals 1 if a given municipality entered compulsory administration status because of mafia infiltration in the city council in the first semester of the year. Source: Ministero dell'Interno.
- S is a binary treatment variable identifying the exit shock. Any entry is determined by the Municipality$\times$Sector$\times$Year indicator which is equal to 1 if a given municipality, sector, year is characterized by at least one seizure order, and 0 otherwise. Source: ANBSC.

- *D2* is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council. Source: Ministero dell'Interno.

Groups of Firms:

- Distribution-Food: Retail, Wholesale, and Vehicles Repair and Maintenance; Accommodation and Food and Beverages Activities; Social and Personal Services.
- Manufacturing-Business-Services: Manufacturing; Transport, Warehousing, and Related; Business Services.
  - Differentiated: Manufacture of basic pharmaceutical products and pharmaceutical preparations, Manufacture of rubber and plastic products, Manufacture of other non-metallic mineral products, Manufacture of fabricated metal products, except machinery and equipment, Manufacture of computer, electronic and optical products, Manufacture of electrical equipment, Manufacture of machinery and equipment n.e.c., Manufacture of motor vehicles, trailers and semi-trailers, Manufacture of other transport equipment, Other manufacturing, Land transport and transport via pipelines, Water transport, Air transport, Warehousing and support activities for transportation, Security and investigation activities, Office administrative, office support and other business support activities, Printing and reproduction of recorded media.
  - Standardized: Manufacture of food products, Manufacture of beverages, Manufacture of tobacco products, Manufacture of textiles, Manufacture of leather and related products, Manufacture of wood and of products of wood and cork, except furniture, Manufacture of articles of straw and plaiting materials, Manufacture of paper and paper products, Manufacture of coke and refined petroleum products, Manufacture of chemicals and chemical products, Manufacture of basic metals, Manufacture of furniture, Repair and installation of machinery and equipment.
- Rest of the Economy: Other Non-financial Services, Agriculture, Construction, Financial Services.

B Definition and Measurement of Markup

B.1 Measurement error

If c denotes marginal cost and p output price, the markup of price over marginal cost, expressed as a percentage of the price, is given by $\frac{p-c}{p} \times 100$. By assuming equality of marginal and average cost of production, the markup can be written as profit over revenue, $\frac{\Pi}{R}$. Given this expression, we rely on the directly observable gross margin of profit to get a proxy of the firm-level markup.

The equality assumption between marginal and average cost of production might introduce a measurement error in our markup measure. If marginal and average costs are different because of the fixed cost F, then a panel regression of the price-cost margin y on the explanatory variable x would result in

$$y_{i,t} = \alpha_i + \beta x_{i,t} + u_{i,t}$$

where $u_{i,t} = \eta_{i,t} + F_{i,t}$ and $\eta_{i,t}$ is the error term of the regression model without measurement error.

The main implication of the measurement error relates to the estimate of α_i—that is, the firm-specific fixed effect in our empirical analysis. If the mean of such error is different from zero, the OLS estimator of α_i would be biased, thus providing a misleading estimate of the time-invariant component of the markup.

More relevant for our analysis is, however, the relationship between the measurement error and the explanatory variable: if F is statistically independent of x, then the OLS estimator of β is unbiased. In our framework, this condition is satisfied as long as the yearly change in the fixed to total cost ratio is not correlated with the occurrences of council dismissals and firm seizures. Arguably, the latter restriction is pretty true. A larger error variance of the estimator of β might result, which implies the potential failure to reject the null hypothesis $\beta = 0$ when it is actually false, that is the Type II error in hypothesis testing.

B.2 Alternative Definition of Markup

The theoretical definition of markup we adopted—that is, percentage markup of price over marginal cost—is quite standard in Microeconomics (see, among others, Besanko and

Braeutigam, 2014). Alternatively, one may consider the ratio between price and marginal cost. Results in Table 19, obtained adopting such alternative definition, make clear that our main evidence is robust to the way markup is defined.

Table 1: Local Shocks

	Episode	Municipality	Population	Firm
Council Dismissal	107	97 (1.23%)	2.80%	2.04%
Seizure	1,829	424 (5.36%)	37.50%	41.60%

Note: Under the heading Episode, we report the number of episodes of council dismissals and seizure orders; under the heading Municipality, we report the number of municipalities involved in those episodes (in parentheses the percentage with respect to the number of Italian municipalities); under the heading Population, the total population as a percentage of the 2017 Italian population; under the heading Firm the total number of firms located in the municipality affected by the shocks as a percentage of the 2017 number of firms in Italy. The headquarter identifies the location of a firm. Time span is 2008-2018.

Table 2: Distribution of Firms by Sector (percent values)

	Basic sample	Enlarged sample
Manufacturing-Business-Services	25.89	31.49
Distribution-Food	38.94	37.07
Other	35.16	31.44
Total	100	100
Number of Firms	90,454	145,423

Note: The table reports the distribution of firms by sector in our restricted and full sample (year 2017). The basic sample refers to municipalities and sectors involved in episodes of council dismissals and/or seizures; the enlarged sample also contains municipalities adjacent to those directly associated with the shocks.

Table 3: Distribution of Firms by Dimension (percent values)

	Basic sample	Enlarged sample
Small	91.89	91.00
Medium	6.21	7.00
Big	1.90	2.00
Total	100	100
Number of Firms	90,454	145,423

Note: The table reports the distribution of firms by dimension in our restricted and full sample (year 2017). Small firms include firms with revenue lower that 10 million euros; Medium firms include firms with revenue between 10 and 50 million euros; Big firms include firms with revenue higher than 50 million euros. The basic sample refers to municipalities and sectors involved in episodes of council dismissals and/or seizures; the enlarged sample also contains municipalities adjacent to those directly associated with the shocks.

Table 4: Summary Statistics

	Mean	Median	S.D.
		All Sectors	
Markup	7.60	6.08	10.84
Revenue	7,894	776	183,163
Total Assets	8,953	750	360,526
Value Added	1,547	196	39,487
N	986,354	986,354	986,354
		Manufacturing-Business-Services	
Markup	7.38	6.54	9.30
Revenue	11,415	1,213	183,742
Total Assets	14,678	1,158	428,928
Value Added	2,531	353	23,480
N	255,731	255,731	255,731
		Distribution-Food	
Markup	6.00	4.87	9.37
Revenue	9,206	900	233,067
Total Assets	5,597	745	88,906
Value Added	1,008	174	12,263
N	384,467	384,467	384,467

Note: The table presents summary statistics (mean, median, standard deviation) of markup and revenue for the whole sample of firms operating in municipalities and sectors characterized by episodes of council dismissals and/or seizures. Markup is earnings before interest, taxes, depreciation and amortization, scaled by total revenue (times 100). Revenue is total revenue in thousands of euros. Time span is 2008-2018.

Table 5: Seized vs. Sample Firms

	All Sectors	Manufacturing-Business-Services	Distribution-Food
		Panel A: Markup	
Difference	2.030	1.258	0.086
	(1.81)	(0.56)	(0.05)
		Panel B: Revenue	
Difference	-4,702.861***	-10257.692	-6,031.231***
	(-4.58)	(-1.78)	(-6.08)
N	987,403	255,897	384,854

Note: The table presents results of mean-difference tests for the seized and sample firms, controlling for industry-specific fixed effect. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Time span is 2008-2018.

Table 6: The Response of Revenue to Demand and Exit Shocks

	(1)	(2)	(3)
S	585.039^{***}	749.779^{***}	668.155^{*}
	(2.68)	(2.59)	(1.75)
D	-316.795^{***}	-275.797^{***}	-200.281^{***}
	(-3.43)	(-3.55)	(-3.05)
L.S		370.313^{**}	327.231^{*}
		(2.56)	(1.86)
L.D2		-190.004^{*}	-224.766^{*}
		(-1.93)	(-1.77)
S*D		-435.859	-511.338
		(-1.27)	(-1.30)
N	986,354	893,035	1,437,505

Note: The results are related to regression equations where the left-hand side is the variable Revenues; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. Each regression also controls for firm-specific and time-specific fixed effects. In column 3 estimates are based on the sample containing also adjacent municipalities and the two-stage estimator only using untreated observations in the first stage. Standard errors are clustered by firm; the *t*-statistics (based on bootstrapped standard errors in column 3) are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: The Response of Markup to Demand and Exit Shocks

	(1)	(2)	(3)
S	0.174^{***}	0.238^{***}	0.328^{***}
	(5.83)	(7.41)	(10.50)
D	-0.114	-0.174	-0.167
	(-0.68)	(-0.94)	(-1.12)
L.S		0.033	0.061^{**}
		(1.16)	(2.42)
L.D2		0.597^{*}	0.608^{**}
		(1.84)	(1.99)
SD		-0.270	-0.254
		(-0.53)	(-0.53)
N	986,354	893,035	1,437,505

Note: The results are related to regression equations where the left-hand side is the variable Markups; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. Each regression also controls for firm-specific and time-specific fixed effects. In column 3 estimates are based on the sample containing also adjacent municipalities and the two-stage estimator only using untreated observations in the first stage. Standard errors are clustered by firm; the *t*-statistics (based on bootstrapped standard errors in column 3) are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Sector Breakdown

	Core Sectors		Manufacturing-Business-Services		Distribution-Food	
	Revenue	Markup	Revenue	Markup	Revenue	Markup
S	$1,149.634^{**}$	0.412^{***}	983.583^{***}	0.483^{***}	$1,131.581^{**}$	0.325^{***}
	(2.52)	(10.60)	(2.75)	(6.11)	(2.05)	(7.18)
D	-370.298^{***}	-0.300	-294.040^{*}	-0.814^{***}	-435.643^{***}	0.159
	(-3.55)	(-1.38)	(-1.83)	(-2.65)	(-3.39)	(0.52)
L.S	577.261^{***}	0.084^{**}	887.115^{**}	-0.034	469.072^{*}	0.095^{**}
	(2.70)	(2.41)	(2.11)	(-0.48)	(1.89)	(2.32)
L.D2	-149.935	0.643^{**}	-8.728	0.114	-250.276	0.944^{***}
	(-1.12)	(2.11)	(-0.06)	(0.18)	(-1.31)	(2.92)
S*D	-777.468	-0.330	-321.341	1.167	-797.725	-1.102
	(-1.36)	(-0.56)	(-0.96)	(1.36)	(-1.06)	(-1.47)
N	580,299	580,299	231,799	231,799	348,500	348,500

Note: The results are related to regression equations where the left-hand side is the variable Revenue or Markup; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. 'Core Sectors' consists of Manufacturing-Business-Services and Distribution-Food. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Standardized vs. Differentiated Products

	M-B-S Standardized		M-B-S Differentiated	
	Revenue	Markup	Revenue	Markup
S	$3,177.747^{***}$	0.251	805.004^{*}	0.604^{***}
	(3.46)	(1.28)	(1.74)	(6.63)
D	-601.160	-0.267	-260.708	-1.513^{***}
	(-1.61)	(-0.55)	(-1.33)	(-3.43)
L.S	$5,459.849^{*}$	-0.115	297.329	-0.055
	(1.65)	(-0.60)	(1.28)	(-0.67)
L.D2	-910.076	0.937	-106.796	-0.210
	(-1.09)	(0.61)	(-0.66)	(-0.28)
S*D	$-2,665.542^{***}$	-1.528	61.967	2.594^{**}
	(-2.90)	(-1.48)	(0.16)	(2.28)
N	48,779	48,779	159,882	159,882

Note: The results are related to regression equations where the left-hand side is the variable Revenues or Markups for the Manufacturing-Business-Services sector; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Sector Breakdown, Enlarged Sample

	M-B-S Differentiated		Distribution-Food	
	Revenue	Markup	Revenue	Markup
		Panel A		
S	644.987^{*}	0.757^{***}	$1,104.415^{*}$	0.367^{***}
	(1.69)	(8.34)	(1.90)	(8.26)
D	-246.359	-1.570^{***}	-352.980^{***}	0.140
	(-1.30)	(-3.55)	(-3.22)	(0.46)
L.S	229.126	-0.017	429.717^{*}	0.125^{***}
	(1.19)	(-0.21)	(1.73)	(3.10)
L.D2	-113.941	-0.253	-216.261	0.946^{***}
	(-0.74)	(-0.33)	(-1.28)	(2.92)
SD	11.379	2.525^{**}	-780.888	-1.116
	(0.03)	(2.23)	(-1.05)	(-1.49)
N	304,871	304,871	533,542	533,542
		Panel B		
S	730.606	0.758^{***}	$1,123.676^{*}$	0.380^{***}
	(1.47)	(7.80)	(1.68)	(7.76)
D	-231.960	-1.360^{***}	-292.953^{***}	0.118
	(-1.41)	(-3.88)	(-2.89)	(0.45)
L.S	308.153	-0.023	550.194^{*}	0.121^{***}
	(0.82)	(-0.29)	(1.72)	(3.38)
L.D2	-144.761	-0.235	-416.172	0.934^{***}
	(-0.83)	(-0.35)	(-1.36)	(3.21)
S*D	-151.085	2.496^{**}	-956.962	-1.019
	(-0.30)	(2.11)	(-1.19)	(-1.33)
N	304,871	304,871	533,504	533,504

Note: The results are related to regression equations where the left-hand side variable is Revenue or Markup; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. Estimates are based on the sample containing also adjacent municipalities. Panel B exploits the two-stage estimator only using untreated observations in the first stage. Standard errors are clustered by firm; the t-statistics (based on bootstrapped standard errors) are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effects on Variable cost

	Panel A			Panel B		
	All	M-B-S Differentiated	D-F	All	M-B-S Differentiated	D-F
S	668.250^{**}	790.507^{*}	$1,139.016^{**}$	623.497	708.379	$1,153.746^{*}$
	(2.52)	(1.75)	(2.03)	(1.59)	(1.42)	(1.68)
D	-256.603^{***}	-211.025	-427.365^{***}	-185.894^{***}	-189.588	-285.097^{***}
	(-3.51)	(-1.16)	(-3.34)	(-3.04)	(-1.24)	(-2.82)
L.S	309.949^{**}	246.233	460.142^{*}	310.283^{*}	244.836	554.815^{*}
	(2.49)	(1.09)	(1.86)	(1.75)	(0.64)	(1.72)
L.D2	-179.716^{*}	-102.859	-250.546	-215.460^{*}	-144.454	-429.572
	(-1.90)	(-0.70)	(-1.33)	(-1.67)	(-0.87)	(-1.39)
SD	-396.045	-44.261	-823.935	-480.252	-247.014	-993.504
	(-1.22)	(-0.12)	(-1.09)	(-1.18)	(-0.49)	(-1.21)
N	893,035	159,882	348,500	1,437,505	304,871	533,504

Note: The results are related to regression equations where the left-hand side is total variable cost; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. Panel A reports results obtained with the restricted sample; Panel B those obtained with the enlarged sample. In the latter case estimates are based on the two-stage estimator where untreated observations are used in the first stage. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics (based on bootstrapped standard errors in Panel B) are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Effects on Labor Share

	Panel A			Panel B		
	All	M-B-S Differentiated	D-F	All	M-B-S Differentiated	D-F
S	-0.268^{***}	-0.307^{***}	-0.222^{***}	-0.324^{***}	-0.340^{**}	-0.226^{***}
	(-7.18)	(-2.66)	(-5.23)	(-8.49)	(-2.56)	(-6.04)
D	-0.018	0.888^{*}	-0.730^{***}	0.000	0.820^{*}	-0.594^{***}
	(-0.08)	(1.74)	(-3.09)	(0.00)	(1.93)	(-4.73)
L.S	-0.026	0.005	-0.049	0.015	0.096	-0.001
	(-0.86)	(0.06)	(-1.41)	(0.64)	(1.22)	(-0.04)
L.D2	-0.277	-0.398	-0.485	-0.307	-0.506	-0.477
	(-0.69)	(-0.34)	(-1.38)	(-0.81)	(-0.65)	(-1.20)
S*D	-0.344	-0.604	0.634	-0.190	-0.309	0.690
	(-0.66)	(-0.33)	(1.39)	(-0.33)	(-0.19)	(1.56)
N	888,603	159,051	347,529	1,431,100	303,624	532,091

Note: The results are related to regression equations where the left-hand side is Labor Cost relative to total variable cost, times 100; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. Panel A reports results obtained with the restricted sample; Panel B those obtained with the enlarged sample. In the latter case estimates are based on the two-stage estimator where untreated observations are used in the first stage. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the *t*-statistics (based on bootstrapped standard errors in Panel B) are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Heterogeneity of Markup Adjustment

	All	M-B-S Differentiated	D-F
S	0.192^{***}	0.515^{***}	0.246^{***}
	(6.41)	(6.01)	(5.58)
S $\times$ L.Markup	-0.018^{***}	-0.026^{**}	-0.020^{***}
	(-4.47)	(-2.00)	(-2.98)
D	-0.222	-1.385^{***}	0.068
	(-1.23)	(-3.29)	(0.23)
L.S	0.011	-0.138^{*}	0.046
	(0.38)	(-1.74)	(1.16)
L.D2	0.491	-0.454	0.872^{***}
	(1.52)	(-0.58)	(2.80)
S$\times$D	-0.310	2.353^{**}	-1.024
	(-0.61)	(2.00)	(-1.36)
L.Markup	0.238^{***}	0.243^{***}	0.243^{***}
	(84.41)	(37.83)	(49.31)
N	893,035	159,882	348,500

Note: The results are related to regression equations where the left-hand side is Markup; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Revenue and Markup

	All	M-B-S Differentiated	D-F
Markup	9.218	28.914^{**}	16.467^{*}
	(1.12)	(2.07)	(1.85)
S × Markup	7.114	-97.687^{***}	-25.113
	(0.19)	(-2.62)	(-0.78)
N	893,035	159,882	348,500

Note: The left-hand side is Revenue; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. Each regression also contains the dummy D, the dummy $D2$, the dummy $D \times S$ as well as firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the *t*-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Number of Firms in the Market, A

	All	M-B-S Differentiated	D-F
S	0.419^{***}	0.815^{***}	0.472^{***}
	(8.68)	(5.46)	(7.00)
S $\times$ No. of Firms	-0.703^{***}	-5.271^{*}	-1.808^{***}
	(-5.04)	(-1.79)	(-3.02)
D	-0.170	-1.512^{***}	0.165
	(-0.92)	(-3.42)	(0.54)
L.S	0.033	-0.025	0.086^{**}
	(1.16)	(-0.30)	(2.11)
L.D2	0.578^{*}	-0.240	0.932^{***}
	(1.78)	(-0.31)	(2.88)
S$\times$D	-0.434	2.415^{**}	-1.236^{*}
	(-0.86)	(2.12)	(-1.65)
N	893,035	159,882	348,500

Note: The results are related to regression equations when the left-hand side is Markup; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. No. of firms refers to the sample number of firms at Municipality level when the entire sample is considered and at Municipality$\times$Sector level for Differentiated and Distribution-Food sub-samples. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Number of Firms in the Market, B

	All	M-B-S Differentiated	D-F
S	0.441^{***}	0.806^{***}	0.481^{***}
	(8.52)	(5.20)	(6.51)
S $\times$ No. of Firms	-0.0439^{***}	-0.468	-0.104^{***}
	(-5.06)	(-1.61)	(-2.80)
D	-0.169	-1.512^{***}	0.165
	(-0.92)	(-3.42)	(0.54)
L.S	0.0319	-0.0278	0.0841^{**}
	(1.11)	(-0.33)	(2.05)
L.D2	0.577^{*}	-0.239	0.932^{***}
	(1.78)	(-0.31)	(2.88)
S$\times$D	-0.445	2.422^{**}	-1.225
	(-0.88)	(2.12)	(-1.63)
N	893,035	159,882	348,500

Note: The results are related to regression equations when the left-hand side is Markup; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. No. of firms refers to the total number of firms (as recorded by ISTAT) at Municipality level when the entire sample is considered and at Municipality$\times$Sector level for Differentiated and Distribution-Food sub-samples. Each regression also controls for firm-specific and time-specific fixed effects. Standard errors are clustered by firm; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Allowing for Spillovers

	All Economy		Core Sectors	
	Revenue	Markup	Revenue	Markup
S-prov	834.386^{*}	0.529^{***}	$1,419.523^{**}$	0.856^{***}
	(1.93)	(3.01)	(2.00)	(5.23)
D-prov	-994.482^{**}	-0.626^{**}	$-1,368.944^{*}$	-0.940^{***}
	(-2.14)	(-2.60)	(-1.75)	(-2.93)
L.S-prov	101.545	0.147	484.352	0.151
	(0.47)	(0.88)	(0.95)	(0.90)
L.D2-prov	-680.423	-0.256	$-1,158.449^{*}$	-0.321
	(-1.24)	(-1.63)	(-1.87)	(-1.65)
S×D-prov	632.060	0.436^{*}	745.591	0.336^{**}
	(1.46)	(1.85)	(1.48)	(2.08)
N	980	980	980	980

Note: For each year, firm-level observations relative to outcome variables and regressors are aggregated by averaging over treated and adjacent municipalities of the same province. Definitions of S, D, and $D2$ are the same as before; the suffix 'prov' denotes province-level average of the corresponding firm-level regressor. 'Core Sectors' consists of Manufacturing-Business-Services and Distribution-Food. Each regression also controls for province-specific and time-specific fixed effects. Standard errors are clustered by province; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Allowing for Spillovers, all Municipalities

	All Economy		Core Sectors	
	Revenue	Markup	Revenue	Markup
S-prov	674.165^{***}	0.692^{***}	992.411^{***}	0.932^{***}
	(3.14)	(4.48)	(2.80)	(6.86)
D-prov	-817.442^{*}	-0.880^{***}	$-1,223.206$	-1.114^{***}
	(-1.75)	(-3.13)	(-1.48)	(-3.12)
L.S-prov	67.019	0.177	116.261	0.156
	(0.39)	(1.22)	(0.25)	(1.02)
L.D2-prov	-518.559	-0.410^{*}	-928.538^{*}	-0.473^{***}
	(-1.26)	(-1.91)	(-1.86)	(-3.24)
S×D-prov	357.406	0.511^{**}	492.328	0.365^{**}
	(1.26)	(1.99)	(1.27)	(2.45)
N	1,070	1,070	1,070	1,070

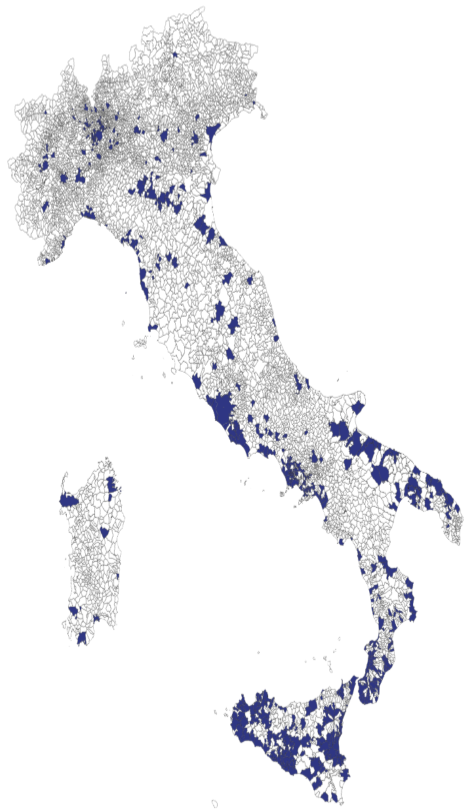
Note: For each year, firm-level observations relative to outcome variables and regressors are aggregated by averaging over all municipalities of the same province. Definitions of S, D, and $D2$ are the same as before; the suffix 'prov' denotes province-level average of the corresponding firm-level regressor. 'Core Sectors' consists of Manufacturing-Business-Services and Distribution-Food. Each regression also controls for province-specific and time-specific fixed effects. Standard errors are clustered by province; the t-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Alternative Definition of Markup

	All	M-B-S Differentiated	D-F
S	0.368*	0.798***	0.245**
	(1.73)	(4.16)	(2.00)
D	-0.836***	-2.726***	-0.348
	(-2.62)	(-3.11)	(-0.65)
L.S	0.321*	0.002	0.436**
	(1.83)	(0.01)	(2.22)
L.D2	1.679	-0.537	1.121**
	(1.30)	(-0.50)	(2.32)
SD	34.375	3.601**	69.176
	(1.01)	(2.42)	(1.00)
N	893,035	159,882	348,500

Note: The results are related to regression equations where the left-hand side is the empirical counterpart of the ratio between price and marginal cost; D is a binary treatment variable identifying the municipality that in the first semester of a given year entered compulsory administration status because of mafia infiltration in the city council; $D2$ is a binary treatment variable identifying the municipality that in a given year entered compulsory administration status because of mafia infiltration in the city council; S is a binary treatment variable identifying the group of firms operating in a given sector and located in a given municipality where at least one firm has been confiscated. M-B-S stands for Manufacturing-Business-Services, D-F for Distribution-Food. Standard errors are clustered by firm; the *t*-statistics are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Distribution of Supply and Demand Shocks, 2008-2018

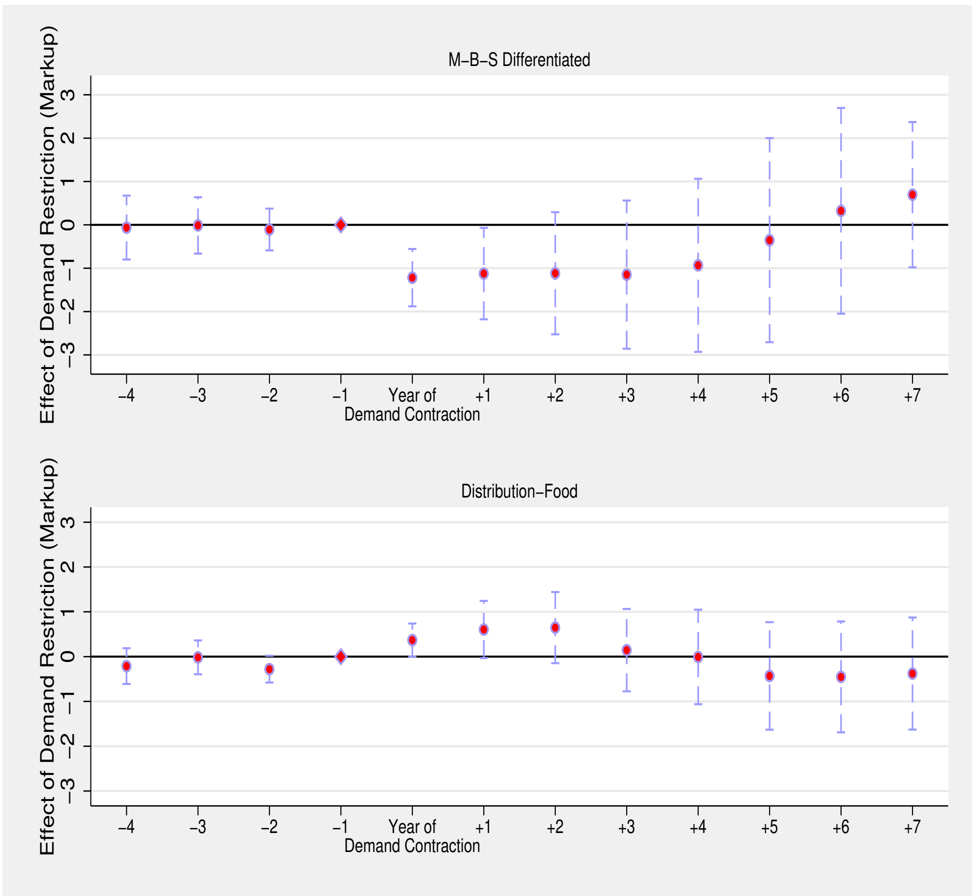


Note: The figure highlights the municipalities affected by at least one episode of firm seizure or compulsory administration during 2008-2018.

Figure 2: Evolution of Average Markups

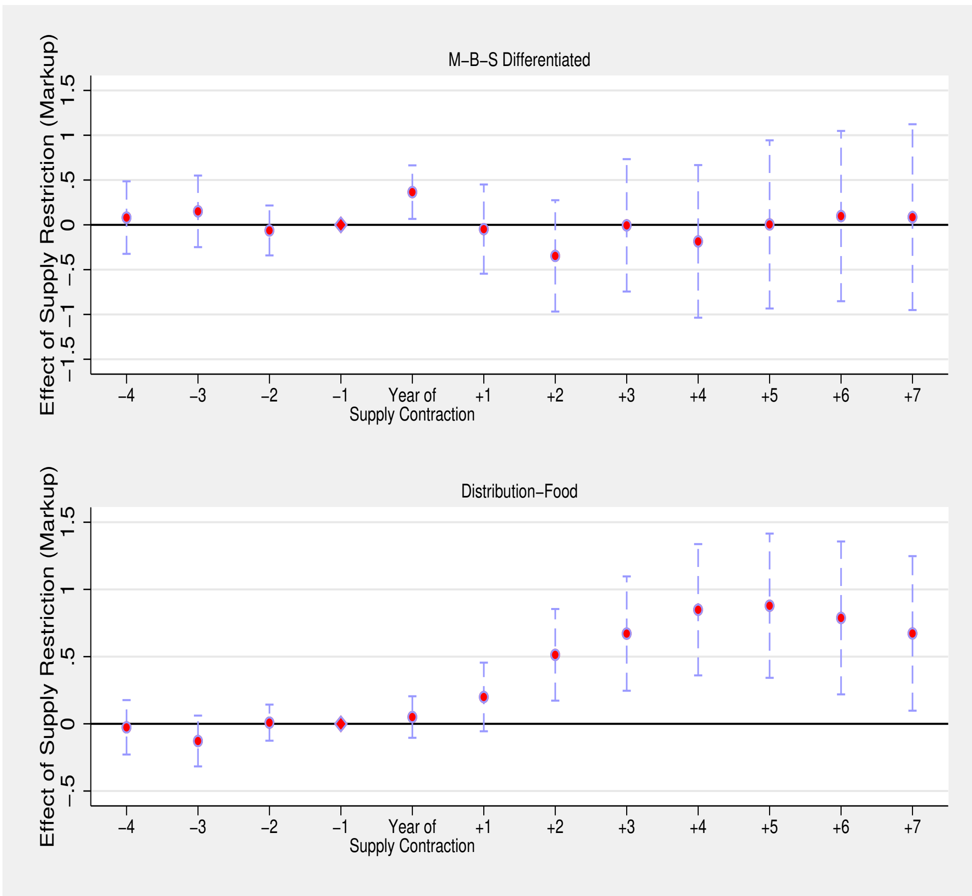
Note: The figure presents the evolution of the average markups and weighted average markups in the sample, across the economy, over time (2008 - 2018), where weights are based on market share of revenues by municipality.

Figure 3: Event Study Plot, Demand Shock



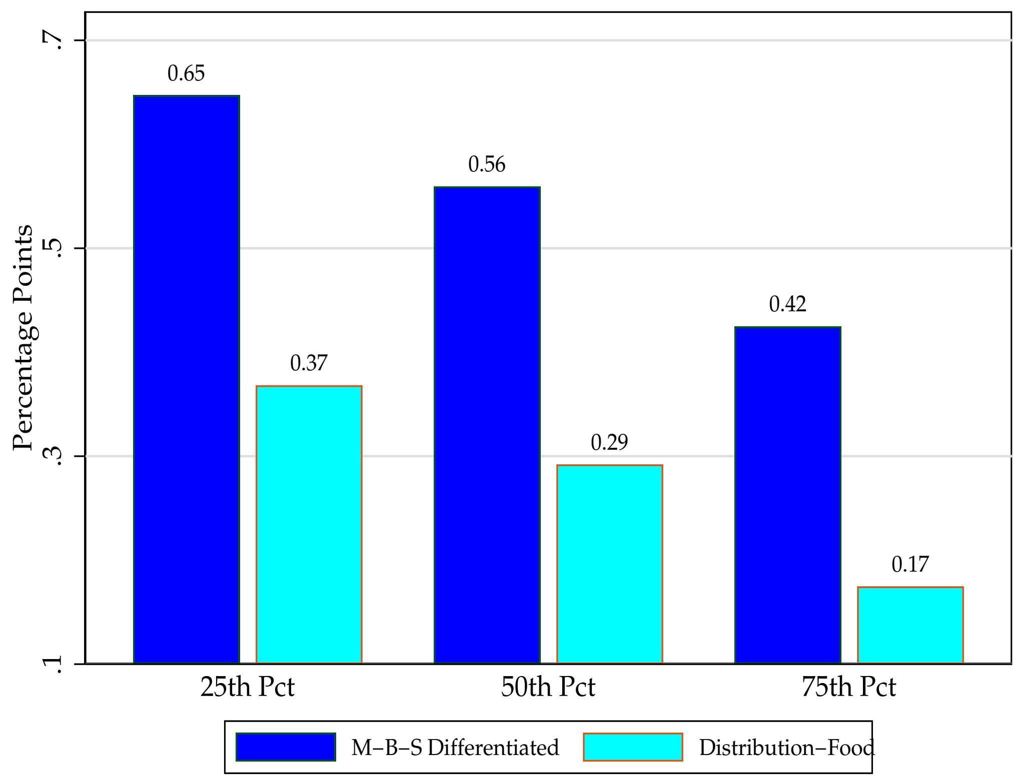
Note: The figure shows cumulative regression coefficients and associated confidence intervals relative to a demand contraction, i.e., the $\sum_{s=-4}^{k} \gamma_s$ from empirical model in (2) in case of a demand shock. The coefficient in $s = -1$ is normalized to zero. The dashed vertical lines denote 90% confidence intervals based on standard errors that are clustered at the firm level.

Figure 4: Event Study Plot, Supply Shock



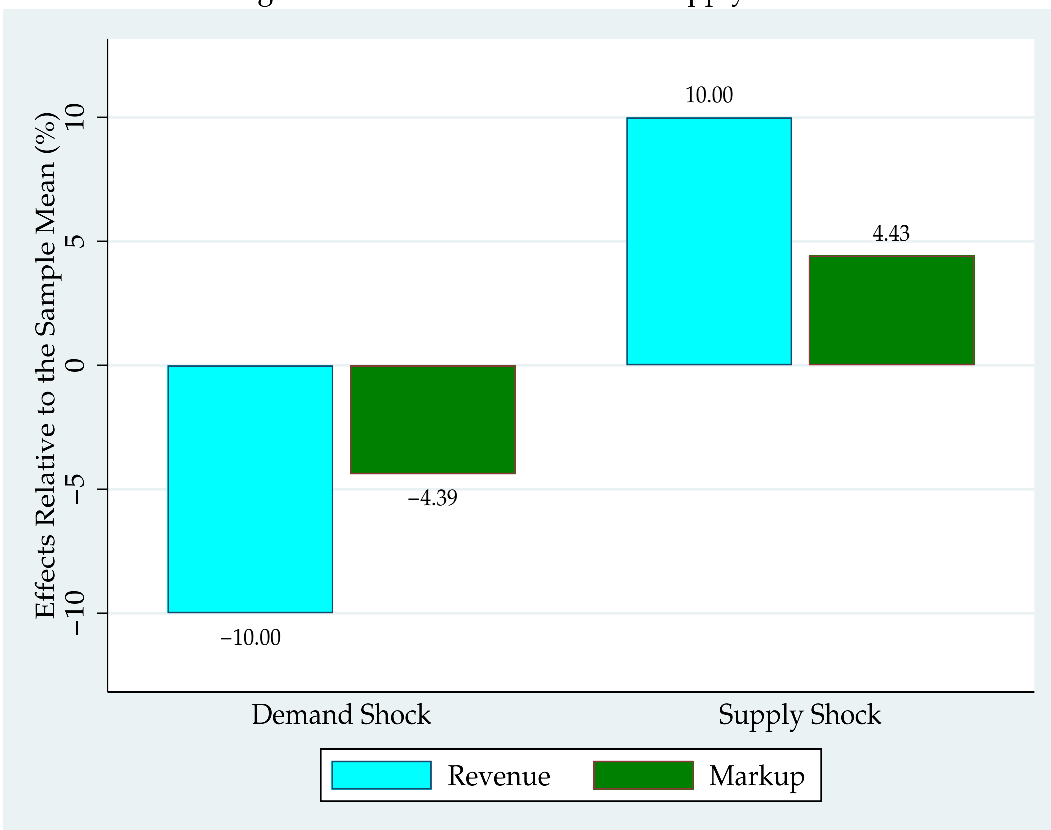
Note: The figure shows cumulative regression coefficients and associated confidence intervals relative to a supply contraction, i.e., the $\sum_{s=-4}^{k} \gamma_s$ from empirical model in (2) in case of a supply shock. The coefficient in $s = -1$ is normalized to zero. The dashed vertical lines denote 90% confidence intervals based on standard errors that are clustered at the firm level.

Figure 5: Effect of Supply Shock by Markup



Note: The figure presents the effect of the supply shock by percentiles of the Markup distribution before the shock.

Figure 6: Effects of Demand and Supply Shock



Note: The figure presents the effects of the two shocks—Table 17, All Economy—relative to the sample means.