Natural Disasters and Markups

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Abstract

Can firm-level markup adjustments affect the aggregate cost of large, localized shocks? Using firm-level data from Italy, we show that natural disasters lead to a persistent decline in markups among affected manufacturing firms, especially for high-productivity ones. We implement an oligopolistic competition model with idiosyncratic shocks directly on firm-level data and invert it to recover productivity for firms impacted by the 2012 Northern Italy earthquake. We then quantify how markup adjustments shape aggregate manufacturing productivity and welfare. Our baseline results suggest that markup changes amplified the aggregate productivity and welfare losses of the earthquake by approximately 20%.

Keywords: Natural Disasters, Markups, Oligopolistic Competition, Aggregate Productivity, Misallocation, Firm Heterogeneity

JEL classifications: D22, D43, L13, O47, Q54

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1 Introduction

Industries are not perfectly geographically concentrated (Ellison and Glaeser, 1997). As a result, local shocks —such as natural disasters, civil unrest or regional supply chain disruptions —can impair the production capacity of affected firms and shift market shares toward competitors in unaffected areas. The extent of this reallocation —and its consequences for aggregate productivity and welfare —depends crucially on the presence of markup dispersion (Baqaee and Farhi, 2020), a persistent feature even within narrowly defined industries (De Loecker et al., 2020). Crucially, if firms adjust their markups in response, this may dampen the reallocation of market shares. In turn, the aggregate implications hinge on *whether* and *which* firms adjust.

In this paper, we focus on large and localized natural disasters and provide causal evidence on how firms' markups adjust in the aftermath of these events. On the one hand, surviving affected firms' markups might increase if natural disasters lead to higher fixed costs, exit of firms, and less competition. On the other hand, their markups might decrease if the price elasticity of demand they face rises. We find that Italian (and French) firms —particularly the more productive ones —decrease their markups following a natural disaster. Moreover, we assess the macroeconomic implications of these adjustments. We quantify the role played by markup adjustments in shaping the aggregate effects of natural disasters, using an oligopolistic macroeconomic model calibrated to Italian micro data and focusing on the 2012 earthquake.

To explore the markup response following a disaster, we use Italian micro data on the universe of manufacturing firms over 2005-2019 and focus on large catastrophic natural events such as earthquakes and floods. The identification of treated firms hinges on precisely delineating affected areas. We base this process on official documents, which cleanly highlight impacted locations. Using this classification, we then define treated firms as those operating within these identified areas. To address challenges in estimating firm-level markups without price-level data, we use a cost-share approach (Syverson, 2004).[1]

We provide evidence on the dynamics of markup adjustments following natural disasters employing an event-study approach (Sun and Abraham, 2021). We find that the markups of affected firms decrease persistently relative to those of unaffected firms. Four years after being hit by a natural disaster, firms charge markups that are approximately one percentage point lower than before the event. However,

[1] See Bond et al. (2021) and De Ridder et al. (2022). Moreover, differences in labor-augmenting productivity can cause markup estimates to vary depending on the type of flexible input used (Raval, 2023b). For this reason, we further account for non-neutral technological differences by using the flexible cost-share estimator proposed by Raval (2023a).

the impact varies across treated firms. Initially more productive firms experience a relatively larger markup decrease, around 1.5 percentage points, while less productive firms do not adjust their markups significantly. These results highlight the heterogeneity in firms' natural disaster pass-through. Notably, the result remains robust when weather-related events (such as floods and storms) are analyzed separately from other disasters like earthquakes.

Some potential confounders may affect our findings, which we address through distinct robustness exercises. First, the control group may be contaminated, as unaffected competitors may also adjust their markups through strategic complementarities. We address this concern by removing more direct competitors of affected firms from the control group. One might also worry that the control group may include firms that are treated indirectly through supply linkages. We account for this by excluding from the control group the direct clients and suppliers of treated firms, identified using the 2019 cross-section of the Italian domestic business-to-business transactions database, firms located within a given radius of treated firms or within the same commuting zone. We also show that other unobserved factors do not influence our findings through simulated placebos. Furthermore, our results are robust to controlling for industry-province shocks, to using alternative markup measures or control groups, and are not driven by the costliest event over the period. Interestingly, although our data do not allow us to fully disentangle the underlying channel, we find that firms located closer to the epicenter of the 2012 earthquake experienced a larger drop in markups compared to those farther away. This finding is arguably consistent with a decline in productive capacity, as further evidenced by corresponding drops in their value added and sales. Finally, to reinforce the external validity of our results, we use Orbis data for France and find that more productive French firms affected by disasters also experience a larger markup decrease, with a magnitude comparable to that observed in Italy.

To rationalize our empirical findings, we rely on a static oligopoly model with endogenous markups (Atkeson and Burstein, 2008; Burstein et al., 2025), which accounts for the possibility that untreated firms also adjust their markups —a point we discuss in the empirical section. In particular, natural disasters enter as an idiosyncratic destruction rate proportionally reducing firms' technical efficiency, as in Barrot and Sauvagnat (2016). In this framework, we show that natural disasters affecting a subset of firms in the industry unambiguously drive down affected firms' markups. Moreover, affected firms that are initially more productive drive this result. This is because firms' markups are increasing in their market shares: when firms' productive capacity is impaired by a disaster, they experience an increase in their marginal costs, lose market shares and thus adjust their markups accordingly.[2]

[2]This result, as we show, is neither a consequence of our modelling choice of disasters as output

This is consistent with firms being hit by a disaster facing a different price elasticity of demand post-shock and permanently decreasing their markups.

How then does the endogenous response of markups affect the transmission of natural disasters to aggregate productivity and welfare? Natural disasters turn out to have ambiguous effects on sectoral productivity. In particular, the direct decrease in technical efficiency induced by disasters may be amplified or dampened by two forces: market share reallocations across firms and markup changes.[3] First, as the economy is inefficient due to markup dispersion across firms, natural disasters may reallocate market shares across firms, from affected to unaffected ones. For instance, a flood affecting less productive firms in an industry may increase that industry's productivity by reallocating market shares of the affected fringe to more productive producers. Second, changes in the distribution of market shares trigger markup responses which, in equilibrium, end up affecting the strength of the market share reallocation effect —since affected firms decrease their markups to retain part of their market shares. Moreover, with elastic labor supply, the aggregate markup level changes following a natural disaster —driven by both market share reallocations and markup adjustments —and acts as a distortionary tax, reducing output relative to its efficient level. Overall, the model highlights that the aggregate effects of natural disasters depend on the set of firms and industries affected.

We quantify the importance of markup adjustments in shaping the aggregate effects of natural disasters as follows. We ask how much aggregate productivity and welfare would change if the economy transitioned from an initial equilibrium to a new equilibrium with decreased technical efficiency induced by disasters, both with and without firm-level markup changes. To do so, we apply the model directly to firm-level data. In other words, firms in the model correspond *one-to-one* to real firms in Italy. We invert the model to recover firm-level productivity from the distribution of firm-level market shares and markups, after having estimated the two main demand elasticities from the empirical relationship between firm-level markups and market shares. This approach allows us to use the actual geographic distribution of firms to simulate the impact of natural disasters and perform our counterfactual analyses without relying on assumptions about the productivity distribution for hypothetical firms.

We use this laboratory to study the contribution of markup adjustments following the 2012 Italian earthquake and hypothetical catastrophic floods in the flood-prone Po river basin. We find that markup adjustments amplified the loss of the earthquake on aggregate productivity by 18%. In terms of aggregate welfare, markup

destruction rates nor of the market structure.

[3] Ex-ante markup heterogeneity is a necessary condition for natural disasters to have ambiguous effects on industry productivity. This ensures that the initial allocation is inefficient and that firms respond to idiosyncratic shocks by adjusting their markups.

adjustments would have amplified the loss by 25%. This is because markup adjustments hinder the reallocation of market shares toward more productive firms as the reduction of markups allows disaster-struck firms to partly retain their market shares. We also conduct various robustness exercises, including varying the magnitude of the shock. Across these specifications, we continue to find similar qualitative effects, with the amplification effect ranging from 8% to 23%. Finally, our preferred calibration suggests that markup adjustments could amplify the aggregate productivity and welfare losses of catastrophic floods in Northern Italy by approximately 11% and 14%, respectively.

Firms' markup adjustments can act either as a stabilizer or an amplifier in response to natural disasters. The direction and magnitude of this channel depend critically on which firms are affected.

Related literature. Our paper contributes to three strands of literature. First, we contribute to the literature on the economic consequences of natural disasters and on firms' adaptation mechanisms. Recent studies investigate the effect of disasters on performance at the micro level (Cavallo et al., 2014; Fatica et al., 2022; Bas and Paunov, 2025; Caggese et al., 2024; Erda, 2024),[4] most notably shedding light on the prominent role played by supply chain linkages (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). Recent work —such as Castro-Vincenzi (2022), Balboni et al. (2023) and Castro-Vincenzi et al. (2024) —studies firms' sourcing or location strategies following floods. Our contribution is to show that firms' markups adjust after being affected by a natural disaster and, at the same time, that this margin of adjustment has sizable macroeconomic implications.

We also build on a growing literature studying the importance of granular shocks in inefficient economies (Baqaee and Farhi, 2020; Baqaee et al., 2024; Burstein et al., 2025). These papers show that, when the initial allocation of resources is inefficient, idiosyncratic shocks may generate reallocations across firms which affect economic aggregates. By focusing empirically on a particular type of idiosyncratic shock —natural disasters —we contribute to these studies by uncovering a previously overlooked dimension of markup changes. Moreover, as emphasized in this literature and in our work, the aggregate consequences on microeconomic shocks depend on the set of affected firms and industries. Following the insight of Brooks et al. (2021) who assessed the impact of industrial clusters in China, we show how the seminal model of Atkeson and Burstein (2008) can be applied directly to firm-level data to study the macroeconomic impact of natural disasters.

Finally, our article contributes to the literature on shock pass-through and markup

[4] Earlier papers have focused on the macroeconomic effects of natural disasters using aggregate data (Noy, 2009; Raddatz, 2009; Strobl, 2012; Cavallo et al., 2013).

adjustments (Berman et al., 2012; Chatterjee et al., 2013; Burstein and Gopinath, 2014; Edmond et al., 2015; Auer and Schoenle, 2016; Amiti et al., 2019; Gaubert and Itskhoki, 2021; Edmond et al., 2023; Alviarez et al., 2023).[5] We add to this literature by quantifying the importance of changes in markups stemming from granular shocks on aggregate productivity and welfare.

The rest of the paper is organized as follows. Section 2 presents our data while Section 3 describes our identification strategy and our empirical results. In Section 4, we introduce the model. Section 5 introduces our quantitative results and Section 6 concludes.

2 Data and markup measurement

2.1 Firm-level data

We use a dataset comprising the universe of Italian limited liability companies, which are provided by CERVED through the registry of the Italian Chambers of Commerce.[6] The data are widely used in studies on the business structures of Italian companies (e.g., Akgicit et al., 2023). Our main focus is on Italian manufacturing firms between 2005 and 2019. For these firms, the coverage of Cerved is close to 80 percent in terms of gross output.

Each observation in the dataset is uniquely identified by a combination of the year and the firm's tax identification number. Besides this information, CERVED contains relevant information such as the value of the firm's total assets, fixed assets, sales, turnover, value added, expenditures on intermediate inputs, main industry of activity, incorporation date, and postcode. For the data cleaning, we follow the procedure described by Kalemli-Özcan et al. (2024), which largely applies to our data. In particular, we drop observations with non-positive or missing labor costs, turnover, costs of goods sold, and tangible fixed assets. Moreover, we exclude outliers in terms of turnover growth rates —those in the bottom and top 1% of turnover growth rates.

We also provide results for French firms using Orbis data from Moody's. We focus on the same time period (2005 to 2019) and select firms in the manufacturing

[5]Our framework abstracts away from vertical linkages and focuses on the effects of disasters on reallocations across firms within the same industry. Grassi (2017), however, is an important example of a model of oligopolistic competition featuring input-output linkages. More recently, Dhyne et al. (2022) document and quantify the importance of buyer-supplier markups, using Belgian data.

[6]Limited liability companies, together with cooperatives, consortia, and other subjects provided by the law must deposit their approved balance sheets in the registry held by the chambers of commerce. For additional information on the CERVED database see Abbate et al. (2017). CERVED is one of the Italian information providers of underlying Orbis, a global database of balance sheet maintained by Moody's.

sector. Since a single entity in Orbis —identified by its internal identifier —can submit multiple balance sheets in a given year, we prioritize unconsolidated accounts over consolidated ones. Unconsolidated accounts more accurately reflect firms' local activities without the potential distortions that may arise from consolidating balance sheets with those of other firms within the group, which possibly operate elsewhere. Observations in our Orbis sample are also defined at the firm-year level. In terms of data cleaning, we follow the procedure suggested by Kalemli-Özcan et al. (2024), consistently with that applied for the case of Italy.

2.2 Natural disaster data

As outlined in Appendix A, we rely on EM-DAT (Delforge et al., 2025) to identify the most impactful natural disasters in Italy and France. While EM-DAT provides a general overview of affected areas, its geographic precision is insufficient for identifying specific areas and firms affected. To address this, we refine the data by identifying affected locations at the postcode level using official reports that we manually collected. This approach allows us to isolate the hardest-hit areas for each disaster. Leveraging this detailed geographic information, we classify firms as treated if their registered address falls within an affected postcode.

We focus on large events, i.e., disasters with estimated damages above US$ 250 mn.[7] From this set, we exclude disasters such as droughts and extreme temperatures, which typically span weeks or even months. Finally, we also exclude wildfires as they typically occur in forests, which are generally characterized by low business density. Table 1 summarizes the events considered in Italy over the time period. The 2012 Northern Italy earthquake is the costliest event.[8]

In general, we define affected areas at the postcode level. This choice allows us to easily match affected postcodes with firms located there. Figure 1a and Figure 1b show postcode areas affected by a natural disaster and the distribution of firms by postcode respectively. In the period, disasters affected several areas of the country, with some of them hitting areas with a high concentration of firms and economic activities (e.g., Emilia-Romagna and Veneto in the north of the country).

2.3 Measuring markups

We now detail how we recover firm-level markups using our production data.[9]

[7] This value is adjusted for inflation. For the considered period, the median estimated damage is US$ 243 million.

[8] Table A2 shows the corresponding table for France and reports the costly events for which we could identify affected postcodes.

[9] See Basu (2019); Berry et al. (2019); Syverson (2019) for important discussions on markup measurement.

Table 1: Costly Natural Disasters in Italy, 2005–2019

Event	Year	Estimated Damage ($ mn)	Regions Affected
Earthquake	2009	3,410	Abruzzo
Storm	2010	1,170	Veneto
Flood	2011	709	Liguria, Tuscany
Earthquake	2012	20,140	Emilia-Romagna, Lombardy
Flood	2013	980	Sardinia
Flood	2014	375	Liguria
Flood	2014	363	Lazio
Earthquake	2016	6,097	Abruzzo, Lazio, Marche, Umbria

Notes: This table describes the natural disasters included in the sample. The list is restricted to natural disasters in Italy from 2005 to 2019 with total estimated direct damages above $250 million in 2021 constant dollars, for which we can identify the affected postcodes. Estimated damages are expressed in millions.

We rely on the seminal work of De Loecker and Warzynski (2012) for this task. The main advantage of this method is that it does not require imposing strong parametric assumptions about market structure or demand. Denoting firms by i and years by t, the formula for firm-level markups μ_{it} is given by —see Appendix B:

$$\mu_{it} = \frac{\beta_{it}^{x}}{\alpha_{it}^{x}} \tag{1}$$

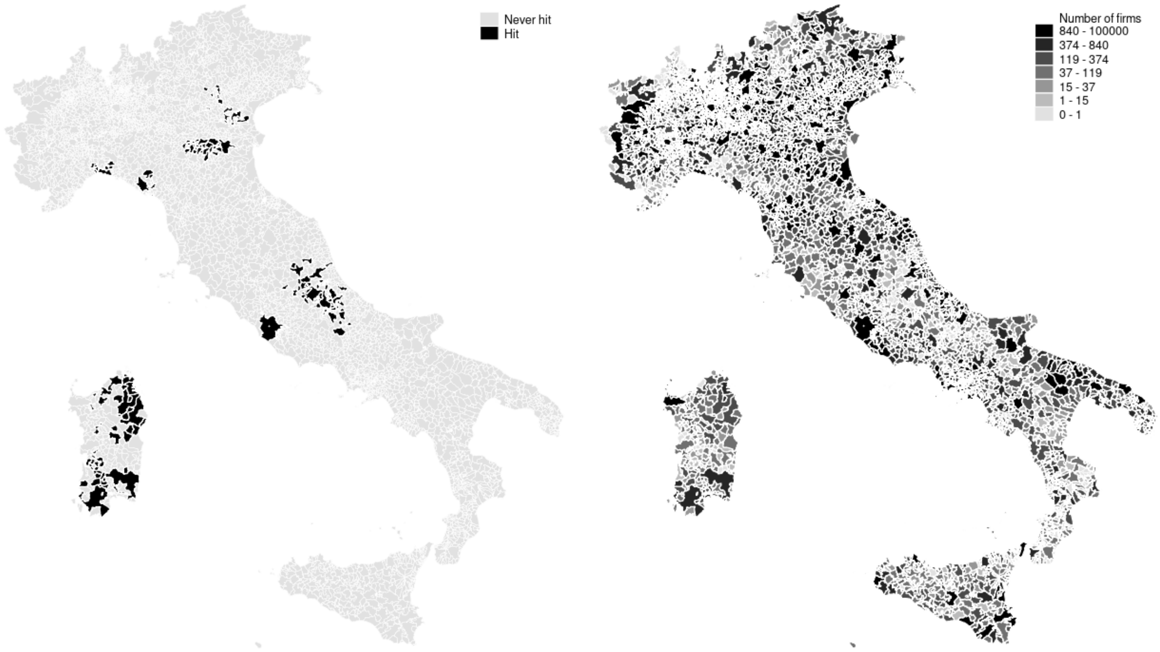
where β_{it}^{x} is the output elasticity of a flexible input x and the denominator is that input's revenue share, i.e. expenditures on that input over firm-level turnover. The idea is that markups drive a wedge between the output elasticity of any flexible input x_{it} and that input's share in total revenue. For a given input's output elasticity, a decrease in its revenue share must drive up markups.

As is now well understood, "only" two pieces of information are required: the output elasticity of a flexible input and the revenue share of that input. While the latter is readily available in our data as well as in most firm-level datasets, the former requires taking a stance on the production function. Most of the work therefore consists of recovering an estimate of the input's output elasticity.

We circumvent the issue of estimating production functions without data on prices recently raised by Bond et al. (2021) —and further explored by De Ridder et al. (2022) —and instead rely on the cost-share approach of Syverson (2004) and Foster et al. (2008).[10] For our baseline results, we use materials as the flexible input. Moreover, because non-neutral technological differences may affect output elasticities across firms and yield different markup estimates depending on the type of flex-

[10]With only revenue data and with firms having market power, profit maximization implies that the output elasticity is not identified from estimating the revenue production function (Bond et al., 2021).

Figure 1: Disaster Location and Firm Location



(a) Affected postcodes (b) Firms by postcode

Notes: This map presents the postcode areas affected by disasters in Table 1 (panel (a)) and firms by postcode area (panel (b)) in Italy. For large municipalities (e.g., Rome, Milan, Naples), only the general postcode is available. Hence, in panel (a) the map for Rome does not accurately reflect the affected areas as only few sub-municipal postcodes were affected by the 2014 flood.

ible input used (Raval, 2023b), we use Raval (2023a)'s cost share estimator, detailed in Appendix B. His estimator is obtained by grouping firms into bins, depending on their observed labor to materials cost ratio, thus accounting for differences in labor augmenting productivity across firms. We then recover output elasticities as input cost shares within each bin. Our output elasticities thus vary at the 5-digit industry-quintile level. We show in robustness checks that our results are robust to using alternative output elasticities and alternative measures of markups.[11]

3 Empirical analysis

This section describes the identification strategy used to assess the impact of natural disasters on firm-level markups and reports our results.

[11]For France, due to data limitation in Orbis (missing values for the cost of materials for a large number of observations), we use the cost of goods sold as the flexible input, similarly to Díez et al. (2021).

3.1 Identification strategy

Our analysis compares firms headquartered in disaster-struck areas with untreated firms, i.e., firms located in unaffected postcodes. Unfortunately, we do not have data at the establishment level. In addition, we lack information on fiscal policies and financial support provided by local governments to firms following a natural disaster, as well as information on firm-level inventories. This lack of information, however, arguably does not undermine our identification strategy; if anything, it is likely to bias the results against finding any effects on firm-level outcomes.

Moreover, while understanding the precise channels through which natural disasters affect firm-level markups may be relevant, we lack the information needed to determine whether these effects arise from disruptions in transport infrastructure, in electric power infrastructure or in productive capital (such as buildings and machinery), fatalities, or other factors. However, we confirm that these events lead to a decrease in firm-level value-added and sales, which is consistent with some of the factors mentioned above.

3.1.1 Characteristics of disaster-area firms

Table 2 reports the mean and the standard deviation of some salient characteristics of treated firms the year before the treatment and for untreated firms between 2005-2019 in Italy. In total, our data for Italy comprise more than 1.3 million observations.[12] The difference between treated firms before the treatment and the control group —as captured by the normalized differences between the means (Imbens and Wooldridge, 2009) —appears to be small, which supports our assumption that treated and untreated firms do not exhibit systematic differences before a natural disaster occurs.[13]

3.1.2 Event study

In order to assess the empirical effects of natural disasters on markups, we use an event study approach and estimate the following specification:

$$\log \mu_{i(s)t} = \sum_{\substack{\tau=-11 \\ \tau\neq-1}}^{10} \delta_\tau \times \mathbb{1}\Big(\text{Disaster}\Big)_{i(s),t-\tau} + \alpha_{i(s)} + \gamma_{st} + \varepsilon_{i(s)t} \tag{2}$$

[12]Table A1 reports some summary statistics for the main variables used in the empirical analysis for Italy.

[13]Differences are below 0.25 in absolute value, which is a threshold frequently used in the literature (Imbens and Wooldridge, 2009; Stuart, 2010).

Table 2: Pre-Disaster Characteristics of Treated and Control Group Firms

	Mean (T)	Mean (C)	Norm. Diff.	Std. Dev.
Markup (ln)	0.062	0.074	0.047	0.266
Turnover (ln)	7.475	7.419	0.038	1.468
Value added (ln)	6.218	6.195	0.016	1.384
Labor (ln)	2.373	2.361	0.010	1.187
Assets (ln)	5.344	5.350	−0.003	2.010
Labor productivity (ln)	3.836	3.811	0.041	0.605
Firms	3,668	149,172		

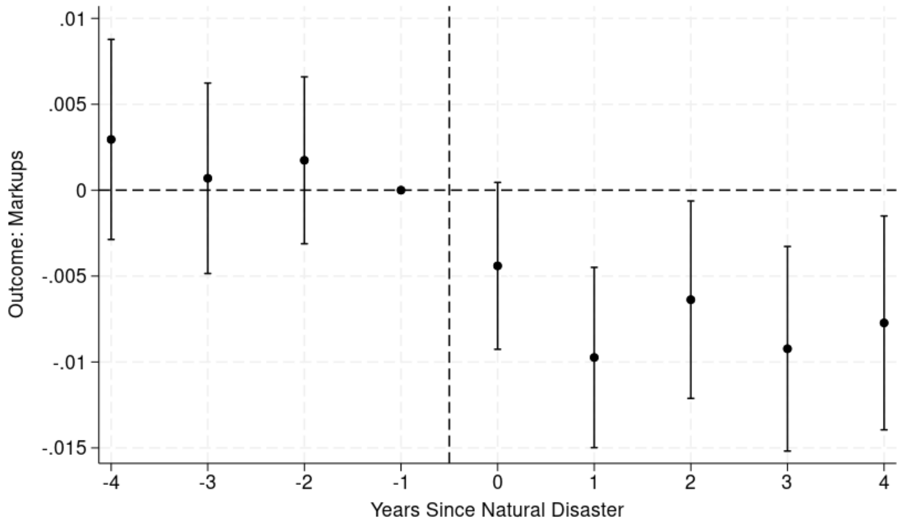
Notes: The table shows averages of selected firm-level variables for the group of firms affected by a natural disaster before the disaster (T) and for those unaffected (C) in our sample. Normalized differences are defined as in Imbens and Wooldridge (2009).

where $\mu_{i(s)t}$ represents the markup of firm i in sector s at time t, $\mathbb{1}\Big(\text{Disaster}\Big)_{i(s),t-\tau}$ is an indicator function equal to 1 if firm i is hit by a natural disaster in year t. δ_τ is the coefficient associated with the $|\tau|$-th lead, if $\tau < 0$, and with the τ-th lag, if $\tau \geq 0$, and all years are included. We choose the year before the natural disaster as the omitted reference period. We account for unobserved firm heterogeneity through the inclusion of firm fixed effects $\alpha_i(s)$, while γ_{st} are 5-digit industry-year fixed effects, which control for demand and supply shocks occurring at this granular level. These fixed effects do not absorb the output elasticities in the numerator of our markup measure, as these elasticities are defined at the 5-digit industry–productivity-quintile level, as detailed above.[14] Standard errors are clustered at the firm level. Moreover, to account for the fact that standard two-way fixed effects specifications may lead to biased leads and lags coefficients, we rely on Sun and Abraham (2021)'s estimator, which consists of using our very large group of untreated firms as the control group.

As standard in the literature on the empirical effects of natural disasters on firm-level outcomes (Barrot and Sauvagnat, 2016; Carvalho et al., 2021), the underlying assumption is that natural disasters hitting firms are homogeneous, i.e., our event study coefficients are common across firms. This restriction is due to data limitations as we do not have establishment-level information within firms. However, we consider an alternative specification which helps us explore the heterogeneous *response* of firms to natural disasters, based on their distance from the sectoral productivity frontier. We use labor productivity (real value added per worker) as our metric for this distance and define a firm as more productive if, before any disaster, its average labor productivity is above the median labor productivity of its 2-digit

[14]Using markups in levels instead leaves the results virtually unchanged. Results available upon request.

Figure 2: Natural Disasters and Markups



Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

sector —classifying it as a high-productivity firm in the aggregate (Aghion et al., 2024).

$$\log \mu_{i(s)t} = \sum_{\substack{\tau=-11 \\ \tau\neq-1}}^{10} \delta_\tau \times \mathbb{1}\Big(\text{Disaster}\Big)_{i(s),t-\tau} + \sum_{\substack{\tau=-11 \\ \tau\neq-1}}^{10} \delta^L_\tau \times \mathbb{1}\Big(\text{Disaster}\Big)_{i(s),t-\tau} \times \mathbb{1}\Big(\text{Productive}\Big)_{i(s)} + \alpha_{i(s)} + \gamma_{st} + \varepsilon_{i(s)t} \tag{3}$$

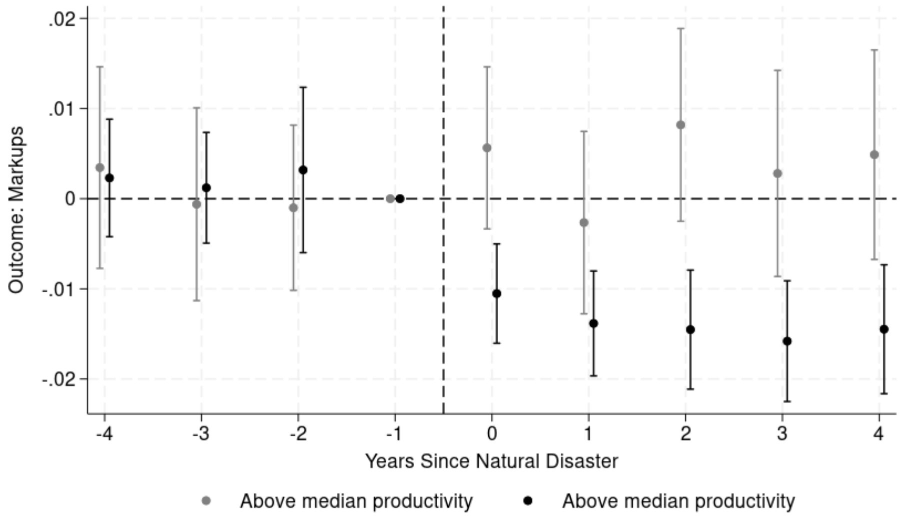
where δ^L_τ represents the differential coefficient for more productive firms while δ_τ is the coefficient for less productive firms.

Finally, we address in robustness checks the possibility that the control group may be contaminated through supply chain linkages or through strategic complementarities.

3.2 Natural disasters and markups

How do natural disasters impact firm-level markups of affected firms? The results from estimating Equation (2) are shown in Figure 2. We do not find any significant coefficients before the treatment, indicating no evidence of pre-event trends. We

Figure 3: Natural Disasters and Markups across Firms



Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019 by size. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry–year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included.

find that the effect of a natural disaster is negative and persistent, as the coefficients are almost all significant at the 5% level after the event. Firm-level markups drop by approximately 1 percentage point and the effect remains significant four years after the disaster. The effect is large: since the average markup in our sample is close to 7%, markups drop by about 14% following a natural disaster. One possible explanation for the relatively long-lasting effect is the presence of product market frictions which affect firms' customer base and the ability to price above marginal costs, rendering the adjustment sluggish (Gourio and Rudanko, 2014). Another potential explanation is that firms experience a persistent increase in their marginal costs, making firms face a higher price elasticity of demand and charge lower markups for a few years. While we cannot disentangle these channels given the available data, our static model generates a decrease in markups following a natural disaster because the price elasticity of demand of firms affected increases (Section 4).

Next, we evaluate whether natural disasters affect firms differently depending on their initial productivity. Figure 3 shows that only high-productivity firms adjust their markup following a natural disaster. We find that more productive firms' markups decrease by approximately 1.5 percentage points and the effect is persistent after four years. Instead, the change in markups for less productive firms is not significantly different from zero. This finding supports the idea that less productive firms operate with narrower operating margins, leaving little room for adjusting their markups.

This result complements the findings of the literature looking at the effects of natural disasters on firm performance. For instance, Cavallo et al. (2014) do not find effects of natural disasters on prices for retailers in Chile and Japan. While we focus on manufacturing and do not have data on prices, our results suggest that affected firms, especially more productive ones, may exhibit muted price responses. Indeed, these firms are able to decrease their markups relatively more under extreme circumstances. Moreover, Figure A1 and Figure A2 show that the result —that more productive firms adjust their markups more than less productive ones —holds when considering weather- and climate-related events (such as floods and storms) and other types of events (such as earthquakes) separately. Overall, this suggests that markup adjustments may be at play following any large, geographically concentrated natural disaster.

Finally, note that if labor were used as the flexible input, firm-level markups would be related to firm-level labor shares. In that case, and with some abuse of notation, the denominator in Equation (1) would reflect the ratio of labor costs to sales instead of value added. Hence, the observed decline in firm-level markups may simply be the by-product of increasing labor shares. Such a pattern could arise if labor adjustment costs prevent firms from optimally reducing employment after a negative sales shock —causing value added to fall more than labor costs. While we cannot definitively determine whether markup changes are a control variable for firms, using materials as the flexible input helps attenuate this direct empirical link to labor shares. Moreover, we find that low-productivity firms do not adjust their markups relative to the control group —despite having labor shares below one. If the adjustment-cost channel were driving the results, we would expect their labor shares and thus markups to respond as well. This suggests that the observed markup changes are not merely a by-product of changing labor shares.[15]

3.3 Robustness tests

Strategic complementarities. As seen in Section 3.2, firms decrease their markup after being affected by natural disasters. A potential problem is that unaffected firms in the same industry can in turn adjust their own markup to take advantage of

[15]Theoretically, firm-level labor shares are inversely related to firm-level markups in a wide class of models of imperfect competition (Edmond et al., 2015; Autor et al., 2020; Panon, 2022). In these papers, changes in labor shares are typically interpreted as reflecting changes in markups. An exception is Autor et al. (2017), who consider constant markups and fixed overhead labor costs. In their model, a negative productivity shock would raise a firm's labor share because fixed labor costs become a larger fraction of value added. However, this mechanism rules out variable markups —contrary to our empirical finding of declining markups. Overall, this suggests that natural disasters may lead to endogenous adjustments in markups, which in turn affect labor shares.

the reduced competitive pressure exerted by the treated firms. Hence, our estimate of the markup adjustment following a natural disaster can incorporate not only the adjustment of firms in the affected postcodes but also that of firms in unaffected areas.

To account for this possibility, we consider two different definitions of the relevant market and remove competing firms from the control group. In the first one, we consider a narrower market definition and eliminate from the control group firms operating in the same 5-digit sector and province (Figure A3). In the second one, we eliminate other firms in the same 5-digit industry from the control (Figure A4) and instead consider 2-digit sector times year fixed effects. Results are in line with the main specifications presented in Section 3.2: more productive firms decrease their markup when they are hit by a natural disaster.

Network. Shock transmission from treated to untreated firms through their production network may represent a potential concern threatening the accuracy of our estimates. While we cannot directly take into account the network of suppliers and customers of treated and untreated firms because we lack the needed data over our entire time period, we tackle these concerns through a set of robustness exercises. First, we exclude firms that are domestic suppliers or buyers of treated firms in 2019 from the control group as they can be indirectly affected by the shock through their buyers or suppliers (Figure A5).[16] Moreover, we exclude firms located within some radius from affected locations. The rationale behind this is that firms tend to trade more extensively with firms located nearby in line with a gravity model of trade (Arkolakis et al., 2023). Second, we exclude firms belonging to affected commuting zones from the control group. Focusing on commuting zones allows us to eliminate untreated firms belonging to the same industrial and production districts, refining the concept of plain geographical distance of the previous robustness check. The results of such analyses are presented in Figures A6 to A8 (exclusion from the control group of untreated firms within a 25 km, 100 km, 250 km radius from treated postcodes), and Figure A9 (exclusion of untreated firms in commuting zones with treated postcodes). Results are aligned with those presented in Section 3.2.

Placebos. Another potential concern is that the drop in markups following a natural disaster may be driven by some unobserved factor not accounted for in our specification and not driven by the natural disaster *per se*. To address this issue, we reassign the treatment randomly and without replacement to firms in our sam-

[16] Since 2019, Italian firms are obliged to issue electronic invoices for their transactions. These data, available at the quarterly level in 2019, contain information on the buyer, seller, and the value of the transaction.

ple and estimate Equation (2) on each synthetic sample. If some factor other than the natural disasters included in our sample drives our main result, we should observe a negative trend in the distribution of the estimated coefficients. However, Figure A10 shows that the distribution of coefficients does not match the results presented in Figure 2.

Distance from the 2012 earthquake. We test an alternative definition of treatment status based on the distance of a firm's headquarters from the disaster. Specifically, we focus on the May 2012 Northern Earthquake that struck Emilia-Romagna. The earthquake had a magnitude of 5.8, with its epicenter located near the municipality of Finale Emilia in the province of Modena.[17] Under this alternative definition, we classify a firm as treated if its headquarters fall within the bottom 50% of the distance distribution from the epicenter. Even using this alternative definition of the treated group, Figure A11 shows that the results are consistent with those discussed in Section 3.2.

Selection of disasters. One potential issue within our empirical setting is the presence of multiple events of different magnitudes (see also Table 1). In particular, our results may be driven solely by the costliest event. To address this, we consider Equation (3) and remove the 2012 Earthquake in Emilia-Romagna, whose estimated damages exceeded USD 20 bn —more than three times the damages of the next most impactful event. If our results were driven solely by the most catastrophic event, we should find a dampening of the effect of natural disasters on markups. Figure A12 shows that this does not appear to be the case.

Selection of control group. In the main specification in Section 3.2, we pool productive and less productive firms and find that the effects on markups is negative and significant only for the former. We also present the results for the regression performed only on less productive firms and more productive ones separately. The results are consistent with our main findings (Figure 3). More productive treated firms decrease their markup following a natural disaster relative to more productive untreated firms (Figure A13). Moreover, we do not find any significant differences between the markups of treated and untreated unproductive firms after a natural disaster (Figure A14) .

Alternative definition of high-productivity firms. In our main specification exploring the heterogeneous response of firms, high-productivity firms are defined

[17]The geographic coordinates of the epicenter are (44.8955, 11.2635) at 10 km depth (https://terremoti.ingv.it/en/event/772691).

as those with labor productivity above the median within their 2-digit sector. As a robustness check, we explore an alternative definition of productivity, classifying productive firms as those whose labor productivity exceeds the median within their 5-digit sector. Figure A15 shows that our results remain robust under this alternative definition.

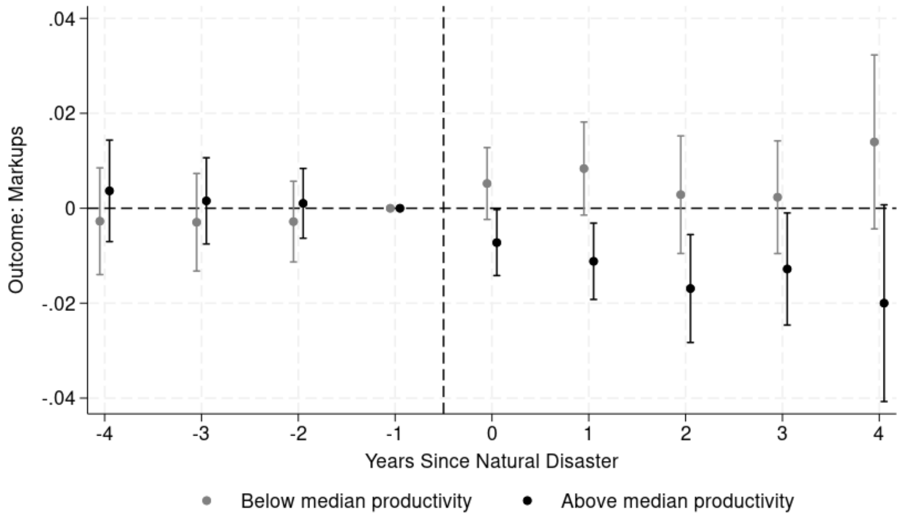
Unobserved local shocks. One may be concerned that markup changes are partially driven by unobserved local shocks correlated with natural disasters that could affect firms' pricing decisions (perhaps due to place-based financial support). To account for this possibility, we consider an alternative specification to Equation (3) where we include province-industry-year fixed effects instead of industry-year fixed effects. Figure A16 shows that the estimated coefficients are close to those in Section 3.2, indicating that our results do not seem to be driven by unobserved local factors.

Output elasticities. The cost-share approach that we rely on assumes constant returns to scale. However, one could allow for some degree of decreasing returns to scale by scaling up the output elasticity (see Appendix B). Having decreasing returns to scale would not change our coefficients as returns to scale are absorbed by our set of fixed effects (industry-year level).

Moreover, our baseline output elasticities are assumed to be constant over time. Since the technology of the firm could change after a natural disaster, we relax this assumption and allow the output elasticities to vary over time across 5-digit industry-quintiles. The results remain robust to this alternative specification (Figure A17). Finally, factor price differences across firms may also lead us to incorrectly adjust for non-neutral technological differences (see Appendix B). Because factor prices are more likely to be similar across firms within a given location, we assign firms with similar labor-to-material cost ratios to different quintile-location groups. Thus, output elasticities are defined at the 5-digit industry-province-quintile level. Our results are robust to this alternative definition of output elasticities (Figure A18).

Alternative measures of markups. We test the robustness of the results to using alternative measures of markups. Figure A19 shows that using labor as a flexible input —after having applied Raval (2023a)'s correction —yields similar results. If anything, high-productivity firms charge even lower markups four years after having been hit by a natural disaster. In Figure A20, we do no correct for non-neutral productivity differences using materials as the flexible input. The results are robust to this specification although the point estimates for more productive firms are slightly smaller in absolute value. Finally, in Figure A21, we follow Antras et al.

Figure 4: Natural Disasters and Markups across French Firms



Notes: The figure reports the effect of natural disasters on French firms' markups between 2005-2019 by size. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry–year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included.

(2017) and define markups as the ratio of turnover to total cost. The results are qualitatively unchanged and remain significant.

3.4 Additional results

Other measures of firm performance. We start by showing that firm-level value-added and sales drop following a natural disaster. As shown in Figure A22 and Figure A23, these two variables decrease by 3% to 4% on impact and the effect is persistent.[18] Natural disasters thus have a negative impact on firm performance, confirming prior findings in the literature (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Fatica et al., 2022). Interestingly, Figure A24 shows that affected firms increase their investment in tangible assets only in the year following a natural disaster. This may reflect efforts to recover from the decline in their economic activity, which would be consistent with recent evidence by Erda (2024). In addition, we find no significant effect of natural disasters on the probability of firm exit, as shown in Table A3.

[18]The persistence of the effects of natural disasters on firms' activities (e.g., fixed assets, sales, productivity) has also been documented in other recent papers (e.g., Fatica et al., 2022; Pelli et al., 2023).

Effect on French firms. We use EM-DAT, Orbis and the publicly available database GASPAR to identify which of the 35,000 French municipalities were affected by natural disasters. Figure 4 shows how natural disasters in France affect firm-level markups of less productive and more productive firms. The message is the same as in Figure 3: four years after having been affected by a natural disaster, high-productivity firms charge markups that are 2 percentage points smaller. This result provides reassuring evidence that our results are not specific to Italy. In that sense, our results are more closely related to Bas and Paunov (2025) who find that Ecuadorian firms affected by excess rainfall caused by El Niño decrease their markups. The response of Italian and French firms' markups to natural disasters suggests that this margin of adjustment is not specific to emerging markets and also operates in economically developed economies.

4 Explaining markup adjustments

To provide intuition about how natural disasters affect firm-level markups and to quantify their aggregate effects, we consider a static oligopolistic competition model with endogenous markups (Atkeson and Burstein, 2008; Burstein et al., 2025). This model has the advantage of capturing strategic complementarities, allowing firms to respond to competitors' cost shocks (Amiti et al., 2019). We model natural disasters as an output destruction rate —a fraction κ_i of firm i's output is destroyed when it is affected by a natural disaster. This assumption is general enough and helps us derive how natural disasters affect *aggregate* outcomes in the clearest way while having an intuitive interpretation.[19]

For the sake of generality, we start with heterogeneous destruction rates. However, to be consistent with the empirical part and the inherent data limitations, our first proposition focuses on disasters that are homogeneous across firms but only hit a subset of them within the industry. As previously discussed, this is motivated by the fact that our 5-digit industries are not particularly geographically concentrated so a given industry may include both disaster-struck and unaffected firms. To illustrate this, the median value of the Ellison and Glaeser (1997) index at the postcode and province level is 0.02 and 0.001, respectively.[20]

[19] We relegate the derivations to Appendix C.1.

[20] We compute Ellison and Glaeser (1997)'s index of concentration (in terms of employment) across geographic areas (postcode and province). Figure A25 reports the distribution of the index across 5-digit industries in Italy in 2012. The index is relatively low both at the postcode and province level.

4.1 Market structure

The economy consists of a finite number of sectors S indexed by s. Gross-output of the final good Y is produced by a competitive firm that combines the outputs from all the sectors $y(s)$ with a CES technology with elasticity of substitution η:

$$Y = \left[\sum_{s=1}^{S} y(s)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}.$$

The inverse demand function for each intermediate output from sector s is given by:

$$\frac{p(s)}{P} = \left(\frac{y(s)}{Y} \right)^{-\frac{1}{\eta}},$$

where P, the price index for final consumption representing the "true cost of living", is a function of the sectoral prices $p(s)$:

$$P = \left[\sum_{s=1}^{S} p(s)^{1-\eta} \right]^{\frac{1}{1-\eta}}.$$

Each sector s is populated by a finite number of firms $N(s)$ indexed by i. Firms are assigned to a single location, and we do not explicitly model geography, as market shares are defined only at the industry level. As such, we abstract from multi-establishment production and regional variation in sales. We assume that when firms maximize profits, they do not take into account that their choices affect economy-wide outcomes and factor prices. This behavioral assumption helps us with the fact that idiosyncratic disruptions arising from natural disasters will affect aggregate outcomes while ruling out a "Ford" effect (Neary, 2003).[21]

The output of sector s is a composite of the firms' outputs, $y_i(s)$, combined with a CES technology with elasticity of substitution ρ:[22]

$$y(s) = \left[\sum_{i=1}^{N(s)} y_i(s)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}. \tag{4}$$

The inverse demand functions within each sector are:

$$\frac{p_i(s)}{p(s)} = \left(\frac{y_i(s)}{y(s)} \right)^{-\frac{1}{\rho}},$$

[21] Firms are granular in their sector but not sufficiently large to affect aggregate prices nor quantities.

[22] Goods are imperfect substitutes, $\rho < \infty$, and more substitutable within than between sectors, $1 < \eta < \rho$.

where the price index $p(s)$ in sector s is a function of firms' prices $p_i(s)$:

$$p(s) = \left[\sum_{i=1}^{N(s)} p_i(s)^{1-\rho} \right]^{\frac{1}{1-\rho}}.$$

For the sake of simplicity, we abstract from free-entry and exit, and we take the number of firms in the economy and each sector as given.[23]

4.2 Technology and input demands

Firm i's gross-output production function with value-added weight ϕ is[24]

$$y_i(s) = (1 - \kappa_i(s))\, z_i(s) \left[\phi^{1/\theta} v_i(s)^{(\theta-1)/\theta} + (1-\phi)^{1/\theta} x_i(s)^{(\theta-1)/\theta} \right]^{\theta/(\theta-1)},$$

where $\kappa_i(s) \in [0, 1)$ is the destruction rate induced by natural disasters (Barrot and Sauvagnat, 2016), $z_i(s)$ is the firm-specific productivity of the firm, and value-added $v_i(s)$ is a composite good of capital $k_i(s)$ and labor $l_i(s)$

$$v_i(s) = k_i(s)^{\alpha} l_i(s)^{1-\alpha}.$$

Firm i in sector s takes input prices as given and faces marginal costs $\Lambda_i(s)$, defined as $\Lambda_i(s) := \frac{\Omega}{(1-\kappa_i(s))z_i(s)}$, where Ω is the input price index. The occurrence of a natural disaster —i.e., a positive destruction rate $\kappa_i(s)$ —thus increases the marginal cost of firms.

4.3 Endogenous markups

We assume that firms compete à la Cournot so that they solve the following maximization problem[25]

$$\max_{y_i(s)} \left[p_i(s) y_i(s) - \frac{\Omega}{(1-\kappa_i(s))z_i(s)} y_i(s) \right],$$

[23] Assuming away exit is consistent with the evidence shown in Table A3.

[24] We follow Edmond et al. (2023) in assuming a CES production function in value-added $v_i(s)$ and materials $x_i(s)$ —which allows us to consider a general production function —with an elasticity of substitution between inputs governed by θ. While this approach is commonly adopted in the literature for its convenience (Edmond et al., 2023; Burstein et al., 2025), the theoretical production function is not internally consistent with the one implicitly used for estimating firm-level markups in the previous section.

[25] The results are qualitatively unchanged if firms were to instead compete in prices. The demand elasticities detailed below would become arithmetic means instead of harmonic means.

subject to the inverse demand function

$$\frac{p_i(s)}{P} = \left(\frac{y_i(s)}{y(s)}\right)^{-\frac{1}{\rho}} \left(\frac{y(s)}{Y}\right)^{-\frac{1}{\eta}}.$$

Profit-maximization implies that the optimal price is a markup $\mu_i(s)$ over the marginal cost of production, where the markup is pinned down by the idiosyncratic demand elasticity $\varepsilon_i(s)$ faced by the firm,

$$\begin{aligned} \mu_i(s) &= \frac{\varepsilon_i(s)}{\varepsilon_i(s)-1} \\ \varepsilon_i(s) &= \left[\frac{1}{\rho} + \left(\frac{1}{\eta} - \frac{1}{\rho}\right)\omega_i(s)\right]^{-1}, \end{aligned} \tag{5}$$

where $\omega_i(s) := \frac{p_i(s)y_i(s)}{\sum_{j=1}^{N(s)} p_j(s)y_j(s)}$ is the sectoral revenue share of firm i. When $\rho > \eta$, i.e., the elasticity of substitution is higher within sectors than across sectors, more productive firms charge lower prices than less productive firms, have larger equilibrium market shares, and, therefore, charge higher markups. The CES demand structure and Cournot competition imply that the demand elasticity that each firm faces in equilibrium is a harmonic weighted average of the within and between-elasticities.

4.4 Natural disasters and firm-level markups

To derive the effects of natural disasters on markups, we take a first-order approximation of changes in markups around the initial equilibrium with no natural disaster ($\kappa_i(s) = 0$ for all firms i in sector s). We denote $\hat{x} := \log x' - \log x$ as the percentage change in x relative to the initial equilibrium. The following proposition clarifies how natural disasters affect firm-level markups of affected firms.

Proposition 1 (Natural disasters and firm-level markups)**.** *Consider the set $\mathcal{L}(s) \subset N(s)$ of firms in industry s being hit by a natural disaster and assume that the shock is homogeneous, i.e $\Delta\kappa_i(s) = \Delta\kappa$ for $i \in \mathcal{L}_s$. Then, natural disasters decrease markups of affected firms and relatively more so for high-productivity firms. In particular:*

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\Delta\kappa\,(\rho-1)\left[-1 + \frac{\sum_{i\in\mathcal{L}(s)} \gamma_i(s)\omega_i(s)}{\sum_{i\in N(s)} \gamma_i(s)\omega_i(s)}\right], \tag{6}$$

where $\Gamma_i(s) := \frac{\partial \log \mu_i(s)}{\partial \log \omega_i(s)}$ and $\gamma_i(s) := \frac{1}{1+(\rho-1)\Gamma_i(s)}$.

Proof. See Appendix C.2. □

Proposition 1 shows that the response of markups to natural disasters depends critically on the markup elasticity with respect to market shares, $\Gamma_i(s)$,[26] and the pass-through rate, $\gamma_i(s)$. In particular, it illustrates that firm-level markups of affected firms decrease when the shock is homogeneous across firms and does not affect all firms within the industry —as the last term in brackets is negative whereas $\Gamma_i(s)$ and $\gamma_i(s)$ are both positive. Indeed, when homogeneous disasters affect *all* firms in the industry, markups remain unchanged because the term in square brackets becomes zero. Intuitively, if all firms face the same proportional shock to their marginal costs, their relative marginal costs stay constant, leaving both the market share distribution and the markup distribution unchanged —as would be the case under a homogeneous shock if industries were defined at the industry-*postcode* level. It is thus sufficient for a single firm to be unaffected for natural disasters to generate markup adjustments with homogeneous destruction rates.[27] Natural disasters thus generate a heterogeneous response of firms, which want to absorb part of the marginal cost shock in their markups. The theory thus predicts that more productive firms should have incomplete "Natural-Disaster Pass-Through" (NDPT). Clearly, this is reminiscent of the heterogeneous price response of firms following exchange rate shocks (Berman et al., 2012; Amiti et al., 2019).[28] One conceptual difference with exchange rate shocks is that natural disasters directly disrupt the productive capacity of firms.[29] On the other hand, firms with a negligible market share exhibit almost perfect NDPT as the markup elasticity is close to zero for these firms.

4.5 Discussion

We now discuss whether the predicted response of markups to natural disasters is robust to alternative modeling assumptions and market structure.

4.5.1 Alternative explanations

The effect of natural disasters on firm-level markups does not hinge on modeling natural disasters as an output destruction rate. We choose to model natural disasters in this way because of its intuitive interpretation and because this formulation delivers tractable aggregation results compared to capital-augmenting shocks. As long as alternative modeling choices predict a drop in the affected firms' market

[26]More specifically, $\Gamma_i(s) = \frac{\left(\frac{\rho}{\eta}-1\right)\omega_i(s)}{\rho-1-\left(\frac{\rho}{\eta}-1\right)\omega_i(s)}$.

[27]Appendix C.2 discusses the general case with heterogeneous $\Delta\kappa_i(s)$.

[28]See Burstein and Gopinath (2014) for a survey of the literature on exchange-rate pass-through.

[29]Exchange rate shocks typically affect the perceived elasticity of demand of exporters (Berman et al., 2012) or the relative price of foreign inputs (Amiti et al., 2019).

shares, they deliver similar qualitative predictions. Nonetheless, we show in Appendix C.3 that modeling natural disasters as an increase in the tax on production (Hsieh and Klenow, 2009), negative Hicks-neutral productivity shocks (Burstein et al., 2025), negative shocks to capital (Carvalho et al., 2021), or negative demand shocks (Gagnon and López-Salido, 2020) produces similar results. This is because all these alternative modeling approaches result in natural disasters affecting firms' market shares —and thus markups.

Natural disasters may involve supply-side disruptions, demand-side disruptions, or both. Demand shocks are likely to stem from a decrease in income among Italian consumers located in disaster-struck areas or other Italian manufacturing companies. However, since our results are robust to the exclusion of other potentially affected firms, the inclusion of 5-digit industry-province-year fixed effects, and given that Italian employees have access to insurance schemes (*Cassa Integrazione Guadagni Ordinaria*) to buffer transitory shocks, we argue that natural disasters in our context are best interpreted as supply-side shocks.

4.5.2 Role of market structure

We focus on a model of oligopolistic competition because it features strategic interactions between firms (see Appendix C.4). Assuming monopolistic competition with non-CES preferences would deliver similar results if natural disasters are modeled as changes in idiosyncratic productivity and if the price elasticity of demand decreases with consumption, which is commonly referred to as Marshall's Second Law of Demand (MSLD).[30] If MSLD holds,[31] firms decrease their markups following a negative idiosyncratic supply-side shock and more productive firms decrease their markups relatively more. However, monopolistic competition with non-CES preferences would shut down the response of non-affected firms to idiosyncratic shocks affecting firms in the economy. This is because there are no strategic complementarities, and firms are atomistic, meaning that treated firms cannot influence aggregate outcomes. The evidence presented in Figure A26 supports the choice of an oligopolistic competition framework, showing that untreated firms react to natural disasters affecting their competitors —with some point estimates statistically significant at the 10% level.

[30] Recent empirical studies have documented patterns of markup adjustments consistent with MSLD (De Loecker et al., 2016; Mayer et al., 2021; Panon, 2022; Aghion et al., 2024).

[31] MSLD typically implies that markups increase with firm size. We estimate eq. (5) and show in Table 3 that inverse markups decrease with market shares, as predicted by the theory.

4.6 Natural disasters and aggregate outcomes

We derive the effect of natural disasters on gross-output productivity at the sector level for the general case of heterogeneous $\Delta\kappa_i(s)$ and discuss how welfare may be affected. Similar results hold for the case of homogeneous destruction rates and are discussed in Appendix C.5.

4.6.1 Sectoral productivity

As standard in this class of models, sectoral productivity is distorted by the fact that firms within sector s charge different markups, i.e. $\mu_i(s) \neq \mu(s)$. The sectoral productivity, accounting for the possibility of natural disasters, is given by

$$z(s) = \left(\sum_i \left(\frac{\mu_i(s)}{\mu(s)} \right)^{-\rho} \left((1-\kappa_i(s))\, z_i(s) \right)^{\rho-1} \right)^{\frac{1}{\rho-1}}.$$

Taking a first-order approximation around the initial equilibrium, we obtain the following proposition where we focus on heterogeneous natural disasters for expositional purposes.[32]

Proposition 2 (Natural disasters and sectoral productivity). *Following a natural disaster, the change in sectoral productivity is given by*

$$\hat{z}(s) = \underbrace{-\mathbb{E}_\omega\left[\Delta\kappa_i(s)\right]}_{\text{technical efficiency}} + \underbrace{(\rho-1)Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s)\right]}_{\text{reallocation}} + \underbrace{\rho Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s)\right]}_{\text{variable markups}}, \tag{7}$$

where $\mathbb{E}_\omega[x_i] = \sum_i \omega_i x_i$ is the $\omega_i(s)$-weighted average of variable $x_i(s)$, while the $\omega_i(s)$-weighted covariance of any two variables x_i and z_i is given by $Cov_\omega[x_i, z_i] = \mathbb{E}_\omega[x_i z_i] - \mathbb{E}_\omega[x_i]\mathbb{E}_\omega[z_i]$.

Proof. See Appendix C.5. □

Proposition 2 states that the effect of natural disasters on sectoral productivity is given by three terms. The first is a technical efficiency term: if the economy is efficient —i.e. there is no markup dispersion and markups are constant so that the last two covariance terms are zero, the impact of natural disasters on sectoral productivity is a weighted average of firm-specific shocks with weights given by firms' sales shares as in Hulten (1978).[33] The first covariance is an intensive-margin reallocation term. When resources are misallocated across firms and the intensity

[32] The corollary of Proposition 2 with homogeneous disasters can be found in Appendix C.

[33] Baqaee and Farhi (2019) derive the impact of microeconomic shocks in efficient economies with a second-order approximation and show that microeconomic and network production structures shape aggregate productivity.

of natural disasters differs across firms, natural disasters can increase or decrease sectoral productivity by altering the firm's technical efficiency distribution in relative terms. The sign of this covariance depends on the set of affected firms, as previously shown in different contexts (Baqaee and Farhi, 2020; Baqaee et al., 2024; Burstein et al., 2025). The second covariance captures the fact that firms endogenously adjust their markups following a natural disaster. This term can be positive or negative, depending on the set of affected firms. For example, imagine that only the most productive firm of the industry is hit by a natural disaster. The decrease in technical efficiency of that firm will drive down sectoral productivity, everything else equal. Moreover, market shares will be reallocated towards less efficient firms that are not affected by the disaster, which will contribute to driving down sectoral productivity. However, since that firm will decrease its markup and thus retain some market share, the strength of the reallocation effect will be dampened. In this case, markup adjustments contribute to attenuating the negative effect coming from intensive-margin reallocations towards less efficient producers.

Overall, this proposition states that markup adjustments can amplify or dampen the sectoral productivity effect of natural disasters. We explore quantitatively the aggregate productivity effects of natural disasters and the importance of markup adjustments in shaping their effect in Section 5.

4.6.2 Aggregate productivity and welfare

Aggregate productivity Z is defined as:

$$Z = \left(\sum_{s=1}^{S} \left(\frac{\mu(s)}{\mathcal{M}} \right)^{-\eta} z(s)^{\eta-1} \right)^{\frac{1}{\eta-1}},$$

where $\mathcal{M} = \left(\sum_{s=1}^{S} \frac{1}{\mu(s)} \omega(s) \right)^{-1}$ is the aggregate markup level and $\omega(s)$ is the sectoral market share, which depends on the sectoral markup and productivity.

We consider the static formula developed in Edmond et al. (2023) to explore the effect of natural disasters on welfare.[34] With elastic labor supply, the level of the aggregate markup acts as a distortionary wedge. Intuitively, an increase in the aggregate markup reduces the aggregate scale of production and decreases the representative consumer's welfare. In the model, the aggregate markup changes as natural disasters lead firms to adjust their markups and generate market share reallocations —see Proposition 1. We compute the welfare change in consumption-

[34]We favor this formula over a standard extension with capital accumulation because it fits our static framework. In a dynamic setting, the static welfare formula can be considered in a steady state version of the model, reducing the computational time and being easier to interpret —it only depends on changes in aggregate productivity and in the aggregate markup level.

equivalent units as detailed in Appendix C.6.

5 Natural disasters and aggregate outcomes

We now turn to the model calibration and illustrate how markup adjustments influence the macroeconomic costs of natural disasters.

5.1 Calibration

A key characteristic of our framework is that it is applied directly to firm-level data so that firms in the model represent actual firms in Italy. The firms for which technical efficiency is affected are those located in disaster-hit locations, as *observed* in the data.

5.1.1 Elasticities of substitution

The key parameters are the within and across-sector elasticities of substitution. To recover these elasticities, we make use of the estimating equation implied by eq. (5)

$$\mu_{i(s)t}^{-1} = \frac{\rho - 1}{\rho} + \left(\frac{1}{\rho} - \frac{1}{\eta}\right)\omega_{i(s)t}.$$

Its empirical counterpart is given by

$$\mu_{i(s)t}^{-1} = \delta + \beta\omega_{i(s)t} + \varepsilon_{i(s)t}. \tag{8}$$

As standard in the literature, firm-level market shares $\omega_{i(s)t}$ are defined as the ratio of firm-level domestic sales to domestic sales of all operating firms within the same 5-digit industry. One should expect $\hat{\beta} < 0$, as the theory predicts that markups smoothly increase with market shares, under the assumption that $\rho > \eta > 1$, with the gap between these two parameters disciplining the extent to which dispersion in market shares translates into markup dispersion.

As Table 3 shows, the point estimate is significant at the 1% level across specifications and yields a value of $\hat{\beta} = -0.443$ in column 4, which we target. Table A4 and Table A5 show that the results are robust to estimating the specification in first-differences or instrumenting market shares by their one- or two-year lags, respectively. We then recover the two demand elasticities by solving the following two equations simultaneously, as in Brooks et al. (2021), for each cross-section and take

Table 3: Firm Inverse Markups and Market Shares

	Dependent variable: $\mu_{i(s)t}^{-1}$			
	(1)	(2)	(3)	(4)
$\omega_{i(s)t}$	-0.055***	-0.056***	-0.357***	-0.443***
	(0.009)	(0.009)	(0.024)	(0.025)
Year FE	No	Yes	No	No
Industry-year FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
Observations	1,335,851	1,335,851	1,335,851	1,335,851
Adj. R^2	0.000	0.002	0.401	0.408

Notes: The dependent variable is the inverse markup of firm i at time t. The independent variable is the firm's market share defined as it domestic sales share within its 5-digit industry. Industry-year fixed effects refer to 5-digit industry times year fixed effects. Standard errors clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%.

the average over time:

$$\begin{aligned} \frac{1}{\hat{\rho}} - \frac{1}{\hat{\eta}} &= \hat{\beta} \\ \frac{\hat{\rho}-1}{\hat{\rho}} &= \frac{1}{N} \sum_{s} \sum_{i(s) \in N(s)} \left(\mu_{i(s)}^{-1} - \hat{\beta}\omega_{i(s)} \right), \end{aligned} \tag{9}$$

where $N := \sum_s N(s)$ is the total number of firms in the economy.

We obtain $\hat{\rho} = 29.19$ and $\hat{\eta} = 2.09$, as shown in Table 4. These elasticities of substitution are higher than those reported by Edmond et al. (2015) but in line with those reported by Edmond et al. (2023). There are at least two reasons why our elasticities of substitution are high. First, the empirical markup distribution that we use is not skewed and the average and aggregate markup is low, implying a high elasticity of substitution within sectors to match this moment. Edmond et al. (2023) find that matching an aggregate markup level of 5% requires an even higher value of $\rho = 59.69$.[35] Second, we do not rely on labor shares as the dependent variable in eq. (9) but instead use markups as predicted by the model.[36] If anything,

[35]Table 5 in Edmond et al. (2023) shows that the elasticity of substitution within sectors increases as the target for the aggregate markup level decreases.

[36]While labor shares are theoretically proportional to markups —see eq. (15) in the Appendix, the elasticity of substitution has to be scaled down by additional parameters to match a given slope coefficient. This is the reason why the elasticity of substitution across sectors that Edmond et al. (2023) report in their Table 5 ranges from 0.99 to 1.62. Without this scaling factor, matching their slope coefficient of 0.21 given their estimate of ρ would imply elasticities of substitution across sectors ranging from 2.49 to 4.41.

Table 4: Baseline Calibration

Interpretation	Parameter	Value	Method
Substitution within sectors	ρ	29.19	Equation (9)
Substitution between sectors	η	2.09	Equation (9)
Productivity	z	Data	Equation (10)
Labor supply elasticity	ψ	1	Assigned

Notes: The table reports the parameters used to estimate the cost of natural disasters.

Brooks et al. (2021) report a relatively low elasticity of substitution within sectors (4.8) —as their markup distribution is more skewed, but a value for the elasticity across sectors of 2.9, closer to ours. Reassuringly, our estimated elasticities imply an own-cost pass-through rate of 0.3 for large firms (those with a market share of at least 20%), which is within the confidence interval of the value reported by Amiti et al. (2019) for large Belgian firms.

5.1.2 Productivity

To recover the initial productivity distribution before the disaster, we invert the following system using the empirical market shares and firm-level markups:

$$\omega_i(s) = \left(\frac{p_i(s)}{p(s)}\right)^{1-\rho} = \frac{p_i(s)^{1-\rho}}{\sum_j p_j(s)^{1-\rho}} = \frac{\left(\frac{\mu_i(s)}{z_i(s)}\right)^{1-\rho}}{\sum_j \left(\frac{\mu_j(s)}{z_j(s)}\right)^{1-\rho}}. \tag{10}$$

To preserve the productivity and size distribution across industries, we re-scale the firm-level productivity vector of each sector by its corresponding estimated average productivity.

5.1.3 Assigned parameters

To study the effect of natural disasters on welfare, we need to assign a value to the Frisch elasticity of labor supply (ψ) as detailed in Appendix C.6. We set that parameter to 1.

5.1.4 Counterfactual

We modify the technical efficiency term of affected firms before computing the new distribution of firm-level market shares $\omega'_i(s)$ and markups $\mu'_i(s)$. Specifically, for our baseline estimates, the new productivity term $z'_i(s)$ induced by the natural disaster is assumed to be 5% smaller ($\Delta\kappa = 5\%$), corresponding to the average drop in value-added and sales found before. We also consider a smaller and larger shock of 1% and 10%, respectively.

Modified firm-level markups and market shares are obtained as follows

$$\frac{1}{\mu_i'(s)} = \frac{1}{\mu_i(s)} + \left(\frac{1}{\rho} - \frac{1}{\eta}\right)\left(\omega_i'(s) - \omega_i(s)\right), \tag{11}$$

$$\omega_i'(s) = \frac{\left(\frac{\mu_i'(s)}{z_i'(s)}\right)^{1-\rho}}{\sum_j \left(\frac{\mu_j'(s)}{z_j'(s)}\right)^{1-\rho}}. \tag{12}$$

Sectoral markups and productivity post-disaster are then given by:

$$\mu'(s) = \sum_i \left(\frac{1}{\mu_i'(s)}\omega_i'(s)\right)^{-1},$$

$$z'(s) = \left(\sum_i \left(\frac{\mu_i'(s)}{\mu'(s)}\right)^{-\rho} z_i'(s)^{\rho-1}\right)^{\frac{1}{\rho-1}}.$$

The counterfactual aggregate productivity level, Z', is computed using the corresponding firm-level and sectoral variables.

Importantly, only firms located in postcodes affected by the natural disaster experience a drop in technical efficiency, while all other firms remain unaffected. However, the market shares and markups of unaffected firms endogenously adjust to the shock experienced by affected firms. Our main counterfactual exercise compares the change in aggregate productivity and welfare induced by the natural disaster under two scenarios: one in which firm-level markups endogenously adjust, and another in which they are held fixed at their pre-shock levels.

5.2 Evaluating the 2012 Italian earthquake

We evaluate the impact of the 2012 Italian earthquake and quantify the aggregate importance of markup adjustments. In this exercise, we use firm-level data from 2011, the year before the event.

5.2.1 Results

In column 1 of Table 5, we consider a 5% decrease in technical efficiency for firms that were hit by the earthquake. While aggregate productivity drops by 0.03% when markups adjust, the effect is weaker (-0.026%) when markups are held fixed to their initial level. These changes are small because the set of affected industries and locations, together with the drop of technical efficiency, are not large from an aggregate

Table 5: Variable versus Constant Markups: 2012 Italian Earthquake

	Δ Markup adjustments (1)	Δ Constant markups (2)	Relative change (3)
Gross-output productivity change in %	-0.030	-0.026	18.0
Static welfare change in %	-0.035	-0.028	25.3

Notes: The table displays the gross-output aggregate productivity and welfare changes associated with the 2012 Italian earthquake for $\Delta\kappa = 0.05$. The model with constant markups holds the distribution of markups constant to that obtained in the baseline calibration. Natural disasters are modeled as a decrease in the technical efficiency of firms. Column 1 (2) reports the change in the relevant aggregate variable when firms (do not) endogenously adjust their markups. Column 3 reports the amplification effect of variable markups by taking the ratio of the change in aggregate productivity and welfare following natural disasters in models with and without variable markups. The contribution of variable markups does not exactly add up to the ratio of the first two columns due to rounding.

perspective. However, variable markups amplify the aggregate productivity loss of the earthquake by 18%. Sectoral and aggregate productivity are affected as the market shares of impacted firms decline, while those of unaffected firms within the same industry rise since the former become less productive in relative terms. Moreover, the markups of affected firms decrease allowing them to partially retain market share. At the same time, the margins of more productive unaffected firms, with higher markups, increase further, dampening the reallocation of market shares towards them. This mechanism amplifies the productivity losses associated with the event. The welfare effect displayed is also negative both when markups can adjust and when they are constant. However, allowing for variable markups amplifies the welfare loss of the event by 25%, since the aggregate markup rises more than it would under constant markups.[37]

5.2.2 Sensitivity analysis

In this section, we consider three sensitivity tests.

Varying shock magnitudes. Columns 1 and 2 of Table A6 explore different declines in the technical efficiency of affected firms (1% and 10%) to trace out a plausible range for the role of markup adjustments in the aftermath of the earthquake. Even under these alternative disruptions, we find that markup adjustments significantly amplify the macroeconomic cost: aggregate productivity losses increase by 8% to 23%, while the welfare impact is magnified by 12% to 36%.

Theory-consistent markups. To recover the distribution of productivity, we need information on the empirical distribution of market shares and markups. However, because markups are estimated, the recovered productivity distribution may

[37]The aggregate markup level goes up even in the constant markup case because market shares are reallocated towards higher-markup firms. As shown in Proposition 2, this effect operates with and without variable markups but may be stronger with variable markups.

introduce noise into the relationship between $z_i(s)$ and $\omega_i(s)$, since the *empirical* relationship between $\mu_i(s)$ and $\omega_i(s)$ may not be perfectly consistent with the theory. While we add a correction term to account for the difference between theoretical and empirical markups in our baseline quantification exercise, we now generate a new distribution of firm-level markups that is theory-consistent. In other words, given our values for ρ, η and $\omega_i(s)$, we compute $\mu_i(s)$ from eq. (5) before estimating $z_i(s)$.

Results are presented in column 3 of Table A6. While this exercise requires taking a stand on the demand elasticities —ρ and η are set to the same values as before using the empirical distribution of markups, it nevertheless provides reassuring evidence that our results are not driven by discrepancies in the relationship between the empirical distributions of markups and market shares. Markup adjustments now amplify the cost of the earthquake by 43% in terms of aggregate productivity, while amplifying its impact on welfare by 37%.

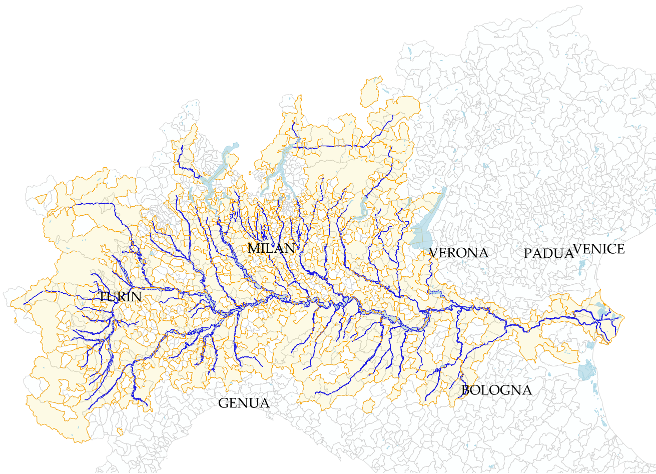
Alternative demand elasticities. To assess the importance of the elasticity of substitution across firms, we now set it to a lower value —$\rho = 12.76$ as in Edmond et al. (2023) when the aggregate markup level is 1.15. The elasticity across sectors is set to $\eta = 1.92$ in order to keep the slope parameter β constant. Table A6 shows that markup adjustments still amplify the aggregate productivity and welfare cost of natural disasters (approximately 13%). This is because firms' markup adjustments are more muted when the elasticity of substitution across firms is smaller —Proposition 1. Finally, column 5 considers a much higher value of $\rho = 59.69$ —which corresponds to the aggregate markup target of 1.05 in Edmond et al. (2023), with $\eta = 2.18$. In this case, the amplification effect reaches nearly 100%. However, we view this result as implausible, given that such a high elasticity of demand is not consistent with the markup estimates in our data.

5.3 Po River basin flood

We now turn to another counterfactual analysis, representing an extremely catastrophic event, to study the importance of markup adjustments. Specifically, we consider a hypothetical flood affecting the Po River basin. To ensure comparability with the exercise addressing the 2012 Northern Italy Earthquake, we use firm-level data from 2011.[38]

[38] For this exercise, we report the market share distribution of treated and untreated firms in Table A7.

Figure 5: Postal Codes and Po Basin



Notes: The map represents the postcode areas intersecting the Po Basin (yellow shaded areas). The Po river and its tributaries are shown in blue along with cities with population above 200,000 inhabitants. Firms with headquarters located in postcodes through which the Po river and its tributaries flow are considered affected.

5.3.1 Context

The Po River basin, located in northern Italy, is the country's largest and most significant river system. It includes the Po, Italy's longest river, as well as the Ticino, Adda, Oglio, and Tanaro rivers, which are among the most important in terms of length and discharge.

The basin covers an area of approximately 71,000 square kilometers and encompasses Lombardy, Veneto, Emilia-Romagna, and Piedmont. These regions are among the most economically significant in Europe in terms of GDP, serving as crucial hubs for industry, transportation, and agriculture. However, the region is vulnerable to flooding, particularly during periods of heavy rainfall or snowmelt in the Alps. Over the past century, several flood events have caused extensive damage, including the catastrophic flood of 1951, which affected Polesine, displacing over 100,000 people, and the 2000 flood, which caused extensive damage to infrastructure and agriculture while displacing over 40,000 people.[39]

For the counterfactual, we rely on the information provided by the Po River District Basin Authority (*Autorità di Bacino Distrettuale del Fiume Po*), an Italian public authority responsible for the basin. We consider the map of flood-prone areas designated under the Flood Risk Management Plan, corresponding to high-probability scenarios and high hazard.[40] We consider firms whose headquarters are located in a flood-prone area as affected, as shown in Figure 5.

[39]Other significant events include the floods of 1994 and 2002.
[40]See here for more information.

Table 6: Variable versus Constant Markups: Potential Po River Basin Flood

Shock $\Delta\kappa$	1% (1)	5% (2)	10% (3)
Panel A: Gross-output productivity losses, %			
Change with markup adjustments	-0.26	-1.01	-1.50
Change with constant markups	-0.25	-0.91	-1.28
Relative change	3.5	10.7	17.3
Panel B: Static welfare losses, %			
Change with markup adjustments	-0.26	-1.05	-1.61
Change with constant markups	-0.25	-0.92	-1.28
Relative change	3.4	14.0	26.3

Notes: The table displays the gross-output aggregate productivity and welfare changes associated with a potential flood of the Po river basin in panels A and B, respectively. The model with constant markups holds the distribution of markups constant to that obtained in the baseline calibration. Natural disasters are modeled as a decrease in the technical efficiency of affected firms. Row 1 (2) reports the change in the relevant aggregate variable when firms (do not) endogenously adjust their markups. Row 3 reports the amplification effect of variable markups by taking the ratio of the change in productivity following natural disasters in models with and without variable markups. The contribution of variable markups does not exactly add up to the ratio of the first two rows due to rounding.

5.3.2 Results

Table 6 presents the results associated with a hypothetical flood in the Po basin. Given the high concentration of firms in the area, many of which rank among the most productive in the country, the potential losses in aggregate productivity and welfare are substantial when firms endogenously adjust their markups. Specifically, with a 5% destruction rate, aggregate productivity and welfare losses are 1% and 1.1%, respectively. These losses increase to 1.5% and 1.6% with a 10% destruction rate.

The aggregate productivity and welfare losses would be smaller if markups were constant. Indeed, with a 5% destruction rate, productivity and welfare losses are 0.9%, respectively, and with a 10% destruction rate, they reach 1.3% for both metrics.

Overall, this additional exercise stresses the critical role of markup adjustments in shaping the macroeconomic impact of natural disasters. In our preferred scenario ($\kappa = 5\%$), the endogenous markup response would amplify the aggregate loss of a catastrophic flood by 11% to 14%, depending on the metric considered.

6 Conclusion

This paper examines a novel mechanism through which natural disasters affect aggregate productivity and welfare in manufacturing: firm-level markup adjustments. By analyzing a comprehensive novel dataset of Italian manufacturing firms affected by natural disasters, we provide causal evidence that natural disasters lead to persistent decreases in markups, particularly for high-productivity firms.

We provide new insights into micro-to-macro linkages in the wake of large and localized shocks and use the widely used oligopolistic macroeconomic model of Atkeson and Burstein (2008) for studying the aggregate implications of such shocks. Markup adjustments may mitigate or exacerbate the effects of natural disasters on aggregate productivity and welfare by interacting with intensive-margin reallocations of market shares across firms. Implementing our model directly on firm-level data, we find that markup adjustments amplified the aggregate productivity loss of the 2012 Italian earthquake by approximately 20% and would play a significant role in the potential occurrence of a catastrophic flood in Northern Italy.

The contribution of variable markups that we estimate may be affected by how we define market shares, which are based on sales shares within a 5-digit industry. Although this definition is typically being used in the literature, it could be imprecise as our data do not allow us to have the breakdown of sales across locations (Rossi-Hansberg et al., 2021), nor the presence of foreign competitors (Amiti and Heise, 2025). Moreover, our results abstract from fatalities that could disrupt firm-level activity further and affect firms' market shares. In addition, the paper inevitably abstracts from other, potentially important, mechanisms. Understanding how firms' markups adjust along the supply chain and affect the macroeconomic cost of natural disasters would certainly be a fruitful area for future research. It also remains an open question to assess why markup adjustments are persistent empirically and if this has implications for macroeconomic stability: allowing for dynamic considerations to study how markup adjustments shape the aggregate cost of natural disasters over time seems an important topic for ongoing research.

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Online Appendix

"Natural Disasters and Markups"

Francesco Paolo Conteduca and Ludovic Panon

A Data appendix

A.1 From EM-DAT to treated postcodes

We rely on EM-DAT (Delforge et al., 2025) to select relevant natural disasters. As of September 2023, the database contains information on the occurrence and impacts of over 26,000 mass disasters worldwide from 1900.

EM-DAT defines a natural disaster as "a situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering" (Delforge et al., 2025, p. 1). Hence, a natural disaster is caused by a natural hazard —as opposed to a man-made or technological catastrophe. EM-DAT collects data through a systematic process that involves multiple sources. The methodology used to collect data in EM-DAT involves the following steps: (*i*) source identification, (*ii*) data verification, (*iii*) data entry, (*iv*) quality control, and (*iv*) data updates. Importantly, EM-DAT also reports the amount of damages associated with the event, which we use to select the most relevant disasters (those exceeding US$ 250 mn).

Regarding the location of the disasters, which is a key aspect of our identification strategy, EM-DAT provides the location of events at a relatively aggregate level: several events are coded at level 2 of the Nomenclature of Territorial Units for Statistics (NUTS), while others are defined at level 3. This level of aggregation is not detailed enough to exploit our data on firms' locations and may increase the likelihood that a treated firm is classified as untreated, and vice versa. Hence, we complement the preliminary, coarser information from EM-DAT with additional sources.

To define disaster areas more precisely, we prioritize official documents issued by local governments and institutions, which often specify the locations affected by a disaster, and, secondly, resort to media sources, such as newspaper articles. This strategy is applied to both Italy and France.[41]

[41] For example, in the case of the Italian earthquakes, the government defines the "crater" area, i.e., the list of municipalities mostly affected by the event. Similar mentions of municipalities are also found in official sources for events affecting France.

This approach allows us to recover the affected areas at the postcode level, enabling accurate matching with the headquarters of the companies in our sample.

A.2 Balance sheet data

We use balance sheet data of Italian and French manufacturing companies between 2005 and 2019. In particular, we use data from CERVED for Italy, which provides balance sheets and income statements for incorporated companies. In addition to financial information, CERVED also contains the location of the headquarter of the company, which we use to assess its treatment status. For France, we instead use Orbis, which provides information on incorporated companies in France. Also in this case, we retrieve information on the location of the headquarter of the reporting company from the Orbis entries.

To obtain a dataset of Italian and French manufacturing companies between 2005 and 2019, we remove firms that never report positive sales and employees. We also remove firms reporting negative or missing sales or reports missing value added. Moreover, we exclude observations with abnormal yearly turnover growth rates (belonging to the top and bottom 1%) and with missing or negative labor costs and sales or non-positive materials costs and employees.[42] We also exclude firms consistently reporting fewer than two employees. Once we remove these observations, we match the postcode of the Italian companies with the treated postcodes for a given disaster. We exclude a subset of firms that are treated more than once. Descriptive statistics on the most relevant variables for Italy that are used in the analysis are reported in Table A1.

In terms of coverage, our final sample covers 78% of gross-output for Italian manufacturing firms over 2005-2019, while for France it is 61%.[43]

B Measuring markups

B.1 Markup estimator

In seminal work, De Loecker and Warzynski (2012) show how to recover firm-level markups using production data. Formally, assume that producers are cost-minimizing and write the Lagrangian

$$\mathcal{L}(x_{it}, k_{it}, \lambda_{it}) = \sum_{x} p^{x}_{it} x_{it} + r_{it} k_{it} + \lambda_{it} \left(y_{it} - F_{it} \left(x_{it}, k_{it} \right) \right)$$

[42] In Orbis, material costs are not available so we dropped observations with negative costs of goods sold.

[43] We rely on OECD STAN (Horvát and Webb, 2020) to compute these ratios.

where p^x_{it} is the price of any variable input x, r_{it} is the rental rate of capital k_{it}, output is given by y_{it}, the production technology is $F_{it(.)}$ and λ_{it} is the Lagrange multiplier associated with the constraint. The first-order condition with respect to any flexible input is thus

$$p^x_{it} = \lambda_{it} \frac{\partial F(.)}{\partial x_{it}} \quad \forall x_{it} \in \mathbf{X}$$

Because the Lagrange multiplier is equal to the change in total cost arising from relaxing the constraint, it is equal to the marginal cost MC_{it} of producing one extra unit of output, or $\lambda_{it} = MC_{it}$. Defining the markup μ_{it} as the ratio of price p_{it} to marginal cost allows us to write the previous equation as

$$p^x_{it} \mu_{it} = p_{it} \frac{\partial F(.)}{\partial x_{it}} \quad \forall x_{it} \in \mathbf{X}$$

Multiplying both sides by $x_{it} F(.)$ and using the fact that $y_{it} = F(.)$ this yields the formula for firm-level markups:

$$\mu_{it} = \frac{\beta^x_{it}}{\alpha^x_{it}}$$

where $\beta^x_{it} := \frac{\partial F(.)/\partial x_{it}}{F(.)/x_{it}}$ is the output elasticity of a flexible input x and $\alpha^x_{it} := \frac{p^x_{it} x_{it}}{p_{it} y_{it}}$ is that input's revenue share.

The denominator α^x_{it} is typically available in standard production data while the output elasticity on the flexible input needs to be recovered, typically through production function estimation or through a cost share approach. The cost share approach is robust to the fact that revenue elasticities differ from output elasticities when markups vary across firms (Bond et al., 2021). We thus choose to rely on that approach, popularized by Foster et al. (2008), and implement Raval (2023a)'s estimator which we now explain briefly.

B.2 Cost share approach

Let us assume that production is CES with elasticity of substitution θ between labor l_{it}, capital k_{it} and intermediates m_{it}. Moreover, b_{it} is a labor-augmenting productivity term while z_{it} is Hicks-neutral. For the sake of simplicity, we omit the time subscript:

$$y_i = z_i \left[(1 - \alpha_l - \alpha_m) k_i^{(\theta-1)/\theta} + \alpha_l (b_i l_i)^{(\theta-1)/\theta} + \alpha_m m_i^{(\theta-1)/\theta} \right]^{\theta/(\theta-1)}$$

Taking factor prices as given and maximizing profits yields the following first-order conditions:

$$\frac{w l_i}{p_i y_i} = \frac{\beta^l_i}{\mu_i} = \frac{1}{\mu_i} \left(\frac{w}{\lambda_i z_i} \right)^{1-\theta} (\alpha_l)^\theta (b_i)^{\theta-1}$$

$$\frac{p_i^m m_i}{p_i y_i} = \frac{\beta_i^m}{\mu_i} = \frac{1}{\mu_i}\left(\frac{p_i^m}{\lambda_i z_i}\right)^{1-\theta}(\alpha_m)^\theta$$
$$\frac{Rk_i}{p_i y_i} = \frac{\beta_i^k}{\mu_i} = \frac{1}{\mu_i}\left(\frac{R}{\lambda_i z_i}\right)^{1-\theta}(1-\alpha_l-\alpha_m)^\theta$$
where λ_i is the marginal cost of production.

B.2.1 Standard approach

Let us assume that the production function is Cobb-Douglas, i.e. $\theta = 1$.

Focusing on materials, combining the first-order conditions yields:

$$\frac{\beta_i^m}{\beta_i^m + \beta_i^l + \beta_i^k} = \frac{p_i^m m_i}{wl_i + p_i^m m_i + Rk_i}$$

One can then recover the output elasticity of materials by further assuming that firms' output elasticities are the same within a given sector ($\beta_i^j = \beta_s^j$) for input j, and assuming that the degree of returns to scale is the same across sectors (RTS $:= \sum_j \beta_s^j$). In this case, the output elasticity in a given industry is given by:

$$\beta_s^m = \text{RTS} \times \frac{p_i^m m_i}{wl_i + p_i^m m_i + Rk_i} \tag{13}$$

Taking averages across firms within a 5-digit industry yields an estimate of the output elasticity of materials. The methodology is the same to recover the output elasticity of labor.

B.2.2 Accounting for non-neutral productivity differences

Raval (2023b) shows that non-neutral technology can explain why markups estimated using different types of flexible inputs are negatively correlated and exhibit opposite time trends. Indeed, when $\theta \neq 1$, the factor-augmenting technology term b_i affects output elasticities differently. Indeed, it affects the output elasticity indirectly through marginal costs λ_i but also directly, through the $b_i^{\theta-1}$ term.

Taking the ratio of the first-order conditions for materials and labor yields:

$$b_i = \left(\frac{\alpha_l}{\alpha_m}\right)^{\frac{-\theta}{\theta-1}} \frac{w_i}{p_i^m}\left(\frac{wl_i}{p_i^m m_i}\right)^{\frac{1}{\theta-1}}$$

Firms assigned to groups based on their labor to materials cost ratio will thus have similar values of b_i and thus output elasticities. We follow Raval (2023a) by assigning firms to different quintiles within their 5-digit industry and output elasticities are the input shares of total cost within a 5-digit industry quintile. In other words, we take averages of the right-hand side of Equation (13) within each 5-digit industry-quintile pair.

Given our identification strategy and the presence of fixed effects, our results do not hinge on the degree of returns to scale which acts as a scaling factor for the output elasticity. Indeed, since our dependent variable is $\log \mu_{it} = \log \beta_s^j - \log \alpha_{it}^j$, assuming returns to scale (RTS) are less than or equal to one does not affect our results, since such variation is absorbed by the fixed effects.

Finally, note that taking the log of firm-level markups does not eliminate variation in the numerator (the output elasticity) through our 5-digit industry–year fixed effects, since these elasticities are measured at the 5-digit industry–quintile level.

B.2.3 Estimation

To estimate markups, we define the cost share of materials as the ratio of expenditures on materials to total cost. Total cost includes expenditures on materials, labor compensation, and capital expenditures. The computation of capital expenditures is somewhat more involved. We define capital expenditures as tangible fixed assets multiplied by the capital rental rate.[44] As a proxy for that variable, we use the real internal rate of return (variable "IRR") from the Penn World Table 10.01 (Feenstra et al., 2015).

We then compute the output elasticity of materials for each 5-digit industry–quintile combination, as detailed above. Finally, we winsorize the distribution of firm-level markups at the 3% level, separately by 2-digit sector.

C Model appendix

In this Appendix, we derive the equations outlined in the main text, our propositions, as well as additional results.

C.1 Key aggregates

In this section, we model natural disasters as a destruction rate —a fraction κ_i of firm i's output is destroyed when it is affected by a natural disaster.

[44] Using tangible fixed assets to measure capital is consistent with the approach followed by De Ridder (2024).

C.1.1 Firm-level outcomes

Firm i's production function is

$$y_i(s) = (1-\kappa_i(s))\, z_i(s) \left[\phi^{1/\theta} v_i(s)^{(\theta-1)/\theta} + (1-\phi)^{1/\theta} x_i(s)^{(\theta-1)/\theta}\right]^{\theta/(\theta-1)}, \quad (14)$$

where $\kappa_i(s)$ is the destruction rate, $z_i(s)$ is a Hicks-neutral productivity term, and value-added $v_i(s)$ is a composite good of capital $k_i(s)$ and labor $l_i(s)$

$$v_i(s) = k_i(s)^{\alpha} l_i(s)^{1-\alpha}.$$

Firm i solves the following cost-minimization problem:

$$\min_{\{l_i(s), k_i(s), x_i(s)\}} Wl_i(s) + Rk_i(s) + x_i(s),$$

subject to eq. (14).

The first-order conditions are given by

$$Wl_i(s) = (1-\alpha)\lambda(1-\kappa_i(s))z_i(s)\left(\frac{y_i(s)}{(1-\kappa_i(s))z_i(s)}\right)^{\frac{1}{\theta}} \phi^{\frac{1}{\theta}} v_i(s)^{\frac{\theta-1}{\theta}},$$

$$Rk_i(s) = \alpha\lambda(1-\kappa_i(s))z_i(s)\left(\frac{y_i(s)}{(1-\kappa_i(s))z_i(s)}\right)^{\frac{1}{\theta}} \phi^{\frac{1}{\theta}} v_i(s)^{\frac{\theta-1}{\theta}},$$

$$x_i(s) = (1-\phi)\left(\lambda(1-\kappa_i(s))z_i(s)\right)^{\theta}\left(\frac{y_i(s)}{(1-\kappa_i(s))z_i(s)}\right),$$

and eq. (14), where λ is the Lagrange multiplier.

We isolate value-added $v_i(s)$ by combining the first-order conditions for labor and capital

$$v_i(s)^{\frac{\theta-1}{\theta}} = \left(\lambda(1-\kappa_i(s))z_i(s)\right)^{\theta-1}\left(\frac{y_i(s)}{(1-\kappa_i(s))z_i(s)}\right)^{\frac{\theta-1}{\theta}} \phi^{\frac{\theta-1}{\theta}} \left(\frac{1-\alpha}{W}\right)^{(1-\alpha)(\theta-1)} \left(\frac{\alpha}{R}\right)^{\alpha(\theta-1)}.$$

Combining the first-order condition for materials and the previous equation into eq. (14), one obtains the value of the Lagrange multiplier which also yields the firm's marginal cost $\Lambda_i(s)$:

$$\lambda_i = \frac{1}{(1-\kappa_i(s))z_i(s)}\left[\phi\left(\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right)^{1-\theta} + (1-\phi)\right]^{1/(1-\theta)}.$$

Plugging the value of the Lagrange multiplier into value-added yields

$$v_i(s) = \phi \left\{ \frac{(R/\alpha)^{\alpha} \left[W/(1-\alpha)\right]^{1-\alpha}}{\Omega} \right\}^{-\theta} \frac{y_i(s)}{(1-\kappa_i(s))\, z_i(s)},$$

where

$$\Omega = \left\{ \phi \left[\left(\frac{R}{\alpha}\right)^{\alpha} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \right]^{1-\theta} + (1-\phi) \right\}^{1/(1-\theta)}.$$

The first-order conditions for labor, capital and materials are finally given by

$$Wl_i(s) = (1-\alpha) \left[\left(\frac{R}{\alpha}\right)^{\alpha} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \right] v_i(s),$$

$$Rk_i(s) = \alpha \left[\left(\frac{R}{\alpha}\right)^{\alpha} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \right] v_i(s),$$

$$x_i(s) = (1-\phi) \left(\frac{1}{\Omega}\right)^{-\theta} \frac{y_i(s)}{(1-\kappa_i(s))\, z_i(s)}.$$

Labor shares and markups. In equilibrium, firms' pricing strategies are given by

$$p_i(s) = \mu_i(s) \times \frac{\Omega}{(1-\kappa_i(s))\, z_i(s)}$$

Combining this expression with the first-order condition for labor and rearranging, we get

$$\frac{Wl_i(s)}{p_i(s) y_i(s)} = \frac{1}{\mu_i(s)} (1-\alpha)\, \zeta, \tag{15}$$

where

$$\zeta := \phi \frac{\left\{ (R/\alpha)^{\alpha} \left[W/(1-\alpha)\right]^{1-\alpha} \right\}^{1-\theta}}{\phi \left[\left(\frac{R}{\alpha}\right)^{\alpha} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \right]^{1-\theta} + (1-\phi)}.$$

C.1.2 Sectoral aggregates

Labor. Rearranging the first-order condition for labor yields

$$\begin{aligned}
l_i(s) &= \phi\frac{(1-\alpha)}{W}\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}\Omega^{\theta}\frac{y_i(s)}{(1-\kappa_i(s))\,z_i(s)} \\
\Longrightarrow l(s) = \sum_i l_i(s) &= \phi\frac{(1-\alpha)}{W}\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}\Omega^{\theta}\sum_i\frac{y_i(s)}{(1-\kappa_i(s))\,z_i(s)} \\
&= \phi\frac{(1-\alpha)}{W}\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}\Omega^{\theta}\frac{y(s)}{z(s)}
\end{aligned}$$

where $q_i(s) := y_i(s)/y(s)$ and sectoral productivity $z(s)$ is given by the following firm-size-weighted harmonic average of firm-level technical efficiency:

$$z(s) := \left(\sum_i q_i(s)\frac{1}{(1-\kappa_i(s))z_i(s)}\right)^{-1}. \tag{16}$$

Capital. Following a similar logic, one obtains

$$k(s) = \sum_i k_i(s) = \phi\frac{\alpha}{R}\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}\Omega^{\theta}\frac{y(s)}{z(s)}.$$

Materials. We thus obtain the following sectoral demand for materials

$$x(s) = (1-\phi)\Omega^{\theta}\frac{y(s)}{z(s)}.$$

Sectoral production function. Integrating value-added and solving for the terms in brackets gives

$$\begin{aligned}
\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha} &= v(s)^{-\frac{1}{\theta}}\left(\frac{y(s)}{z(s)}\right)^{\frac{1}{\theta}}\phi^{\frac{1}{\theta}}\Omega \\
\Longrightarrow \Omega &= \left(\phi^{\frac{1}{\theta}}\Omega^{1-\theta}\left(\frac{y(s)}{z(s)}\right)^{\frac{1-\theta}{\theta}}v(s)^{\frac{\theta-1}{\theta}} + (1-\phi)\right)^{\frac{1}{1-\theta}} \\
\Longrightarrow 1 &= \phi^{\frac{1}{\theta}}\left(\frac{y(s)}{z(s)}\right)^{\frac{1-\theta}{\theta}}v(s)^{\frac{\theta-1}{\theta}} + (1-\phi)^{\frac{1}{\theta}}x(s)^{\frac{\theta-1}{\theta}}\left(\frac{y(s)}{z(s)}\right)^{\frac{1-\theta}{\theta}} \\
\Longrightarrow y(s) &= z(s)\left[\phi^{\frac{1}{\theta}}v(s)^{\frac{\theta-1}{\theta}} + (1-\phi)^{\frac{1}{\theta}}x(s)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}
\end{aligned}$$

Sectoral markups. Let us define the sectoral markup as the wedge between the marginal revenue product of labor and the marginal cost of labor. Formally

$$\mu(s) := \frac{p(s)\frac{\partial y(s)}{\partial l(s)}}{W}$$

Note that

$$\begin{aligned}
\frac{\partial y(s)}{\partial l(s)} &= (1-\alpha)\frac{z(s)}{l(s)}\phi^{\frac{1}{\theta}}\left(\frac{y(s)}{z(s)}\right)^{\frac{1}{\theta}} v(s)^{\frac{\theta-1}{\theta}} \\
&= (1-\alpha)\frac{z(s)}{l(s)}\phi^{\frac{1}{\theta}}\left(\frac{y(s)}{z(s)}\right)^{\frac{1}{\theta}} \phi^{\frac{\theta-1}{\theta}} \left\{(R/\alpha)^{\alpha}\left[W/(1-\alpha)\right]^{1-\alpha}\right\}^{1-\theta} \Omega^{\theta-1}\left(\frac{y(s)}{z(s)}\right)^{\frac{\theta-1}{\theta}} \\
&= \frac{(1-\alpha)y(s)}{l(s)}\phi\frac{\left\{(R/\alpha)^{\alpha}\left[W/(1-\alpha)\right]^{1-\alpha}\right\}^{1-\theta}}{\phi\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}+(1-\phi)},
\end{aligned}$$

where we used the fact that the input price index can be expressed as

$$\Omega^{\theta-1} = \left\{\phi\left[\left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\right]^{1-\theta}+(1-\phi)\right\}^{-1}.$$

We thus have

$$\mu(s) = (1-\alpha)\zeta\frac{p(s)y(s)}{Wl(s)}. \tag{17}$$

Combining eq. (15) and eq. (17)

$$\frac{p_i(s)y_i(s)}{p(s)y(s)} = \frac{\mu_i(s)}{\mu(s)} \times \frac{l_i(s)}{l(s)}, \tag{18}$$

which gives sectoral markups

$$\mu(s) = \sum_i \mu_i(s)\frac{l_i(s)}{l(s)} = \left(\sum_i \frac{1}{\mu_i(s)}\frac{p_i(s)y_i(s)}{p(s)y(s)}\right)^{-1}.$$

Using eq. (16) in the previous equation gives

$$p(s) = \mu(s)\frac{\Omega}{z(s)}.$$

C.2 Proof of Proposition 1

Proposition 1. (Reminded) *Natural disasters decrease markups of affected firms and relatively more so for high-productivity firms.*

Proof. We start with a general result with heterogeneous shocks before moving on to our main result with homogeneous shocks.

Let us first note that a first-order approximation of changes in prices around the equilibrium without natural disasters yields

$$\hat{p}_i(s) = \hat{\mu}_i(s) + \hat{\Lambda}_i(s),$$

where $\hat{x} := \log x' - \log x$ represents the percentage change in x relative to the initial equilibrium.

Moreover, market shares are defined as $\omega_i(s) := \frac{p_i(s)y_i(s)}{\sum_j p_j(s)y_j(s)}$. From the first-order conditions for profit maximization within sectors we get

$$\omega_i(s) = \frac{p_i(s)^{1-\rho}}{\sum_j p_j(s)^{1-\rho}} = \frac{\left(\mu_i(s)\Lambda_i(s)\right)^{1-\rho}}{\sum_j \left(\mu_j(s)\Lambda_j(s)\right)^{1-\rho}},$$

which yields the following first-order approximation of changes in market shares around the equilibrium without natural disasters

$$\hat{\omega}_i(s) = (1-\rho)\left(\hat{p}_i(s) - \hat{p}(s)\right).$$

Let us now define $V_i(s) := \Lambda_i(s)^{1-\rho}$. We get

$$\hat{\omega}_i(s) = \hat{V}_i(s) - (\rho-1)\,\hat{\mu}_i(s) - \sum_j \omega_j(s)\left(\mu_j(s)\hat{V}_j(s) - (\rho-1)\,\hat{\mu}_j(s)\right).$$

From eq. (5), the change in markups at the first-order is given by

$$\hat{\mu}_i(s) = \left(\frac{\rho-\eta}{\eta\rho}\right)\mu_i(s)\omega_i(s)\hat{\omega}_i(s).$$

Moreover, the elasticity of markups with respect to market shares is

$$\Gamma_i(s) := \frac{\partial \log \mu_i(s)}{\partial \log \omega_i(s)} = \left(\frac{\rho-\eta}{\eta\rho}\right)\mu_i(s)\omega_i(s) = \frac{\left(\frac{\rho}{\eta}-1\right)\omega_i(s)}{\rho - 1 - \left(\frac{\rho}{\eta}-1\right)\omega_i(s)},$$

where we have used the expression for markups in the last equality to express the elasticity as a function of market shares. The markup elasticity is thus strictly increasing in the market share as long as $\rho > \eta$ and $\omega_i(s) > 0$. Plugging this expression into the previous one yields the change in markups at the first-order

$$\hat{\mu}_i(s) = \Gamma_i(s)\hat{\omega}_i(s). \tag{19}$$

Combining the previous equations and rearranging yields:

$$\hat{p}_i(s) = \gamma_i(s)\hat{\Lambda}_i(s) + (1 - \gamma_i(s))\,\hat{p}(s),$$

where $\gamma_i(s) := \frac{1}{1+(\rho-1)\Gamma_i(s)}$ is the pass-through rate, which pins down how firm i's price responds to a natural disaster affecting its productivity. We can further express prices and markups as functions of natural disasters by noticing that a first-order approximation of the sectoral price index around the initial equilibrium is

$$\hat{p}(s) = \sum_i \omega_i(s)\hat{p}_i(s) = \frac{\sum_i \gamma_i(s)\omega_i(s)\hat{\Lambda}_i(s)}{\sum_i \gamma_i(s)\omega_i(s)}.$$

where we have used the previous equation and rearranged terms noticing that $\sum_i \omega_i(s) = 1$.

Plugging the previous two equations into the change in market shares expressed as a function of prices yields

$$\hat{\omega}_i(s) = (\rho - 1)\,\gamma_i(s)\left(-\hat{\Lambda}_i(s) + \frac{\sum_j \gamma_j(s)\omega_j(s)\hat{\Lambda}_j(s)}{\sum_j \gamma_j(s)\omega_j(s)}\right).$$

From eq. (19), the change in firm-level markups following a natural disaster is:

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\,(\rho - 1)\left(-\hat{\Lambda}_i(s) + \frac{\sum_j \gamma_j(s)\omega_j(s)\hat{\Lambda}_j(s)}{\sum_j \gamma_j(s)\omega_j(s)}\right). \tag{20}$$

Using the fact that $\hat{\Lambda}_i(s) = \Delta\kappa_i(s)$ in eq. (20) yields:

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\,(\rho - 1)\left[-\Delta\kappa_i(s) + \frac{\sum_j \gamma_j(s)\omega_j(s)\Delta\kappa_j(s)}{\sum_j \gamma_j(s)\omega_j(s)}\right]. \tag{21}$$

Considering a set $\mathcal{L}(s) \subset N(s)$ of firms in industry s being hit by a natural disaster and assuming that the shock is homogeneous, i.e $\Delta\kappa_i(s) = \Delta\kappa$ for $i \in \mathcal{L}(s)$ immediately yields Proposition 1 in the text. $\square$

Equation (21) shows the effect of a natural disaster on markups in the general case with heterogeneous $\Delta\kappa_i(s)$. In particular, natural disasters decrease firm-level markups if and only if $\Delta\kappa_i(s) > \frac{\sum_j \gamma_j(s)\omega_j(s)\Delta\kappa_j(s)}{\sum_j \gamma_j(s)\omega_j(s)}$, which holds if firm i faces a relatively large destruction rate. Moreover, in such cases, more productive firms experience a larger reduction in markups. To see this, notice that firm i's markup response depends on its markup elasticity, pass-through rate and the relative size of the shock. If the condition for markups to decrease holds, low-productivity firms, which have a low markup elasticity and near-unit pass-through rate, adjust their markup less in response to a disaster. On the other hand, more productive firms face a higher markup elasticity allowing them to respond to natural disasters by adjusting their markups relatively more. If the condition were reversed, firm i would increase its markup: despite the increase in marginal costs, the firm gains market shares because it has been relatively less affected by the disaster.

C.3 Alternative channels

The effect of natural disasters on firm-level markups does not hinge on modeling natural disasters as a destruction rate. When natural disasters act as a destruction rate, firm i's change in marginal costs is $\hat{\Lambda}_i(s) = \Delta\kappa_i(s) > 0$. We choose to model natural disasters as a destruction rate because of its intuitive interpretation and because this formulation delivers tractable aggregation results compared to capital-augmenting shocks. In general, what is key for alternative modeling choices to deliver similar qualitative predictions is that affected firms' market shares decrease following a natural disaster. When natural disasters are modeled as supply-side disruptions, this occurs when the marginal cost of firm i increases relatively more than the weighted average of marginal costs of other firms in the industry —see eq. (20). We assume that this holds and focus on showing how marginal costs evolve depending on the modeling assumption.

Revenue shocks. Instead of assuming that natural disasters affect output of the firm, let us assume that they act as a revenue tax $\tau_i(s)$ in the profit-maximization problem of firms as in Hsieh and Klenow (2009). In this case, the *after-disaster* price is expressed as a markup over marginal cost and $\hat{\Lambda}_i(s) = \Delta\tau_i(s) > 0$.

Hicks-neutral productivity shocks. Let us instead model natural disasters as negative Hicks-neutral productivity shocks $\hat{z}_i(s)$. In this case, the production function of firm i is given by eq. (14) with $\kappa_i(s) = 0$, as in Burstein et al. (2025). Marginal costs are now given by: $\Lambda_i(s) := \frac{\Omega}{z_i(s)}$. A negative Hicks-neutral productivity shock ($\hat{z}_i(s) < 0$) increases firm-level marginal costs as $\hat{\Lambda}_i(s) = -\hat{z}_i(s)$.

Capital-augmenting shocks. When natural disasters are instead assumed to destroy capital as in Carvalho et al. (2021), the firm's production function becomes:

$$y_i(s) = z_i(s)\left[\phi^{1/\theta}\left((k_i(s)(1-\kappa_i(s)))^{\alpha}\, l_i(s)^{1-\alpha}\right)^{(\theta-1)/\theta} + (1-\phi)^{1/\theta} x_i(s)^{(\theta-1)/\theta}\right]^{\theta/(\theta-1)}$$

Firms' marginal costs are now given by $\Lambda_i(s) := \frac{\Omega_i(s)}{z_i(s)}$ where

$$\Omega_i(s) = \left\{ \phi \left[\left(\frac{R}{\alpha(1-\kappa_i(s))} \right)^{\alpha} \left(\frac{W}{1-\alpha} \right)^{1-\alpha} \right]^{1-\theta} + (1-\phi) \right\}^{1/(1-\theta)}$$

In this case, the destruction of capital $\Delta\kappa_i(s) > 0$ increases the input price index —$\hat{\Omega}_i(s) > 0$—and thus firms' marginal costs as $\hat{\Lambda}_i(s) = \hat{\Omega}_i(s)$, triggering markup adjustments.

Idiosyncratic demand shocks. Natural disasters also affect the demand for goods (Gagnon and López-Salido, 2020). Let us assume that natural disasters only affect the demand for goods through some idiosyncratic demand shifter $\varphi_i(s)$ and leave the productivity term constant for all firms in the economy. Equation (4) now becomes:

$$y(s) = \left[\sum_{i=1}^{N_s} \varphi_i(s)^{\frac{1}{\rho}} y_i(s)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}.$$

In this case, firm-level market shares reflect these demand shifters (Burstein et al., 2025), so that $\omega_i(s) = \frac{\varphi_i(s)\left(\frac{\mu_i(s)}{z_i(s)}\right)^{1-\rho}}{\sum_j \varphi_j(s)\left(\frac{\mu_j(s)}{z_j(s)}\right)^{1-\rho}}$. Negative demand shocks thus generate observationally equivalent patterns in terms of markup adjustments to those caused by negative Hicks-neutral shocks, as both affect firms' market shares in the same way.

C.4 Strategic complementarities

Unaffected firms in the same industry also adjust their markups when some of their competitors are affected by a natural disaster. From eq. (20), the change in markups of unaffected firms is given by

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\,(\rho-1)\left(\frac{\sum_{j\in\mathcal{L}} \gamma_j(s)\omega_j(s)\Delta\kappa_j(s)}{\sum_{j\in N_s} \gamma_j(s)\omega_j(s)} \right).$$

All the terms in the above equation are positive so that unaffected firms that are large enough increase their markups following a natural disaster. This is because they gain market shares as demand is reallocated away from disaster-struck firms.

C.5 Proof of Proposition 2

Proposition 2. (Reminded) *Following a natural disaster, the change in sectoral productivity is given by*

$$\hat{z}(s) = \underbrace{-\mathbb{E}_\omega\left[\Delta\kappa_i(s)\right]}_{\text{technical efficiency}} + \underbrace{(\rho-1)Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s)\right]}_{\text{reallocation}} + \underbrace{\rho Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s)\right]}_{\text{variable markups}}.$$

Proof. Using the definition of sectoral productivity in eq. (16) and the fact that $\frac{y_i(s)}{y(s)} = \left(\frac{p_i(s)}{p(s)}\right)^{-\rho}$ from the first-order condition for profit-maximization, sectoral productivity can be written as

$$z(s) = \left(\sum_i \left(\frac{p_i(s)}{p(s)}\right)^{-\rho} ((1-\kappa_i(s))z_i(s))^{-1}\right)^{-1}.$$

Since $p_i(s) = \mu_i(s)\frac{\Omega}{(1-\kappa_i(s))z_i(s)}$ and $p(s) = \mu(s)\frac{\Omega}{z(s)}$, one obtains

$$z(s) = \left(\sum_i \left(\frac{\mu_i(s)}{\mu(s)}\right)^{-\rho} ((1-\kappa_i(s))z_i(s))^{\rho-1}\right)^{\frac{1}{\rho-1}}.$$

Sectoral productivity is distorted by the fact that firms within sector s charge different markups.

We now express sectoral productivity as a function of firm-level markups and firm-level productivity terms only.

$$\mu(s) = \left(\sum_i \mu_i(s)^{-1}\omega_i(s)\right)^{-1} = \left(\frac{\sum_i \mu_i(s)^{-\rho}\Lambda_i(s)^{1-\rho}}{\sum_i \mu_i(s)^{1-\rho}\Lambda_i(s)^{1-\rho}}\right)^{-1}.$$

We thus get:

$$z(s) = \frac{\left(\sum_i \mu_i(s)^{1-\rho}\left((1-\kappa_i(s))z_i(s)\right)^{\rho-1}\right)^{\frac{\rho}{\rho-1}}}{\sum_i \mu_i(s)^{-\rho}\left((1-\kappa_i(s))z_i(s)\right)^{\rho-1}}.$$

Taking a first-order approximation around the initial equilibrium, we get

$$\begin{aligned}
\hat{z}(s) &= \frac{\rho}{\rho-1}\sum_i ((1-\rho)\omega_i(s)\hat{\mu}_i(s) - (\rho-1)\omega_i(s)\Delta\kappa_i(s)) \\
&- \sum_i \left(\frac{\mu_i(s)^{-\rho} z_i(s)^{\rho-1}}{\sum_i \mu_i(s)^{-\rho} z_i(s)^{\rho-1}} (1-\rho)\Delta\kappa_i(s) - \rho \frac{\mu_i(s)^{-\rho} z_i(s)^{\rho-1}}{\sum_i \mu_i(s)^{-\rho} z_i(s)^{\rho-1}} \hat{\mu}_i(s) \right) \\
&= \frac{\rho}{\rho-1}\sum_i ((1-\rho)\omega_i(s)\hat{\mu}_i(s) - (\rho-1)\omega_i(s)\Delta\kappa_i(s)) \\
&- \sum_i \left(\frac{\mu(s)}{\mu_i(s)} (1-\rho)\omega_i(s)\Delta\kappa_i(s) - \rho \frac{\mu(s)}{\mu_i(s)} \omega_i(s)\hat{\mu}_i(s) \right) \\
&= \sum_i \omega_i(s) \left((\rho-1)\frac{\mu(s)}{\mu_i(s)} - \rho \right) \Delta\kappa_i(s) - \rho \sum_i \omega_i(s)(1 - \frac{\mu(s)}{\mu_i(s)})\hat{\mu}_i(s).
\end{aligned}$$

Denote the sales-weighted —$\omega_i(s)$ —average of $x_i(s)$ by $\mathbb{E}_\omega[x_i] = \sum_i \omega_i x_i$. Denote the sales-weighted covariance of any two variables x_i and z_i by

$$Cov_\omega\left[x_i, z_i\right] = \mathbb{E}_\omega[x_i z_i] - \mathbb{E}_\omega[x_i]\mathbb{E}_\omega[z_i].$$

The previous expression now writes:

$$\begin{aligned}
\hat{z}(s) &= \sum_i \omega_i(s) \left((\rho-1)\frac{\mu(s)}{\mu_i(s)} - \rho \right) \Delta\kappa_i(s) - \rho \sum_i \omega_i(s) \left(1 - \frac{\mu(s)}{\mu_i(s)}\right) \hat{\mu}_i(s) \\
&= (\rho-1)\sum_i \omega_i(s) \left(\frac{\mu(s)}{\mu_i(s)} - \frac{\rho}{\rho-1} \right) \Delta\kappa_i(s) - \rho \sum_i \omega_i(s) \left(1 - \frac{\mu(s)}{\mu_i(s)}\right) \hat{\mu}_i(s) \\
&= (\rho-1)\mathbb{E}_\omega \left[\left(\frac{\mu(s)}{\mu_i(s)} - \frac{\rho}{\rho-1} \right) \Delta\kappa_i(s) \right] - \rho \mathbb{E}_\omega \left[\left(1 - \frac{\mu(s)}{\mu_i(s)}\right) \hat{\mu}_i(s) \right] \\
&= (\rho-1) Cov_\omega \left[\frac{\mu(s)}{\mu_i(s)} - \frac{\rho}{\rho-1}, \Delta\kappa_i(s) \right] + (\rho-1)\mathbb{E}_\omega \left[\frac{\mu(s)}{\mu_i(s)} - \frac{\rho}{\rho-1} \right] \mathbb{E}_\omega\left[\Delta\kappa_i(s)\right] \\
&- \rho \left(Cov_\omega \left[1 - \frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s) \right] + \mathbb{E}_\omega \left[1 - \frac{\mu(s)}{\mu_i(s)} \right] \mathbb{E}_\omega\left[\hat{\mu}_i(s)\right] \right) \\
&= (\rho-1) Cov_\omega \left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s) \right] - \rho Cov_\omega \left[1 - \frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s) \right] \\
&+ (\rho-1)\mathbb{E}_\omega \left[\frac{\mu(s)}{\mu_i(s)} - \frac{\rho}{\rho-1} \right] \mathbb{E}_\omega\left[\Delta\kappa_i(s)\right] \\
&= (\rho-1) Cov_\omega \left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s) \right] - \rho Cov_\omega \left[1 - \frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s) \right] - \mathbb{E}_\omega\left[\Delta\kappa_i(s)\right] \\
&= (\rho-1) Cov_\omega \left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s) \right] + \rho Cov_\omega \left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s) \right] - \mathbb{E}_\omega\left[\Delta\kappa_i(s)\right].
\end{aligned}$$

$\square$

Corollary 1. *If all affected firms face the same destruction rate $\Delta\kappa > 0$, the effect on sectoral productivity is proportional to $\Delta\kappa$ but does not have a predetermined sign.*

Proof. Assume that $\Delta\kappa_i(s) = \Delta\kappa$ for all $i \in \mathcal{L}(s)$. From Proposition 2, we know that

$$\hat{z}(s) = \underbrace{-\mathbb{E}_\omega\left[\Delta\kappa_i(s)\right]}_{\text{technical efficiency}} + \underbrace{(\rho-1)Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s)\right]}_{\text{reallocation}} + \underbrace{\rho Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s)\right]}_{\text{variable markups}}.$$

Define as $\sum_{i\in\mathcal{L}(s)}\omega_i(s) = \mathcal{P}(\mathcal{L}(s))$ the measure of firms affected by the natural disaster in sector s.

Regarding the first term, we note that $\mathbb{E}_\omega\left[\Delta\kappa_i(s)\right] = \Delta\kappa\cdot\mathcal{P}(\mathcal{L}(s))$, which is positive and proportional to $\Delta\kappa$. Hence, the technical efficiency component in the change of sectoral productivity is unambiguously negative.

Consider the covariance between markup ratios and the shock, $Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s)\right]$. We show that this term is proportional to $\Delta\kappa$. However, its sign is ambiguous. In particular,

$$\begin{aligned}
Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \Delta\kappa_i(s)\right] &= \mathbb{E}_\omega\left[\frac{\mu(s)}{\mu_i(s)}\Delta\kappa_i(s)\right] - \mathbb{E}_\omega\left[\frac{\mu(s)}{\mu_i(s)}\right]\mathbb{E}_\omega\left[\Delta\kappa_i(s)\right] \\
&= \Delta\kappa\sum_{i\in\mathcal{L}(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)} - \Delta\kappa\cdot\mathcal{P}(\mathcal{L}(s))\sum_{i\in N(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)} \\
&= \Delta\kappa\left((1-\mathcal{P}(\mathcal{L}(s)))\sum_{i\in\mathcal{L}(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)} - \mathcal{P}(\mathcal{L}(s))\sum_{i\in N(s)\setminus\mathcal{L}(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)}\right) \\
&\propto \Delta\kappa.
\end{aligned}$$

Moreover, the term in parentheses can be either positive or negative depending on the measure of affected firms, their market power and size. Hence, the reallocation term can be positive or negative.

Finally, we consider the covariance between markup ratios and markup changes, $Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s)\right]$. We show that this term is also proportional to $\Delta\kappa$ and has no pre-determined sign. By definition, this term can be written as

$$Cov_\omega\left[\frac{\mu(s)}{\mu_i(s)}, \hat{\mu}_i(s)\right] = \mathbb{E}_\omega\left[\frac{\mu(s)}{\mu_i(s)}\hat{\mu}_i(s)\right] - \mathbb{E}_\omega\left[\frac{\mu(s)}{\mu_i(s)}\right]\mathbb{E}\left[\hat{\mu}_i(s)\right].$$

Note that the change in markups for treated firms under the assumption that $\Delta\kappa$ is the same for all treated firms is

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\Delta\kappa\,(\rho-1)\left[-1 + \frac{\sum_{i\in\mathcal{L}(s)}\gamma_i(s)\omega_i(s)}{\sum_{i\in N(s)}\gamma_i(s)\omega_i(s)}\right].$$

For untreated firms, instead, the change in markups is given by

$$\hat{\mu}_i(s) = \Gamma_i(s)\gamma_i(s)\Delta\kappa\,(\rho-1)\left[\frac{\sum_{i\in\mathcal{L}(s)}\gamma_i(s)\omega_i(s)}{\sum_{i\in N(s)}\gamma_i(s)\omega_i(s)}\right].$$

Hence, $\mathbb{E}_\omega\left[\hat{\mu}_i(s)\right] \propto \Delta\kappa$. Finally

$$\begin{aligned}
\mathbb{E}_\omega\left[\frac{\mu(s)}{\mu_i(s)}\hat{\mu}_i(s)\right] &= \sum_{i\in N(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)}\hat{\mu}_i(s) \\
&= \sum_{i\in\mathcal{L}(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)}\Gamma_i(s)\gamma_i(s)\Delta\kappa\,(\rho-1)\left[-1+\frac{\sum_{i\in\mathcal{L}(s)}\gamma_i(s)\omega_i(s)}{\sum_{i\in N(s)}\gamma_i(s)\omega_i(s)}\right] \\
&+ \sum_{i\in N(s)\setminus\mathcal{L}(s)}\omega_i(s)\frac{\mu(s)}{\mu_i(s)}\Gamma_i(s)\gamma_i(s)\Delta\kappa\,(\rho-1)\left[\frac{\sum_{i\in\mathcal{L}(s)}\gamma_i(s)\omega_i(s)}{\sum_{i\in N(s)}\gamma_i(s)\omega_i(s)}\right] \propto \Delta\kappa.
\end{aligned}$$

Moreover, the two summands can be positive or negative depending on the measure of affected firms and the relative strength of markup responses of treated and untreated firms.

Overall, $\hat{z}(s) \propto \Delta\kappa$ —being the sum of terms proportional to κ —and $\hat{z}(s) \gtrless 0$ as the sign of the reallocation and variable markups terms in Proposition 2 is ambiguous.

□

C.6 Consumption-Equivalent Welfare

We follow Edmond et al. (2023) who show that one can obtain a simple static welfare formula that connects the level of the aggregate markup and aggregate productivity to welfare.

The utility of the representative consumer in the economy is given by:

$$U\Big(C,L\Big) = \frac{C^{1-\sigma}}{1-\sigma} - \frac{L^{1+\psi}}{1+\psi}, \tag{22}$$

where C denotes the consumption of the household, L is its labor supply and ψ is the inverse of the Frisch elasticity of labor supply. The aggregate production function is given by $Y = ZL$.

The representative household chooses consumption C and labor L to maximize utility

$$\max_{C,L} \quad \frac{C^{1-\sigma}}{1-\sigma} - \frac{L^{1+\psi}}{1+\psi} \tag{23}$$

subject to the budget constraint

$$C = WL, \tag{24}$$

where W denotes the real wage.

We form the Lagrangian:

$$\mathcal{L} = \frac{C^{1-\sigma}}{1-\sigma} - \frac{L^{1+\psi}}{1+\psi} + \lambda(WL - C), \tag{25}$$

where λ is the Lagrange multiplier associated with the budget constraint and represents the marginal utility of income.

The first-order conditions are:

$$\frac{\partial \mathcal{L}}{\partial C} = C^{-\sigma} - \lambda = 0 \quad \Rightarrow \quad \lambda = C^{-\sigma} \tag{26}$$

$$\frac{\partial \mathcal{L}}{\partial L} = -L^{\psi} + \lambda W = 0 \quad \Rightarrow \quad L^{\psi} = \lambda W \tag{27}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = WL - C = 0 \quad \Rightarrow \quad C = WL. \tag{28}$$

Substituting the expression for λ, we obtain:

$$L^{\psi} = WC^{-\sigma} \quad \Rightarrow \quad C^{\sigma}L^{\psi} = W \tag{29}$$

This is the labor supply condition, relating consumption and labor supply to the real wage. In the presence of a distortionary markup $\mathcal{M}$, the wage is below the marginal product of labor: $W = Z/\mathcal{M}$, and the condition becomes

$$C^{\sigma}L^{\psi} = \frac{Z}{\mathcal{M}}. \tag{30}$$

The goods market clearing condition implies $C = Y = ZL$, which allows us to solve for C and L as a function of $\mathcal{M}$ and Z:

$$L = \mathcal{M}^{-\frac{1}{\sigma+\psi}} Z^{\frac{1-\sigma}{\sigma+\psi}}, \tag{31}$$

$$C = \mathcal{M}^{-\frac{1}{\sigma+\psi}} Z^{\frac{1+\psi}{\sigma+\psi}}. \tag{32}$$

The associated utility level before the natural disaster is

$$\begin{aligned} U(C,L) &= \frac{1}{1-\sigma}\mathcal{M}^{-\frac{1-\sigma}{\sigma+\psi}} Z^{\frac{(1-\sigma)(1+\psi)}{\sigma+\psi}} - \frac{1}{1+\psi}\mathcal{M}^{-\frac{1+\psi}{\sigma+\psi}} Z^{\frac{(1-\sigma)(1+\psi)}{\sigma+\psi}} \\ &= \left(\frac{1}{1-\sigma} - \frac{1}{1+\psi}\frac{1}{\mathcal{M}}\right)\mathcal{M}^{-\frac{1-\sigma}{\sigma+\psi}} Z^{\frac{(1-\sigma)(1+\psi)}{\sigma+\psi}}. \end{aligned} \tag{33}$$

The associated utility level after the natural disaster is given by

$$U(C_{\text{disaster}}, L_{\text{disaster}}) = \left(\frac{1}{1-\sigma} - \frac{1}{1+\psi}\frac{1}{\mathcal{M}_{\text{disaster}}}\right)\mathcal{M}_{\text{disaster}}^{-\frac{1-\sigma}{\sigma+\psi}} Z_{\text{disaster}}^{\frac{(1-\sigma)(1+\psi)}{\sigma+\psi}}. \tag{34}$$

We denote $\mathcal{W}_{\text{disaster}}$ the level of consumption that solves $U(\mathcal{W}_{\text{disaster}}, 0) = U(C, L)$ for the allocation with a natural disaster. More specifically, we solve for $\mathcal{W}_{\text{disaster}}$ as follows

$$\frac{\mathcal{W}_{\text{disaster}}^{1-\sigma}}{1-\sigma} = \left(\frac{1}{1-\sigma} - \frac{1}{1+\psi}\frac{1}{\mathcal{M}_{\text{disaster}}}\right)\mathcal{M}_{\text{disaster}}^{-\frac{1-\sigma}{\sigma+\psi}} Z_{\text{disaster}}^{\frac{(1-\sigma)(1+\psi)}{\sigma+\psi}},$$

which yields

$$\mathcal{W}_{\text{disaster}} = \left(1 - \frac{1-\sigma}{1+\psi}\frac{1}{\mathcal{M}_{\text{disaster}}}\right)^{\frac{1}{1-\sigma}} \mathcal{M}_{\text{disaster}}^{-\frac{1}{\sigma+\psi}} Z_{\text{disaster}}^{\frac{1+\psi}{\sigma+\psi}}. \tag{35}$$

Similarly, the level of consumption $\mathcal{W}$ solves $U(\mathcal{W}, 0) = U(C, L)$ for the allocation without natural disasters and we obtain

$$\mathcal{W} = \left(1 - \frac{1-\sigma}{1+\psi}\frac{1}{\mathcal{M}}\right)^{\frac{1}{1-\sigma}} \mathcal{M}^{-\frac{1}{\sigma+\psi}} Z^{\frac{1+\psi}{\sigma+\psi}}. \tag{36}$$

The consumption-equivalent change from shocks is given by:

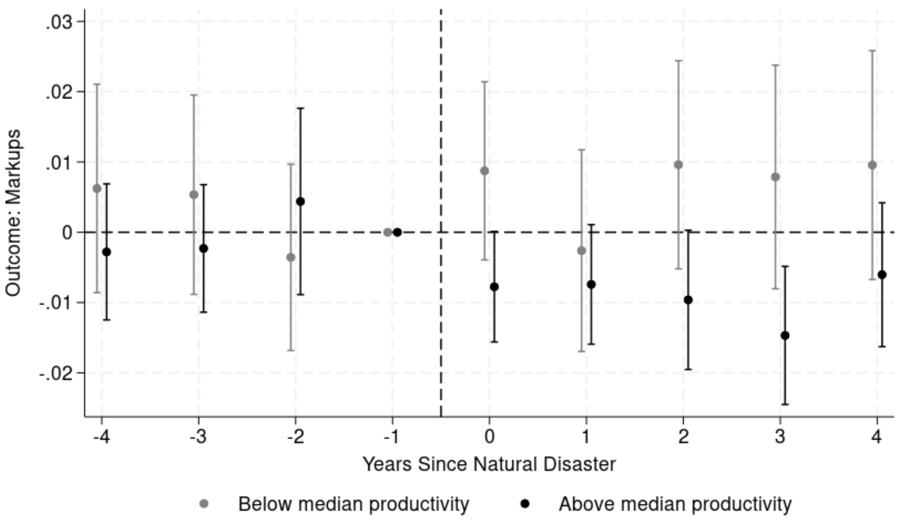
$$\frac{\mathcal{W}_{\text{disaster}}}{\mathcal{W}} = \left(\frac{1 - \frac{1-\sigma}{1+\psi}\frac{1}{\mathcal{M}_{\text{disaster}}}}{1 - \frac{1-\sigma}{1+\psi}\frac{1}{\mathcal{M}}}\right)^{\frac{1}{1-\sigma}} \left(\frac{\mathcal{M}_{\text{disaster}}}{\mathcal{M}}\right)^{-\frac{1}{\sigma+\psi}} \left(\frac{Z_{\text{disaster}}}{Z}\right)^{\frac{1+\psi}{\sigma+\psi}} \tag{37}$$

With logarithmic utility ($\sigma \to 1$), we obtain the consumption-equivalent welfare change from natural disasters

$$\frac{\mathcal{W}_{\text{disaster}}}{\mathcal{W}} = \exp\left(\frac{1}{1+\psi}\left(\frac{1}{\mathcal{M}} - \frac{1}{\mathcal{M}_{\text{disaster}}}\right)\right)\left(\frac{Z_{\text{disaster}}}{Z}\right)\left(\frac{\mathcal{M}_{\text{disaster}}}{\mathcal{M}}\right)^{-\frac{1}{1+\psi}}. \tag{38}$$

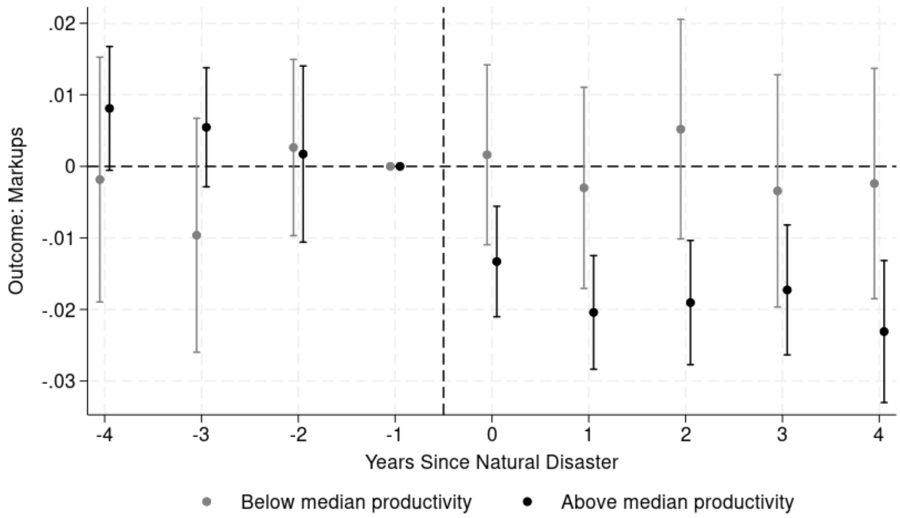
D Additional Figures

Figure A1: Natural Disasters and Markups across Firms: Considering Only Floods and Storms



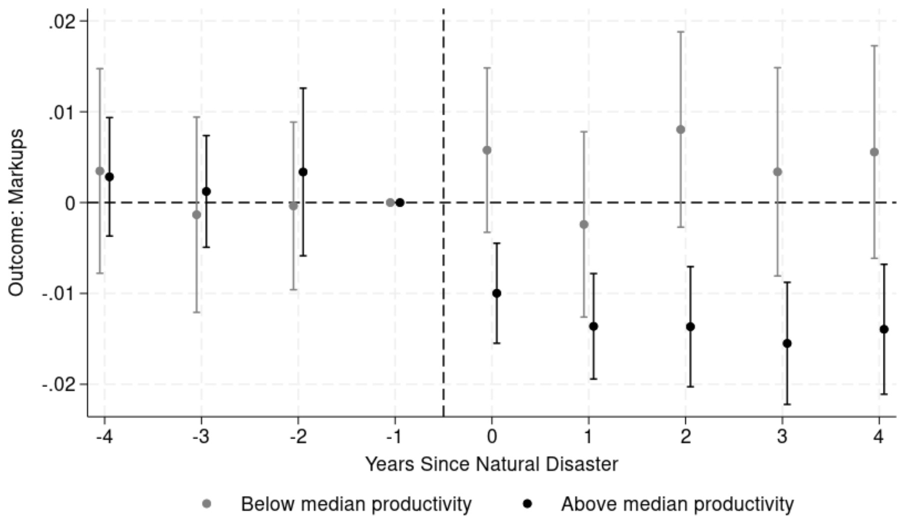
Notes: The figure reports the effect of floods and storms on Italian firms' markups between 2005-2019 by size. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry–year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included.

Figure A2: Natural Disasters and Markups across Firms: Considering Only Earthquakes



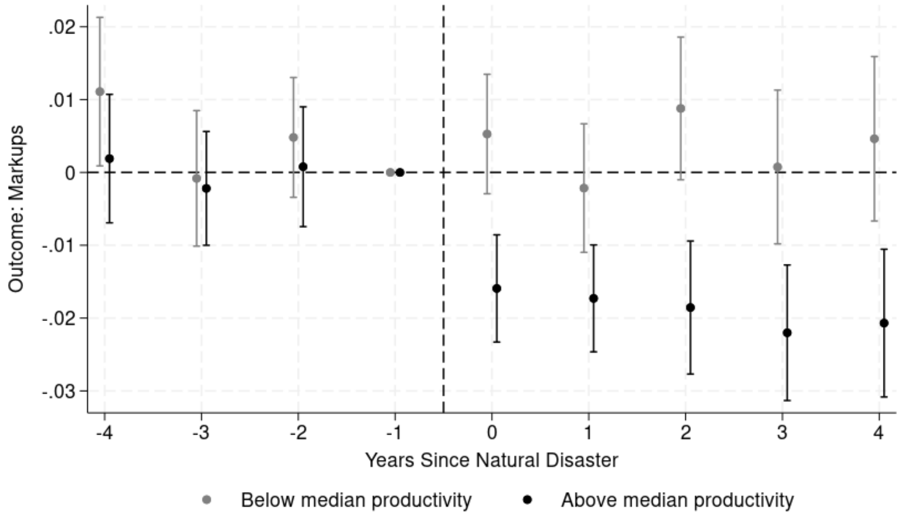
Notes: The figure reports the effect of earthquakes on Italian firms' markups between 2005-2019 by size. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry–year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included.

Figure A3: Eliminating Competitors within the same Industry-Province



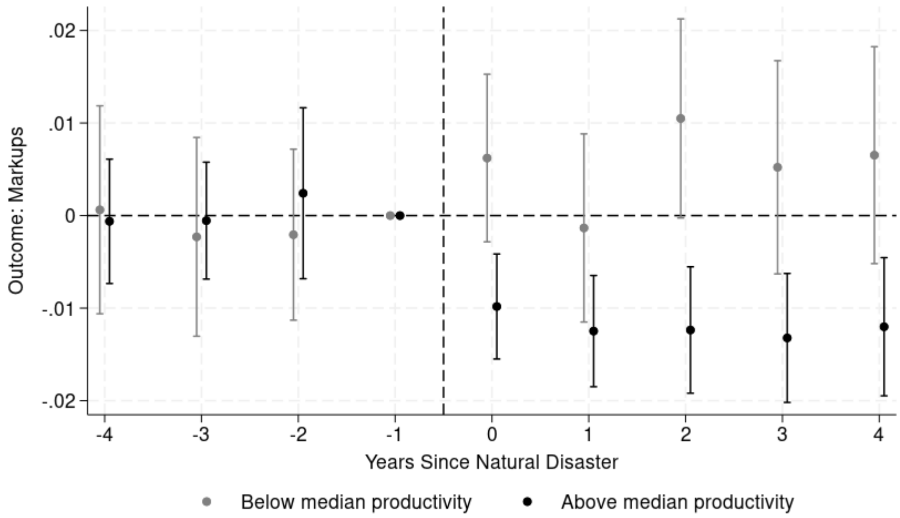
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located in the same industry and province as treated firms.

Figure A4: Eliminating Competitors within the same Industry



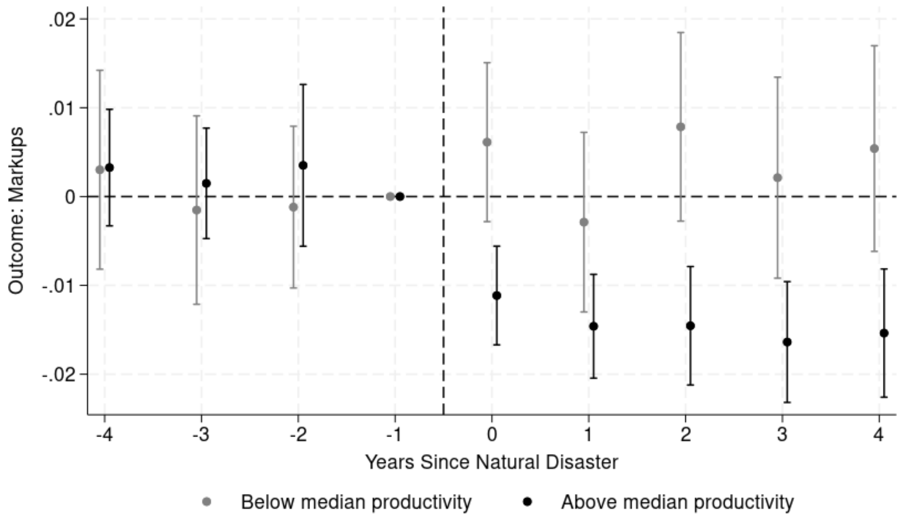
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 2-digit sector-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located in the same industry as treated firms.

Figure A5: Robustness: Eliminating Direct Clients and Suppliers of Treated Firms



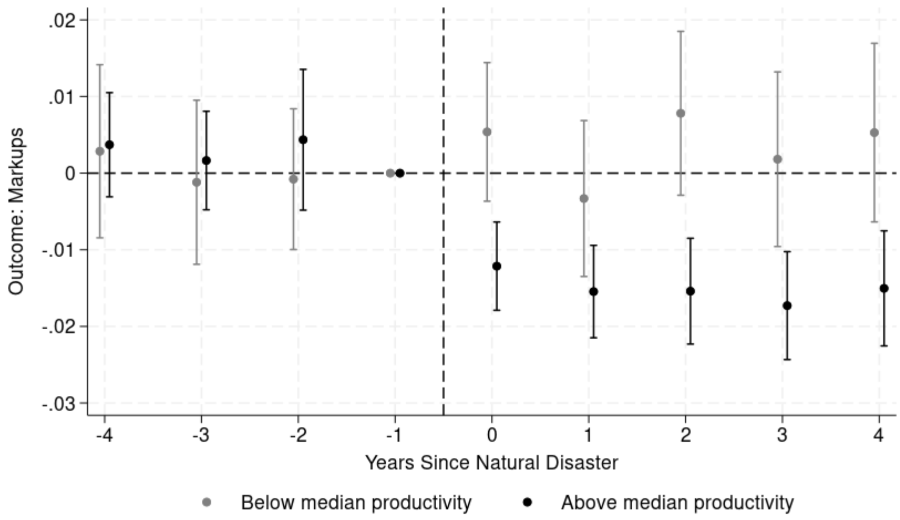
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We identify the direct clients and suppliers of the treated firms using the 2019 cross-section of the domestic firm-to-firm data, and we exclude these firms from the control group.

Figure A6: Robustness: Eliminating Indirectly Treated Firms (Distance $\leq$ 25 km)



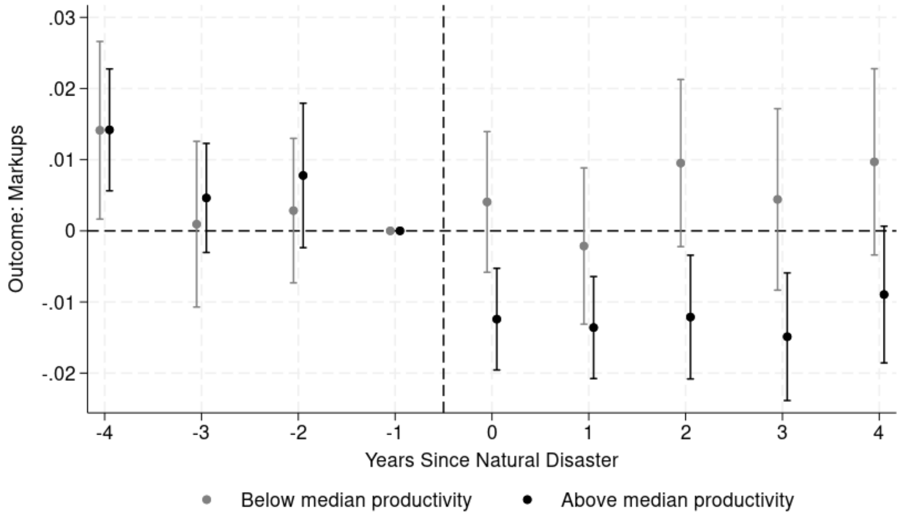
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located within a 25 km radius of treated firms.

Figure A7: Robustness: Eliminating Indirectly Treated Firms (Distance $\leq$ 100 km)



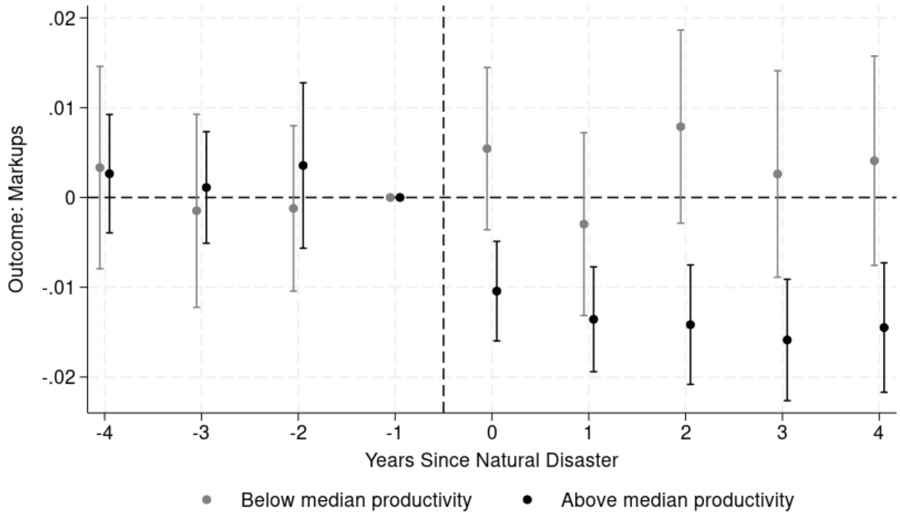
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located within a 100 km radius of treated firms.

Figure A8: Robustness: Eliminating Indirectly Treated Firms (Distance $\leq$ 250 km)



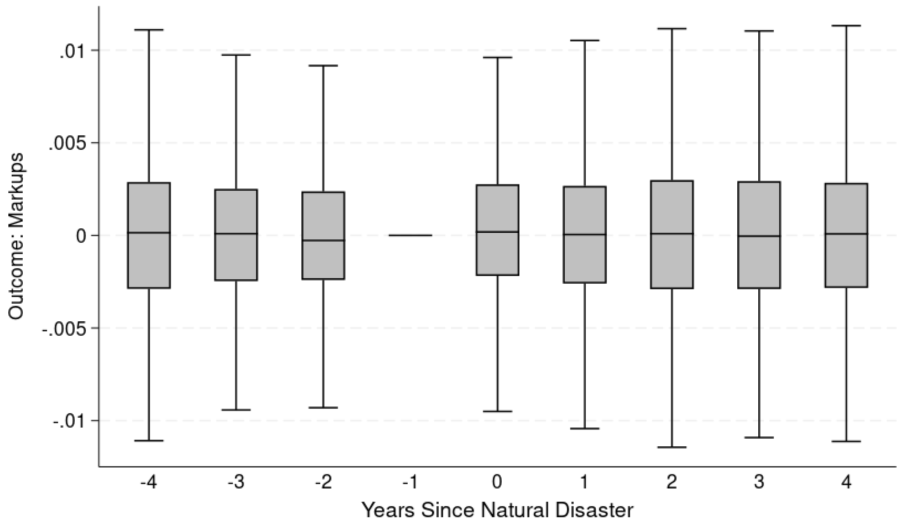
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located within a 250 km radius of treated firms.

Figure A9: Robustness: Eliminating Indirectly Treated Firms, Same Commuting Zone



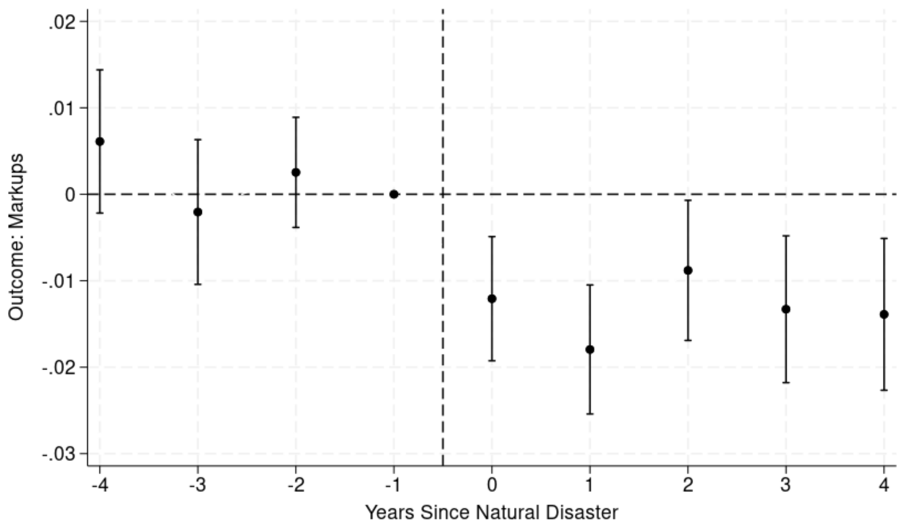
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. We exclude untreated firms located in the same commuting zones (Istat's *Sistemi locali del lavoro*) as treated firms.

Figure A10: Treatment placebo



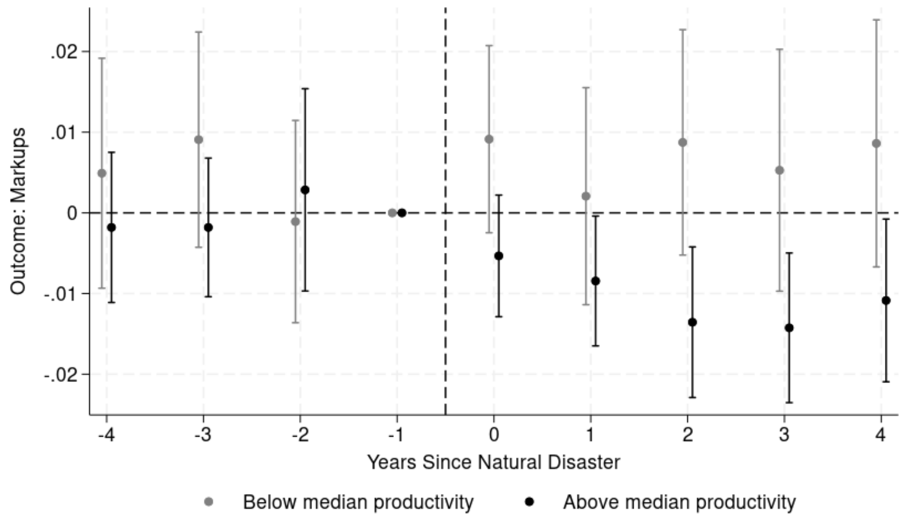
Notes: The figure plots the median, 25th and 75th percentile (edges of the box), and lower and upper adjacent values for the frequency distribution of estimates of the event study coefficients from running 1,000 regressions on simulated data. The simulated data are generated by randomly replacing the natural disaster dummy with that of another firm.

Figure A11: Treatment Assignment Based on Distance from 2012 Earthquake



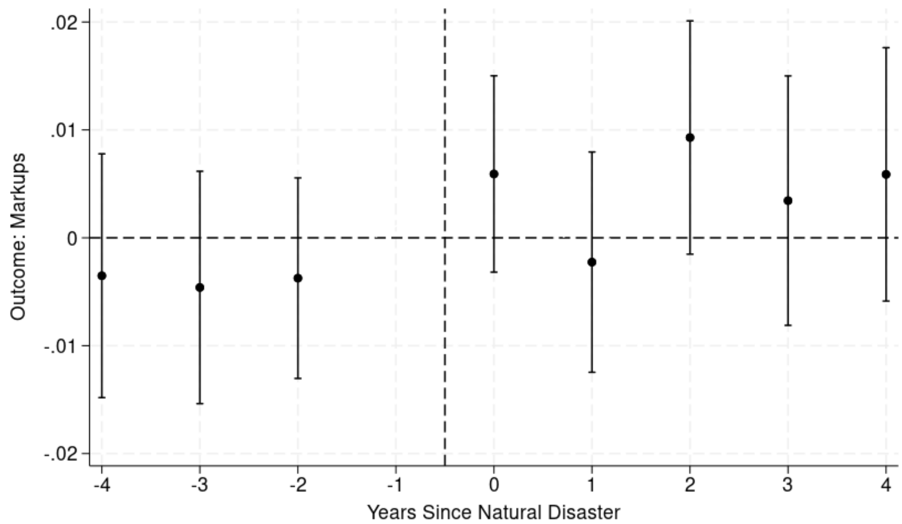
Notes: The figure reports the effect of the 2012 earthquake on Italian firms' markups between 2005-2019. We identify the epicenter of the 2012 earthquake in Emilia-Romagna and calculate the distance between each firm's headquarters and the epicenter. Firms are then split into two groups based on this distance: those in the bottom 50% of the distribution are classified as treated, while those in the top 50% are considered untreated. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. All leads and lags coefficients are included in the estimation.

Figure A12: Robustness: Removing Costliest Event



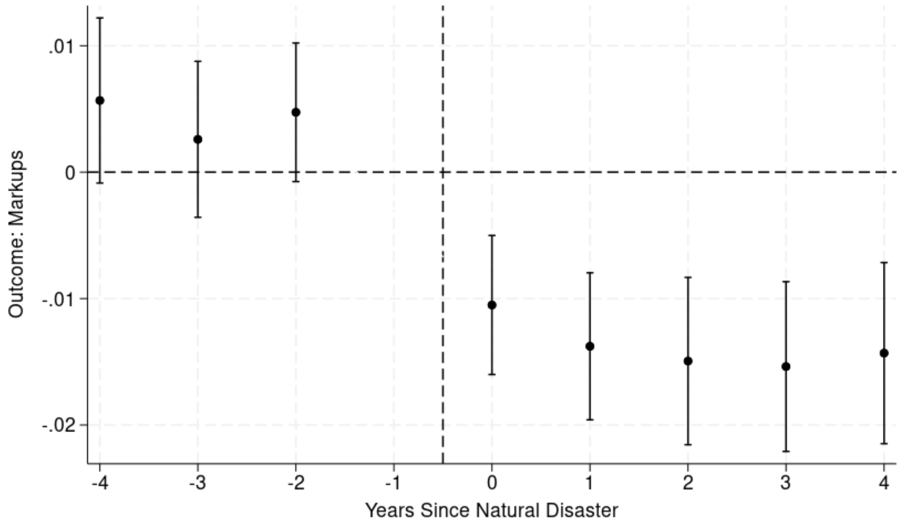
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019 after having removed the costliest event, the 2012 Italian earthquake. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A13: Robustness: Separate sample, less productive firms



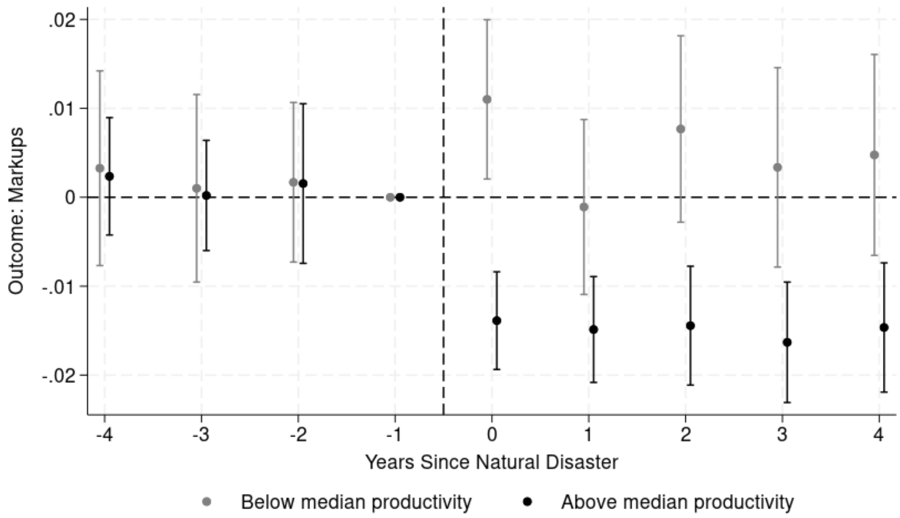
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. The treated and control groups only include less productive firms, defined as those in the bottom 50% of the labor productivity distribution.

Figure A14: Robustness: Separate sample, large firms



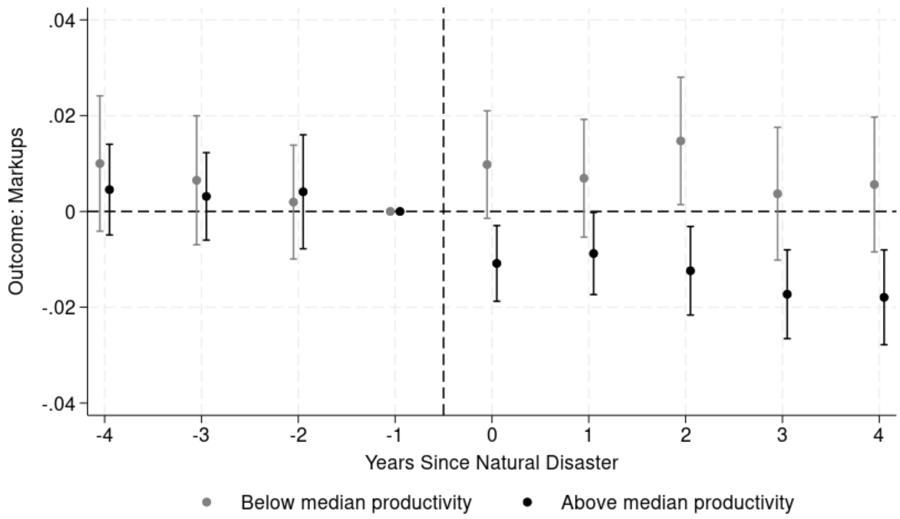
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation. The treated and control groups only include high-productivity firms, defined as those in the top 50% of the labor productivity distribution.

Figure A15: Robustness: Alternative Definition of High-Productivity Firms



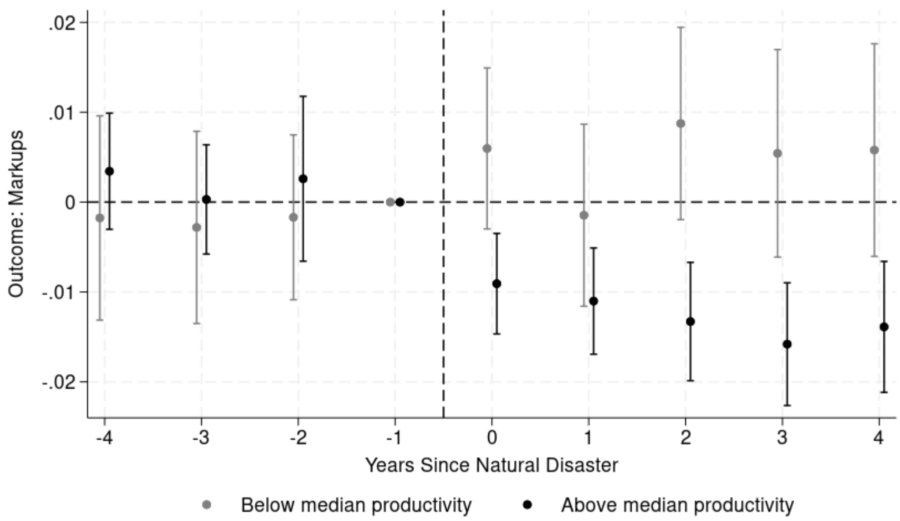
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 5-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A16: Robustness: Industry-Province-Year Fixed Effects



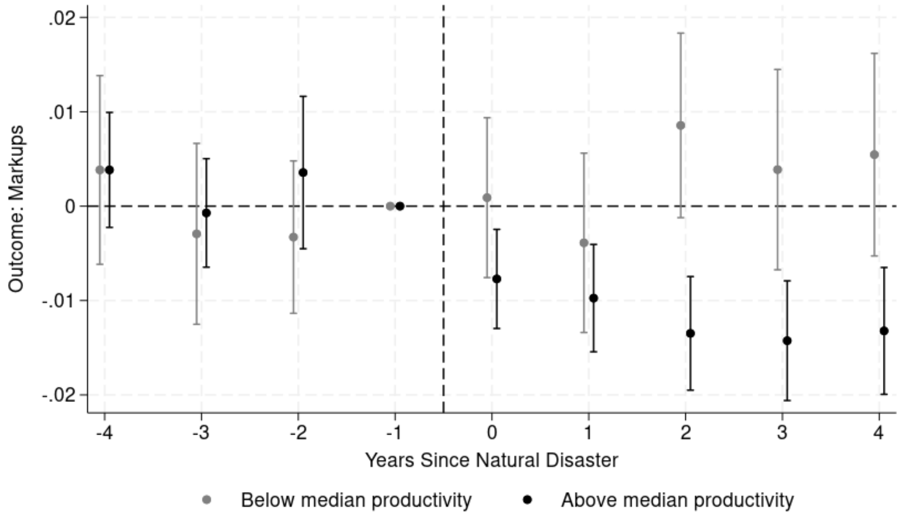
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-province-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A17: Robustness: Time-Varying Output Elasticities



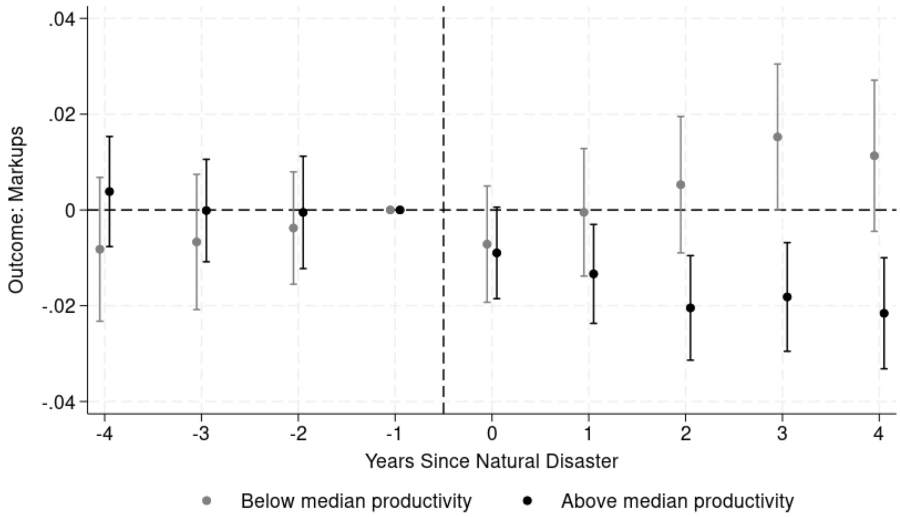
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. The output elasticity used to define firm-level markups is time-varying. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A18: Robustness: Accounting for Factor Price Differences



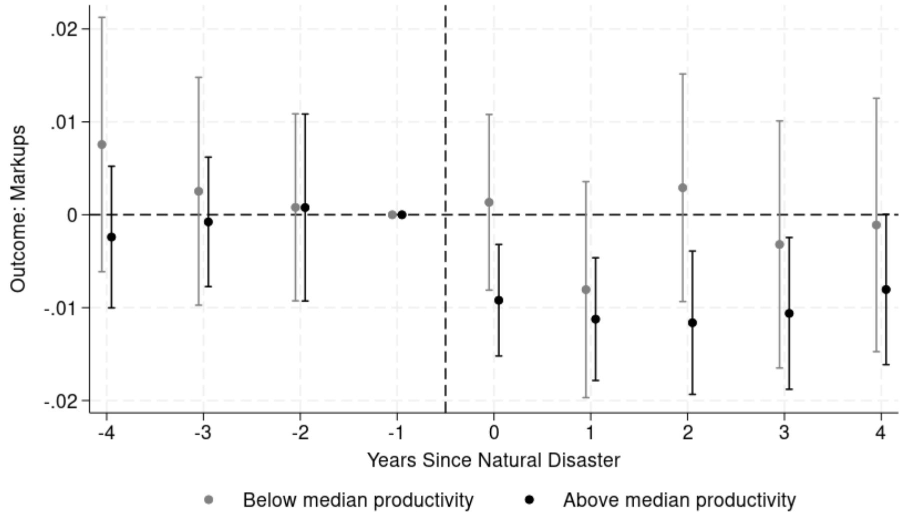
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. The output elasticities used to define firm-level markups are defined at the 5-digit industry-province-quintile to account for factor price differences. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A19: Robustness: Alternative Definition of Markups, Labor Markups



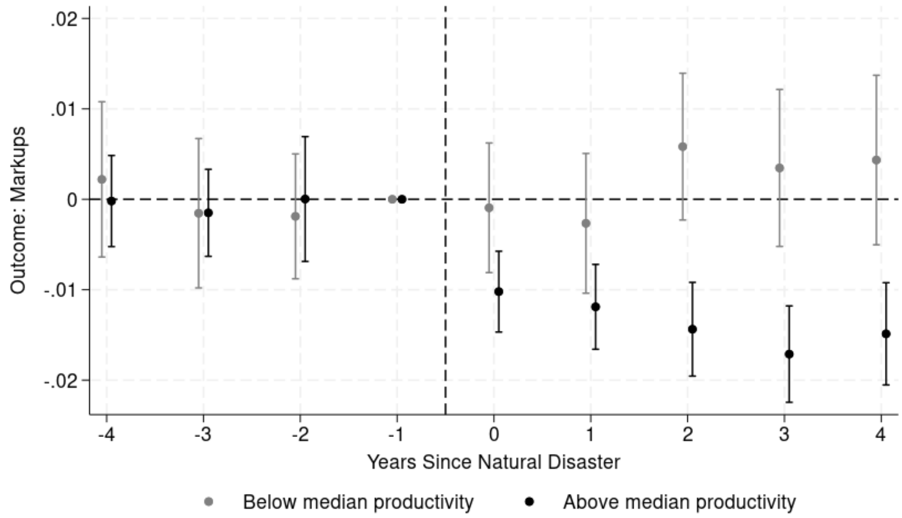
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. The dependent variable uses labor as the flexible input to measure firm-level markups. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A20: Robustness: Alternative Definition of Markups, Standard Materials Markups



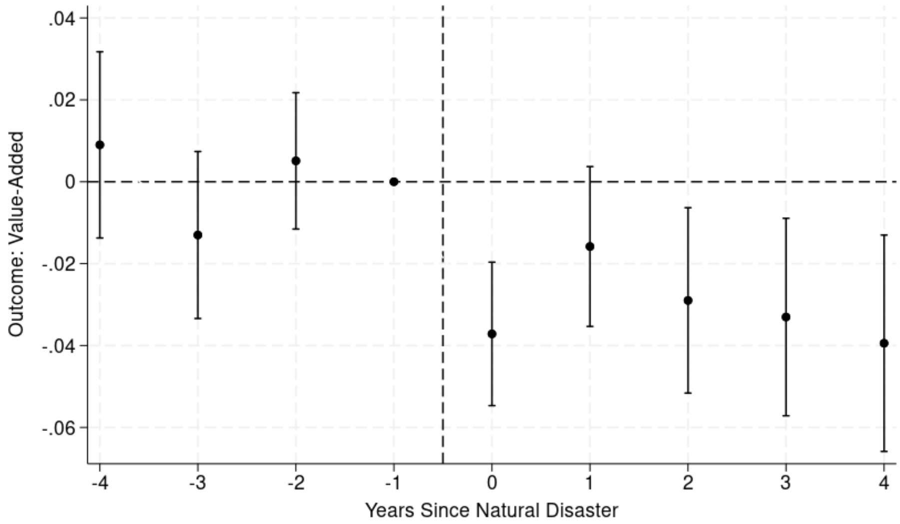
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. The dependent variable uses materials as the flexible input without applying Raval (2023a)'s correction. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A21: Robustness: Alternative Definition of Markups, Lerner Index



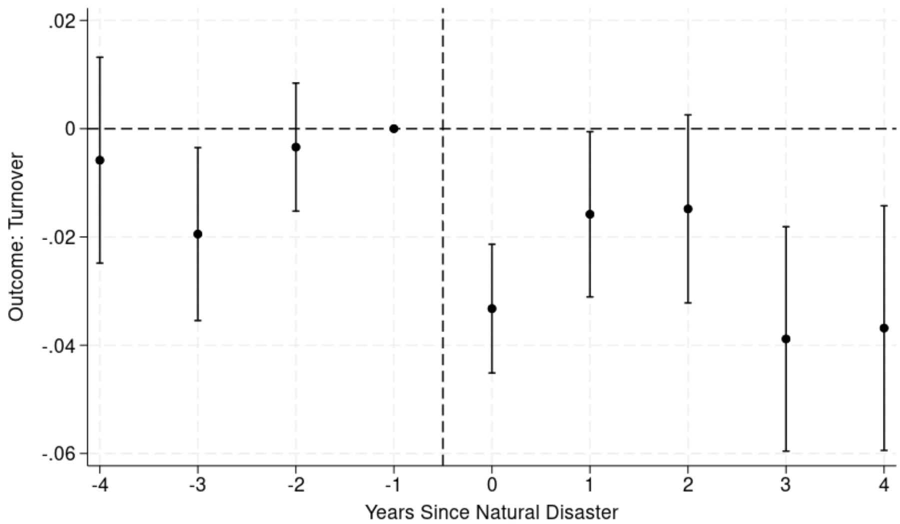
Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. Firm-level markups are defined as the ratio of turnover to total cost. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. High-productivity firms are defined as those whose labor productivity exceeds the median within their respective 2-digit sector. Estimation based on Equation (3) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A22: Value-Added



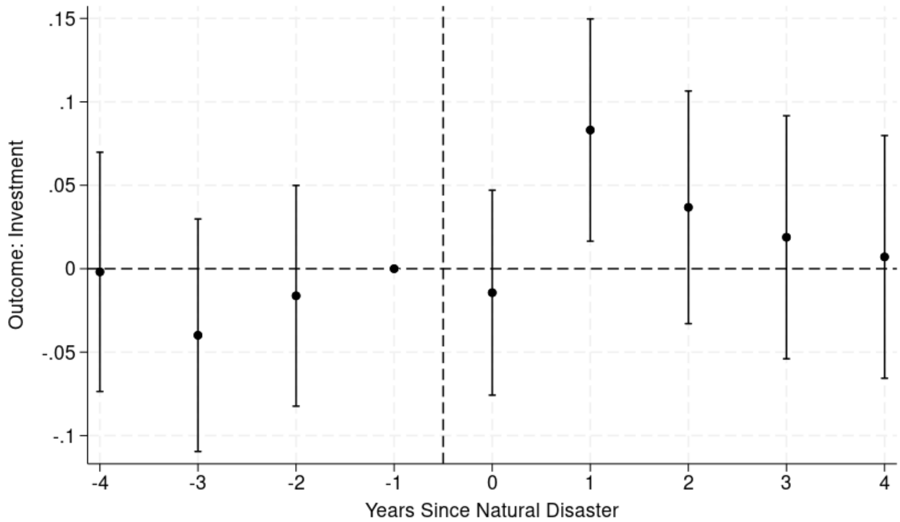
Notes: The figure reports the effect of natural disasters on Italian firms' value-added between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A23: Sales



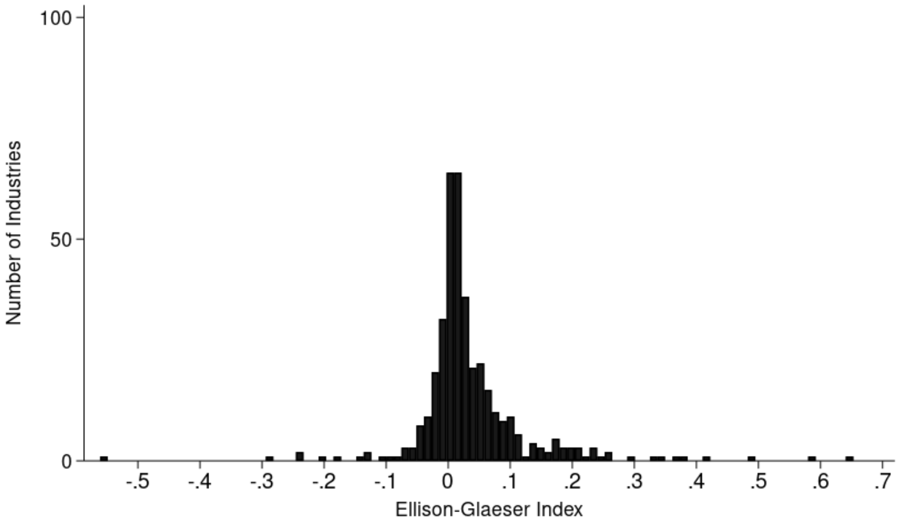
Notes: The figure reports the effect of natural disasters on Italian firms' turnover between 2005-2019. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A24: Investment

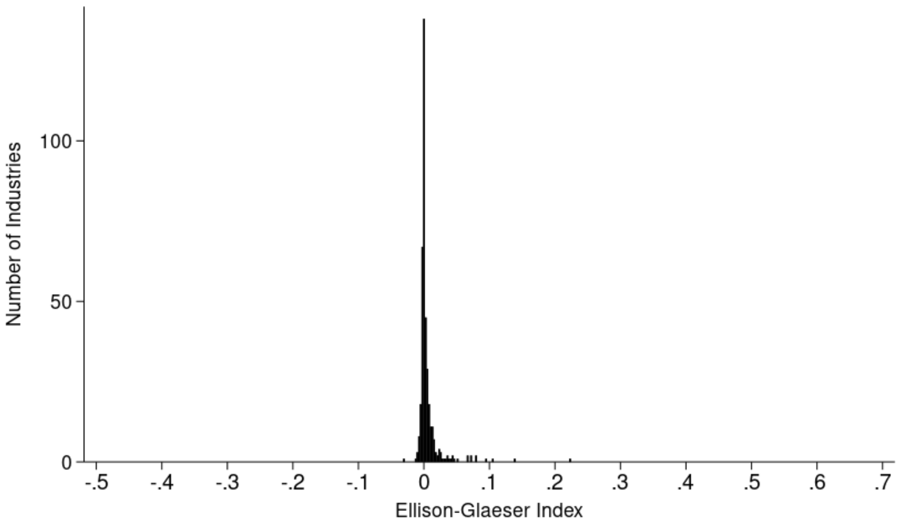


Notes: The figure reports the effect of natural disasters on Italian firms' investment between 2005-2019. Investment only includes tangible goods. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. The control group consists of never treated firms. All leads and lags coefficients are included in the estimation.

Figure A25: Geographic Concentration in Italy



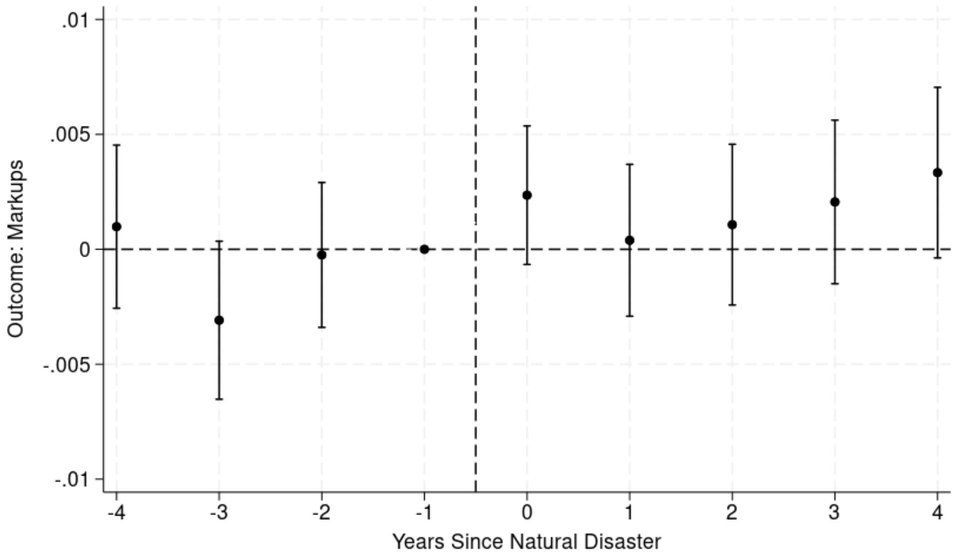
(a) Municipality Level



(b) Province Level

Notes: The figure reports Ellison and Glaeser (1997)'s index computed in 2012 for Italy. Industries are defined at the 5-digit industry level. In panel (a) areas are defined as postcodes, while in panel (b) areas are defined as provinces.

Figure A26: Effects of Natural Disasters on Untreated Firms



Notes: The figure reports the effect of natural disasters on Italian firms' markups between 2005-2019. The treated group is defined as untreated firms located in the province with treated firms. The control group consists of firms located in provinces without treated firms. Actually treated firms are excluded from the sample. Each dot represents the coefficient with the 95% confidence interval. The regression includes 5-digit industry-year and firm fixed effects. Standard errors are clustered at the firm level. Estimation based on Equation (2) using Sun and Abraham (2021)'s method. All leads and lags coefficients are included in the estimation.

E Additional Tables

Table A1: Summary Statistics for Italian Manufacturing Firms, 2005-2019

	Mean	Median	SD	Min	Max
Markup	1.07	1.05	0.18	0.43	2.11
Turnover (in € mn)	8.20	1.46	99.03	0.00	2889.00
Value added (in € mn)	1.84	0.43	12.89	-635.82	3002.61
Labor	27.80	10.00	163.65	0.08	33035.33
Assets (in € mn)	1.82	0.21	17.21	0.00	5100.96
Labor productivity (ln)	3.81	3.83	0.64	-3.48	12.26

Notes: The table reports summary statistics for Italian manufacturing firms between 2005 and 2019. The data come from CERVED.

Table A2: Costly Natural Disasters in France

Event	Year	Estimated Damage ($ mn)	Regions Affected
Flood	2010	2,013	Var
Storm	2010	5,677	Charente-Maritime, Deux-Sevres, Vendee, Vienne
Flood	2013	823	Haute-Garonne, Hautes-Pyrenees, Pyrenees-Atlantique
Flood	2014	375	Aude, Gard, Pyrenees-Orientales, Var
Flood	2015	1,141	Alpes-maritimes, Var
Flood	2016	2,926	Calvados, Eure, Manche, Marne, Orne, Seine-Maritime, Yvelines

Notes: This table describes the natural disasters included in the sample. The list is restricted to natural disasters in France from 2005 to 2019 with total estimated direct damages above $250 million in 2021 constant dollars, for which we can identify the affected postcodes. Estimated damages are expressed in millions.

Table A3: Natural Disasters and Firm Exit

	Dependent variable: Exit					
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster	0.008*	0.004	0.003	0.001	0.000	-0.006
	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)	(0.008)
Financial Debt-to-Assets Ratio (lag)			0.032***	0.032***	0.032***	0.031***
			(0.002)	(0.002)	(0.002)	(0.002)
Natural disaster $\times$ Financial Debt-to-Assets Ratio (lag)					0.011	0.027
					(0.022)	(0.026)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	No	Yes	No	No	No
Sector-Year-Province FE	No	Yes	No	Yes	Yes	Yes
Observations	1,163,824	1,077,836	1,015,547	936,208	1,015,547	936,208
Adj. R^2	0.158	0.157	0.165	0.165	0.164	0.164

Notes: The dependent variable is a dummy that indicates whether firm i exits at time t following a natural disaster. In columns 3–6, we control for the lagged financial debt-to-assets ratio of firm i. All specifications include firm fixed effects. Standard errors are clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A4: Firm Inverse Markups and Market Shares: First-Differences

	Dependent variable: $\Delta\mu^{-1}_{i(s)t}$		
	(1)	(2)	(3)
$\Delta\omega_{i(s)t}$	-0.367***	-0.365***	-0.400***
	(0.028)	(0.028)	(0.029)
Year FE	Yes	No	No
Sector-Year FE	No	Yes	No
Industry-Year FE	No	No	Yes
Observations	1,182,107	1,182,107	1,182,107
Adj. R^2	0.000	0.003	0.005

Notes: The dependent variable is the first difference in the inverse markup of firm i at time t. The independent variable is the first difference in firm i's market share, defined as it domestic sales share within its 5-digit industry. Sectors (industries) are defined at the 2-digit (5-digit) level. Standard errors clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A5: Firm Inverse Markups and Market Shares: Instrumental Variable

	Dependent variable: $\mu^{-1}_{i(s)t}$	
Instrument	$\omega_{i(s)t-1}$	$\omega_{i(s)t-2}$
	(1)	(2)
ω_{it}	-0.406***	-0.364***
	(0.042)	(0.067)
Industry-year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	1,144,792	981,215
Adj. R^2	-0.004	-0.004
F statistic	718.8	146.8

Notes: The dependent variable is the inverse markup of firm i at time t. The independent variable is firm i's market share, defined as it domestic sales share within its 5-digit industry. The one- (two-) year lag of the independent variable is used as an instrumental variable in column 1 (2). Industries are defined at the 5-digit level. Standard errors clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%. The dependent variable is the inverse of firm-level markups.

Table A6: Robustness: 2012 Earthquake

	$\Delta\kappa = 1\%$	$\Delta\kappa = 10\%$	Theory-consistent μ	$\rho = 12.76$	$\rho = 59.69$
	(1)	(2)	(3)	(4)	(5)
Panel A: Gross-output productivity losses, %					
Change with markup adjustments	-0.009	-0.039	-0.030	-0.042	-0.021
Change with constant markups	-0.008	-0.031	-0.021	-0.038	-0.008
Relative change	7.8	23.3	42.7	12.2	167.3
Panel B: Static welfare losses, %					
Change with markup adjustments	-0.010	-0.047	-0.036	-0.047	-0.026
Change with constant markups	-0.009	-0.035	-0.026	-0.042	-0.013
Relative change	12.0	35.5	36.7	13.6	96.2

Notes: The table displays the gross-output aggregate productivity and welfare changes associated with the 2012 Italian Earthquake in panels A and B, respectively. The model with constant markups holds the distribution of markups constant to that obtained in the baseline calibration. Natural disasters are modeled as a decrease in the technical efficiency of affected firms. Row 1 (2) reports the change in the relevant aggregate variable when firms (do not) endogenously adjust their markups. Row 3 reports the amplification effect of variable markups by taking the ratio of the change in productivity following natural disasters in models with and without variable markups. The contribution of variable markups does not exactly add up to the ratio of the first two rows due to rounding. In columns 1-2, we consider a smaller (1%) and larger (10%) shock to the technical efficiency of affected firms. In columns 3-5, we are recomputing the underlying distribution of markups so that it is consistent with eq. (5) before recovering $z_i(s)$. Column 3 uses our baseline elasticities, while columns 4 and 5 set ρ to 12.76 ($\eta = 1.92$) and 59.69 ($\eta = 2.18$), respectively.

Table A7: Distribution of Firms Market Shares, Po River Basin Flood

Percentile	Treated	Untreated
1st	0.00	0.00
5th	0.01	0.00
10th	0.01	0.01
25th	0.02	0.02
Median	0.08	0.06
75th	0.26	0.21
90th	0.81	0.64
95th	1.71	1.34
99th	7.99	6.65
Mean	0.52	0.44

Notes: Distribution of market shares for treated and untreated firms under the counterfactual catastrophic Po River flood scenario. Treated firms are those whose headquarters are located within the Po River basin.