Markups And Firm Entry: Evidence From The 2012 Emilia Earthquake *

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Abstract

The cyclical behaviour of price markups is key for the propagation of shocks throughout the economy. Yet, the empirical evidence about this issue is mixed. In this paper I provide direct evidence of markup counter-cyclicality, conditioning on a positive demand (government expenditure) shock. I exploit the exogenous increase in publicly subsidized housing reconstruction after the 2012 earthquake in Emilia-Romagna (Italy) as a natural experiment. I construct a granular measure of earthquake disruptiveness, which is used to identify the causal effect of interest. I find that markups decreased on average by 4 percentage points following the expansionary shock. Moreover, I show that the drop in markups is mainly driven by a reduction in prices due to firm entry in the face of increasing marginal costs of labour.

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1 Introduction

"How markups move, in response to what, and why, is however nearly terra incognita for macro." Blanchard (2008)

How do markups respond to fluctuations in aggregate economic variables is a key, yet unsettled, question in Macroeconomics. Markup cyclicality plays an important role in the propagation of shocks to the aggregate macroeconomy, making the understanding of its behaviour vital for the design of policy responses. More specifically, in the context of fiscal policies, markup cyclicality affects the sign and size of fiscal multipliers as it helps explaining the evolution of industries' competitive structures, their barriers to entry and their openness to new markets and products. Although a large number of papers has contributed already to this literature, theoretical models and empirical studies often provide opposite evidence, leaving the debate still open (Nekarda and Ramey (2013), Anderson, Rebelo, and Wong (2018) and Galeotti and Schiantarelli (1998)).

Motivated by the need of a greater understanding, this paper contributes to the current debate on this issue by exploiting a natural experiment as a way to clearly identify markups response to a government expenditure shock. I study the effect of the demand shock faced by construction firms involved in subsidized housing-reconstruction on price markups. I use the Emilia-Romagna (Italy) housing reconstruction plan - a plan sponsored by the Italian government to support housing reconstruction after the devastating 2012 earthquake - as the main laboratory for my study. Subsidies for housing reconstruction were substantial and mattered for a quick recovery. The earthquake hit a densely populated area, causing overall estimated damages that exceeded €13bln, out of which 4.5bln were devoted to residential housing. The reconstruction plan set up by the Italian government had the twofold objective of avoiding a rapid disappearance of small towns and of their local production activities, as well as of employing local firms for reconstruction. Households were provided with the freedom to choose the most preferred construction firms, conditionally on presenting at least two competing quotes to the local government. Upon selection of the cheapest quote, the government would then pay the selected firms directly.

This setting allows me to exploit a novel dataset that collects detailed information on government-subsidized contracts for housing reconstruction. The data provides granular information for all households applying for government subsidies to the local municipality. Information includes contract-level variables such as the total value of the contract, the size of the houses destroyed by the earthquake, the number of working days for each contract and the damage level of each house. The richness of this data allows me to compute per-square-meter prices and markups for each reconstruction contract. I then combine this information with standard balance sheet data at the firm-level from Analisi Informatizzata delle Aziende Italiane (AIDA) dataset, which includes balance sheet data, financial variables as well as income statement. The resulting dataset matches contract-level information with firms' characteristics at the firm level.

Data availability affects my markup estimates, as marginal costs are not directly observable. To overcome this issue, macro models have often estimated marginal costs assuming a functional form of the production function. At the same time, the empirical literature has also employed more general markup estimation, measuring marginal costs with average costs when the amount of fixed costs over total costs is low. As the construction industry considered in this paper features low fixed costs - the main input to production are raw materials and labor - I first estimate firm-level markups using average costs as a proxy for marginal costs[1]. Second, at the contract-level, I estimate markups as the inverse of the labor share[2]. The construction industry is a characterized by a labor-intense technology and by a local labor market, making labor margins a meaningful measure of marginal costs.

[1] I follow De Loecker and Eeckhout (2017), Domowitz, Hubbard, and Petersen (1986) and Anderson et al. (2018) who use gross margins as a measure for markups. Gross margins are defined as the ratio between operating margin and sales value.

[2] I follow Bils (1987), Rotemberg and Woodford (1999) and Nekarda and Ramey (2013) who use labour input margins to estimate marginal costs.

Direct selection of construction firms by households poses significant identification challenges on the causal effects of positive demand shocks on markups. As the reconstruction plan allows households to select preferred firms, contracts are not randomly assign to firms and OLS estimation would lead to selection bias. I address selection bias in two ways. I first exploit the exogenous variation in firms' headquarters location and compare municipalities differently affected by the earthquake. Firm-level data allow me to estimate the intention-to-treat (ITT) by comparing markups for firms which headquarter is located in provinces hit by the earthquake with markups of firms located in provinces not hit by the earthquake. As balance sheet data spans for 10 years around the earthquake event, I also exploit the pre/post time variation induced by the earthquake, by nesting the ITT within a diff-in-diff setting. At the contract level, I exploit within firm variation as I compare different contracts signed by the same construction firm. The benefits of within firm variation are twofold. On one hand, it removes many confounding variables that would instead be present in comparing contracts signed by different firms. On the other hand, it benefits the estimation issues related to marginal costs. As I compare the contracts signed by the same firm, marginal costs are the same for the two contracts and hence all differences in markups are due to variation in prices.

This paper provides evidence of counter-cyclical markups and shows that the decrease in markups is driven by a drop in prices and by a contextual increase in marginal costs. On one hand, the decrease in prices is driven by firm-entry, as firms headquartered in other regions move to Emilia-Romagna and new firms locate in the municipalities affected by the earthquake. On the other hand, it also shows that labour costs are procyclical and increases more for firms exposed to a higher demand shock. Both results provide evidence of countercyclical markups, which decrease for firms affected by a positive demand shock and the more so, the larger is the demand shock.

These results support the countercyclical findings of the theoretical literature and contradict the more recent results of the empirical side of the debate. The theoretical literature has provided supporting evidence in favour of countercyclical markups in a number of different settings. Bils (1987) and Rotemberg and Woodford (1999) use labour input margins to estimate marginal costs in a New Keneysian framework. They show that, under the assumption of marginal costs of labour being more procyclical than average labour costs[3], markups decrease because of higher labour costs. My results indeed confirm that labor costs are procyclical and that, consequently, markups defined as the inverse of the labour share are conutercyclical. Rotemberg and Saloner (1986) develop a game-theoretic approach and show that firms reduce markups in booms rather than in recessions, as the incentives to deviate from cartels and undercut your competitors are stronger when output increases. Jaimovich and Floetotto (2008) provide instead theoretical evidence that markups' cyclicality can be explained by an increase in competition due to firm-entry. As demand for goods increases, new firms enter the market and compete by reducing prices. My results confirm that lower prices are indeed driven by higher competition due to firm entry.

On the other hand, recent empirical papers provide greater evidence of procyclical markups. Nekarda and Ramey (2013) revisit the New Keneysian framework with a set of more general assumptions and new data to find that markups are procyclical conditioning on a positive demand shock. Anderson et al. (2018) use four levels of data aggregation to show that markups are mildly procyclical over time and display positive correlation with local income. Kim (2018) explores the relationship between markups and financial constraints, arguing that, in recessions, financially constrained firms decrease markups to liquidate inventories and to increase their revenues and cash holdings. A sample splitting result in the diff-in-diff section also confirms that markups are more procyclical for financially constrained firms.

Finally, as most of funding for reconstruction is subsidized by the government, this paper

[3] Rotemberg and Woodford (1999) allow for overhead labour

also assesses the effectiveness of expansionary fiscal policy in getting out of a recession. Following Hart (1982) seminal paper, for a long time it was thought that the fiscal multiplier was strictly increasing in the monopoly degree, as pure profits are generated, stimulating households' income and consequently aggregate demand. However, most of these models use Dixit and Stiglitz (1977) monopolistic competition where each firm faces a constant-elasticity demand function, so that the markup is also constant. This assumption is not consistent with the evidence presented in Gali (1995), and Rotemberg and Woodford (1995) that support the hypothesis of counter-cyclical markups. In this paper, following the theoretical arguments made by Startz (1989), I present empirical evidence based on a natural experiment showing that markups behave counter-cyclically when pure profits induces firms entry, interpreted as more firms per industry. As a result, fiscal policy produces an aggregate demand externality by stimulating entry, pushing the markup downwards, and therefore introducing efficiency gains in the economy.

The rest of the paper is structured as follows: Section 2 explains the setting and the data used; Section 3 presents the firm level analysis; section 4 illustrates the contract level analysis and Section 5 concludes.

2 Setting and Data

This section describes the 2012 Emilia Romagna earthquake, the reconstruction plan organized by the government and the data sources used.

2.1 Government Subsidies for Reconstruction

In May 2012, Emilia-Romagna faced two intense earthquakes nine days one from the other. The first earthquake, on May 20th 2012, had a magnitude of 6.1 on the Richter scale and the epicenter set in the small town of Finale Emilia. The second earthquake, instead, occurred on May 29th, it had a magnitude of 5.9 and its epicenter was located in the nearby Mirandola. Both earthquakes had disruptive effects to buildings close to the epicenter as well as in the neighbouring municipalities.

Insert Figure 1 here

Figure 1 displays a chart of all municipalities in Emilia-Romagna and it highlights with a darker tone those that were more affected by the earthquake. The overall estimated damages exceed €13bln, of which €4.5bln were estimated for residential housing. The Italian Government and the Emilia-Romagna region immediately announced government subsidies and a reconstruction plan that had a twofold objective. On one side, it wanted to avoid a rapid disappearance of small villages and of their local production activities, which account for around 2%[4] of the national GDP. On the other, it aimed at employing local firms for reconstruction, helping them to restart production and benefitting the whole local economy through the fiscal multiplier.

Government subsidies involved both residential units as well as productive units. As of February 2017, more than 9,766 buildings filed for a government subsidy, for a total of around 26,786 building units, 15,201 of which were for first homes. Out of the 9,766 requests, 7,700 have been already approved and have gone through - or are still under - reconstruction. The amount of subsidies for residential reconstruction already approved by the local government amount to approximately €4bn, most of which has been already liquidated. This paper focuses on the effects of this massive inflow of money to those firms involved in the reconstruction of residential housing.

Applications for subsidies to housing reconstruction opened in late 2012 and are still ongoing. In order to apply, a beneficiary would need to get a damage certificate from an independent technician, together with at least two quotes from two competing firms, firms $F1$ and $F2$ in Figure 2. Subsidies are capped, both on size and on the level of the damage reported. Household H would then need to submit the two quotes and the damage certificate to the local municipality as last step of the application (figure (a)). If the subsidy gets approved, the municipality must select the cheapest quote, although the household always has the possibility to top up the government subsidy with private

[4] www.istat.it

funds. Once all - or part of - the construction works are terminated the municipality pays construction firms directly and no cash goes through the household (figure (b)).

Insert Figure 2 here

2.2 Data

In this section, I describe the data set construction and the data sources used.

I combine information from various sources. First, I use a new and extremely detailed contract-level (c, d, l, f, m, t) dataset, where c is the contract, d is the building's level of damage, l is the municipality where the building is located in, m is the municipality where the firm is located in, f is the construction firm hired to repair the building and t is the year in which the subsidy is approved. The dataset provides information on the value of the subsidy, the total amount of construction costs, the size of the house in square meters, the damages to the house, its geographic location and dates of payments made to the firm. This dataset has been collected by the earthquake commission of the Emilia-Romagna region and it is provided disaggregated, so that considerable effort has been put in place to match all firms with contracts and with the geographical location of firms. It is updated regularly as new subsidies are approved or payments to firms are made.

Secondly, I use balance sheet information at the firm f, municipality m and time t level (f, m, t), from AIDA, a Bureau Van Dijk database comprehensive of all Italian firms that are required to file an official account. I download balance sheet information for all Italian construction companies which I identify using the NACE Rev 2 code for a total of 285,229 firms. Starting from this set of firms I then exclude those ones that do not report a valid tax code and those ones that do not report the province where the legal entity is set. I consider all companies with a NACE Rev 2 code equal to both 41, labelled as *building constructors* and to 43, labelled as *specialized construction works.* AIDA provides information on the size of the firm (total assets, equity, revenues), on its profitability (net profits, ROE, ROA) and on its financing position (liquidity, bank debt, total debt and cost of external financing). The firm level dataset contains a number of missing observations that reduce the number of firms to approximately 85,000. Moreover, not all of the firms reported in the contract dataset have their balance sheet stored in the AIDA dataset. Out of 2153 firms involved in residential reconstruction, only 895 also appear in the AIDA dataset.

Finally, I use information at the municipality level m on the intensity of the earthquakes. I download geographic locations for all of the epicenters of both May, 20th and May 29th events from the Italian Institute of Geophysics and Vulcanology. I also use information on the intensity - measured as damages to buildings - and magnitude, measured using the Richter scale of the earthquake.

3 Firm level evidence

In this section I estimate the effect of a positive demand shock to firms on firm-level markups. I first describe the challenges related to markup estimation and I then explain the identification strategy understudy.

3.1 Markup estimation and identification

Markups are defined as the ratio between prices and marginal costs and their estimation raises serious empirical challenges. As marginal costs are not directly observable, the markup literature has proposed a number of different way to estimate them. I define firm-level markups using firms' gross margins as in Anderson et al. (2018) and De Loecker and Eeckhout (2017). Their definition assumes that average costs are used as a measure of marginal costs, which holds true for industries with very low fixed costs. This assumption fits well with the features of the construction industry, which is characterized by very little fix costs and mostly by labour and variable costs. Gross margins are defined as

$$\mu_{fmt} = \frac{\text{Total value of production}_{fmt} - \text{Total cost of production}_{fmt}}{\text{Total cost of production}_{fmt}} \tag{1}$$

where the total value of production is defined as *sales* + *inventory change*, while total costs of production are defined as *raw material* + *payroll* + *services*. Inventory change measures account for distortions in markup measurement that are due to costs for inputs used to produced outputs that are not sold. As inventories are priced at the lower value between the market value and the sales value, I follow Anderson et al. (2018) and Nekarda and Ramey (2013) and I include them in the gross margin numerator. These inventory changes are relevant in the construction industry as they account for unfinished construction units when the balance sheet is drawn up on December, 31st. Anderson et al. (2018) provide similar price markup estimates to assess cyclicality, although, unlike this paper, they do not condition the increase in output to a demand or a technology shock.

Markup estimation is not the only empirical challenge that I face in this setting. The institutional framework also affects identification of the causal effect of the positive demand shock on markups. As households can choose the firms they want them to carry out reconstruction work, estimating the effect of a demand shock on markups would lead to biased OLS estimates. Consider the following equation

$$\mu_f = \alpha + \beta D_f + \epsilon_f \tag{2}$$

where D_f is a dummy that equals 1 if firm f is involved in housing reconstruction. As D_f is not randomly assigned to firms, estimates of β would be affected by selection bias. To avoid selection bias, I exploit the exogenous variation induced by the earthquake using location of firms' headquarters to determine firms' assignment to treatment. I thus compare those firms located in municipalities affected by a severe earthquake with firms located in municipalities which are not affected by the earthquake. This analysis provides Intention-To-Treat (ITT) of the demand shock on prices. The population of firms I refer to in this firm-level analysis is composed by all Italian construction firms that are required to file a balance sheet statement to the local chamber of commerce. The balance sheet of these firms is reported in AIDA and accounts to approximately 285,000 units.

Figure 3 plots markups, as computed in equation (1), for firms located in treated municipalities versus firms that are located in municipalities that have not been affected by the earthquake. I identify firms in treated municipalities as the ones with legal headquarters in a municipalities that has been affected by the earthquake. Gross margins are averaged on the two groups using total asset as relative weights.

Insert Figure 3 here

Figure 3 shows that gross margins of firms in treated municipalities have a similar pattern to the gross margins in non-treated ones in the years before the earthquake. Instead, they decrease in treated provinces from 2012 onwards and they never get back to pre-crisis levels. Theses patterns provide suggestive evidence of a reduction in markups following a positive demand shock, as gross margins drop for construction firms located in Emilia Romagna after the earthquake.

Figure **??** shows firms' return on equity (ROE) for treated and control provinces. ROE for firms in treated municipalities raises in the years after the earthquake, suggesting that the increase in construction work helped Emilia firms recovering from the downward trend in productivity.

I also compare firms in treated and control provinces on other balance sheet variables. Table 2 compares firms on balance sheet variables averaged in the years before 2012. Firms located in treated provinces show similar markups and profitability to the non-treated ones. At the same time they are on more leveraged, more exposed to banks and they also have bigger revenues than the control group. All other differences in the remaining variables are statistically significant different among the two groups. This however, does not invalidate the empirical identification adopted as location in a given municipality is orthogonal to firms' characteristics.

Insert Table 2 here

3.2 Difference-in-differences

Evidence presented in Figure 3 shows that, following the earthquake, gross margins decrease in treated municipalities, while they do not vary for firms in the control group. I test formally this result in a difference-in-differences (diff-in-diff) set-up, where I compare firms located in treated versus control municipalities before and after the earthquake. The identifying assumption behind the diff-in-diff is that firms located in treated municipalities would have kept grossmargins equal to the ones in control municipalities, had the treatment been absent. Absence of pre-trends is formally checked and confirmed by an event study.

I exploit the random allocation of treatment on different municipalities and I estimate the following equation

$$\mu_{fmt} = \alpha_f + \lambda_t + \beta T_m + \gamma post_t + \delta(T_m \times post_t) + \theta X_f + \zeta(T_m \times t) + \epsilon_{fmt} \qquad (3)$$

where μ_{fmt} is the gross margin of firm f headquartered in municipalities m, at time t. T_m is a dummy variable that equals one if the municipality where the firm is located is hit by the earthquake and zero otherwise, and $post_t$ is a dummy that equals 1 in the post period. X_f are ex-ante firms' characteristics, while δ captures the interaction term and represents the parameter of interest.

Insert Table 3 here

Table 3 provides estimation results. Column (1) reports OLS coefficients without firm and year fixed effect, while columns (2) to (3) include them first separately and consider them then jointly in column (4). Results show that gross margins decrease in the post period, but they decrease more for firms located in treated provinces. The estimated coefficient on the interaction term shows that gross margins decrease by approximately 4.3 percentage points more in firms located in treated provinces than the ones located in other provinces. Column (5) includes firms controls variable X_f averaged in the prepe-riod, and show that the effect remains strong and significant. Gross margins decrease more for less profitable firms and for firms with a greater number of employees. It also drops more for firms with greater liquidity and for firms that have smaller inventories. Finally, column (6) includes a time trend component, to allow for differences in parallel trends in the pre-period. Results still hold in sign, although the size of the coefficient drops by half of its value.

I test for parallel trend assumption in Figure 4, by checking for the presence of pre-trends. I estimate the following equation which consists in an event study that estimates the baseline regression with different treatment years.

$$\mu_{fmt} = \alpha_f + \lambda_t + \sum_{\tau=2007}^{2010} \beta_\tau T_m \mathbf{1}(t = \tau) + \sum_{\tau=2012}^{2016} \beta_\tau T_m \mathbf{1}(t = \tau) + \epsilon_{fmt} \tag{4}$$

Insert Figure 4 here

Indeed, as showed in Figure 4, pre-trends are absent between the two groups, validating parallel trend assumption and allowing for causal interpretation of the diff-in-diff exercise.

Results at the firm level are also confirmed by regressions at the municipality level in Appendix A.

3.3 Heterogeneity

The estimation results of the baseline regression showed a decrease in gross margins following a positive demand shock. Gross margins for firms in treated provinces decreased more than the ones of firms in non treated provinces, providing suggesting evidence for countercyclical markups. Nothing has been said yet on the mechanism behind this drop.

In this subsection I argue that the decrease in gross margins are driven by provinces with a higher degree of competition in the construction market, and by firms that are not liquidity constrained. I run two sample splitting exercises to test for these intuitions on a number of different subsamples.

3.3.1 Competition

I compute the Herfindahl-Hirschman Index (HHI) as a measure of competition for each province, using firms' revenues in the pre-period to measure markets' concentration. The HHI ranges from 0 to 1, where 0 denotes a perfectly competitive market, while 1 characterizes a monopoly. I then split the sample into four quartiles, according to the HHI values, ranking them from the lowest to the highest value.

I estimate the baseline equation 5 for the four different quartiles.

$$\mu_{fmt} = \alpha_f + \lambda_t + \beta T_m + \gamma post_t + \delta(T_m \times post_t) + \epsilon_{fmt} \tag{5}$$

Results are shown in Table 4. Column (1) report the baseline estimates and column (2) excludes the first quartile of firms located in the most competitive markets. Column (3) includes the estimated results for the firms located in the provinces that represent the half less competitive market, while column (4) only considers the quartile with most concentrated provinces.

Insert Table 4 here

As expected, the interaction coefficient δ decreases in absolute value as the more competitive quarters are left out of the sample. The results of the baseline regression are therefore driven by firms located in the most competitive provinces, where the HHI is the lowest.

3.3.2 Financial Constraints

Competition is not the only force driving lower gross margins in the baseline. Chevalier and Scharfstein (1996) and, more recently, Gilchrist, Schoenle, Sim, and Zakrajsek (2017) and Kim (2018) show that markups have a countercyclical behaviour, and that part of this effect is reinforced by financially constrained firms following a negative demand shock. As financially constrained firms get most of their funding from revenues, they are willing to forego part of market share and to set markups above their competitors when they hit their financial constraint.

Construction firms have cash-in-advance constraints as they need to finance construction works for some time before getting paid. I explore the role of financial constraints in this setting by splitting the sample of firms on their cost of debt. Cost of debt is a variable included in the AIDA dataset, which provides information on how expensive it is for firms to access external debt. I compute the average cost of debt for each firm in the pre-period and I split the sample of firms in 4 quartiles, ranking them from the ones with the lowest cost of debt to the highest.
I estimate equation 4 for the four different quartiles, dropping out each time a fourth of the firms with the lowest cost of debt.

Insert Table 5 here

Table 5 shows the estimated results for the baseline (column(1)) and for the three subgroups (columns (2)-(4)). The point estimates show that the baseline results are driven by those firms that are less financially constrained in the pre-period. Following a positive demand shock, some of the firms hit the borrowing limit as they need to finance an increase in production. Since revenues are their main source of funding, they forego some of the market share to increase their liquidity by raising markups.

4 Contract-Level Analysis

I now exploit a rich and novel dataset containing all reconstruction contracts that are subsidized by the local government. This new data allows me to identify those firms that are actively involved in housing reconstruction and to estimate their contract-level prices and markups. Moreover, it also allows me to study what are the driving forces behind the fall in markups depicted in Figure (3) and to understand the related underlying economic mechanism.

The contract-level dataset on reconstruction provides detailed information on the number of contracts, the active construction firms f, the total value of the contract V, the building's level of damage d, the number of square meters rebuilt per house Y and the number of working days spent per each contract L. It does not provide, however, information on other inputs used in construction, nor information on marginal costs. I use this detailed information to define two new outcome variables: the per square meter reconstruction price and a new proxy for markups defined as the inverse of the labour share.

Identification of the causal effect of demand shocks on markups poses similar concerns on selection bias as for the firm level analysis. Reconstruction contracts are not randomly assigned to selected firms, so that regressing contract-level demand shocks on markups would provide biased results. I overcome selection bias in two ways. I first compute the (ITT), defining an exogenous measure of earthquake disruptiveness at the municipality level as the number of square meters destroyed by the the earthquake. I then use that measure as an instrument for the actual demand shock faced by firms at the contract level.

4.1 Contract level prices and markups

I define the per-square-meter price P_{cdlfmt} as the ratio between the value of the contract V_{cdlfmt} and the total size of the house Y_{cdlfmt}.

$$P_{cdlfmt} = \frac{V_{cdlfmt}}{Y_{cdlfmt}} \tag{6}$$

where V_{cdlfmt} is the nominal value of the contract expressed in euros for contract c, related to a building with a level of damage d, located in municipality l, signed by firm f, located in municipality m, at time t. Y_{cdlfmt} is instead the number of square meters of the damaged house, as reported in the Italian recorder's office.

As for contract-level markups, I define them as the inverse of the labour share introduced by Bils (1987) and Rotemberg and Woodford (1999):

$$\mu_{cdlfmt} = \frac{V_{cdlfmt}}{L_{cdlfmt} \times \mathrm{W}_{ft}} \tag{7}$$

where μ_{cdlfmt} is the markup for the reconstruction of contract c, related to a building with a level of damage d, located in municipality l, signed by firm f, located in municipality m at time t. L_{cdlfmt} is the number of working days and W_{ft} is the daily wage for all employees of firm f at time t. This markup definition implies an inverse relation between markups and labour share, so that a higher labour share is associated to lower markups. Marginal costs MC_{cdlfmt} are instead defined as the additional labor cost associated to the reconstruction of one extra square meter.

$$MC_{cdlfmt} = \frac{L_{cdlfmt}}{Y_{cdlfmt}} \times \mathrm{W}_{ft} \tag{8}$$

The definition of markups as the inverse of the labour market share display countercyclical behaviour in Bils (1987) and Rotemberg and Woodford (1999). Both papers show that, by adding assumptions on standard labour to a standard Cobb-Douglas production function, markups display display countercyclical behaviour as opposed to the procyclical ones that the Cobb-Douglas production function would have originally suggested. Using the same theoretical framework, Nekarda and Ramey (2013) show instead that under less stringent assumptions, markups display procyclical behaviour as a response to a positive demand shock.

Both measures represent a considerable improvement in the markup measure at the firm level. Not only the use of labour share as a proxy for markup fits well with the construction industry under study, but they also provide a more accurate measure of the effect of the demand shock on markups. Labour is the main production input used by construction firms and it is the production factor that firms have greater market power on. Moreover, labour inputs are higher than in other industries, as lower capital investments are required[5]. In this specific case of housing reconstruction, a different labour

[5]Source: Eurostat at http://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do

share might also reflect different materials, machinery and techniques used to restore buildings with different levels of damages rather than a difference in markups. As the identification strategy proposed in the next section hinges on comparing contracts with the same level of damage, I rule out this possibility. I use total labour costs $w_{f,t}$ from the Aida balance-sheet dataset and I compute the daily wage per-worker $W_{f,t}$, dividing the yearly value by the number of days in one year. As not all firms in the contract data-set are required to file a balance-sheet statement, a subsample of contracts will be used in the analysis.

Table 7 provides some descriptive statistics on the contract-level variables used in the following section, split by the damage level cathegories.

Insert Table 7 here

The price per square meter increases as the damage is more serious, as well as the working days that are necessary to complete reconstruction and the days to get an approval from the municipality. As expected, there is no clear trend in house size across different level of damage.

4.2 Firm Entry

In this section I show that lower markups are due to lower prices, as a consequence of firm-entry. Public procurement increases competition among reconstruction firms as it induces more firms to enter the Emilia-Romagna housing-reconstruction market. Firm-entry increases competition, which lowers in turn prices of reconstructed houses. I use two measures of firm entry. The first one is defined as the number of firms which headquarter is located in a different municipality from the reconstructed house. The second one instead is defined as the number of firms that are established in different municipalities after the earthquake hits. I show that firms price discriminate, charging lower prices to houses located in municipalities with higher firm-entry.

4.2.1 Firm Entry Measures

I first provide a spatial definition of firm-entry as I measure it as the number of construction firms which headquarter is located in a different municipality with respect to the one where the damages house is located. Let E_{dl} be the number of firms active in municipality l that reconstruct houses with damage level d. I define F^1_{dl} as the number of firms that rebuild houses in municipality l and which headquarter is not located in municipality $m = l$, that is the number of firms for which $m \neq l$.

My second measure of firm-entry has a temporal dimension as it is defined by the number of construction firms that are founded in the years following the earthquake. F^2_{dl} is equal to the number of firms active in municipality l for damage-level d, that have been established after 2011. The greater is F_{dl}, the larger is the amount of firm entry in municipality l for a given level damage d, as more firms enter the market.

Table 12 provides descriptive statistics of firm-entry measures for different levels of damage. Around 30% of construction firms are local, as they reconstruct houses located in the same municipality where their headquarters are located. This measure is greater for lower levels of damages, suggesting the presence of different markets for reconstruction depending on the levels of damage. The average number of firms active in a given municipality is, on average, equal to 77 and each firm signs, on average, 7 contracts. Finally, although the number of square meters destroyed is different for each level of damage, the average number of square meters rebuilt by firms is similar across different levels of damage.

4.2.2 Identification Strategy

I exploit the within-firm variation for different contracts signed by the same firm and for the same level of damage. This identification strategy has two advantages. On one hand, it makes markup estimation unnecessary. By comparing contracts signed by the same firm, I only exploit variation in markups which are due variations in prices as marginal costs do not vary for similar contracts signed by the same firm. A second advantage of within-firm comparison is to reduce the possibility of having confounding factors affecting my results. Comparing contracts signed by different firms may lead to selection bias as firms are selected by different households. Within firm analysis avoids potential biased results as it compared contracts signed by the same firm in different municipalities.

Figure 5 shows the two contracts c_1 and c_2 compared in the regression. The two contracts are signed by the same firm f and have the same level of damage $\overline{d}$. The only source of difference between the two contracts is given by the location of the house l.

Consider the following equation

$$\log(P_{cldfmt}) = \alpha_{fd} + \lambda F_{dl} + \rho_{cldfmt} \tag{9}$$

where P_{cldfmt} is the price-per-square-meter defined at the contract level, α_{fd} is the firm-damage fixed effect and F_{dl} are the two measures of firm-entry defined above.

Since the amount of firm-entry is not exogenous, OLS estimates are biased as households can choose their preferred construction firms. To estimate the causal effect of a demand shock on prices, I then only use that part of variation in firm-entry which is purely random. To do so, I compute the predicted change in firm-entry by exploiting the exogenous variation induced by the disruptiveness of the earthquake. I thus use the total sum of square meters within each municipality as a measure of disruptiveness for a given level of damage

$$Y_{dl} = \sum_m \sum_f \sum_t \sum_c Y_{cdlfmt}$$

To assess whether there is a first stage I estimate the following equation

$$F_{dl} = \xi_d + \theta Y_{dl} + \tau_{dl} \tag{10}$$

where ξ_d captures the damage fixed effects and θ is the estimated coefficient of interest. The more disruptive the earthquake is, the greater is the level of firm entry in a given municipality and the lower is the price per square meter charged to households.

The identifying assumption underlying my analysis is that, absent higher competition in a given municipality, the price per square meter signed by the same firm would have not been different in two municipalities. Still, one may argue that lower prices in more affected municipalities are the result of a lower income, which resulted in building being of worse quality. Lower quality buildings are cheaper to restore and are more easily destroyed by the earthquake.

To address this concern, I employ two robustness checks. I first use an alternative measure of earthquake intensity, based on the richter scale, which measures the intensity of the earthquake independently from the quality of buildings. Moreover, I control for municipalities' characteristics, by including the number of firms located in a given municipality, the population and the number of bank-offices as measures of size, competition and GDP at the municipality level.

4.2.3 Results

I start by examining whether firm-entry plays a role on markups by estimating equation (9). Table 13 reports OLS estimates in columns (1) and (2). Column (1) provides elasticity estimate for the effect of firm-entry, defined as the number of firms active in a given municipality l for a given level of damage d, on the price per square meter. The equation includes damage-firm fixed effects as it compares contracts signed by the same firm and with the same level of damage. Column (2) provides instead results for the same equation, where firm-entry is defined as the number of newly created firms that rebuild houses with a level of damage d in municipality l. Elasticities in both columns are very small and not significant. Columns (3) and (4) of Table 13 provide instead IV estimates for equation (9). The coefficients capture the effects of firm-entry that is mainly driven by an exogenous variation in the measure of disruptiveness of the earthquake. IV estimates indeed provide evidence in favour of a price-discrimination behaviour of firms, induced by firm-entry. By comparing contracts signed by the same firm in two different municipalities, results show that firms charge lower prices in municipalities where firm-entry is the highest. The table also includes Kleibergen-Paap F statistics, which values rule out weak instrument bias.

Table 14 reports first stage estimates of equation 10. Estimates are expressed as elasticities and show strong and positive effect of the earthquake disruptiveness on firm-entry, indicating that, indeed, municipalities that suffered disruptive earthquakes also faced greater firm entry. Table 15 show instead the results for the reduced form equation CITE. It shows that contracts for houses located in municipalities affected more by the earthquake display lower prices. This result suggests that higher competition triggered by firm-entry deceased prices in spite of a higher demand for reconstruction. In other wards, the increase in competition was big enough to overcome the positive pressure on prices given by the positive demand shock.

4.3 Procyclical marginal costs

In this section I estimate the effect of a positive demand shock on firms' markups through an increase in marginal cost of labour. I first provide OLS estimates of actual demand shocks faced by firms on contract-level markups. Since the actual demand shock faced by each single firm is endogenous, as it is the result of selection, I then provide causal evidence using the exposure to demand shock variable z_{dm} described in the previous section.

I define the firm-level demand shock as the cumulative sum of the square meters rebuilt in every contract for all level of damages and all municipalities:

$$x_{cdfmt} = \sum_{l} \sum_{b=1}^{c} Y_{bdlfmt} \tag{11}$$

The cumulative sum of square meters of different contracts allows me to consider how firms' pricing decisions are affected by the sum of subsequent contracts and not as a response to the single contract only. All contracts that persist when a firm signs a new one matter in terms of pricing decision.

I estimate the following regression

$$y_{cdlfmt} = \alpha_{dl} + \lambda_t + \beta \log(x_{cdfmt}) + \delta \Psi_{cdlfmt} + \delta X_f + \upsilon_{cdlfmt} \tag{12}$$

where y_{cdlfmt} labels the log marginal cost of labour $\log(MC_{cdlfmt})$ as defined in equation (8), the log price $\log(P_{cdlfmt})$, and the log markup $\log(\mu_{cdlfmt})$. α_{dl} are the damage-location fixed effects, x_{cdfmt} is the firm-level demand shock, X_f are firms' characteristics and Ψ_{cdlfmt} are contract-level characteristics. Equation (12) compares contracts for buildings located in the same municipality l with the same level of damage d, but signed by firms located in different municipalities m. Comparing contracts signed in the same municipality l allows me to shut down the competition channel from my results, as firms building houses in the same municipality l are subject to the same level of competition. Moreover, comparing contracts with the same level of damage d makes marginal costs and prices more comparable, as the amount of labour/raw materials employed for reconstruction of one square meter is similar within each level of damage. Finally, X_f and Ψ_{cdlfmt} assures that estimation compares firms with the same balance-sheet characteristics and similar contract-level characteristics. Table 8 provides OLS estimates of equation (12). Columns (1) and (2) display the estimated elasticity of x on marginal cost of labour, displaying a positive correlation. Columns (3) and (4) report instead the estimated elasticities of demand shocks to prices, while columns (5) and (6) report the estimated elasticities to markups. Price elasticity estimates are negative but very small, almost equal to zero. These results provide evidence of firms competing against each other for reconstruction of houses located in the same municipality, independently from where the firms are located and from their increase increase in marginal costs. Columns (5) and (6) report instead the estimated elasticity on markups. Since prices don't move, while marginal costs increase, markups are lower for firms that face a higher exposure to demand shock. The number of observations is smaller than the one in the contract-level dataset, as not all of the firms in the contract-level data are also included in the AIDA data. For robustness I have also estimated column (1) for all observations available and results do not change neither economically, nor statistically[6]. The number of observation between columns (1)-(2), (3)-(4) and (5)-(6) are due to wages not being observed for all remaining firms.

I now turn to costs of labour and assess what drives the result of higher marginal cost

4.3.1 Instrumental Variable Strategy

The results presented in Table 8 cannot be interpreted as causal, as contracts are not randomly assigned to firms. Since households can choose which firm to hire for reconstructing their house, the total demand shock x_f faced by firm f can be potentially endogenous, leading estimates to be affected by sample selection bias. I address selection bias by exploiting the random location of firms' headquarters in municipalities that have been differently affected by the earthquake. I construct a measure that describes the exposure to demand shock for a given firm, located in municipality m and for different levels of damage d.

Exposure to demand shock

I use two measures of exposure to demand shock, both of them at the municipality level. I define the first measure as the total amount of square meters of houses that need to be repaired or rebuilt within each municipality m for a given level of damage d, divided by the number of firms which legal headquarters are located in that municipality.

$$z_{dm} = \frac{Y_{dm}}{N_m} \tag{13}$$

where N_m is the total number of firms located in municipality m, while Y_{dm} is the total amount of square meters affected by the earthquake in municipality m with damage level d, $Y_{md} = \sum_f \sum_t \sum_c Y_{cdmft}$ across all firms f and all times t.

[6] Results are in appendix

This variable captures the exposure of construction firms to demand shocks in the municipality where their headquarter is located, as it measures the potential increase in demand that firms located in each municipality could receive from houses located in the same municipality. It is thus a better measure of demand shock for firms than the simple number of square meters that need to be rebuilt, as the potential supply by firms located in each municipality is taken into account.

Insert Figure 6 here

Figure 6 shows the distribution of z_{dm}, and reports the frequency of the damage-municipality average square meters per firm. Most of the distribution lies between 0 and $2,000$ square meters for any level of damage, averaged per every firm.

Insert Figure 7 here

Figure 7 instead shows how $z_{d=1m}$ is distributed across different municipalities, for the lowest level of damage. Indeed municipalities that suffer the highest level of magnitude have the largest amount of damaged buildings.

I also estimate exposure to a demand shock using the epicentral magnitude of the earthquake, measured by the Italian Institute of Geophysics and Vulcanology[7]. The epicentral magnitude is a different measure from the intensity and it captures the strength of the earthquake, abstracting from its effects on the buildings. Differently from the total amount of square meters, this measure does not depend on the quality of the existing buildings and I use it as robustness in the appendix.

Firms located in municipalities where the earthquake is more disruptive face a higher exposure to demand shock as compared to firms that are located in a less disruptive one provided that households chose firms which are close to their home.

Insert Figure 11 here

[7] https://emidius.mi.ingv.it/CPTI15-DBMI15/query_eq/

Figure 11 shows that indeed this is the case, as the distribution of the distance between firms and damaged houses is skewed towards zero and displays a median equal to 11km. To assess whether there is a first stage, I estimate the following equation

$$\log(x_{cdfmt}) = \alpha_d + \lambda_t + \beta \log(z_{dm}) + \eta \Psi_{cdlfmt} + \zeta X_f + \upsilon_{cdfmt} \tag{14}$$

Table 9 provides results for the full sample and for the different levels of damage. It shows that firms exposed to a higher demand shock indeed faced higher demand shock as households, on average, select firms close to their homes. Results show that the first stage is stronger the greater is the damage of the house.

By substituting equation (14) into (12), one gets the following reduced form equation

$$y_{cdlfmt} = \alpha_{dl} + \lambda_t + \beta \log(z_{dm}) + \phi \Psi_{cmdft} + \xi X_f + \nu_{cmdft} \tag{15}$$

which estimates exposure to demand shock on marginal costs and prices. The only source of variation employed in estimation, is driven by the exogenous variation in z_{dm}, which randomly affects firms located in different municipalities. I thus exploit the exogenous variation induced by different intensity of the earthquake to capture the variation in the demand shock faced by firms.

Insert Table 8 here

Table 8 reports estimation results for contract prices, marginal costs and markups. Columns (1) and (2) display the estimated elasticity of demand shock to marginal cost of labour, which is approximately equal to 0.3%. The estimated elasticity decreases to 0.2% in column (2) when I also include firm-level characteristics and contract characteristics.

Finally, Table 11 provides IV and OLS estimates of equation (12). IV estimates only exploit the exogenous variation induced by the different exposure to a positive demand shock. It compares contracts with high demand shocks received by firms subject to higher exposure to demand shock, with contracts subject to a smaller demand shock as they are located in a municipality subject to a low exposure to demand shock.

5 Conclusion

This paper provides evidence on markups cyclicality by studying how price markups react to a positive government expenditure shock. The paper focuses on construction firms in Emilia-Romagna (Italy) and it studies how they react to an increase in demand for housing reconstruction after a devastating earthquake. I exploit a very detailed contract-level dataset that contains granular information on the different contract that are signed by different firms. The paper shows that markups decrease by 4 percentage points after the earthquake and that this decrease is partly driven by a reduction in prices. The reduction in prices is partly due to firm-entry, which is the result of firm entry. Public procurement that followed the earthquake increased the number of construction firms active in Emilia-Romagna, raising competition. In terms of methodologies, this paper addresses two different issues, one on markup estimation and a second on identification. As for markup estimation, measuring marginal costs poses serious challenges as marginal costs are not observable. Identification poses instead issues due to selection bias as households are able to choose construction firms that carry out construction work. This may lead to biased OLS estimates since higher markups can lead to greater-firm entry. I address these challenges jointly by exploiting within-firm variation and comparing contracts signed by the same firm (therefore facing the same marginal cost) and subject to different levels of firm entry that are exogenously determined by the earthquake disruptiveness. This paper contributes to the literature as it is the first one to provide evidence of this mechanism conditioning to a demand shock and it is the first one to use a natural experiment to assess markup cyclicality.

6 Appendix A

$$\mu_{pt} = \alpha + \lambda_t + \beta T_p + \gamma post_t + \eta(T_p \times post_t) + \theta(t \times T_p) + \epsilon_{pt} \tag{16}$$

This Table provides estimation results of province level equation 16. As treatment is

Table 1 – Intention To Treat - Diff in Diff - Unweighted

	(1) Markup	(2) Markup	(3) Markup
Post	-0.0211***	-0.0404***	-0.0390***
	(0.0026)	(0.0052)	(0.0054)
T	0.0212***	0.0212***	8.4043*
	(0.0049)	(0.0046)	(4.3404)
T × Post	-0.0441***	-0.0441***	-0.0232**
	(0.0070)	(0.0066)	(0.0116)
T × Year			-0.0042*
			(0.0022)
Observations	1070	1070	1070
Time Fixed Effects		✓	✓
Time Trends			✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

defined at the province level, I collapse the firm-level dataset at the province-level to exploit the variation between different provinces. Results are similar both in terms of significance as well as for economic magnitude to the ones reported in Table 3.

7 Figures

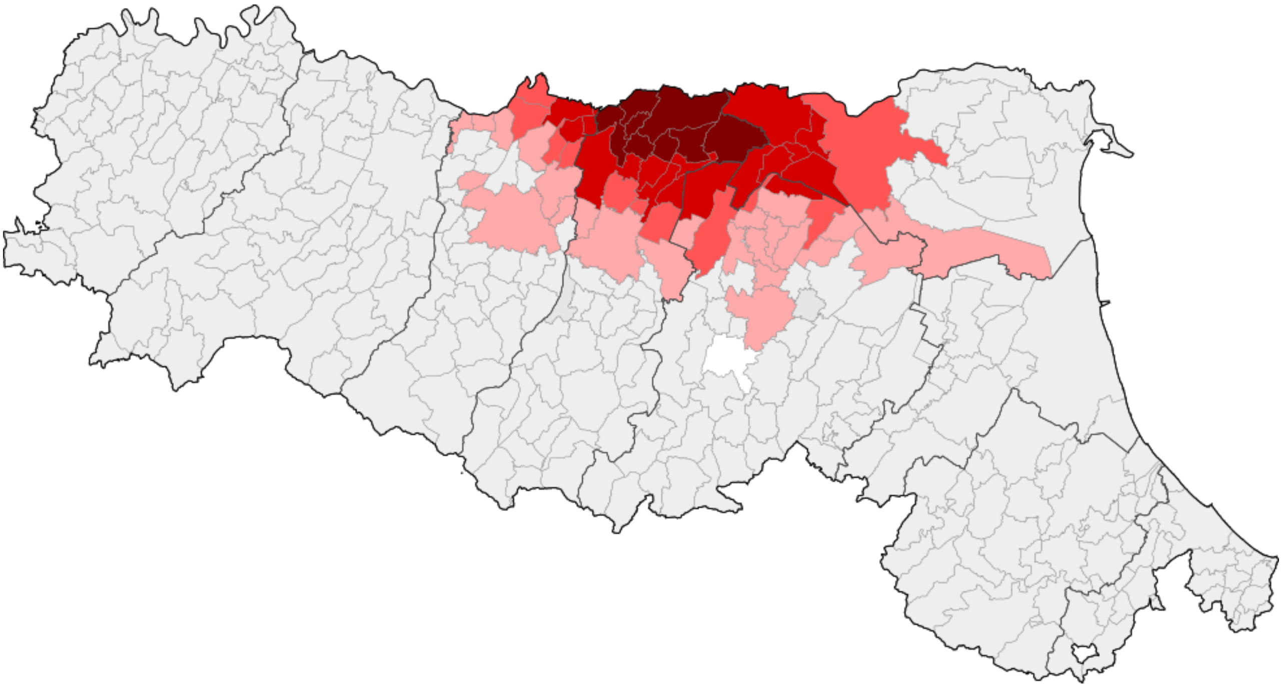

Figure 1 – Municipalities in Emilia-Romagna

Note. This Figure shows municipalities in Emilia-Romagna affected by the earthquake. The darker the colour, the greater is the intensity of the earthquake, measured using an Intensity index from the Italian Earthquake and Vulcanology statistics.

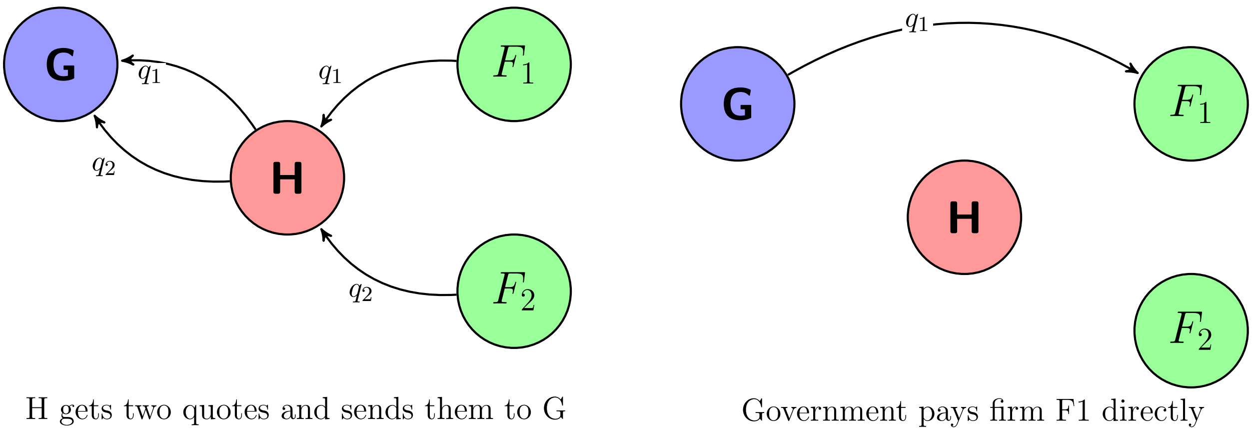

Figure 2 – Reconstruction Subsidy Application

Note. This Graph shows the application process to obtain funding from the Governement. First Households H obtain quotes from two firms F_1 and F_2. Quotes are then sent to the Government G, who approves the cheapest one. Finally G pays F_1

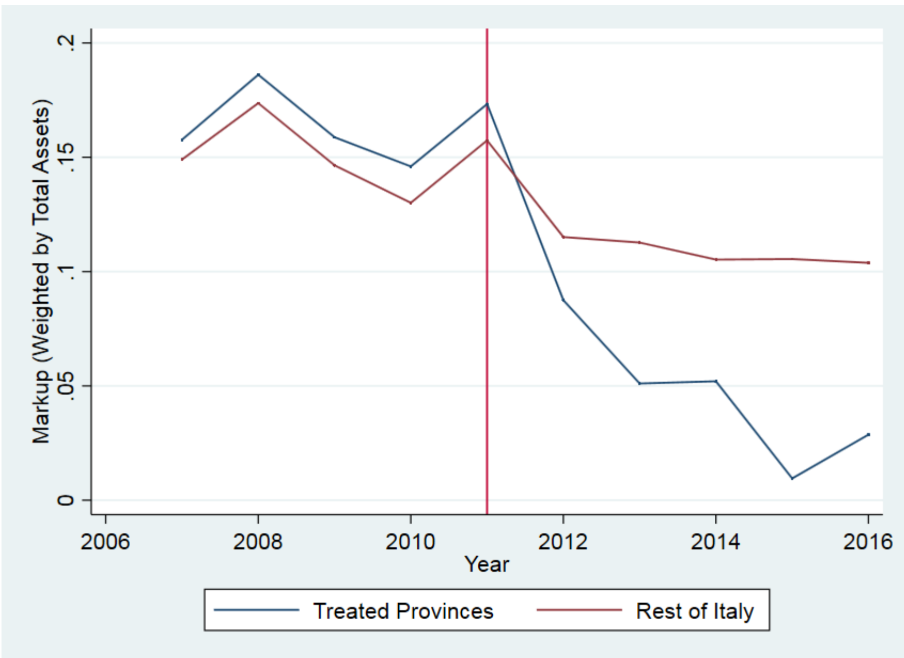

Figure 3 – Firms' Markup

Note. This Figure plots the return on Gross Margins for treated provinces and for untreated ones. Gross Margins are weighted by firm's size, measured as total assets.

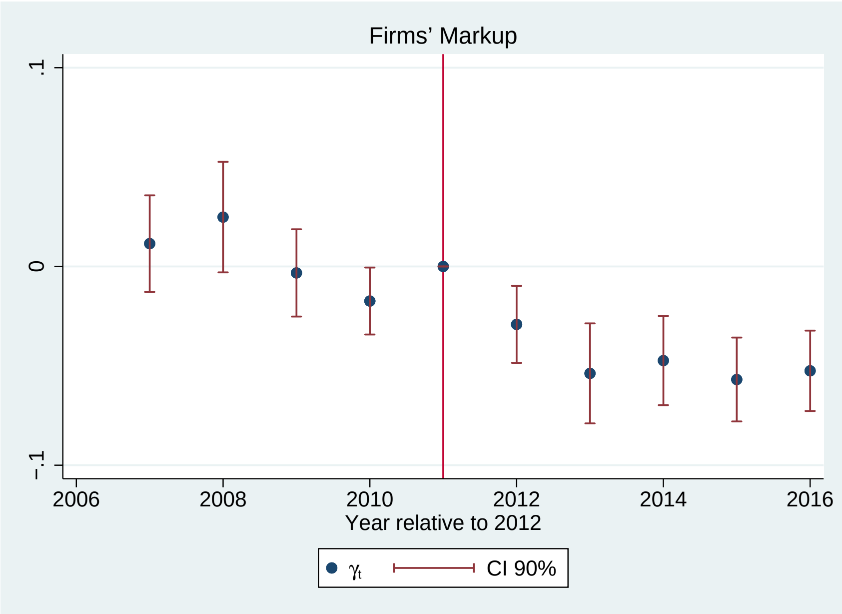

Figure 4 – Event Study

Note. This Figure plots the Event-Study for pre-trends in the difference-in-differences. Difference of the coefficient estimated using each year as treatment year against 2011 are tested to be different from zero. Confidence intervals reported around the estimates are at 90% level.

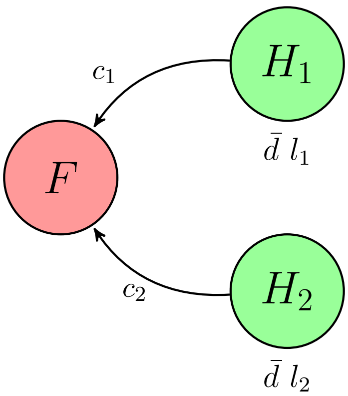

Figure 5 – Identification Strategy

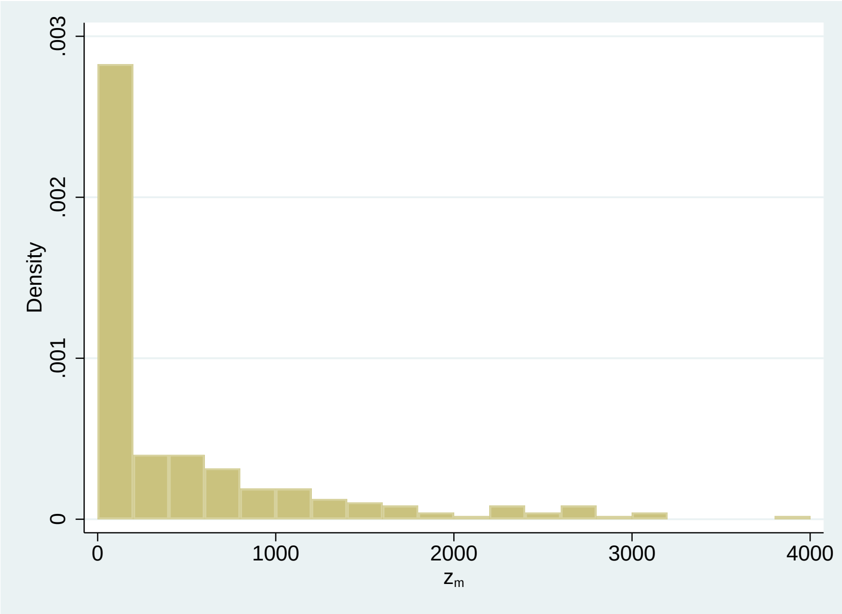

Figure 6 – Square meters distribution

Note. This Figure displays the distribution of the average number of square meters per firm across municipalities and damages. The figure plots z_{dm} for all levels of damages and all municipalities.

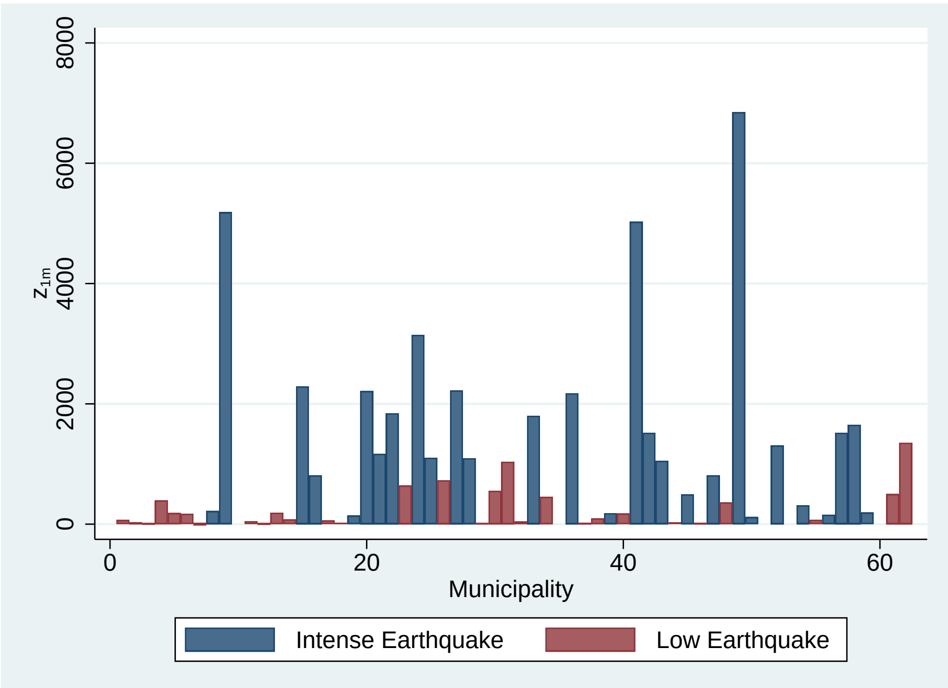

Figure 7 – Square meters on municipality

Note. This Figure shows the distribution of the average square meter per firm across municipalities, for a given level of damage equal to 1.

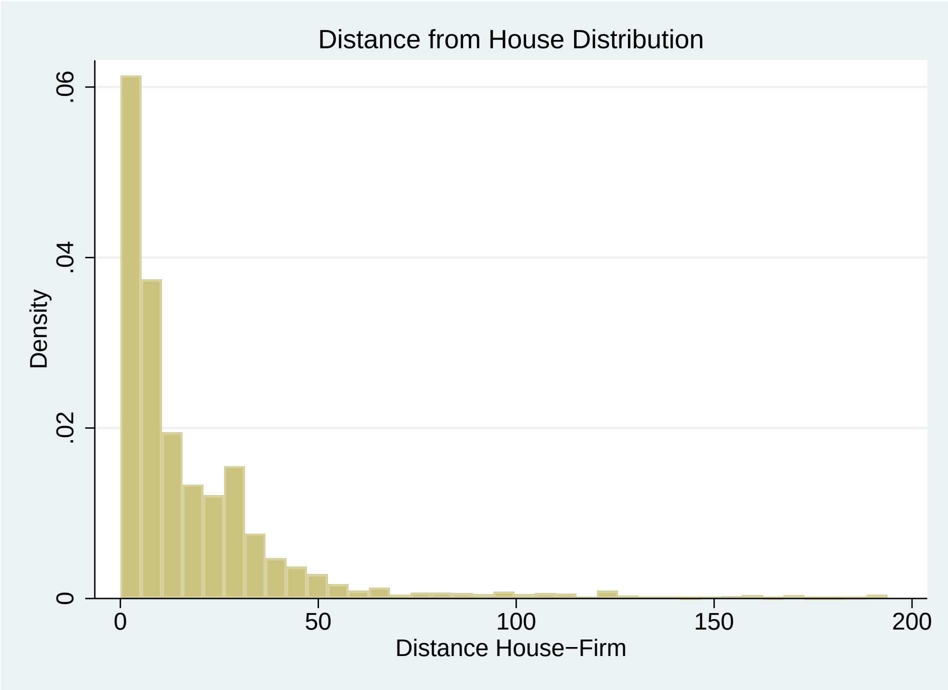

Figure 8 – House-Firm Distance

Note. This Figure illustrates the distribution of the firm-house distance for all contracts included in the contract database.

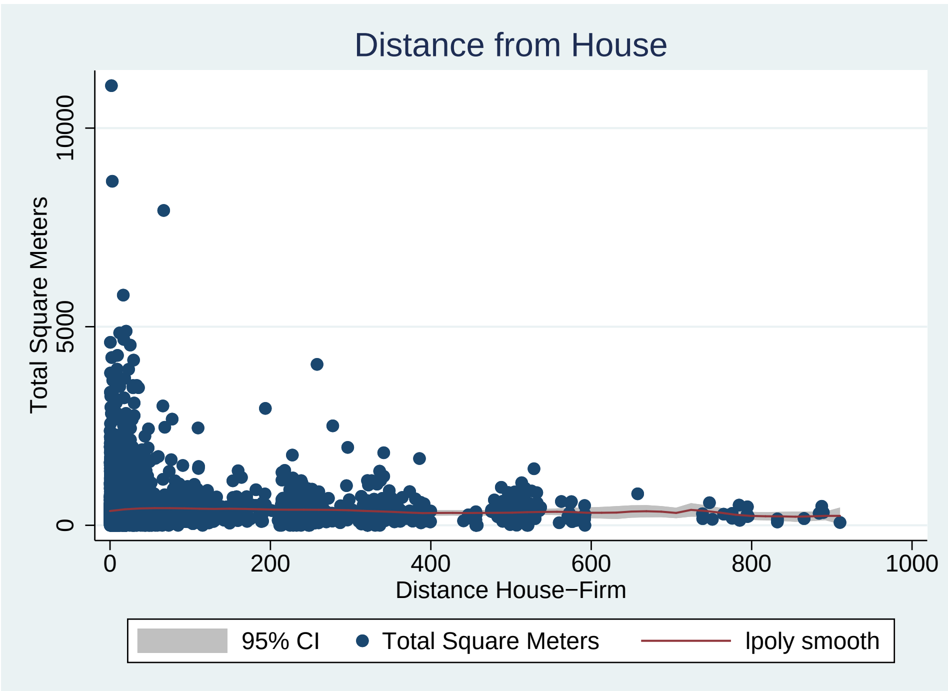

Figure 9 – Total Amount of square meters on Distance

Note. This Figure plots the firm-level demand shock on the weighted average distance from the epicenters.

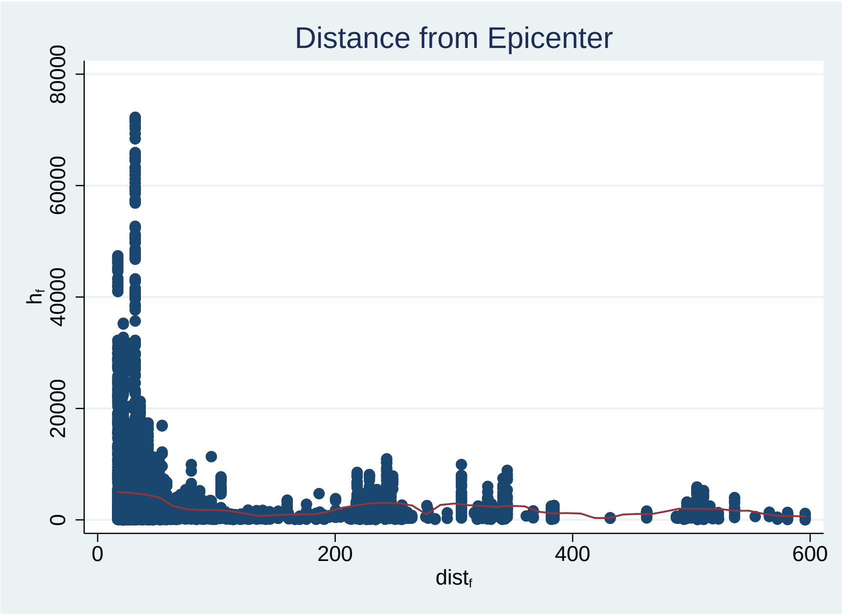

Figure 10 – Total square meters on distance

Note. This Figure plots the first stage. It measures the firm-level demand shock on the weighted average distance from the epicenters.

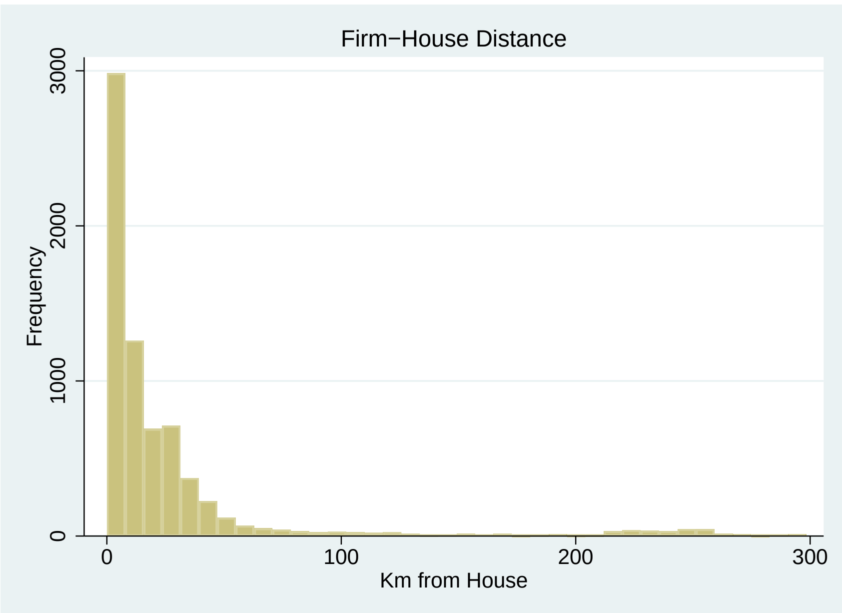

Figure 11 – Cost Index

Note. This Figure plots the distribution of the distance between houses and firms that carried out reconstruction.

8 Tables

Table 2 – Summary Statistics - Averages 2007-2011

	Treated Provinces	Control Provinces
Gross Margins	.1358212	.1287287
Revenues	2274.621	1841.499
Cost of Debt	7.035542	7.674332
Total Assets	3442.163	2810.357
ROE	10.16379	11.53092
EBITDA	148.4466	146.5433
Working Capital	576.1273	585.5012
Number of Workers	8.69428	7.739714
Leverage	6.177751	5.175905
Bank Debt	36.01382	32.67766
Total Production Value	2177.097	1797.674
Observations	6434	70192

Table 3 – Intention To Treat - Diff in Diff

	(1)	(2)	(3)	(4)	(5)	(6)
	μ	μ	μ	μ	μ	μ
Post	-0.0204***	-0.0205***	-0.0393***	-0.0066	-0.0471***	-0.0053
	(0.0025)	(0.0019)	(0.0047)	(0.0040)	(0.0057)	(0.0041)
T	0.0181***		0.0182***	0.0000	0.0000	
	(0.0047)		(0.0041)	(.)	(.)	
T × Post	-0.0432***	-0.0430***	-0.0431***	-0.0430***	-0.0400***	-0.0173**
	(0.0067)	(0.0056)	(0.0060)	(0.0048)	(0.0067)	(0.0084)
Cost of Debt					-0.0030***	
					(0.0003)	
Log(Total Assets)					-0.0000	
					(0.0000)	
ROA					0.0066***	
					(0.0002)	
Log(Number Employees)					-0.0002***	
					(0.0001)	
Leverage					0.0002***	
					(0.0000)	
Log Total Liquidity					-0.0050***	
					(0.0007)	
Log Total Inventories					0.0081***	
					(0.0006)	
Bank Debt/ Revenues					0.0006***	
					(0.0000)	
T × Year						-0.0053***
						(0.0016)
Observations	855384	855384	855384	855384	359456	855384
Firms Fixed Effects		✓		✓	✓	✓
Time Fixed Effects			✓	✓	✓	✓
Time Trends					✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 – Competition - Sample Splitting HH Index

	(1) Baseline	(2) HH> 25	(3) HH> 50	(4) HH> 75
Post	-0.0066	-0.0358***	-0.0264***	-0.0173***
	(0.0040)	(0.0046)	(0.0050)	(0.0060)
T × Post	-0.0430***	-0.0426***	-0.0352***	-0.0268***
	(0.0048)	(0.0056)	(0.0064)	(0.0074)
Observations	855384	645825	428048	211261
Province Fixed Effects	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 – Financial Constraints - Sample Splitting Cost of Debt

	(1) Baseline	(2) HH> 25	(3) HH> 50	(4) HH> 75
Post	-0.0066	-0.0281***	-0.0455***	-0.0277***
	(0.0040)	(0.0044)	(0.0040)	(0.0039)
T × Post	-0.0430***	-0.0397***	-0.0320***	-0.0199***
	(0.0048)	(0.0054)	(0.0057)	(0.0062)
Observations	855384	679638	559354	444434
Firms Fixed Effects	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 – Probability of Signing Contract

	(1) Signed Contract
Log Earthquake Intensity	0.0123***
	(0.0007)
Cost of Money	-0.0001**
	(0.0001)
Bank Debt / Revenues	-0.0000
	(0.0000)
Log Numb. Employees	-0.0002
	(0.0002)
Gross margins	-0.0006
	(0.0009)
Log Total Production Value	0.0030***
	(0.0003)
Log Total Liquidity	-0.0000
	(0.0001)
Debt / Ebitda	0.0000
	(0.0000)
Log Total Inventories	-0.0000
	(0.0001)
ROA	0.0001***
	(0.0000)
Observations	65408

Standard errors in parentheses
are clustered at the firm level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 – Descriptive Statistics

	Level of Damage					
	B/C mean	E0 mean	E1 mean	E2 mean	E3 mean	Total mean
Total Square Meters (Y)	471.6749	458.2373	365.7988	367.8174	388.2618	420.9476
Per Square Meter Price (P)	287.0014	965.9844	1394.414	1740.897	1958.891	1165.408
Markup	11.90099	54.03573	5.333768	67.41778	12.18817	22.11081
Working Days (L)	270.3611	575.6233	665.3717	709.9844	706.8586	532.2973
Approval Days	135.5931	156.5623	185.5969	209.3958	197.5759	170.923
Observations	3428					

Table 8 – OLS Demand Shock

	(1) Log(MC)	(2) Log(MC)	(3) Log(Price)	(4) Log(Price)	(5) Log(μ)	(6) Log(μ)
Log(x)	0.4972***	0.5833***	-0.0433***	0.0011	-0.5405***	-0.5822***
	(0.0736)	(0.0906)	(0.0139)	(0.0131)	(0.0699)	(0.0906)
Log(m^2)		-0.9394***		-0.3760***		0.5633***
		(0.0532)		(0.0380)		(0.0525)
Log(Approval Days)		0.0249		0.0039		-0.0209
		(0.0589)		(0.0256)		(0.0553)
Observations	2195	1665	2195	1665	2195	1665
Damage Fixed Effects	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Controls		✓		✓		✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 – First Stage

	(1) Full Sample	(2) Full Sample	(3) B/C	(4) E0-E2	(5) E3
Log(z_{dm})	-0.0545	-0.0674	-0.0308	-0.0934***	-0.0859*
	(0.0497)	(0.0565)	(0.0805)	(0.0248)	(0.0500)
Observations	4335	1985	1902	1329	1084
Damage Fixed Effects	✓	✓			
House-Location Fixed Effects	✓	✓	✓	✓	✓
Firm Controls		✓			

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 – Reduced Form

	(1) Log(MC)	(2) Log(MC)	(3) Log(Price)	(4) Log(Price)	(5) Log(μ)	(6) Log(μ)
Log(z_{dm})	-0.2546***	-0.2487***	0.0065	-0.0256***	0.2611***	0.2231***
	(0.0467)	(0.0580)	(0.0066)	(0.0093)	(0.0466)	(0.0547)
Log(m^2)		-0.8114***		-0.3705***		0.4409***
		(0.0515)		(0.0395)		(0.0558)
Log(Approval Days)		0.0868		0.0028		-0.0840
		(0.0638)		(0.0296)		(0.0562)
Observations	2020	1516	2020	1516	2020	1516
Damage Fixed Effects	✓	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Firm Controls		✓		✓		✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11 – IV

	(1) Log(MC)	(2) Log(MC)	(3) Log(Price)	(4) Log(Price)	(5) Log(μ)	(6) Log(μ)
Log(x)	5.03**	3.48***	-0.13	0.36	-5.16**	-3.12***
	(2.34)	(1.30)	(0.13)	(0.22)	(2.37)	(1.12)
Log(m^2)		-1.75***		-0.47***		1.28***
		(0.43)		(0.09)		(0.36)
Observations	2020	1516	2020	1516	2020	1516
Fstat	3.37	3.73	3.37	3.73	3.37	3.73
Damage-Location Effects	✓	✓	✓	✓	✓	✓
Firm Controls		✓		✓		✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 – Descriptive Statistics

	Level of Damage					
	B/C mean	E0 mean	E1 mean	E2 mean	E3 mean	Total mean
Per Square Meter Price (P)	303.52	1087.81	1465.01	1882.91	2034.47	1462.80
Share of local firms	0.77	0.78	0.87	0.81	0.79	0.80
N. of entrant firms	73.05	31.98	35.49	40.44	79.67	64.25
N. of new firms	5.97	2.06	2.39	2.80	5.74	4.75
N. of resident firms	27.88	12.28	12.07	13.00	13.19	16.46
N. of active firms	184.77	195.25	187.00	181.09	182.54	184.38
N. of contracts per firm	5.72	3.02	3.49	3.47	8.28	6.09
z_{dl}	74610.15	23427.91	21023.83	32692.37	72658.65	58130.19
N. (m^2) per entrant firm	1000.74	789.70	634.49	776.76	869.63	853.87
Observations	1808					

Table 13 – OLS Firm Entry

	OLS		IV	
	(1) Log(Price)	(2) Log(Price)	(3) Log(Price)	(4) Log(Price)
Log(F^1_{dl})	-0.0081		-0.0573**	
	(0.0184)		(0.0248)	
Log(F^2_{dl})		-0.0001		-0.0874**
		(0.0217)		(0.0335)
Observations	6599	5462	6599	5462
Fstat			917.6034	159.8545
Damage-Firm FE	✓	✓	✓	✓

Standard errors in parenthesis are clustered at the municiaplity level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14 – First Stage - Firm Entry

	(1) Log(F^1)	(2) Log(F^2)
Log(z_{dl})	0.6812***	0.5505***
	(0.0225)	(0.0435)
Observations	6599	5462
Damage-Firm FE	✓	✓

Standard errors in parenthesis are clustered at the municiaplity level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15 – Reduced Form - Firm Entry

	(1) Log(Price)	(2) Log(Price)
Log(z_{dl})	-0.0388**	-0.0388**
	(0.0160)	(0.0160)
Observations	6605	6605
Damage-Firm FE	✓	✓

Standard errors in parenthesis are clustered at the municiaplity level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Anderson, E., Rebelo, S., & Wong, A. (2018, March). Markups across space and time [Working Paper]. (24434).

Bils, M. (1987). The cyclical behavior of marginal cost and price. *American Economic Review*, *77*(5), 838-55.

Blanchard, O. J. (2008, August). The state of macro [Working Paper]. (14259).

Chevalier, J., & Scharfstein, D. (1996). Capital-market imperfections and countercyclical markups: Theory and evidence. *American Economic Review*, *86*(4), 703-25.

De Loecker, J., & Eeckhout, J. (2017, August). The rise of market power and the macroeconomic implications [Working Paper]. (23687).

Dixit, A. K., & Stiglitz, J. E. (1977, June). Monopolistic Competition and Optimum Product Diversity. *American Economic Review*, *67*(3), 297-308.

Domowitz, I., Hubbard, R. G., & Petersen, B. C. (1986, Spring). Business Cycles and the Relationship Between Concentration and Price-Cost Margins. *RAND Journal of Economics*, *17*(1), 1-17.

Galeotti, M., & Schiantarelli, F. (1998, May). The Cyclicality of Markups in a Model with Adjustment Costs: Econometric Evidence for US Industry. *Oxford Bulletin of Economics and Statistics*, *60*(2), 121-142.

Gali, J. (1995). Product diversity, endogenous markups, and development traps. *Journal of Monetary Economics*, *36*(1), 39-63.

Gilchrist, S., Schoenle, R., Sim, J., & Zakrajsek, E. (2017). Inflation dynamics during the financial crisis. *American Economic Review*, *forthcoming*.

Hart, O. (1982). A model of imperfect competition with keynesian features. *Quarterly Journal of Economics*, *97*, 109-138.

Jaimovich, N., & Floetotto, M. (2008). Firm dynamics, markup variations, and the business cycle. *Journal of Monetary Economics*, *55*(7), 1238-1252.

Kim, R. (2018). The effect of the credit crunch on output price dynamics: The corporate inventory and liquidity management channel.

Nekarda, C. J., & Ramey, V. A. (2013, June). The cyclical behavior of the price-cost markup [Working Paper]. (19099).

Rotemberg, J. J., & Saloner, G. (1986). A supergame-theoretic model of price wars during booms. *The American Economic Review*, *76*(3), 390–407.

Rotemberg, J. J., & Woodford, M. (1995). Dynamic general equilibrium models with imperfectly competitive product markets. *Frontiers of Business Cycles Research*, *Princeton University Press*, Princeton.

Rotemberg, J. J., & Woodford, M. (1999, August). The cyclical behavior of prices and costs. , *1*, 1051-1135.

Startz, R. (1989). Monopolistic competition as a foundation for keynesian macroeconomic models*. *The Quarterly Journal of Economics*, *104*(4), 737-752.