Do protests induce accountability? Evidence and theory from Brazil's 2013 mass protests

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June 2024

Abstract

The effectiveness of mass street protests as an accountability mechanism remains uncertain, particularly concerning the quality of the messages produced and their subsequent impact. This paper empirically analyzes the effects of the large street protests in Brazil in 2013 on both voter and federal legislator behavior. Leveraging geolocated Twitter data, we construct two distinct measures: protest intensity and the quality of protesters' demands at the municipal level, where quality refers to protesters articulating few and clear demands. Our findings provide causal evidence that more intense protests lead to higher levels of pork barrel spending, while protests with less focused demands negatively affect legislators' responsiveness. Additionally, we find a negative causal impact of less focused protest demands on legislators' vote share. However, legislators who responded to protest demands are less negatively impacted by protests. These results support the idea that protests can be effective political accountability mechanisms, as long as they have clear demands. Finally, our results can be interpreted within the framework of a noisy persuasion game between protesters and the government. Our model demonstrates that protests lacking clear demands and encountering a noisy communication channel not only achieve diminished success but can also be ex-ante inefficient as mechanisms of persuasion. Intriguingly, noisy protests help differentiate politicians who address protesters' demands from those who do not, thereby enhancing electoral accountability.

Keywords: Protests; Legislative Behavior; Elections; Bayesian Persuasion; Learning

JEL Classification: C72, D72, D83

[1]We are grateful to Arianna Degan, Eduardo Faingold, Marcelo Griebeler, Helios Herrera, Ming Li, Andrew Little, Elias Tsakas, Nikolas Tsakas, Huan Xie, participants of the Insper applied microeconomic workshop, participants of the Virtual Seminar Series in information economics and experiments from Concordia University, the 2021 SIOE meeting, participants of the UFRS, PIMES, UNB, FEA-USP seminar series, of the 2023 LACEA/LAMES meetings, and of the CEPR We_ARE series. We are particular grateful to Luís Antonio Alvarez for his comments and suggestions regarding our identification strategy. We would like to thank Vivek Venkata for excellent RA work.

1 Introduction

The use of political protests as a means for citizens to express their preferences or dissatisfaction with the government has become increasingly common. Ortiz, Burke, Berrada, and Cortés (2013) mention that the number of political protests has risen over time, reaching a peak in 2011 with an average of 28 protests per year in the 2010s compared to 18 in the 2000s. However, despite the increase in protests, their effectiveness remains uncertain.[1] The authors found, for example, that only 37% of the 843 protests studied from 2013 to 2016 were successful in achieving their stated demands.[2]

Despite a burgeoning literature on what determines protests and how citizens coordinate to solve the collective action problem to mobilize, little is known about the effects of protests on politicians' actions and their subsequent electoral outcomes. This paper presents causal empirical evidence that the success of protests as an accountability mechanism is influenced by the quality of the information provided by protesters. We focus on the interplay between the quality of information delivered by protesters and the intensity of these protests, and their impact on political accountability. We conceptualize accountability in two ways. First, we see accountability as *effective accountability*: politicians acting in accordance with voters' preferences. Secondly, we focus on *electoral accountability*: voters rewarding politicians who deliver what was requested to them.

We focus on Brazil's 2013 mass street protests as our empirical case study. Here, public protests serve as a mechanism through which voters can signal their preferences to elected politicians. This is particularly interesting because these protests began with a very clear demand related to lower transportation fares in the main cities of Brazil. However, as the protests evolved, demands became more widespread, ranging from the rejection of Brazil's hosting the World Cup and the Olympic Games to general dissatisfaction with incumbent politicians and even popular rejection of Bills being discussed in Congress that could limit the investigative power of the Prosecutor's Office (PEC 37/2013).

In order to study the effects of protests on politicians and voters actions, we have collected over 5 million geolocated Twitter textual data from July 2013 in Brazil. With this extensive data, we construct two distinct measures: *protest intensity* and *protest noise*, which define the quality of protesters' demands at the municipal level. In our context, quality refers to protesters articulating few and clear demands during their participation. We focus on three political outcomes. First, we analyze how legislators responded to protests in terms of pork barrel spending and presence in plenary sessions.[3] Then, we focus on voter behavior, analyzing the vote share of legislators that ran for reelection in the federal election in 2014 in comparison to their vote share in the 2010 election.

The reason we focus on federal legislative activity – and not on local legislative or executive activity – is because protests can be taken as given by federal legislators. In 2013, the trigger for mass street protests was higher transportation costs in important municipalities in Brazil—a deci-

[1] Ortiz, Burke, Berrada, and Cortés (2013) recorded 843 protests during the period of 2006-2013. The authors note a "steady increase in the overall number of protests every year, from 2006 (59 protests) to mid-2013 (112 protests events in only half a year)". A more updated list of protests and riots kept by Wikipedia indicates that, while the peak of protests and riots registered in the world happened in 2011, the average number of protests per year increased to 28 in the 2010's from 18 in the 2000's.

[2] For Ortiz, Burke, Berrada, and Cortés (2013), an an achievement is "taken to be the set of direct-, mixed- and indirect-responses from targeted opponents or by society to a protest episode, responding in some measure to the grievances raised by protesters".

[3] We can also observe the number and category of Bills proposed during that period. There is little variation in this regard, which is intuitive given that the expected instrument for legislators to quickly use to respond to the demands of the streets is indeed pork barrel spending.

sion made by the local executive office on which federal legislators had no say. Our causal identification strategy leverages legislators' local differential exposure to protest intensity and noise, depending on each legislator's pre-protest vote share. We estimate a difference-in-differences regression of the change in the three main outcomes mentioned above, pork barrel spending, presence in plenary sessions, and the vote share of incumbents. These changes are regressed on the change in protest intensity and noise, using a shift-share treatment intensity measure. The "shift" is the set of intensity or noise experienced by each federal legislator in their electoral base at the municipal level, and the "share" is the pre-protest vote share of each legislator.[4]

We first focus our analysis on the impact of protests on legislators' actions, particularly on pork barrel spending and presence in plenary sessions. We find that a 1 standard deviation increase in protest intensity exposure increased pork barrel spending by 1.5 percentage points. While intense protests are beneficial for effective accountability, noise can hinder this process. We find that a 1 standard deviation increase in protest noise exposure decreased pork barrel spending by 3.5 percentage points. This effect is quite significant, as it corresponds to an 8.3% decrease relative to the pre-protest mean. The effect is robust to alternative measures, including specifications that consider only legislators running for reelection, a subset of municipal-level data for pork barrel spending, or even a subset of municipalities that experienced both real-life protests and "social media protests."

The next step is to understand the impact of protests on electoral accountability. We focus on the vote share of incumbents who were running for reelection. We find that the mere occurrence of a protest close to an election period resulted in a 15 percentage point decrease in the vote share of incumbents running for reelection. Additionally, a 1 standard deviation increase in protest intensity exposure decreased the vote share of incumbents by 3.8 percentage points, while a 1 standard deviation increase in protest noise exposure decreased the vote share of incumbents by 5.2 percentage points. This effect is quite significant, as it corresponds to a 5% decrease relative to the pre-protest mean.

At first glance, it may seem that protests are not conducive to electoral accountability, as they generally reduce the vote share of incumbents. However, when we examine the heterogeneous effect of protests on legislators who met the protesters' demands, we see that voters rewarded incumbents who delivered what was being asked. We find that the marginal effect of a 1 standard deviation increase in protest noise resulted in only an 11.2 percentage point decrease in the vote share of incumbents who spent pork barrel above the mean, compared to a 17.9 percentage point decrease in the vote share of incumbents who spent pork barrel below the mean.

We see these results as supporting causal evidence that protests can be an effective political accountability mechanism, both in terms of effective and electoral accountability. However, too many demands or noisy information produced during protests can hinder their effectiveness. Our main contribution is to highlight the importance of the quality of information produced, unconfounded by the intensity of protests.

The political economy literature has mostly focused on the determinants of protests. Protests can be a mechanism that allows citizens to inform an incumbent government of their private preferences (Lohmann (1993), Lohmann (1994)). Citizens may also decide to go out on the streets to express their demands motivated by a sense of unfairness (Passarelli and Tabellini (2017)), a sense of belonging to a group of citizens (Barbera and Jackson (2016)), dissatisfaction with their income underperformance (Campante and Chor (2012)), a way to reveal that public good provision is below their expectations (Martinelli and Xiao (2023)), or the lack of strong institutions through which

[4]For other applications of shit-share treatments, we refer to Autor, Dorn, and Hanson (2013), Acemoglu and Restrepo (2020), Dix-Carneiro and Kovak (2017) and Felix (2024).

they can participate in the political process (Machado, Scartascini, and Tommasi (2011)). We take protests as given. Our citizens are motivated because they want to signal their preferences to the incumbent and tilt the government's actions towards their preferred point.[5]

The fact that protests are not always successful has been noted in the literature. In fact, part of the literature on protests has focused on the importance of size of protest to explain their success, as in Battaglini (2017), Battaglini, Morton, and Patacchini (2020) and Correa (2021), since size can improve information aggregation from heterogeneous voters.[6] We follow a different approach, modeling protests as an information mechanism and focusing on the quality of the message transmitted by protests. For us, the more messages a protest has, or the less clear the messages are, the noisier the protest will be. Confirming the literature, we see size of protests as important for their success. In our wording, more intense protests mean better effective accountability (legislators spend more on pork barrel) but worse electoral accountability (incumbents have lower vote shares when protests are intense).[7]

Our main contribution is to decouple the intensity effect to the quality of information effect. We see it as crucial to separate protest intensity and quality of information, or how we define it, how noisy protest demands are. We show that while protests can be intense, if there are too many demands or they are unclear, protests may fail as an accountability mechanism in both the effective and electoral accountability sense.

In order to help us understand the mechanisms behind our empirical results, we also build a theoretical model of Bayesian persuasion. In our theoretical model, protesters and the incumbent may disagree on their preferred outcomes for a public policy or set of policies. A public protest serves as an information mechanism designed to persuade the incumbent government to deliver the protesters' preferred action. Formally, our model follows the Bayesian persuasion literature (Kamenica and Gentzkow (2011)), where a sender—the protesters—designs an information device that produces a message aimed at tilting the receiver's beliefs to the point that aligns with the receiver's prior. While protesters can design this information mechanism to maximize the chances of persuading the government, the delivered message can go through a noisy communication channel (Tsakas and Tsakas (2017)), misleading the government. A protest with "too many demands" will be considered a noisy protest.

We find that protests can increase both effective and electoral accountability, but the impact of noise on accountability is not straightforward. First, protests improve accountability in the sense of effective accountability by increasing the chances that the incumbent delivers the preferred action of the protesters. However, the noisier the protest, the less likely the legislator is to respond. Importantly, if the noise is "big enough," protests can be ex-ante inefficient as an accountability mechanism since they won't be able to tilt the incumbent's actions towards the one preferred by voters above the threshold of 50%.

Secondly, protests can also function as a form of electoral accountability. Contrary to common wisdom, noisy protests may help voters better distinguish between high and low-quality politicians. By attending to the demands from the street, the incumbent government has a higher chance of being reelected because it will be perceived as a high-quality politician – and this separation is

[5]For excellent documentation and literature review on protests, we refer to Cantoni, Kao, Yang, and Yuchtman (2023).

[6]In Battaglini (2017), the author mentions that "Naturally the fact that full information aggregation is theoretically feasible in this case, doesn't mean that the error will be zero or even small with finite population: the expected number of citizens who are willing to be informative may be drastically reduced, implying a reduction in the quality of information aggregation if "n" is finite," making it explicit that, in the author's environment, quantity and quality of information are, indeed, interchangeable.

[7]Correa and Corvalan (2023) find that only a promise of a constitutional change de-escalated mass street protests in Chile during 2019.

only possible when protests are noisy. If the politician does not deliver on the demands from the streets, they will be perceived as a low-quality politician, facing lower chances of reelection—and this perception also increases with noise. In other words, the greater the noise, the higher the separation between low and high-quality types in the eyes of the voters.

This paper also aims to contribute to the literature that studies how effective political engagement can complement formal checks and balances mechanisms, such as the role of "social accountability" in promoting transparency and political efficiency. Institutions that perform audits and other types of checks and balances are important mechanisms that can complement electoral accountability by providing more information for voters to evaluate a politician's performance, for example. While there is a vast literature on the impact of those formal mechanisms on electoral accountability, less is known about political engagement by civil society and, importantly, the political mechanisms through which this type of civil engagement can work for accountability.[8] Throughout the paper, we will refer to social accountability as simply accountability, highlighting only the difference in terms of the channel through which social engagement operates: through politicians' choices (effective accountability) or voters' choices (electoral accountability). Therefore, a tentative contribution of this paper is to the discussion on the conditions under which citizens' direct participation in democracies may be effective in improving accountability. How effective civil engagement, such as public protests, will be depends on the capability of leaders to respond to citizens, as our model and empirical evidence suggests, and on other institutions that determine the political process in a country.[9]

The paper is organized as follows. Section 2 provides a brief background on Brazil's 2013 mass street protests. Section 3 describes the data used in the empirical analysis. Section 4 presents our empirical strategy, Section 5 presents the results. Section 6 presents the theoretical model of protests as Bayesian persuasion and its results, and Section 7 concludes the paper.

2 Background - The 2013 Protests

The mass street protests in Brazil in 2013 were a series of widespread demonstrations that took place across the country. The protesters expressed a range of demands, including calls for better public services such as healthcare and education, as well as improved urban transportation. They also demanded greater fiscal discipline and political reform, including changes to the legislative branch. Specific demands included the revocation of a constitutional proposal that limited the power of prosecutors to conduct criminal investigations, the criminalization of all forms of corruption, and the end of secret voting in Congress.

The trigger for the protests was an increase in public transportation costs in the main cities of Brazil. However, as the protests evolved, social demands became more widespread, including the rejection of Brazil's hosting the World Cup and the Olympic Games, general dissatisfaction with incumbent politicians, and popular rejection of bills being discussed in Congress that could limit the investigative power of the Prosecutor's Office (PEC 37/2013).

During the political protests in Brazil in June 2013, over 775 protests took place in 433 municipalities, attracting 2.8 million people from all over the country.[10] The map in Figure 14 shows

[8]For a more detailed discussion on this topic, refer to Khemani, Dal Bó, Ferraz, Finan, Stephenson Johnson, Odugbemi, Thapa, and Abrahams (2016) and Grandvoinnet, Aslam, and Raha (2015).

[9]Mass street protests may be guaranteed by constitutions in some countries and banned in others. Since we study this particular accountability mechanism in a democratic environment, our focus is on the effectiveness of mass street protests that will not lead to changes in a political regime. We take for granted that citizens have a constitutional right to protest, and we focus on how effective this social accountability mechanism can be in this political environment.

[10]These numbers are estimates from G1, the largest news portal in Brazil. Our benchmark analysis follows municipal-

the distribution of the protests across the municipalities. The protests occurred in every state of Brazil, with a concentration in the Southeast and South regions. The percentage of the population from each state that lived in a municipality with a protest is shown in Table 12 in Appendix B. In the next section, we explore to what extent these events had a direct impact on politicians' and voters' behavior.

3 Data

Tweets – We constructed a dataset of tweets to capture the intensity and noise of the protests. We collected over 3 million tweets from 4,086 municipalities, each of which had an active place ID on the former Twitter platform between June 1st and 30th, 2013. Figure 1 shows the number of tweets downloaded per day during the period we considered for constructing our sample:

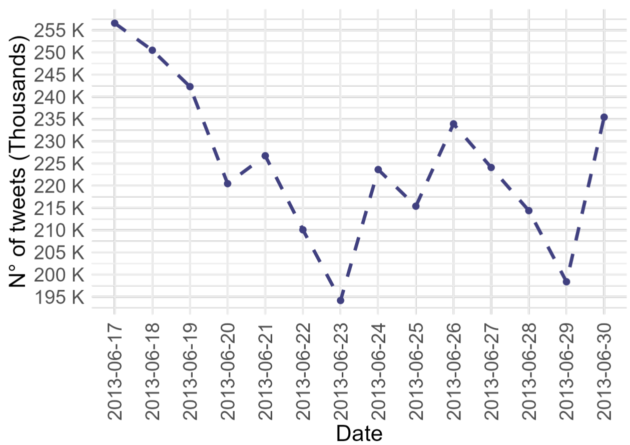


Figure 1: Distribution of Tweets per day

In order to create a random sample of tweets in those municipalities, we queried tweets containing the most common words (MCW, as noted in Table 2) of the Portuguese language.[11] This approach allowed us to collect a random general sample of tweets for all municipalities, with which we created a measure of general Twitter activity in each municipality during the period we analyzed. While this measure should be strongly correlated with population size in a municipality, by directly calculating Twitter activity, we allow for variation in this measure independently of population size.

Since the Twitter API works better with keywords to help identify relevant tweets for analysis, we also used keywords related to protests to create a new dataset, as shown in Table 2. These keywords were chosen from a preliminary smaller dataset constructed by querying tweets containing the words "protest" or "manifestation" during the days when most cities registered protests. This approach allowed us to identify other relevant words related to protests that were frequently mentioned in tweets during this period.

Therefore, our Twitter dataset was created with two main subsets: (i) one with the most common words of the Portuguese language, and (ii) another with tweets that used words related to

ities that experienced Twitter activity related to protests, which we find in 1,500 municipalities. We conduct robustness checks to see how our results change if we restrict our analysis to municipalities that experienced a real-life protest as registered by G1. We find that the results are stronger in this subsample. The main results of these robustness checks can be found in Tables 8 and 25.

[11]We collected tweets from a maximum of 10% of the population in each municipality to avoid bias in our sample.

Table 1: **List of words used for Twitter query**

MCW Set	*Protest Set*
de	protest
em	manifest
para	movimento passe livre
por	democracia
com	20 centavos
a	ogiganteacordou
e	vem pra rua
o	
isso	

Notes: Twitter API uses a "fuzzy matching" technique for their queries, which allows us to find tweets using only the root of the words.

protests, which were defined after an initial frequentist analysis of tweets related to protests. The first subset will be used to control for general Twitter activity in each municipality. The second subset allows us to obtain quantitative and qualitative information on social media activity about protests.

Given that we have an unbiased dataset that can serve as a proxy for the intensity of Twitter activity in a certain municipality, as well as a dataset containing tweets related to protests, we construct a Twitter Intensity Index for each municipality in our sample, defined as follows:

$$Protest\ Intensity\ Index_m = \frac{\sum_i 1_{Protest\ Tweets_{i,m}}}{\sum_i 1_{Tweets_{i,m}}} \tag{1}$$

where i, m refers to a tweet i observed at municipality m, $ProtestTweets$ accounts for a tweet related to protests, and $Tweets$ refers to any tweet in that municipality, i.e., the sum of total tweets that were downloaded for a certain municipality, whether related to protests or not. The $TwitterIntensity\ Index$ captures the percentage of tweets in municipality m that were related to protests. This measure will be used to better identify the intensity with which a municipality was discussing protests, separately from the quality of the discussion related to protest demands, which is the main variable of our study.

To analyze the quality of protest demands, we classified tweets into nine categories: Transportation, World Cup, Education, Health, Corruption, PEC 37, Police, Security, and Inflation, as indicated in Table 2 below. These categories were included for two reasons. First, most of them are commonly mentioned in qualitative surveys as the issues Brazilians frequently complain about or demand from the government.[12] Moreover, during the protests, the media was covering the main issues that were being mentioned by protest participants. The biggest Brazilian research company, Ibope, surveyed protest manifestants asking them what were their demands.[13]

A few comments are worth mentioning. There are six categories of usual issues discussed by Brazilians, as shown by the Datafolha survey: transportation, education, health, corruption, security, and inflation. The World Cup was added since the country was hosting the event at the time, and the public was divided on the issue. Additionally, we split "police" from "security" to capture

[12]Datafolha, one of the main surveys in the country, showed that in 2018 the main issues in the country were perceived to be health, violence, corruption, unemployment, and education. Source: https://www1.folha.uol.com.br/poder/2018/09/para-eleitores-saude-e-violencia-sao-os-principais-problemas-do-pais.shtml.

[13]Source: https://g1.globo.com/brasil/noticia/2013/06/veja-integra-da-pesquisa-do-ibope-sobre-os-manifestantes.html.

Table 2: **List of words used for Demands**

Categories of Demands								
Pec 37	**World Cup**	**Education**	**Health**	**Corruption**	**Transportation**	**Police**	**Security**	**Inflation**
pec37	stadium	education	public health system	corruption	transportation	police	security	inflation
	cup	schools	health	corrupt	fare	officers	insecurity	tax
	football	school	hospitals		ticket			tax-related
			hospital					
			hospitals					
			medical act					
			medicalact					

Notes: Twitter API uses a "fuzzy matching" technique for their queries, which allows us to find tweets using only the root of the words.

general concerns over security in the country and the role of the police force during the protests separately. Finally, a main issue debated in Brazil at the time was the Proposed Constitutional Amendment 37 (PEC 37). This amendment aimed to alter the country's constitution by restricting the investigative powers of public prosecutors, including the Federal Public Ministry (MPF) and state public prosecutors' offices (MPE).

We focus on two measures of the quality of the demands of protests in each municipality. The first measure indicates if a tweet mentions protests but does not include a clear demand. We refer to this measure as the $NoClearDemand\ Index$:

$$No\ Clear\ Demand\ Index_m = \frac{\sum_i 1_{No\ Demand_{i,m}}}{\sum_i 1_{Protest\ Tweets_{i,m}}} \tag{2}$$

where $1_{No\ Demand_{i,m}}$ is one if there is no demand being mentioned in tweet i at municipality m. It is worth mentioning that, although no demand was mentioned, the tweet belongs to the set of tweets that have at least one word related to protests.

The second measure relates to how concentrated the demands were in each municipality. We refer to this measure as the $Protest\ NoiseIndex$. If a municipality m has no clear demand in its collection of tweets, the municipality will not be considered in the sample. This means that our focus is restricted to municipalities that have at least one tweet expressing a demand.

Before we proceed with the formula, let's consider a clarifying example. For simplicity, let's assume there are three possible categories of protest demands and there were three tweets in a certain municipality:

- "They will try to shut us up. but our indignation goes further. no to **corruption**. yes to **health** and **education**!!" protests
- "The protest has already taken on a larger dimension and people are also asking for **health** and an end to **corruption**.."
- "How about a public **health** protest? #change Brazil"

In the first tweet, three demands are mentioned; in the second, two demands; and in the third, only one demand is mentioned. Therefore, there is a total of six demands mentioned across all tweets in this municipality.[14] The protest demand category "health" is mentioned three times, "education" one time, and "corruption" two times. This leads to a share of 0.5 for health, 0.17 for

[14]It is true that there is a different sentiment for the category corruption (negative) compared to the categories education and health (positive). We will ignore this dimension of analysis, which proved difficult in the analysis of Twitter texts that are very informal and lack a clear linguistic structure.

education, and 0.33 for corruption. We can now compute the inverse of the Herfindahl-Hirschman Index (HHI) to measure how unconcentrated the demands are. In the case of our example, the *Protest Noise Index* would be calculated as $100.000 - ((1000.50)^2 + (1000.17)^2 + (100 * 0.33)^2) = 3.878$. The general formula for the $Protest\ Noise\ Index_m$ is given by:

$$Protest\ Noise\ Index_m = 100,000 - 100 * \frac{\sum_i 1_{Category\ Tweet_{i,j,m}}}{\sum_j \sum_i 1_{Category\ Tweet_{i,j,m}}}^{2} \quad (3)$$

where $j \in J = \{1, 2, ..., 9\}$ is one of the category demands, $1_{Category\ Tweet_{i,j,m}}$ indicates that a protest tweet mentions the category j, and $\sum_j \sum_i 1_{Category\ Tweet_{i,j,m}}$ indicates the total number of times any demand was mentioned in all tweets related to protests at the municipality m. The *Protest Noise Index* is, therefore, an inverse of a HHI index, measuring the lack of concentration, or how noisy, protest demands were. The higher the index value, the less concentrated are the demands in a certain municipality and, therefore, the noisier protests were in that municipality.

The reason we work with these three indices is to differentiate between social media activity related to the quantity of individuals discussing protests, or the intensity of the discussion about protests, as expressed in the *Twitter Intensity Index*, from social media activity related to the quality of the protest demands. This quality is measured both in terms of a lack of clear demands in the discussion (*No Clear Demand Index*) and how unfocused those demands were (*Protest Noise Index*). For example, in a municipality m, we can have a high intensity of tweets related to protests but a very noisy discussion regarding the demands mentioned by protesters, indicating an unfocused discussion on what protesters wanted. Conversely, in a municipality k, we can have a low intensity of discussions but a well-identified demand from the protesters. With these three measures, we can avoid confounding the sources of variability in our data, whether it comes from general social media discussion, from many demands being mentioned in the tweets related to protests, or from a lack of clarity in the demands being proposed. Our indices potentially allow us to identify these cases separately.

Effective accountability: legislators' behavior – We collected data on the performance of 642 legislators who held a seat between 2011-2014, focusing on 513 legislators who served during the protests. We analyzed two performance variables: presence in plenary sessions and pork barrel spending.[15] Presence in plenary sessions was collected from the Chamber of Deputies' website and pork barrel spending from the Federal Senate's website.[16] We selected the share of pork barrel spending related to typical protest demands (education, health, transportation, and cities). This was done by considering both the share of the total number of pork barrel allocations and the value of pork barrel spending for each legislator. In Brazil, the budget is implemented by the Federal Government, so a Ministry is always indicated to execute this spending. We checked if the pork barrel was assigned to the Ministry of Health, Education, Transportation, or Cities (the Ministry responsible for infrastructure spending in Brazil). Table 3 shows that, on average, 50% of all pork barrel spending was related to the protesters' demands. We did not work with the total value of pork barrel spending because this is fixed for all legislators, who have a pre-assigned amount of pork barrel spending they can request per year. Most of our analysis is done at the legislator level. However, legislators can direct pork barrel spending both to the municipal or state level. When

[15]We also considered analyzing the number of proposed bills per trimester and legislator, classifying bill proposals by the Commission to which they were assigned in the Chamber of Deputies. However, since, on average, legislators proposed 0 bills per trimester and given the recent importance parliamentary amendments have received in Brazil, we chose to focus on pork barrel spending as it should be more informative.

[16]Politicians respond to electoral incentives by changing their absenteeism in plenary sessions. More on Gagliarducci, Nannicini, and Naticchioni (2011).

the pork barrel is directed to the municipal level, we can identify to which municipality the budget was sent. Therefore, in this case, we can work with pork barrel spending that was earmarked for the municipal level. Our analysis will consider these two dimensions: pork barrel spending at the legislator level, which is our benchmark case, and pork barrel spending at the municipal level. We collected a total of 22,306 pork barrel requests made during this period, out of which 4,840 (22%) had a municipality identifier.

Our choice to focus on pork barrel spending is twofold. Although there is no evidence of a direct link between pork and electoral success, there is evidence of an indirect impact. Samuels (2002) shows that pork in Brazil is traded for money, which can potentially affect the electoral prospects of legislators. Moreover, Firpo, Ponczek, and Sanfelice (2015) find that politicians tend to favor municipalities that represent a larger share of the votes they obtained. They also provide evidence that voters support candidates who have brought resources to their localities, which explains why legislators might use pork barrel spending to respond to protesters' demands.

Moreover, in Brazil, the federal government has the prerogative to draft the annual budget proposal, while legislators are allowed to amend the budget bill and propose pork barrel allocations to favor their electoral strongholds (Leoni, Pereira, and Renno (2004)). They can propose a limited number of pork barrel amendments, up to a total of R15*millionperyear*(*nearlyUS*5.8 million).[17] Congress only authorizes the budget; it is the federal government that decides if and when to disburse the funds. In this regard, we look at data on the federal budget amendments proposed by each legislator, considering that looking at the amendments actually implemented by the Executive could bias the analysis. The idea is that legislators might have used these amendments as political tools to please voters from municipalities that had protests.

Finally, to check if legislative work was more intense following the protests, we also collected data on the presence of legislators in all plenary sessions on a weekly basis. Following Nannicini, Stella, Tabellini, and Troiano (2013), we use this variable to measure rent-seeking behavior. Legislators receive a salary, and it is minimally expected that they participate in parliamentary debates to contribute to the legislative process of creating relevant laws. If they are not contributing to legislative activities while being paid by society, they may be allocating their time to personal activities unrelated to their legislative duties. The period considered is from February 2013 to December 2013.[18] The average presence rate is 0.84, as seen in Table 3.

In Table 3, we can also see the average characteristics of municipalities that experienced a protest. The difference between municipalities that experienced protests and those that did not is further clarified in Table **??**. We can see that protests happened in municipalities with higher population, internet, TV, and radio penetration, a more literate population, and an older demographic. Inequality, measured by the Gini index, was roughly the same in municipalities that experienced protests and those that did not.

Electoral accountability: electoral outcomes – We used data from the Superior Electoral Court (TSE), the highest judicial entity in Brazil responsible for overseeing and publishing information related to elections. From the TSE database, we created two datasets. Firstly, we established a dataset of legislators' vote share in individual municipalities in the 2010 and 2014 elections. To do this, we calculated the percentage of votes received by each legislator in a given municipality in

[17] These values are from the period of analysis, 2013-2014. The rules for pork barrel spending changed in 2021, increasing the amount of spending that can be redirected. The name of the legislator who will receive the funds is no longer mandatory, as the transfer can be made from the legislator responsible for proposing the budget, which reduced transparency and accountability in Brazil. This does not impact our analysis.

[18] Although we have information from the beginning of the legislature, there was a change in the rules of the Chamber in October 2012, making presence in plenary sessions mandatory from Tuesday till Thursday, instead of from Monday till Friday. This might have changed the dynamics of the presence rate, so we consider the legislative year of 2013.

Table 3: **Summary Statistics**

Variables	N	mean	sd
Legislators' characteristics			
Legislator Intensity Index [untransformed]	513	.0363	0.147
Legislator Noise Index [untransformed]	513	55861.51	25576.52
Run for reelection	513	0.713	0.452
Electorate's characteristics			
Urban (%)	513	0.817	0.127
Internet penetration (%)	513	0.267	0.128
Literate (%)	513	0.885	0.067
Legislators' performance - baseline			
% budget amend. related to protests by year	451	51	20
Presence rate by week	513	98	12

Notes: Data on legislators were taken from TSE, Chamber of Deputies and Federal Senate websites. *Protest Exposure* is an index reflecting the percentage of the legislator's electorate that lives in a municipality that had a demonstration: the higher the index, more exposure to the protests the legislator had. *Noise Exposure* is an index that refers to the share of tweets related to protest at each municipality that present no clear demand. Municipal and Electorate's characteristics use data from the 2010 census and from TSE.

Table 4: **Summary Statistics**

	Did not Have Protests		Had Protests			
	N	Mean	N	Mean	*Difference*	*P-value*
Population (total)	1454	12772.25	1968	76062.350	63290.11	0
Internet penetration (%)	1454	.13	1968	.21	.08	0
Radio penetration (%)	1454	.78	1968	.8	.03	0
Television penetration (%)	1454	.9	1968	.93	.03	0
Gini Index	1454	.49	1968	.49	0	.492
Youngster (%)	1454	.21	1968	.17	-.04	0
Iliterate (%)	1454	.83	1968	.88	.04	0

relation to the total votes of that municipality.[19] Secondly, we used individual characteristics of the legislator that are available from TSE, such as the party of the legislator—which can change from one election to another and, therefore, cannot be considered an individual fixed effect.

Controls – We mainly use data from the 2010 census, IDEB, and IDSUS, such as access to the internet, education, and health at the municipal level. Access to the internet refers to the share of households in a municipality with at least one computer with internet access. Education level uses information on the share of citizens aged 10 years or older who are literate.

[19] We use this variable instead of the vote share relative to the total votes of each legislator, since the variation in the treatment is at the municipal level.

4 Empirical Strategy

Identification – The reason we focus on federal legislative activity—and not on local legislative or executive activity—is because protests can be taken as given by federal legislators. As discussed in the introduction, in 2013, the trigger for mass street protests was higher transportation costs in important municipalities in Brazil—a decision made by the local executive office on which federal legislators had no say. Our causal identification strategy leverages legislators' local differential exposure to protest intensity and noise, depending on each legislator's pre-protest vote share.

We construct a legislator-level index that quantifies protest exposure. This index is a weighted average of the municipal-level indexes we have constructed. The weight used is the vote share of legislators in the election that happened before the protests. We argue that variation in protest intensity and noise are exogenous from the legislators' perspective, since federal legislators had no say in the increase in public transportation fares. This enables us to identify the causal effect of protests on legislator behavior (Borusyak, Hull, and Jaravel (2022))."[20] Specifically, it measures the weighted average intensity or quality of protests at the legislator level:

$$\begin{aligned} \textit{Legislator Intensity Index}_d &= \sum_M \textit{Vote share}_{m,d}.\textit{Protest Intensity Index}_m \\ \textit{Legislator Noise Index}_d &= \sum_M \textit{Vote share}_{m,d}.\textit{Protest Noise Index}_m \\ \textit{Legislator No Clear Demand Index}_d &= \sum_M \textit{Vote share}_{m,d}.\textit{No Clear Demand Index}_m \end{aligned} \tag{4}$$

where M is the set of all municipalities covered in our sample, $\textit{Vote share}_{m,d}$ is the weight given to each municipality (the vote share a legislator d received at municipality m as a percentage of her total number of votes), $\textit{Protes tIntensity Index}$ is the protest intensity index at the municipality level, *Protest Noise Index* is the protest noise index at the municipality level, and *No Clear Demand Index* is the no clear demand index at the municipality level. These indexes are shift-share indexes, as in Borusyak, Hull, and Jaravel (2022). The "shift" is the set of intensity or noise experienced by each federal legislator in their electoral base at the municipal level, and the "share" is the pre-protest vote share of each legislator. The level of analysis will be clear not only by the name of the indices, but also by the subscript m when regressions are run at the municipal level or d when they are run at the legislator level using the weighted aggregated indices.

We employ a data normalization technique to enhance the interpretability of our Twitter-based indexes: the Twitter Intensity Index, Twitter Noise Index, and Twitter No Demands Index, as well as the adapted indexes at the deputy level weighted by their vote shares in the 2010 elections. By transforming these indexes to have a mean of 0 and a standard deviation of 1, we ensure that the values are centered around a common scale. This normalization not only facilitates comparability among the different indexes but also simplifies their interpretation. With this standardized approach, variations in the indexes can be more readily understood in terms of their deviation from the mean and relative to the standard deviation, making our empirical results more intuitive.

Effective accountability: legislators' behavior –. Following this, we estimate a difference-in-differences regression of the change in the three main outcomes mentioned above: pork barrel spending, presence in plenary sessions, and the vote share of incumbents. These changes are

[20] Exogeneity of protest intensity enables point identification of the causal effect of interest, even if there is potential endogeneity in legislative behavior with respect to the exposure to shocks, i.e. even if vote shares correlate with counterfactual legislative behavior in the absence protest. This is true because aggregate exposure to shocks is the same across legislators, since vote shares always sum up to unity. See Section 4.2 of (Borusyak, Hull, and Jaravel (2022)) for details.

regressed on the change in protest intensity and noise, using a shift-share treatment intensity measure. With our identification strategy in mind, we proceed with our first estimation:

$$\begin{aligned}
Performance_{d,t} = & \ \theta Post_t \times Legislator\ Intensity\ Index_d \\
& + \beta Post_t \times Legislator\ No\ Demand\ Index_d \\
& + \delta Post_t \times Legislator\ Intensity\ Index_d \times Legislator\ No\ Demand\ Index_d \\
& + \alpha_d + \gamma_t + \varepsilon_{d,t}
\end{aligned} \tag{5}$$

where $Performance_{d,t}$ can be one of our two legislator performance variables (the share of pork barrel spending related to protest demands and presence in plenary sessions), $Post_t$ is a dummy that indicates a period ex-post protests, *Legislator Intensity Index* and *Legislator No Demand Index* are the shift-share indexes defined by equation (4), α_d is the legislator fixed-effect, and γ_t is the time fixed-effect.

This equation identifies whether the protests affected legislators' behavior through the estimation of θ, β, and δ. θ quantifies the influence of protest intensity, while β assesses the effect of protest noise. The interaction between noise and intensity is captured by δ, enabling us to discern the overall impact of both channels simultaneously influencing the outcomes.

Due to the different nature of the performance variables of legislators' performance, t will refer to different time periods depending on the variable used as the dependent variable. For presence in plenary sessions, we aggregated data weekly, while for pork barrel spending, we use data annually. This is due to the different response times a legislator can have regarding these variables. Changing their behavior with respect to attending plenary sessions is much less demanding than proposing new pork barrel spending.

We follow a similar identification strategy as the one used in the estimation of equation (5), but instead of focusing on the *Legislator No Demand Index* that tells us how many municipalities had zero demands from the perspective of the legislator, we now focus on the *Legislator Noise Index*, which measures how noisy the demands were:

$$\begin{aligned}
Performance_{d,t} = & \ \theta Post_t \times Legislator\ Intensity\ Index_d \\
& + \beta Post_t \times Legislator\ Noise\ Index_d \\
& + \delta Post_t \times Legislator\ Intensity\ Index_d \times Legislator\ Noise\ Index_d \\
& + \alpha_d + \gamma_t + \varepsilon_{d,t}
\end{aligned} \tag{6}$$

where all variables follow the same definitions as above, except that we now focus on *Legislator Noise Index* as defined by equation (4). θ is the coefficient that tells us how protest intensity impacts the performance of legislators, β shows how noise impacts the performance of legislators, and finally δ captures the interaction between intensity and noise, given *Post*, the protest event. Thus, this equation identifies whether the protests affected the legislators' behavior through the estimation of θ, β, and δ.

Effective accountability: legislators' behavior at the municipal level –. For the subset of pork barrel spending that has a municipality identifier, we can run the regression of performance at the municipal level. This subset allows us to conduct a more granular analysis, providing robustness to our findings. By focusing on municipal-level data, we can better capture the local impact of pork barrel spending and understand how legislators allocate resources in response to protest demands within specific municipalities. This approach enhances the credibility of our results by ensuring that the observed effects are not merely driven by aggregated data but are evident at a more detailed level. Additionally, running the regression at the municipal level allows us to control for local characteristics and variations, offering a robust check for our causal estimates conducted at the legislator level.

$$\begin{aligned} Performance_{d,m,t} = & \theta Post_t \times Twitter\ Intensity\ Index_m \\ & + \beta Post_t \times Twitter\ No\ Demand\ Index_m \\ & + \delta Post_t \times Twitter\ Intensity\ Index_m \times Twitter\ No\ Demand\ Index_m \\ & + \alpha_m + \gamma_t + \varepsilon_{m,t} \end{aligned} \tag{7}$$

where $Performance_{d,m,t}$ is the share of pork barrel spending related to protest demands for legislator d at municipality m, $Post_t$ is a dummy that indicates a period ex-post protests, *Protest Intensity Index* and *Protest No Demand Index* are defined by equations 1 and 2, α_m is the municipal fixed-effect, and γ_t is the time fixed-effect.

As before, we follow with the same analysis but replace the *Protest No Demand Index* with the *Protest Noise Index* as indicated by equation (3).

$$\begin{aligned} Performance_{d,m,t} = & \theta Post_t \times Protest\ Intensity\ Index_m \\ & + \beta Post_t \times Protest\ Noise\ Index_m \\ & + \delta Post_t \times Protest\ Intensity\ Index_m \times Protest\ Noise\ Index_m \\ & + \alpha_m + \gamma_t + \varepsilon_{m,t} \end{aligned} \tag{8}$$

Electoral accountability: voters' behavior – We move to the second layer of accountability, focusing on the behavior of voters, known as electoral accountability. We use data from the elections to test whether, in the sample of municipalities where there was a protest, legislators who decided to run for reelection and responded more positively to protests were rewarded in the 2014 elections. We construct a balanced panel and estimate the following equation:

$$\begin{aligned} Vote\ Share_{d,m,t} = & \theta Election_t \times Twitter\ Intensity\ Index_m \\ & + \beta Election_t \times Twitter\ Noise\ Index_m \\ & + \delta Election_t \times Twitter\ Intensity\ Index_m \times Twitter\ Noise\ Index_m \\ & + \alpha_m + \varepsilon_{m,t} \end{aligned} \tag{9}$$

where $Vote\ Share_{d,m,t}$ is the vote share of legislator d at municipality m in the 2014 and 2010 elections, $Election_t$ is a dummy that refers to the period ex-post the 2014 elections, and all other variables are as in equation (6). Through this equation, we test the hypothesis that the quality of the protest (more vs. less noise) would influence voters to reward legislators who responded more positively to protest demands or punish those who did not. Conditional on the quality of the protest at each municipality, the coefficient δ captures whether voters in each municipality are punishing incumbents. Note that this regression is at the legislator-municipal level.

In order to make this exercise more comparable to the former one, we can also run the vote share regression at the legislator level:

$$\begin{aligned} Vote\ Share_{d,t} = & \theta Election_t \times Legislator\ Intensity\ Index_d \\ & + \beta Election_t \times Legislator\ Noise\ Index_d \\ & + \delta Election_t \times Legislator\ Intensity\ Index_d \times Legislator\ Noise\ Index_d \\ & + \alpha_d + \varepsilon_{d,t} \end{aligned} \tag{10}$$

where $Vote\ Share_{d,t}$ is the vote share of legislator d in the 2014 elections, $Election_t$ is a dummy that refers to the period ex-post the 2014 elections, and all other variables are as in equation (6).

Through this equation, we test the hypothesis that the quality of the protest (more vs. less noise) influences voters to reward legislators who responded more positively to protest demands or punish those who did not. Conditional on the quality of the protest at each municipality, the coefficient δ captures whether voters in each municipality are punishing incumbents.

5 Results

5.1 Legislator's behavior

We begin by presenting estimates for equation 5. In particular, we are interested in the effect of the level of protest intensity experienced by each legislator, captured by the *Legislator Intensity Index*, on our two performance outcomes: pork barrel spending and presence in plenary sessions. Table 5 presents the results from estimating equation 5. The results, shown in columns (1) and (4) of Table 5, indicate that more intense protests, as captured by the *Legislator Intensity Index* , correlate with higher performance from the legislators. This means more pork barrel spending directed to typical protest demands and higher presence in plenary sessions. Only the coefficient for pork barrel spending is statistically significant, as shown in column (1). A one standard deviation increase in the *Legislator Intensity Index* after the protest is associated, on average, with a 1.5 percentage point increase in the share of pork barrel spending, representing 2.9% of the variable mean. In the case of presence in plenary sessions, the impact is 0.2 percentage points, or 0.3% of the variable mean.

When we focus on the impact of the lack of demands in protests, captured by the *Legislator No Demand Index*, columns (2) and (5) from Table 5 present this impact. The results suggest that when legislators experience more municipalities with no clear demands, they respond less in terms of pork barrel spending. In fact, a one standard deviation increase in the Legislator No Demands Index after the protest is associated, on average, with a 3.6 percentage point decrease in the share of pork barrel spending, representing 7.1% of the variable mean. For presence in plenary sessions, the result is roughly zero and statistically not significant. This shows the effect of the quality of the demands of mass street protests, whether they were clear or not, independent of the intensity of the protests.

Since our focus is on the interplay between the intensity and clarity of protest demands simultaneously influencing the outcome, we want to explore the triple interaction between protests, intensity, and lack of clarity in the demands. This can be partially seen in columns (3) and (6) from Table 5 but is mostly evident in the analysis of the total impact of noise on the performance variable, which is the sum of the direct impact and the indirect impact given a certain level of intensity. Figure 2 plots the marginal effect of protest exposure for five different intensity levels (values at the 10th, 25th, 50th, 75th, and 90th percentiles of the *Legislator Intensity Index* distribution). We see that, for pork barrel spending, the marginal effect of noise is lower, i.e., less negative, as the protest becomes more intense. The opposite is true for the presence in plenary sessions. The more intense the protest, the greater the marginal impact of noise, i.e., more negative.

It is worth noting that the marginal effect of the *No Clear Demand Index* is roughly the same for all levels of protest intensity, as shown in Figure 2. This suggests that our *No Clear Demand Index* is not sufficient to disentangle the effects between intensity and the quality of the message that protesters are producing. Therefore, we proceed with the analysis of the *Noise* index, which is a better measure of how concentrated the protest demands were.

We proceed to the analysis of our main result, which considers how noisy the demands from the street were. Throughout the paper, we will focus on the *Noise Index* rather than the *No Clear*

Table 5: **Effect of Protests on Legislators' Behavior**

	Pork Barrel (%)			Presence in Plenary		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	1.538**		1.798**	0.237		0.0239
	(0.685)		(0.809)	(0.376)		(0.404)
Post x No Demands Index		-3.751***	-3.757***		0.114	-0.00303
		(0.667)	(0.705)		(0.449)	(0.428)
Post x Leg. Intensity Ind. x Leg. No Dem. Index			-0.0390			-0.646
			(0.965)			(0.516)
Observations	928	928	928	21,767	21,767	21,767
Adjusted R-squared	0.660	0.675	0.677	0.226	0.226	0.226
Number of periods	2 years	2 years	2 years	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	513	513	513
Mean Dep. Var. pre-protest	51	51	51	98	98	98
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and *LegislatorIntensityIndex* is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. *LegislatorNoDemandIndex* is an index reflecting twitter activity with no clear demands in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

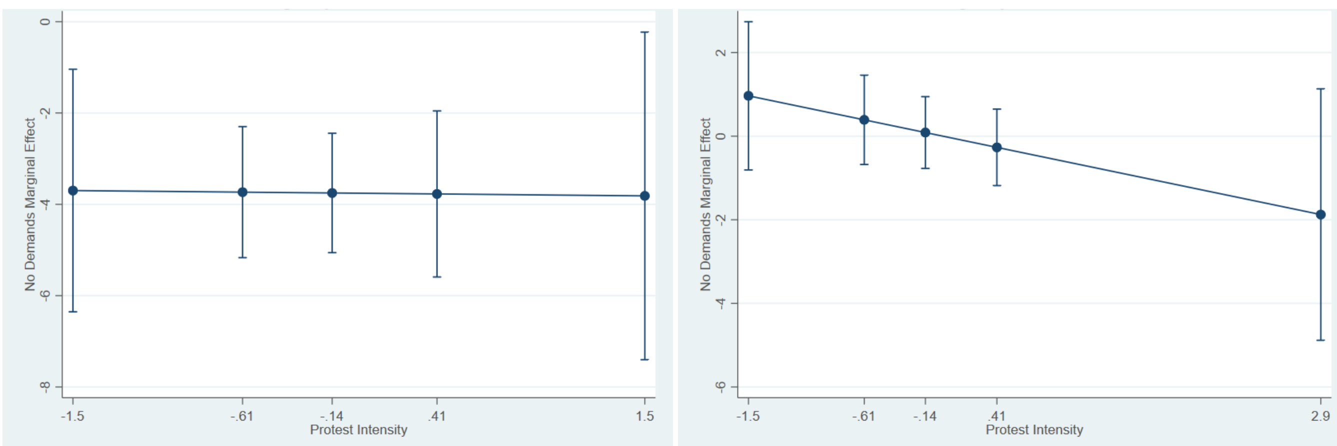


Figure 2: Total marginal effect of *No Demands* index on pork barrel spending (left) and on presence in plenary sessions (right).

Demand Index. The analysis of the impact of the *Legislator Intensity Index* remains the same and can be seen in columns (1) and (4) of Table 6.

When we focus on the quality of the messages delivered by protests, represented now by the *Legislator Noise Index* in columns (2) and (5) of Table 6, we see that both pork barrel spending and presence in plenary sessions responded negatively to noisier mass street protests. A one standard deviation increase in the Legislator Noise Index after the protest is associated, on average, with a 3.5 percentage point decrease in the share of pork barrel spending, which represents 6.9% of the variable mean. For presence in plenary sessions, the result is again roughly zero and statistically not significant.

When we include both the intensity and the quality of the message of mass street protests in

Table 6: **Effect of protests on legislators' behavior**

	Pork Barrel (%)			Presence in Plenary		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	1.538**		3.054***	0.237		-0.00492
	(0.685)		(0.842)	(0.376)		(0.515)
Post x Legislator Noise Index		-3.515***	-3.422***		-0.109	-0.134
		(0.725)	(0.708)		(0.431)	(0.421)
Post x Leg. Int. Ind. x Leg. Noise Ind.			2.200**			-0.419
			(0.953)			(0.506)
Observations	928	928	928	21,767	21,767	21,767
Adjusted R-squared	0.660	0.672	0.679	0.226	0.226	0.226
Number of periods	2 years	2 years	2 years	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	513	513	513
Mean Dep. Var. pre-protest	51	51	51	98	98	98
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more noise to protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

the same equation, we observe that the overall effect is still negative. This requires the analysis of the total impact of noise on the performance variable, which we plot in Figure 21. For pork barrel spending, the marginal effect of noise is lower, i.e., less negative, as the protest becomes more intense. In fact, if the protest is "too intense," the impact of noise is roughly zero, since the coefficient is statistically not significant. The opposite is true for the presence in plenary sessions. The more intense the protest, the greater the marginal impact of noise, i.e., more negative. However, the overall impact is not significant. It is worth noting that a "too intense" protest is not frequently observed in our data sample. We can see this by checking the distribution of the *Legislator Inteensity Index* at the legislator level, standardized to have a mean of 0 and a standard deviation of 1. The plots for the distributions can be seen in Appendix D.

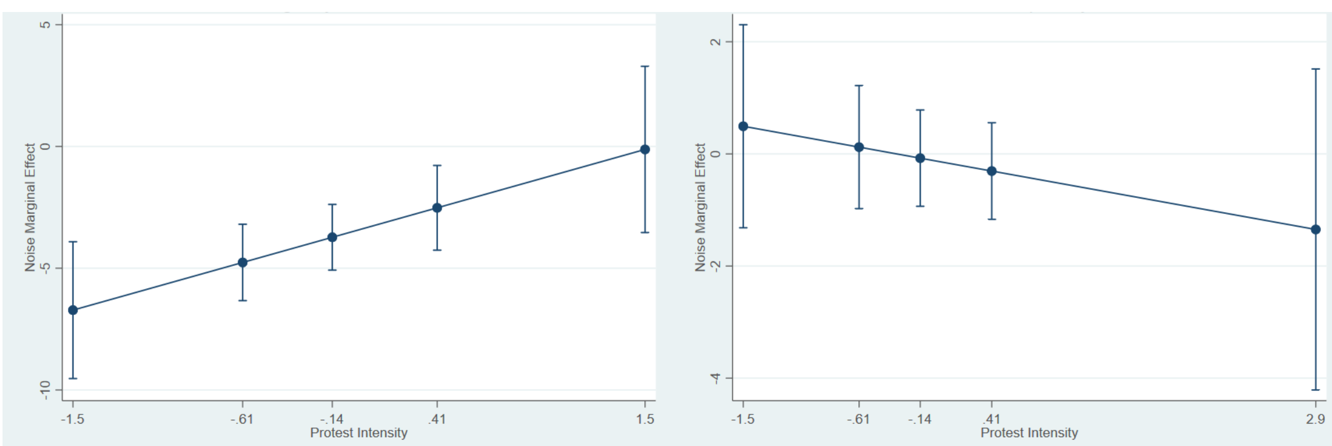


Figure 3: Total marginal effect of *Noise* index on pork barrel spending (left) and on presence in plenary sessions (right).

Note that our measure of pork barrel spending is the share of the value of pork barrel spending that was related to the protests demands as discussed in Section 3. This is given the fact that the total value of pork barrel spending doesn't vary much from legislator to legislator given they all have a fixed amount of pork barrel to spend every year. In any case, we show results for the estimation of equations (5) and (6) for alternative measures of pork barrel spending (total value and total number of pork barrel requests). We present results in the Appendix F. They are all not statistically significant.

Legislator's response to protests and reelection –. The above regressions considered the total pool of legislators, including the ones that were not going to run for reelection in the following elections that took place 14 months after protests. Our focus is to understand how effective protests are both in terms of effective accountability – legislators responding to protest demands, and on electoral accountability – if voters rewarded politicians that delivered what they requested. Since when we study below the effect of protests on electoral accountability we will have to focus on legislators that were running for reelection, we show below the same results focusing on the pool of legislators that were indeed running for reelection.

Table 7 presents the result of the same specification presented in equation 6, but splitting the sample between legislators that decided to run for reelection in 2014 ($N = 366$) and those that did not ($N = 147$). Overall, we see in all columns that the previous results for the full sample were mainly driven by the pool of legislators that decided to run reelection for the case of pork barrel spending – which is the performance variable that showed significant responses to mass street protests in the main regressions above. Interestinly, the direct impact of noisy street protests into pork barrel spending are stronger for legislators that were not running for reelection rather than legislators that were not running. In fact, a one standard deviation increase in Legislator Noise Index after protest is associated, on average, with a 5.3 percentage point decrease in the share of Pork Barrel spending for legislators that were not running for reelection, as shown in column (3) of Table 7, and with a 2.8 percentage point decrease in the share of Pork Barrel spending for legislators that were running for reelection, as shown in column (4) of Table 7. The overall impact of both intensity and noise of protests vanishes for the case of legislators that were running for reelection, as shown in column (3) of Table 7, but remained significant for the case of legislators that were running for reelection, as shown in column (4) of Table 7. Total marginal effects illustrated in Figure 4 confirm the overall results. Mass street protests impacted pork barrel spending negatively, the result was more negative the less intense were mass street protests, and this impact was driven mostly by legislators that were running for reelection. The impact of mass street protests on pork barrel spending was not statically significant.

Results for the impact of protests in presence in plenary sessions remain statistically not significant for both samples. For the rest of the paper, we will focus on the *Noise Index*. Regressions for the *No Clear Demand Index* can be found in the Appendix G.

Municipal level data for pork barrel spending – We also run the same specifications as above at the municipal level, as indicated by equations (7) and (8), for the subsample of pork barrel spending that has a municipal identifier, as discussed in Section 3. The results are overall in line with our main findings so far: the *Noise* index has a negative impact on pork barrel spending and appears to be a better index to disentangle the impact of protest intensity from noisy protest demands. The detailed results can be seen in Appendix H.

Moreover, we also run the same specifications as above at the municipal level, as indicated by equations (7) and (8), for the subsample of pork barrel spending that has a municipal identifier, as

Table 7: **Effect of Protests on Legislators' Performance**

	% Pork Barrel				Presence Rate			
	reelection=0	reelection=1	reelection=0	reelection=1	reelection=0	reelection=1	reelection=0	reelection=1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x Legislator Intensity Ind.	2.087	1.404*	2.950	3.305***	1.513	-0.0697	1.111	-0.234
	(1.699)	(0.740)	(1.784)	(0.933)	(1.182)	(0.354)	(1.510)	(0.502)
Post x Legislator Noise Ind.			-5.227***	-2.790***			-0.370	-0.117
			(1.211)	(0.858)			(0.897)	(0.446)
Post x Leg. Int. Ind. x Leg. Noise Ind.			-0.337	3.050***			-0.754	-0.285
			(1.549)	(0.980)			(1.404)	(0.451)
Observations	258	670	258	670	6,132	15,635	6,132	15,635
Adjusted R-squared	0.685	0.647	0.716	0.664	0.229	0.218	0.229	0.218
Number of periods	3 years	3 years	3 years	3 years	43 weeks	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	322	513	513	513	513
Mean Dep. Var. pre-protest	49	50	49	50	84	84	84	84
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. We split the sample between those legislators that ran in the 2014 elections and those that did not. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more noise to protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

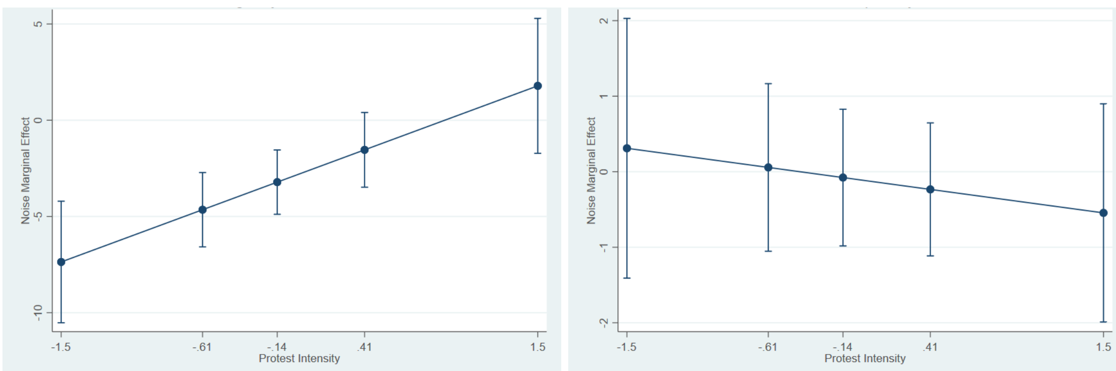


Figure 4: Total marginal effect of *No Demands* index on pork barrel spending (left) and on presence in plenary sessions (right): reelection subsample

discussed in Section 3. The results are overall in line with our main findings so far: the *Legislator Noise Index* has a negative impact on pork barrel spending and appears to be a better index to disentangle the impact of protest intensity from noisy protest demands. The detailed results can be seen in Appendix H.

Real *vs* virtual protests – A concern that may arise is how social media manifestation is related to the occurrence of real protests—or more specifically, what matters most to legislators: a real protest or a social media protest. To analyze these two issues, we collected data from a leading Brazilian news website, G1, to check for real occurrences of street protests in the country by municipality. G1 created a special section to cover issues related to the nationwide protests. The data from this source includes information on whether a particular municipality experienced a protest and the number of protest days within the municipality during the June 17th to June 30th period of interest. This data source helps us to check if the real occurrence of a protest is also correlated with stronger Twitter activity related to protests.

In Figure 5, we can observe that our measures of Twitter activity are only slightly stronger in municipalities where a real protest was registered. Therefore, we view our Twitter measure as a reliable proxy for assessing the impact of real protests on legislators' and voters' behavior, rather than the impact of social media manifestations on legislators' and voters' behavior.[21]

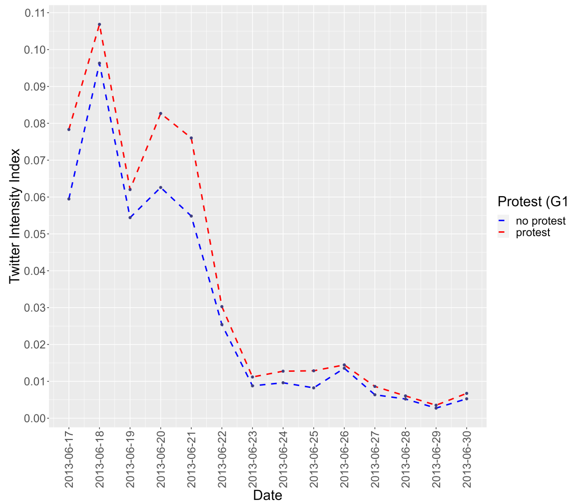


Figure 5: Twitter Intensity Index in municipalities with real protests and without. Source: G1 News Portal.

We will run the same specifications as indicated by equations 5 and 6, but focusing on the sample of municipalities that had a real-life protest registered in the G1 news portal. This means that the legislator-level indices calculated in (4) will not have a positive level of *Legislative Intensity Index*, *Legislative Noise Index*, or *Legislative No Demand Index* index for municipalities that did not have a real-life protest registered in the G1 news portal. Below, we present results for the *Legislative Noise Index* index and leave the results for the *Legislative No Demand Index* index in Appendix I. We see in Table 8 that the overall results are in line with those we have presented so far, but they are stronger.

Table 8: **Effect of protests on legislators' behavior: only G1 sample**

	Pork Barrel (%)			Presence in Plenary		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	-1.464*		5.137***	-0.0971		-1.097
	(0.789)		(1.708)	(0.434)		(0.951)
Post x Legislator Noise Index		-6.982***	-7.083***		-0.347	1.245
		(1.585)	(1.602)		(0.410)	(0.868)
Post x Leg. Int. Ind. x Leg. Noise Ind.			-0.809			-0.297
			(0.855)			(0.411)
Observations	928	928	928	21,767	21,767	21,767
Adjusted R-squared	0.660	0.673	0.673	0.226	0.226	0.226
Number of periods	2 years	2 years	2 years	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	513	513	513
Mean Dep. Var. pre-protest	51	51	51	98	98	98
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

A one standard deviation increase in the *Legislator Intensity Index* after the protest is associated, on average, with a 1.4 percentage point increase in the share of pork barrel spending, representing

[21] Müller and Schwarz (2023) find that social media activity has an impact on real life by measuring Twitter use in a county and observing a sizeable increase in anti-Muslim hate crimes after the 2016 presidential primaries. Baylis (2020) uses Twitter data to analyze people's sentiments towards climate change.

2.9% of the variable mean—the same value found when we ran the regression for all municipalities, not just the ones that registered a real-life protest according to G1. Moreover, a one standard deviation increase in the Legislator Noise Index after the protest is associated, on average, with a 7.0 percentage point increase in the share of pork barrel spending, representing 13.7% of the variable mean—more than double the 5.9% increase when we worked with the whole sample of municipalities. Finally, while the triple interaction between the *Legislator Intensity Index* and the *Legislator Noise Index* is itself not significant, the total marginal effect of the *Legislator Noise Index* on pork barrel spending is significant, as illustrated in the left plot of Figure 24. Results are still not significant for the case of presence in plenary sessions.

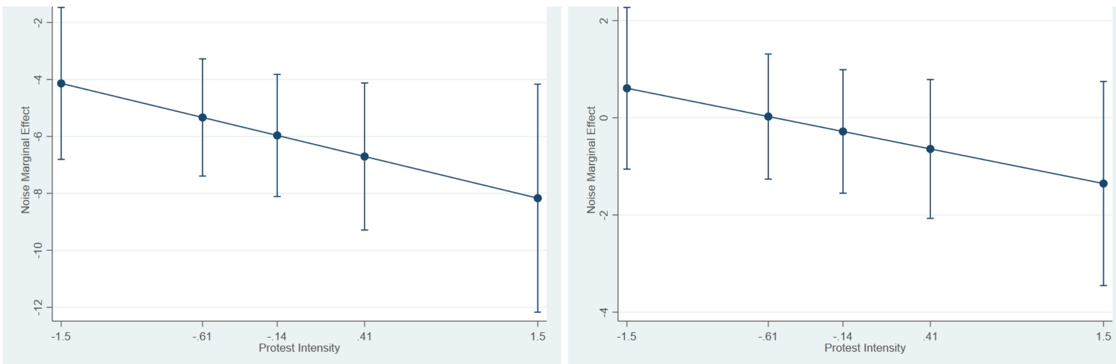


Figure 6: Total marginal effect of *Noise* on pork barrel (left) and presence in plenary session (right) for subsample of municipalities that have registered a real life protest accordingly to G1.

These results are in line with our theoretical finding that protests may work as an accountability mechanism in the persuasion sense by impacting legislators' choices, with higher noise leading to worse performance from legislators. We provide details in Section 6. Before that, we present results for the case of electoral accountability, i.e., how voter behavior was impacted by mass street protests.

5.2 Voter's behavior

In this section, we test how legislators were impacted by protest intensity and the quality of protest demands, measured by our *Legislator Noise Index* or *Twitter Noise Index*. To do this, we constructed a balanced panel with legislators who were seeking reelection, presenting their vote share on a 0-100 scale. Our benchmark measure of vote share indicates how many votes a legislator d received in a municipality m as a share of the total votes registered for all legislators in that same municipality. We also present an alternative measure of vote share that considers the contribution of each municipality m to the total vote share of legislator d. Results are presented in Appendix J.

Since we have information for vote share at the municipal level, we will start by running estimations at this more granular level of data. Table 9 present the result of equation (9) at the municipal, legislator, time level:

Column (1) shows that all legislators seeking reelection were punished for the protests in the 2014 election, with an average 15.1 percentage point decrease in the vote share of the legislator, as indicated by the dummy that marks a reelection. When the intensity of protests is added, as shown in column (2), we can see that a one standard deviation increase in the Legislator Intensity Index after the protest is associated, on average, with a 3.8 percentage point decrease in the vote share of the legislator, which represents 3.5% of the variable mean.

Table 9: **Effect of protests on legislators' vote share, municipality level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.151***	-0.158***	-0.130***	-0.141***
	(0.0190)	(0.0207)	(0.0258)	(0.0272)
Election x Twitter Intensity Index		-0.0383*		-0.194**
		(0.0228)		(0.0955)
Election x Twitter Noise Index			-0.0522**	-0.0499**
			(0.0204)	(0.0202)
Election x Twitter Int. Index x Twitter Noise Index				-0.156*
				(0.0808)
Observations	264,120	174,576	49,746	49,746
Adjusted R-squared	0.762	0.786	0.841	0.842
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	1.11	1.11	1.11	1.11
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity at municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

When the level of noise in protests is added, as shown in column (3), one standard deviation increase in the Legislator Noise Index after protest is associated, on average, with 5.2 percentage point decrease in the vote share of the legislator. The triple interaction illustrated in the figure 7, and shown in column (4), is also negative and statistically significant. In the Appendix K we show results for the same specification, but changing the *Twitter Noise Index* index for the *Twitter No Demand Index* index. The overall intuition is the same, but the *Twitter No Demand Index* index is less significant on average than the *Twitter Noise Index*.

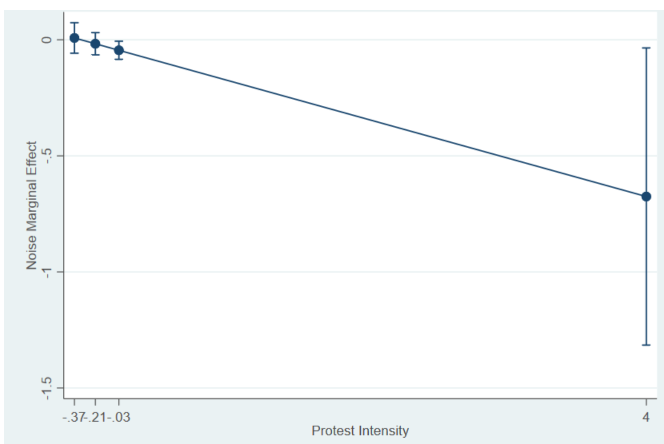


Figure 7: Total marginal effect of *Noise* on the vote share of legislators at the municipal level.

We also present regressions at the legislator level to make the results of this section more comparable with our main performance findings from the previous section. Results for the estimation of equation 10 are provided in Appendix L. Overall, these results are consistent with those presented at the municipal-legislator level.

One of our main interests is whether legislators' responses to protests correlate with voters' decisions to punish or reward incumbents, as we will discuss further in Section 6. We divided our sample of municipalities into those with a high level of *Noise Index* (above the median) and those with a low *Noise Index*. Table 10 presents these results. For example, Columns (1) and (3) display the results of our main specification for vote share among legislators with below-average pork barrel spending, while Columns (2) and (4) show results for legislators with above-average pork barrel spending. The same applies to presence in plenary sessions, as shown in Columns (5)-(8).

The election immediately following the protests had a similarly negative impact on both legislators who performed above and below average. As shown in Column (1), legislators with below-average performance experienced a 20.9 percentage point decrease in their vote share, while those with above-average performance saw an 11.9 percentage point decrease (Column (2)). When considering the overall impact of protests, incorporating measures of both intensity and noise, legislators with below-average performance had, on average, a 17.9 percentage point decrease in their vote share (Column (3)), whereas those with above-average performance experienced an 11.2 percentage point decrease (Column (4)). Results for the impact on presence in plenary sessions exhibit similar qualitative trends and are detailed in Columns (5)-(8).

Table 10: **Effect of protests on legislators' vote share, municipality level**

	Pork Barrel				Presence in Plenary			
	below md	**above md**	**below md**	**above md**	**below md**	**above md**	**below md**	**above md**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Election	-0.209***	-0.119***	-0.205***	-0.0878***	-0.188***	-0.136***	-0.206***	-0.0938***
	(0.0381)	(0.0208)	(0.0408)	(0.0327)	(0.0263)	(0.0235)	(0.0389)	(0.0312)
Election * Twitter Intensity Index	0.00688	-0.0835***	-0.158	-0.228***	-0.0518**	-0.0271	-0.182*	-0.202*
	(0.0265)	(0.0248)	(0.119)	(0.0846)	(0.0223)	(0.0290)	(0.0980)	(0.107)
Election * Twitter Noise Index			-0.0441	-0.0585**			-0.0204	-0.0709***
			(0.0327)	(0.0255)			(0.0307)	(0.0228)
Election*Twitter Int. Ind. * Twitter Noise Ind.			-0.179*	-0.112			-0.144*	-0.165*
			(0.0995)	(0.0730)			(0.0835)	(0.0902)
Observations	79,588	94,988	22,582	27,164	74,346	100,230	20,676	29,070
Legislator-municipality FE	Yes	Yes	Yes	Yes				

We also present results for the same specifications and sample split but restrict our analysis to cities that experienced real-life protests according to the G1 news portal, detailed in Appendices M and N. Table 25 in the Appendix demonstrates that focusing solely on municipalities with registered protests shows more pronounced effects of protest intensity and noise. When we divide the sample by above and below average performance, as shown in Table 25, we observe an overall negative impact of noise on legislators' vote share. However, this impact is less negative for legislators who performed above the mean in terms of pork barrel spending. This finding aligns closely with the aggregate results previously discussed.

Overall, protests negatively impacted legislators' vote share, with intense and noisier protests having an even greater impact. Legislators who responded to protest demands above average experienced less negative effects. These results are consistent with our theoretical findings, as discussed below.

6 Theoretical Model

6.1 Protests as Noisy Bayesian Persuasion

Our modeling strategy conceptualizes protesters as information designers aiming to persuade a benevolent, albeit uninformed incumbent government to adopt their preferred actions, following the Bayesian persuasion framework introduced by Kamenica and Gentzkow (2011). Although governments are not inherently benevolent, we find this assumption suitable in our context. During mass street protests, governments often prioritize understanding protesters' demands, potentially shifting other incentives politicians typically prioritize to a secondary role.

Protests thus serve as an information mechanism that reveals insights into protesters' preferences. While participants can influence the design of the information they produce, they cannot fully control its outcome or compel the government to adopt their exact preferences. In other words, the messages conveyed are *Bayes plausible*. This approach situates protests within a democratic framework, distinct from studies such as Cantoni, Yang, Yuchtman, and Jane Zhang (2019), which explore protests leading to regime changes.

A central aspect of our model is the variation in governments' abilities to interpret messages designed by protesters. High-quality governments accurately perceive messages without noise, whereas low-quality governments may misconstrue the intended message, akin to findings in Tsakas and Tsakas (2017). The noise encountered by low-quality governments is linked to the inherent clarity of the protest itself. In our empirical analysis, noise manifests as either the lack of clarity in protest demands, captured by the *No Demand Index*, or the volume of demands expressed by protesters, captured by the *Protest Noise Index*.

Bayesian persuasion models rely on the assumption that senders commit to their informational strategies once designed, even before observing the true state of the world. We find this assumption plausible in our context for two key reasons. First, during periods of protest, it's uncertain whether voters fully understand the aggregated preferences expressed. Secondly, since the information strategy emerges collectively from a group of protesters, the commitment assumption implies that once a protest begins, it becomes prohibitively costly to mobilize and aggregate everyone again to optimize communication strategy. Essentially, after a protest commences, individual control over the strategy diminishes.

In Section 6.4, we explore how this commitment assumption influences our findings, framing our analysis as a *cheap talk model*. While specific quantitative outcomes may vary, the qualitative results persist: noisy messages generally undermine persuasion efforts. We present the game between protesters and incumbent government, arguing that protests can function as a persuasion mechanism. Our main results demonstrate that protests can be effective, but noise diminishes their ex-ante effectiveness, while also aiding voters in distinguishing between low and high-quality politicians.

6.2 Players, policy and state

In this economy, there are two players: an incumbent government (G) and a group of protesters (P). The state of the world is denoted by $\omega \in \Omega = 0, 1$, representing, for instance, protesters' preferences. The incumbent's benevolence extends to caring about policy actions $a \in A = 0, 1$ that align with the state of the world. Therefore, her payoff depends on both her action and the unknown state of the world. An example of a payoff function that reflects this setup is $u_G = \mathbb{1}_{a=\omega}$. The incumbent's ability, denoted by $\tau \in \Gamma = L, H$, affects her capacity to interpret information accurately regarding the state of the world. High-ability governments interpret signals about the state without any noise, while low-ability governments may interpret signals with noise, as detailed further in the information structure section below. Protesters are driven by their own motivations and derive utility only when $a = 1, \forall \omega \in \Omega$. Thus, the protesters' payoff function can be represented as $u_P = \mathbb{1}_{a=1}$.

The payoffs described above depict an extreme scenario of conflicting interests between the government and protesters, which is particularly insightful for analysis as it highlights the maximum disagreement between the two parties. Alternatively, we could adopt a modeling approach where both players care, albeit to varying degrees, about the true state of the world and a specific policy outcome. While this adjustment might diminish the role of protests as a persuasion mechanism, it would not fundamentally alter our theoretical findings.

6.3 Information structure

Our modeling strategy is to define protesters as information designers that aim to persuade the rational incumbent to take the protester's desired action, as in the Bayesian persuasion literature, following Kamenica and Gentzkow (2011). One may think that protesters would gather to decide how they will inform the government on which action to take. Protesters are farsighted and take into account how the government will react to the protest and how likely it will be for the government to take the desired action, $a = 1$. As information designers, protesters design a signal device that will deliver signals such that the chances the government will be persuaded are maximized. In other words, protesters will design the signal structure in such a way they can choose from the set of all possible posteriors the government can form after they observe the realization of the protest.

Therefore, a protest consists of a finite realization over the space S – that define all possible signal realizations, and a family of distributions $\{\pi(s|\omega)_{\omega\in\Omega}\}$ – that define the probability attached to each signal realization. Following Kamenica and Gentzkow (2011), we restrict our attention to a specific class of signals $s \in S$, the ones that are *straightforward*, i.e., $S \in A$. This means that that $s \in S$ can be reduced to an action recommendation to the incumbent.[22] Both government and protesters have a common prior $\mu_0 = \Pr(\omega = 1)$ and $\lambda_0 = \Pr(\tau = H)$.[23] In our example of binary states that follow with signals and types that are also binary, the information structure that will be designed can be represented by a pair of probabilities for $t \in \Gamma = \{H, L\}$:

	$\pi(s = 0\|\omega, \tau = t)$	$\pi(s = 1\|\omega, \tau = t)$
$\omega = 0$	$1 - q_0^t$	q_0^t
$\omega = 1$	$1 - q_1^t$	q_1^t

Table 11: Signal structure $\pi \in \Pi : (\Omega, \Gamma) \to \Delta(S)$.

From Table 11 we see that protesters want to maximize q_0^t and q_1^t, i.e., they want to maximize the chances that the protest signal will be such that it recommends the government to take action $a = 1$. The protesters cannot set $q_0^t = q_1^t = 1$ because that would not be Bayes plausible in the sense of Kamenica and Gentzkow (2011). This means that protesters cannot ignore the previous information that the government already has - her prior. This is clear in the solution for the optimization problem solved by protesters, shown in Appendix O.

But not all governments are alike. Some high ability incumbents ($\tau = H$) may interpret with clarity the information received from the signal device of protests, while low ability types ($\tau = L$) may mistake the signal received. For the low ability case, we follow Tsakas and Tsakas (2017) who have added a noisy message channel to the classic Bayesian persuasion model. In our case, noise

[22] This is not without loss of generality in the environment where signals are noisy. A richer signal-space would be beneficial to protesters, as shown by Tsakas and Tsakas (2017). We abstract from this to keep the model tractable and easier to communicate with the empirical analysis performed later in the paper.

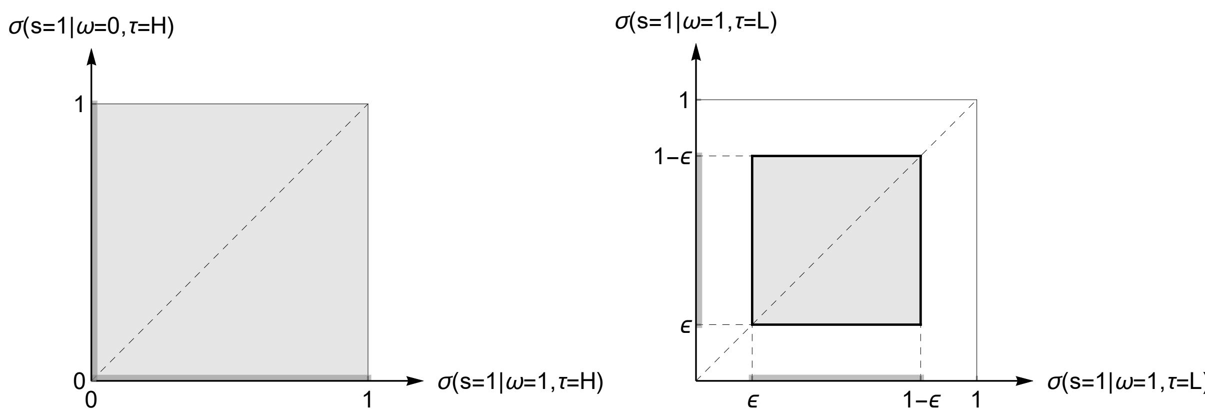
[23] The government also doesn't know her type. This is a common assumption in the literature to prevent another layer of strategic interaction between the government and the protesters.

can only happen when the politician is low quality. In fact, the low type of government mistakes a signal $s = 1$ for one of $s = 0$ and a signal $s = 0$ for one of $s = 1$ with probability ϵ. We assume $\epsilon < \mu_0$ for consistency of results.

Therefore, a noisy signaling mechanism consists of a message from protesters $\pi \in \Pi : (\Omega, \Gamma) \rightarrow \Delta(S)$ optimal to the sender, and an exogenous noisy channel $p : (S, \Gamma) \rightarrow \Delta(S)$ that may distort the message that was produced by the protest. Thus, $p(s'|s, \omega)$ denotes the probability that the receiver observes s' when s has been realized by protesters. A signaling structure (π, p) induces a signal $\sigma : (\Omega, \Gamma) \rightarrow \Delta(S)$ such that

$$\sigma(s|\omega) = \sum_{t \in \Gamma} \sum_{i \in S} p(s|i, t)\pi(i|\omega, t) \tag{11}$$

The set of feasible signals is denoted by $\sum_p \subset \Pi$, for a given p. Each feasible signal $\sigma \in \sum_p$ induces a mapping from the state space $\omega \times \tau$ to $\Delta(B_p) \subset \Delta(S)$, with $B_p = \{p(.|s = 0, t), p(.|s = 1, t)\}$.We borrow from Tsakas and Tsakas (2017) an illustration of the set of feasible signals $\sum_p$ for our binary example:



(a) High quality government

(b) Low quality government.

Figure 8: The set of feasible signals $\sum_p$ for the binary channel p and for both high and low quality governments. We borrow the figure on the right from Tsakas and Tsakas (2017).

The figure above depicts the set of feasible signals for each type of government. On the left side of Figure 8, we show the the feasible message space of the high quality government, which is the entire message space. Each element of this space represents a probability attached to $s = 1$. The low quality government $\tau = L$ receives a signal from protesters with noise. This means that the message space that is feasible is the convex hull of $B_p = \{\epsilon, 1 - \epsilon\}$ where $\sigma(s = 1|\omega, \tau = L) = 1 - \epsilon$ if $\pi(s = 1|\omega, \tau = L) = 1$ and $\sigma(s = 1|\omega, \tau = L) = \epsilon$ if $\pi(s = 1|\omega, \tau = L) = 0$.

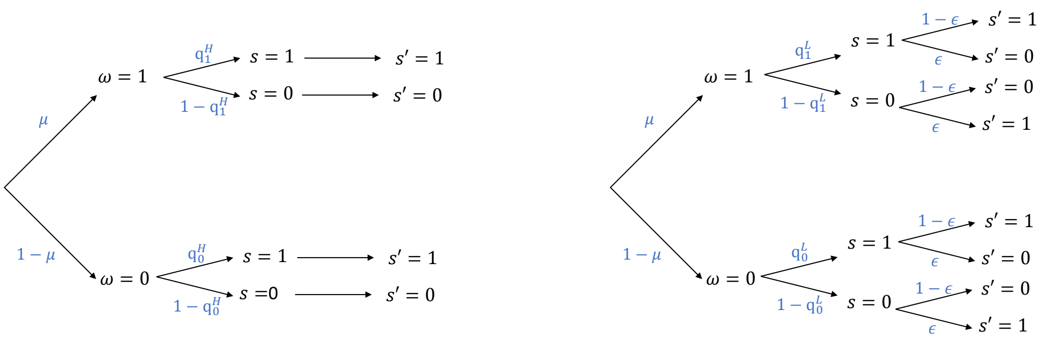
After the protesters have designed the signaling mechanism and given a type τ and a noise mechanism ϵ, the government of type τ will update her belief about the true state of the world. For each signal realization $s \in S \cap A$ there will be a posterior belief $\mu_s^\tau \in \Delta(\Omega)$, found by Bayes rule. For each $\omega \in \Omega$

$$\mu_s^\tau(\omega) = \frac{\sigma(s|\omega)\mu_0(\omega)}{\sum_{\omega' \in \Omega} \sigma(s|\omega')\mu_0(\omega')}$$

Following, we will denote $\mu_s^\tau(\omega = 1)$ simply as μ_s^τ for the sake of clearer notation. Each signal σ induces a two-dimensional profile of posteriors $(\mu_1^\tau(\omega), \mu_2^\tau(\omega)), \forall \tau \in \{H, L\}$ – since we are focusing on signals that are *straightforward*. Also, each posterior $\mu_s^\tau(\omega)$ happens, from an ex-ante perspective, with probability given by

$$\tau(\mu_s^\tau(\omega))) = \sigma(s|\omega)\mu_0(\omega)$$

An illustration of the probability trees that the protesters face is depicted in Figure 9 below.



(a) High quality government – probability λ_0 (b) Low quality government – probability $1 - \lambda_0$

Figure 9: The noise structure depends on the quality of the government.

Protests as persuasion mechanism

Our benchmark case is the classic Bayesian persuasion model from Kamenica and Gentzkow (2011), which corresponds to the high type $\tau = H$ incumbent. Following their result, we find that protests are an effective persuasion tool for protesters. The addition of noise, however, makes protests a less efficient tool for the protesters.

Proposition 1 *The optimal signaling structure is given by:*

$$q_1^L = q_1^H = 1$$
$$q_0^L = \frac{\mu_0 - \epsilon}{(1-p)(1-2\epsilon)}$$
$$q_0^H = \frac{\mu_0}{1-\mu_0}$$

This signaling structure induces the following set of posteriors from the government:

$$\mu_1^L = \mu_1^H = \Pr(\omega = 1|s' = 1) = 0.5$$
$$\mu_0^L = \Pr(\omega = 1|s' = 0, \tau = L) = \frac{\epsilon\mu_0}{1 - 2(1-\epsilon)\mu_0}$$
$$\mu_0^H = \Pr(\omega = 1|s' = 0, \tau = H) = 0$$

All the proofs can be found in the Appendix O. When the state is such that $\omega = 1$, there is no incentive for protesters to deliver any other action recommendation rather than $s = 1$. Therefore, $q_1^L = q_1^H = 1$. When the state is such that $\omega = 0$, protesters have an incentive to persuade until the government is indifferent, in expected terms, between choosing $a = 0$ or $a = 1$, which delivers $q_0^L = \frac{p-\epsilon}{(1-\mu_0)(1-2\epsilon)}$ and $q_0^H = \frac{\mu_0}{1-\mu_0}$. This signal message probabilities will induce posteriors that are characterized as above.

The intuition for the result of Proposition 1 can be found below in Figure 10. If there are no protests, the probability that the government behaves accordingly to protesters interest, that is to take $a = 1$, is given by their prior probability μ_0 as shown in the dashed black line. When protests happen and all governments are high type ($\tau = H$) – meaning there is no noise in the communication channel, protesters are an effective persuasion tool, doubling the probability that the government delivers the preferred action of protesters – as shown in the garment solid line with circles. When all governments are of low type ($\tau = L$), protesters are less efficient. When all governments are high type ($\tau = H$), this probability can be reached from $\mu_0 > 0.25$ on – the intersection between the gray dashed line and the garment solid line with circles. However, when all governments are low type ($\tau = L$), this can only be achieved from the point $\mu_0 > 0.42$ on – the intersection between the gray dashed line and the blue solid line with squares. In this case, if protesters face a noisy communication channel, unless we start from a point in which governments are pretty inclined to already deliver $a = 1$, protesters are less likely to be an effective persuasion mechanism.

It is ex-ante optimal for the government to choose $a = 1$ if and only if her posterior $\mu_s(\omega) \geq 0.5$. While $\mu_1(1) = 0.5$, it is easily shown that $\mu_0(1) < 0.5$ for $\epsilon < 0.5$ – a reasonable assumption.[24]

In fact, we could think that protesters would like to persuade the government until, from an ex-ante perspective, she is indifferent between taking $a = 1$ or $a = 0$, which would be at the point in which $\Pr(a = 1|s) = 0.5$ – represented by the gray dashed line above. We formalize how noise can reduce the efficiency of protesters as a persuasion mechanism for different levels of λ_0, the prior probability that the government is high type.

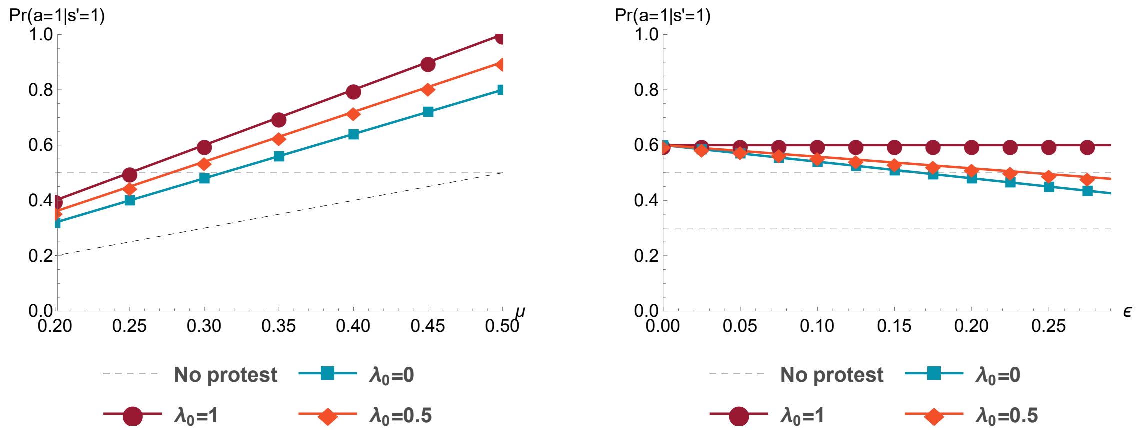
Corollary 1 *The optimal signaling structure induces a set of posteriors and the following action behavior from the government:*

$$\begin{aligned} \Pr(a = 1|s' = 1) &= 2\mu_0 \left(1 - \epsilon(1 - \lambda_0)\right) \\ \Pr(a = 1|s' = 0) &= 0 \end{aligned}$$

Since the government will choose $a = 1$ if and only if her posterior is higher than 0.5 and this happens only when $s' = 1$, the probability that the government will choose $a = 1$ is the same as the one that $s' = 1$ is delivered. Therefore, we can think about the effectiveness of protests is measured by the probability that protesters persuade the government, i.e., the probability that the government chooses $a = 1$, or that $s' = 1$ is delivered. This can happen when protesters intended to say that $s = 1$ and there was no noise in the communication channel, or when protesters said $s = 0$ but there was noise in the communication. How the signaling mechanism will impact this effectiveness will depend on (i) the size of the noise, ϵ; and (ii) on the mass of governments that are low type, λ_0. Note that when $\epsilon = 0$ then $\Pr(a = 1|s' = 1) = 2\mu_0$, the main result from Kamenica and Gentzkow (2011) that shows that Bayesian persuasion doubles the chances of senders getting what they want from receivers.

From the right plot depicted in Figure 10, we can see that the probability that the protest is successful - in the sense of increasing the chances that the government takes the preferred action

[24] One could think that $\epsilon \geq 0.5$. This would mean the mistake is so significant that there are higher chances that the message sent by protesters will be misunderstood by the government. If that is common knowledge – as it is the case in our environment, the protesters would take into account and would choose a signal device that would take this into account, swapping the optimal signaling structure we saw above.



(a) Efficiency of protests for μ_0 and $\epsilon = 0.1$.

(b) Efficiency of protests for ϵ_0 and $\mu_0 = 0.3$.

Figure 10: How protests are efficient depend on initial prior and noise size.

from protesters which is $a = 1$, is decreasing with the size of the noise ϵ and increasing with the probability that the government is high type λ_0, an intuitive result. Since our measure of ex-ante successful is such that the probability that the government takes the preferred actions of protesters $a = 1$ at least with probability $\frac{1}{2}$, we plot below the whole parameter space of ϵ and λ_0 such that protests are ex-ante successful:

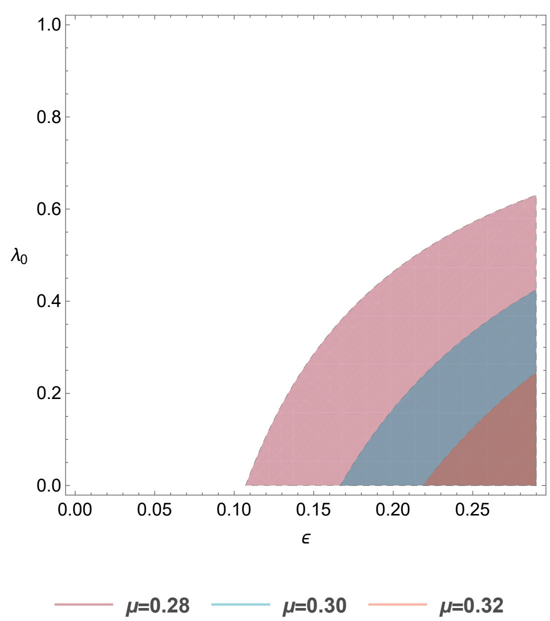


Figure 11: Efficiency of protests for pairs of ϵ and λ_0 and for selected priors μ_0.

Persuasion, anti-establishment bias and accountability

So far in our analysis we have asked how protests could be a useful persuasion tool. We have seen that there are higher chances of success the less noisy protests are. Now, we focus on how protests can change the perception of the electorate regarding the quality of the government. In order to do that, we have added a third player to this game, a citizen (C) that wants a high quality government and that shares the common priors μ_0 and λ_0. The citizen observes the action a of the incumbent and updates her prior belief on the quality of the government λ_0. If the posterior probability that the incumbent is high quality ($\lambda_1 = \Pr(\tau = H|a)$) is higher than the probability from an opponent from the common pool of candidates – that are high quality with probability λ_0 – the incumbent is reelected. Otherwise, the incumbent is replaced.

Corollary 2 *The updated belief of the citizen after observing the action of the government a is given by:*

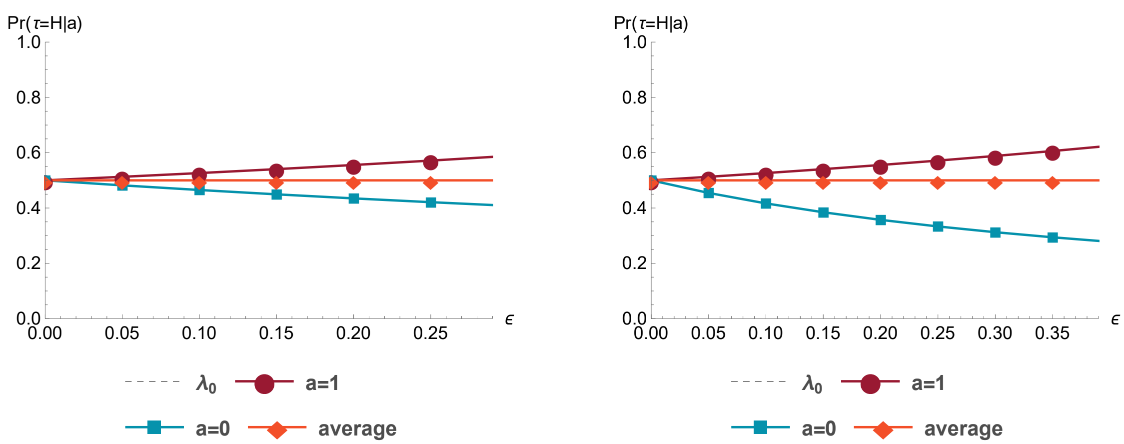
$$\Pr(\tau = H|a = 1) = \frac{\lambda_0}{1 - \epsilon(1 - \lambda_0)}$$
$$\Pr(\tau = H|a = 0) = \frac{(1 - 2\mu_0)\lambda_0}{1 - 2(1 - \epsilon(1 - \lambda_0))\mu_0}$$

The ex-ante posterior equals the prior, i.e.

$$\lambda_1 = \Pr(\tau = H|a = 1)\Pr(a = 1) + \Pr(\tau = H|a = 0)\Pr(a = 0) = \lambda_0$$

The result still holds ex-post if there is no noise in the communication channel, $\lambda_1 = \lambda_0$. When there is noise, however, $\lambda_1 > \lambda_0$ if $a = 1$ – and the incumbent is reelected, and $\lambda_1 < \lambda_0$ if $a = 0$ – and the incumbent is replaced.

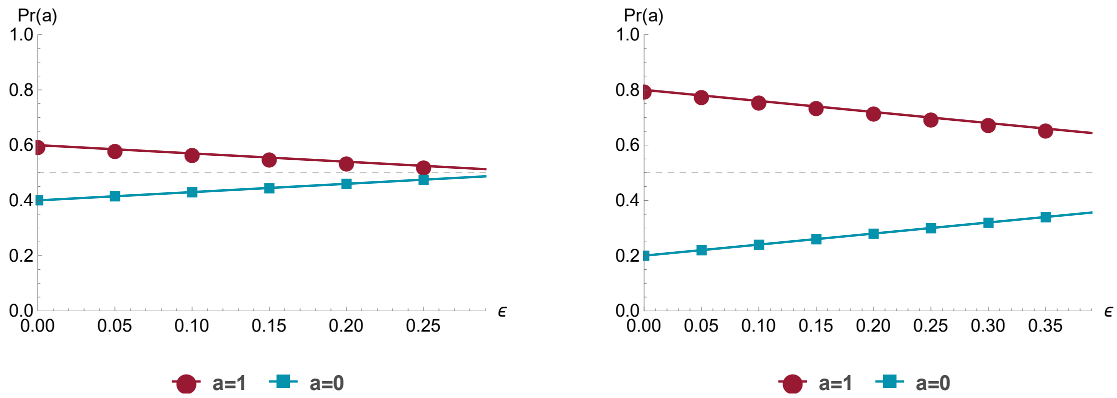
The intuition from Corollary 2 can be better given in the set of Figures 12 and 13. In the absence of noise, $\epsilon = 0$, regardless of the action a taken by the government, $\lambda_1 = \lambda_0$, as we can see by the initial point of the garment line with circles and the blue line with squares in both plots on Figure 12. When noise increases, the perception that the government is high quality $\tau = H$ increases if $a = 1$ and decreases if $a = 0$. This shows that, conditioning on the action taken by the government, the citizen will update her believes on the quality of the government in different ways. Noisy protests, therefore, can improve separation of low and high quality politicians conditioning on their actions after the protest.



(a) λ_1 for $\mu_0 = 0.3$ and $\lambda_0 = 0.5$.

(b) λ_1 for $\mu_0 = 0.4$ and $\lambda_0 = 0.5$.

Figure 12: Efficiency of protests to separate low and high quality politicians depends on initial prior and noise size.



(a) $\Pr(s')$ for $\mu_0 = 0.3$ and $\lambda_0 = 0.5$.

(b) $\Pr(s')$ for $\mu_0 = 0.4$ and $\lambda_0 = 0.5$.

Figure 13: Probability that each signal is delivered.

6.4 Commitment Revisited

An essential assumption in Bayesian persuasion games is that of commitment: signaling strategies are chosen before the sender knows the true state of the world, and she commits to that signaling strategy. We find this assumption plausible in our context for two main reasons. Firstly, it is uncertain whether voters fully discern their aggregated preferences during protests. Secondly, since the information mechanism is collective among protesters, the commitment assumption implies that once a protest begins, it becomes prohibitively costly to mobilize and aggregate everyone again to optimize their communication strategy. In essence, after a protest commences, it is beyond individual control.[25]

We could model the interaction between protesters and the government without the commitment assumption, akin to a cheap talk game. Let's examine the scenario where $\tau = H$ (no noise in the communication channel). When $\omega = 1$, protesters reveal $s = 1$, aligning with their interests. However, when $\omega = 0$, there exists a profitable deviation from truth-telling. Thus, truth-telling does not constitute a Bayes Nash Equilibrium. While a deceptive equilibrium is possible, it merely preserves equal priors and posteriors, offering little analytical interest.

Now consider the scenario where noise exists in the communication channel as described above. When $\omega = 1$, protesters reveal $s = 1$, and the government perceives $s' = 1$ with probability $1 - \epsilon$, and $s' = 0$ with probability ϵ. Since $\epsilon < \mu$ by our assumption, protesters have no incentive to deviate. Conversely, when $\omega = 0$, protesters reveal $s = 0$, and the government perceives $s' = 0$ with probability $1 - \epsilon$, and $s' = 1$ with probability ϵ. Here, since $\epsilon < \mu$, the government has an incentive to deviate. Thus, a truth-telling Bayes Nash Equilibrium with noise is also unattainable. While a deceptive equilibrium remains feasible, it again results in equal priors and posteriors.

The pivotal question here is whether noise in the communication channel permits a partial truth-telling equilibrium. Suppose when $\omega = 1$, protesters reveal the truth state, $s = 1$, and the government perceives $s' = 1$ with probability $1 - \epsilon$, and $s' = 0$ with probability ϵ. Conversely, when $\omega = 0$, protesters reveal $s = 0$ with probability $1 - \alpha$ and lie with probability α. For this to constitute a Bayes Nash Equilibrium, we require $\Pr(\omega = 1|s' = 1) > \frac{1}{2}$ and $\Pr(\omega = 1|s' = 0) > \frac{1}{2}$ – otherwise protesters have an incentive to deviate. This condition necessitates that both $\frac{\mu}{1-\mu} \geq \frac{\alpha\epsilon}{1-\epsilon}$ and $\frac{\mu}{1-\mu} \geq \frac{1-\alpha\epsilon}{\epsilon}$, which is impossible given $\epsilon < \mu$. Therefore, in our scenario where the conflict of

[25] For further insights into information games and the impact of the commitment assumption, see Fréchette, Lizzeri, and Perego (2022) and Little (2023).

interests between protesters and the government is maximized without rendering their strategic interaction uninteresting, the commitment assumption is crucial for noise to influence outcomes.

7 Conclusion

Although the political economy literature extensively examines elections as an accountability mechanism, less is known about other social accountability mechanisms, such as protests. In particular, to the best of our knowledge, no work has analyzed the effect of the quality of the information delivered by protesters on accountability.

We estimate the effect of Brazil's mass street protests from 2013 on both legislators' and voters' behavior. Our empirical evidence shows that the quality of information provided in protests significantly impacts accountability, particularly regarding voters achieving their desired outcomes from the government. A lack of clear demands from protesters can increase the amount of pork barrel spending directed toward protest demands. This evidence aligns with recent research indicating that street movements with clear goals, such as environmental concerns, can lead to long-term effects on citizens' beliefs and behavior (Hungerman and Moorthy (2023)).

Theoretically, we model protests as a noisy Bayesian persuasion mechanism. We demonstrate that while protests can be successful as an accountability mechanism from a persuasion perspective, the noisier the protest message, the less successful the protest will be. In fact, protests can be ex-ante unsuccessful if the level of noise is too high. We also explore how noise impacts electoral accountability. Interestingly, noisier protests can help differentiate high-quality politicians from low-quality ones, thus improving electoral accountability, depending on the policy actions delivered by politicians after the protest. The intuition behind this result is that noisier protests are harder for politicians to interpret. Therefore, if voters observe that a politician has delivered their preferred action, they are more likely to believe that the politician is of high quality.

We consider our findings crucial for understanding the effects of social accountability mechanisms, such as mass street protests, on political accountability. It is particularly important to distinguish the intensity of protests from the clarity of the messages they deliver to politicians. If citizens choose to protest, some level of coordination is required for the protests to be a successful persuasion mechanism.

Future research could explore how the presence and behavior of political challengers are impacted by the demands and intensity of protests. Specifically, it would be valuable to investigate how protests influence the polling and electoral success of challengers compared to incumbents. Understanding this dynamic could provide deeper insights into how protests reshape the political landscape, offering a more comprehensive view of their role as an accountability mechanism. This line of inquiry could also help in determining the conditions under which protests not only pressure incumbents but also empower challengers, thereby contributing to a more competitive and responsive political environment.

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Appendix

A Municipalities that experienced a protest in 2013

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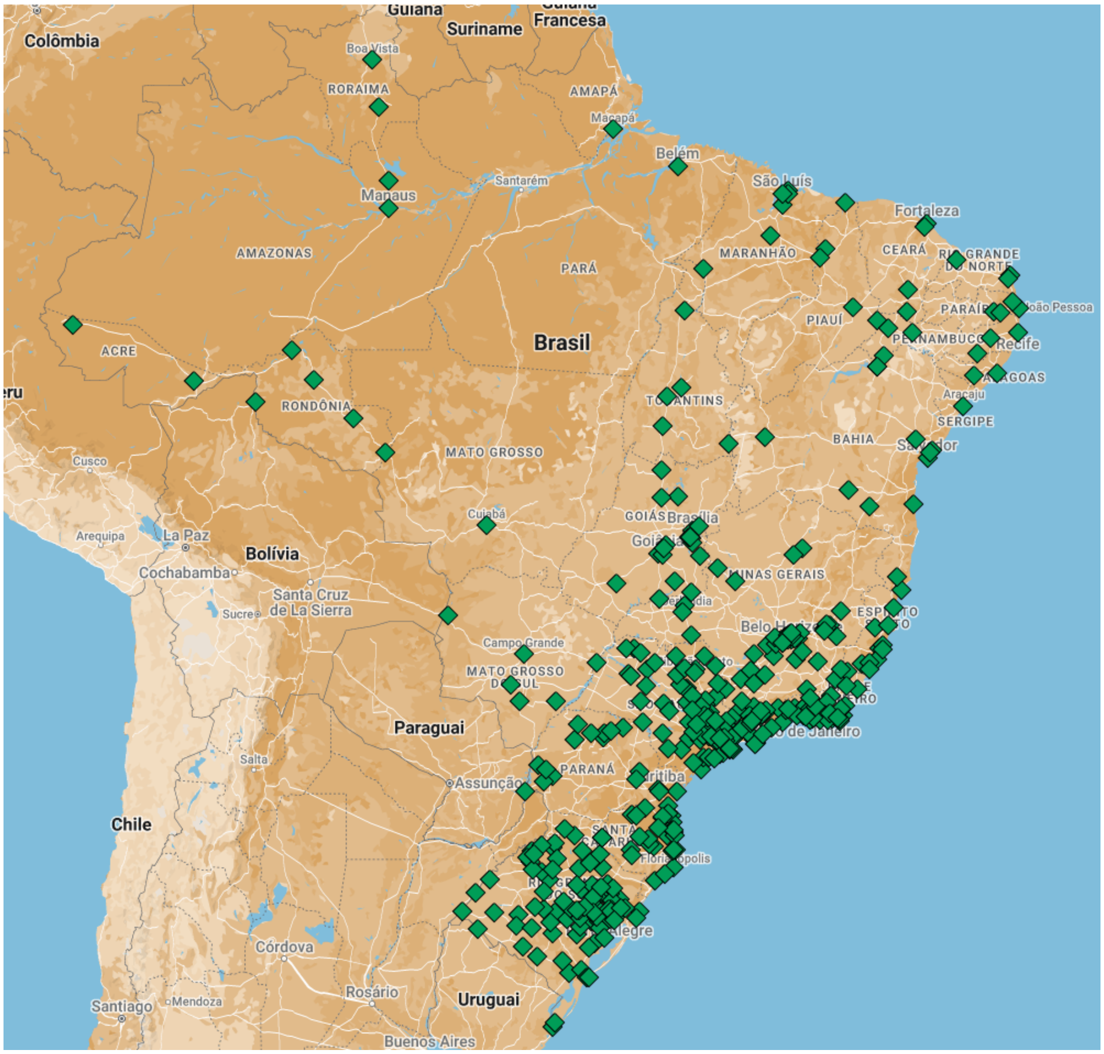


Figure 14: **Municipalities that experienced at least one protest in 2013.**

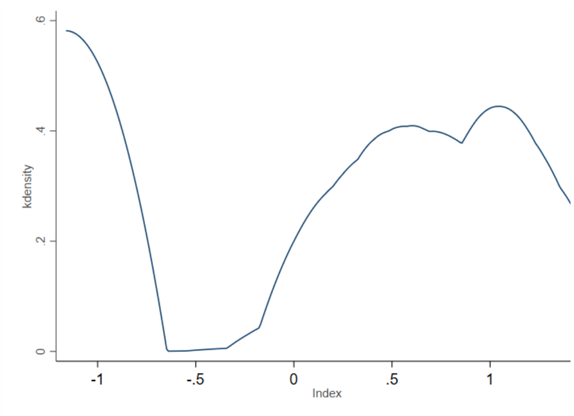
B Population

Table 12: **Protest occurrence by state**

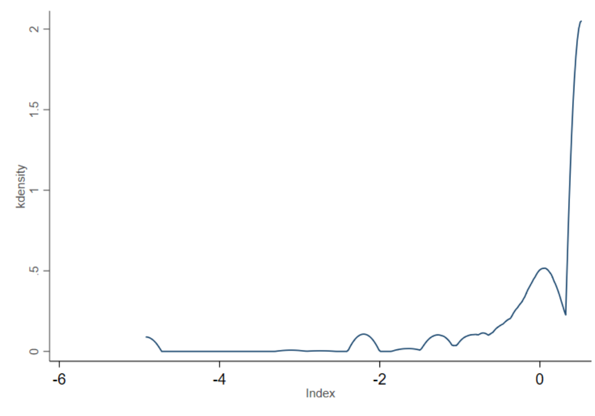
State	% municipalities that had a protest	% population that lives in a municipality that had a protest
DF	100,0%	100,0%
RJ	41,3%	84,4%
RS	19,8%	70,7%
SP	16,3%	69,5%
RR	13,3%	68,5%
AP	6,3%	59,5%
SC	10,9%	52,6%
AM	3,2%	52,5%
MS	7,7%	51,9%
ES	12,8%	50,9%
AC	9,1%	47,8%
GO	6,9%	47,7%
RO	9,6%	45,8%
MG	5,5%	44,4%
PR	4,3%	43,5%
RN	1,8%	40,0%
AL	2,0%	36,7%
CE	2,2%	35,6%
PI	1,8%	34,3%
TO	3,6%	34,3%
BA	2,6%	33,2%
PB	1,8%	31,0%
PE	4,3%	28,4%
SE	1,3%	27,6%
MA	2,8%	23,8%
PA	0,7%	18,4%
MT	0,7%	18,2%

Notes: Data from protests collected from G1, a news website. Population data extracted from 2010 census.

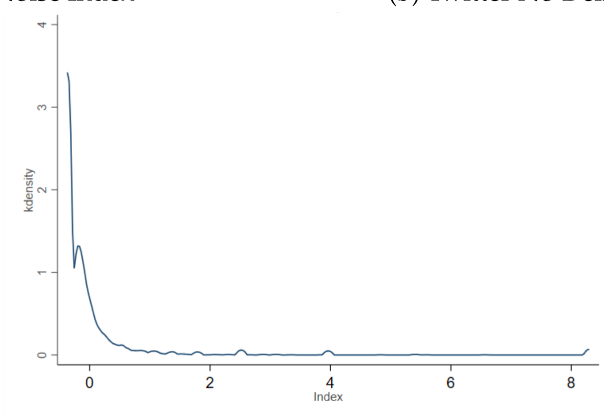
C Twitter Indexes: municipal level data



(a) Twitter Noise Index



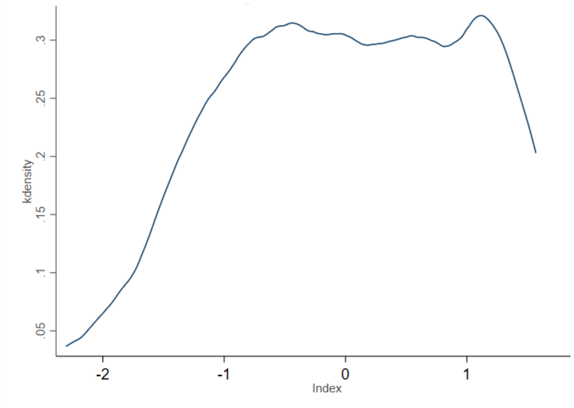
(b) Twitter No Demands Index



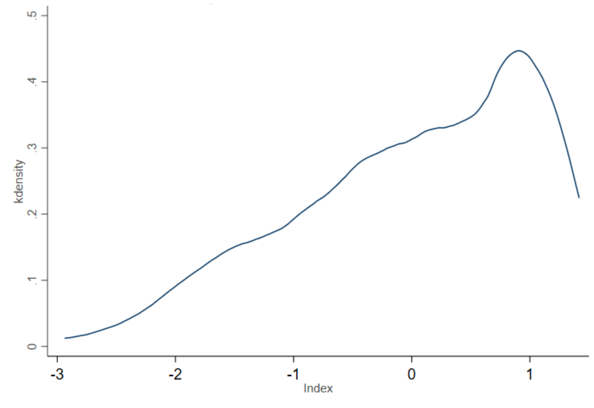
(c) Twitter Intensity Index

Figure 15: Summary Statistics of Twitter Indexes, scaled

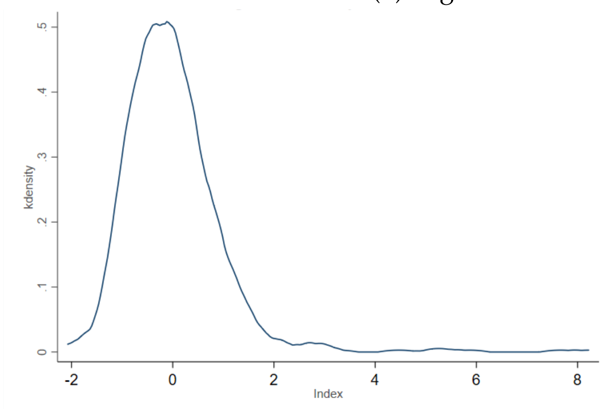
D Twitter Indexes: legislator level data



(a) Legislator Noise Index



(b) Legislator No Demands Index



(c) Legislator Intensity Index

Figure 16: Summary Statistics of Legislator Indexes, scaled

E Effective accountability: pork barrel spending distribution split by protest intensity and noise.

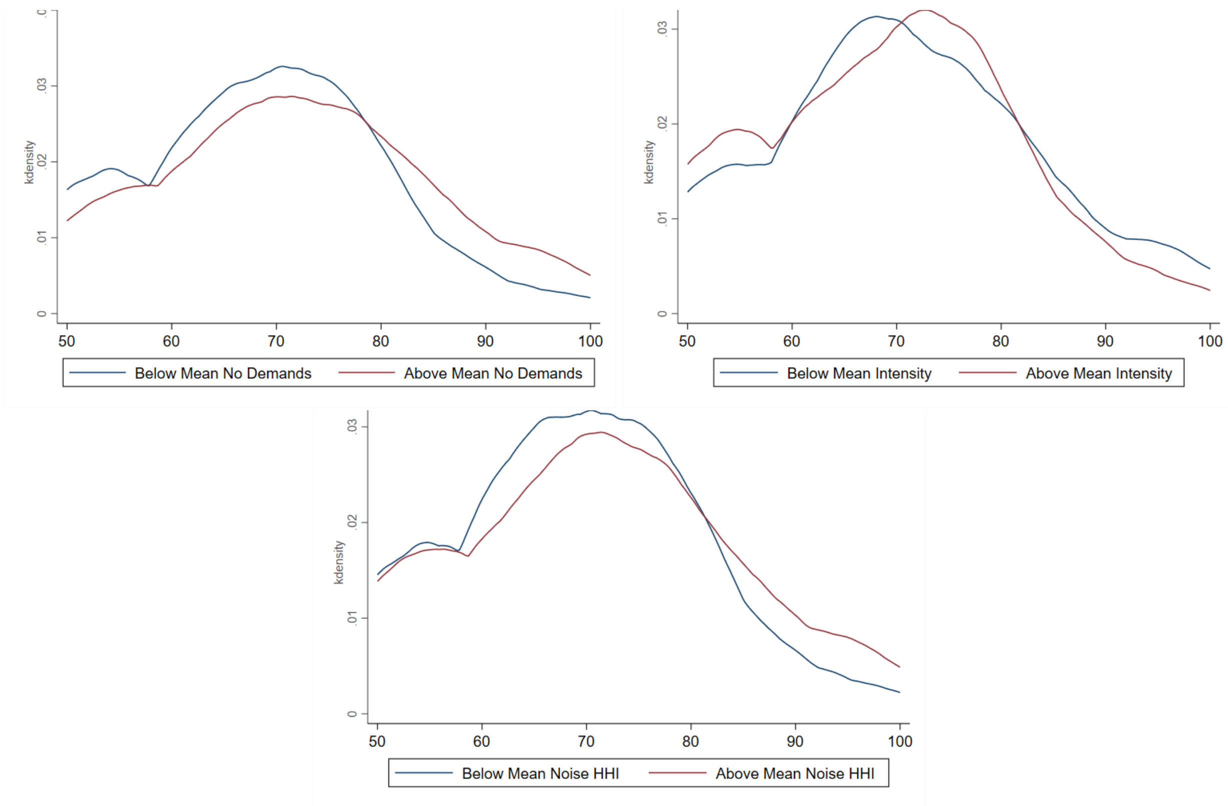


Figure 17: Distribution of pork barrel spending after protests: above and below *No Demands* mean index (top left), *Intensity* mean index (top right), and *Noise* mean index (bottom) plot.

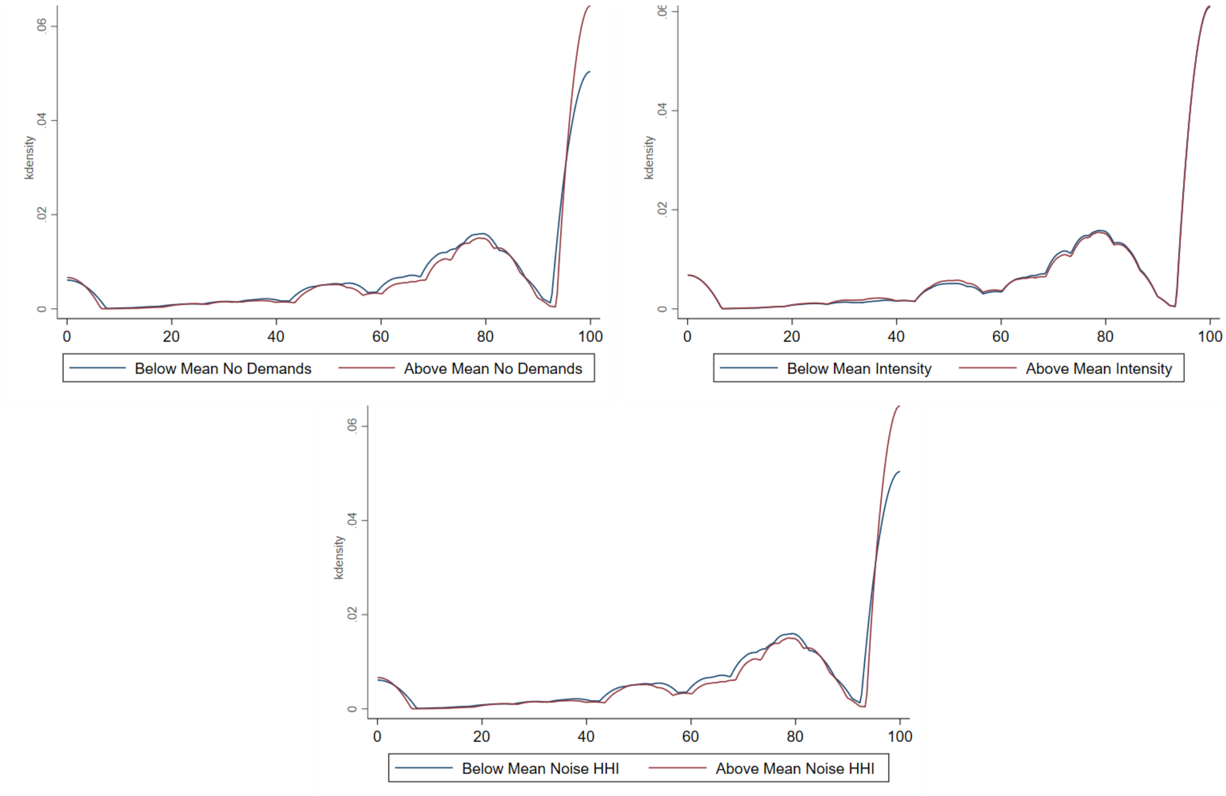


Figure 18: Distribution of presence in plenary sessions spending after protests: above and below *No Demands* mean index (top left), *Intensity* mean index (top right), and *Noise* mean index (bottom) plot.

F Effective accountability – alternative measures of pork barrel: *No Demand* and *Noise* indexes.

No Demands **index –.**

Table 13: **Effect of protests on legislators' behavior**

	Pork Barrel(Total R$)			Pork Barrel (Total N)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	-1.84e-06		-2.45e-06	0.00251		0.00194
	(1.70e-06)		(2.48e-06)	(0.0202)		(0.0227)
Post x Legislator No Demands Index		-7.00e-06	-7.42e-06		-0.00951	-0.0103
		(6.65e-06)	(7.12e-06)		(0.0192)	(0.0198)
Post x Leg. Int. Ind. x Leg. No Dem. Ind.			-3.77e-06			-0.00430
			(4.14e-06)			(0.0264)
Observations	928	928	928	928	928	928
Adjusted R-squared	1.000	1.000	1.000	0.608	0.608	0.607
Number of periods	3 years	3 years	3 years	3 years	3 years	3 years
Number of legislators	322	322	322	322	322	322
Mean Dep. Var. pre-protest	16.52	16.52	16.52	2.52	2.52	2.52
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoDemandIndex$ is an index reflecting twitter activity with no clear demands in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

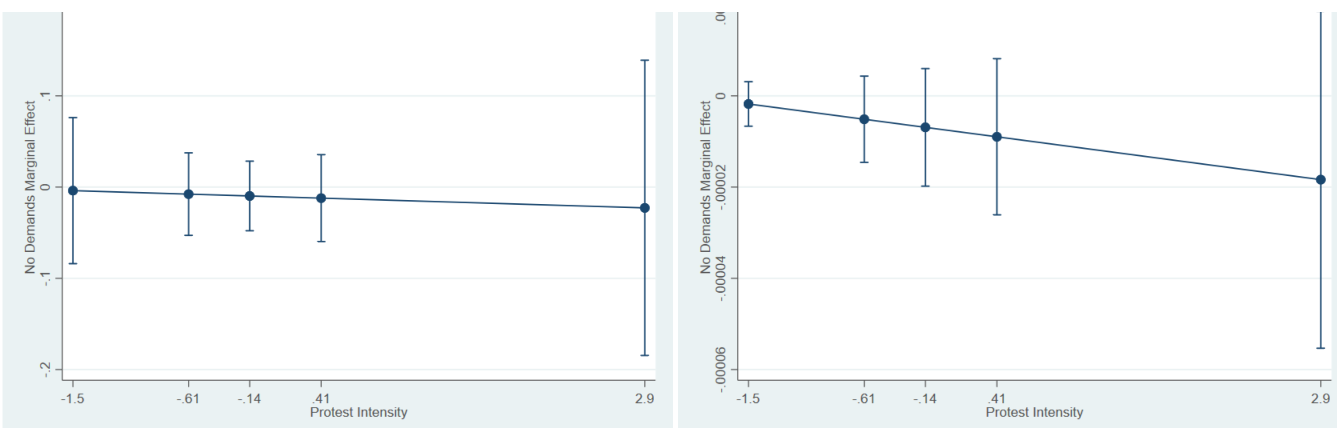


Figure 19: Total marginal effect of *No Demands* index in the total value of pork barrel spending (left) and on the total number of pork barrel requests (right).)

Noise **index –.**

Table 14: **Effect of protests on legislators' behavior**

	Pork Barrel(Total R$)			Pork Barrel (Total N)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	-1.84e-06		-3.87e-06	0.00251		-0.00711
	(1.70e-06)		(3.77e-06)	(0.0202)		(0.0252)
Post x Legislator Noise Index		-9.41e-06	-9.53e-06		-0.0165	-0.0175
		(8.62e-06)	(8.75e-06)		(0.0201)	(0.0202)
Post x Leg. Int. Ind. x Leg. Noise Ind.			-4.49e-06			-0.0182
			(4.70e-06)			(0.0235)
Observations	928	928	928	928	928	928
Adjusted R-squared	1.000	1.000	1.000	0.608	0.608	0.607
Number of periods	3 years	3 years	3 years	3 years	3 years	3 years
Number of legislators	322	322	322	322	322	322
Mean Dep. Var. pre-protest	16.52	16.52	16.52	2.52	2.52	2.52
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more noise to protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

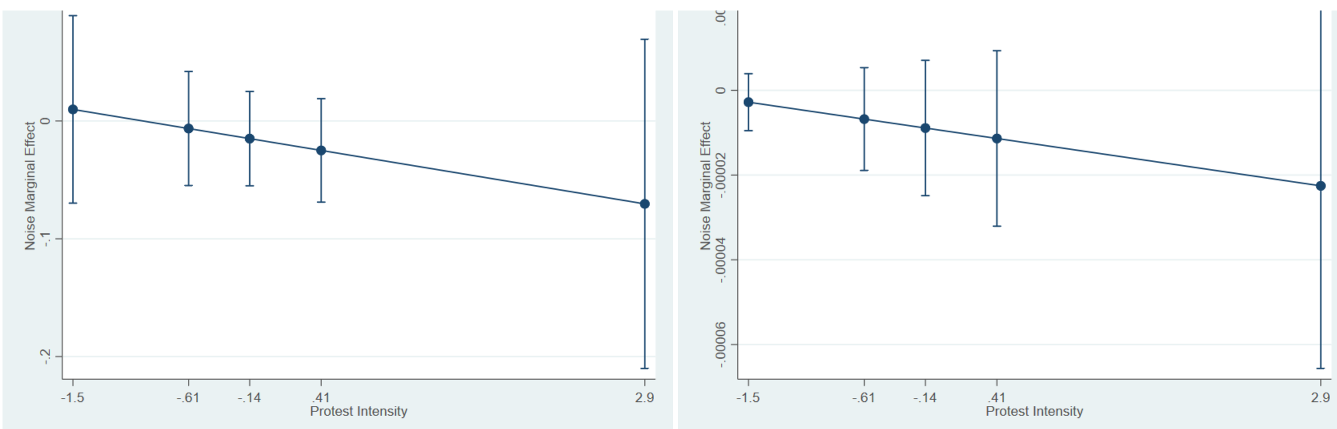


Figure 20: Total marginal effect of *Noise* index in the total value of pork barrel spending (left) and on the total number of pork barrel requests (right).)

G Effective accountability – only legislators that were running for reelection: *No Demand* index.

Table 15: **Effect of Protests on Legislators' Performance**

	% Pork Barrel				Presence Rate			
	reelection=0	reelection=1	reelection=0	reelection=1	reelection=0	reelection=1	reelection=0	reelection=1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x Legislator Intensity Ind.	2.087	1.404*	2.241	1.678*	1.513	-0.0697	0.723	-0.137
	(1.699)	(0.740)	(1.839)	(0.898)	(1.182)	(0.354)	(1.502)	(0.381)
Post x Legislator No Demand Ind.			-4.853***	-3.308***			-0.105	-0.0147
			(1.160)	(0.901)			(0.873)	(0.474)
Post x Leg. Int. Ind. x Leg. No Demand Ind.			-0.362	0.218			-1.205	-0.270
			(1.492)	(1.279)			(1.406)	(0.417)
Observations	258	670	258	670	6,132	15,635	6,132	15,635
Adjusted R-squared	0.685	0.647	0.715	0.659	0.229	0.218	0.229	0.218
Number of periods	3 years	3 years	3 years	3 years	43 weeks	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	322	513	513	513	513
Mean Dep. Var. pre-protest	49	50	49	50	84	84	84	84
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. Each column presents the result of an OLS regression where the dependent variable is listed in the column. We split the sample between those legislators that ran in the 2014 elections and those that did not. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoDemandIndex$ is an index reflecting twitter activity with no clear demands in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more noise to protests demands the legislator had. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

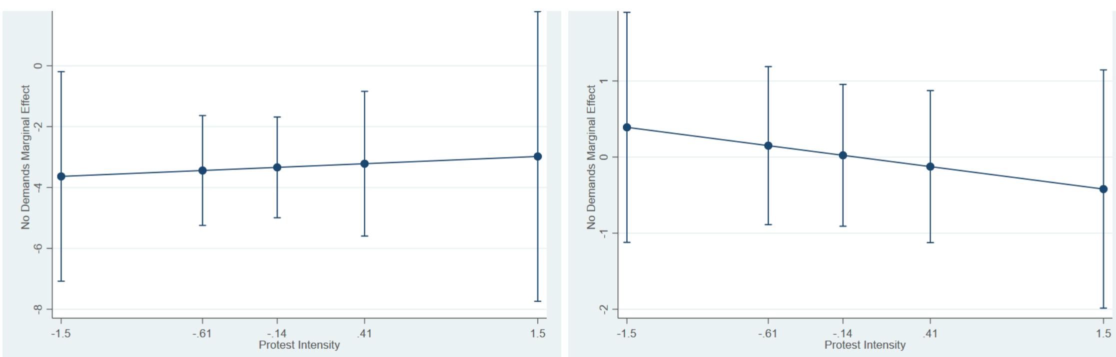


Figure 21: Total marginal effect of *No Demand Index* for the subsample of legislators that were running for reelection.

H Effective accountability – only pork barrel that has a municipal identifier: *No Demand* and *Noise* indexes.

No demands index –.

Table 16: **Effect of protests on legislators' behavior**

	Pork Barrel (% R$ total spent mun)			Pork Barrel (% R$ protests mun)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post*Twitter Intensity Index	-0.000343		0.00215	0.00210		-0.0109
	(0.00101)		(0.00132)	(0.0180)		(0.0201)
Post*Twitter No Clear Demands Index		0.00228	0.00260		0.115***	0.124***
		(0.00194)	(0.00212)		(0.0339)	(0.0370)
Post*Twitter No Clear Demands Index*Twitter Intensity Index			-0.000447			-0.0166**
			(0.000464)			(0.00840)
Observations	209,478	126,452	126,452	209,478	126,452	126,452
Adjusted R-squared	0.559	0.570	0.570	0.329	0.345	0.345
Number of periods	2 years	2 years	2 years	2 years	2 years	2 years
Mean Dep. Var.	0.20	0.20	0.20	1.87	1.87	1.87
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator-municipality FE	Yes	Yes	Yes	Yes		

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t and municipality m. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity in municipality m. The higher the index, more exposure to the protests the legislator had. $TwitterNoDemandIndex$ is an index reflecting twitter activity with no clear demands - i.e, how diffuse were protesters demands - in municipality m. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

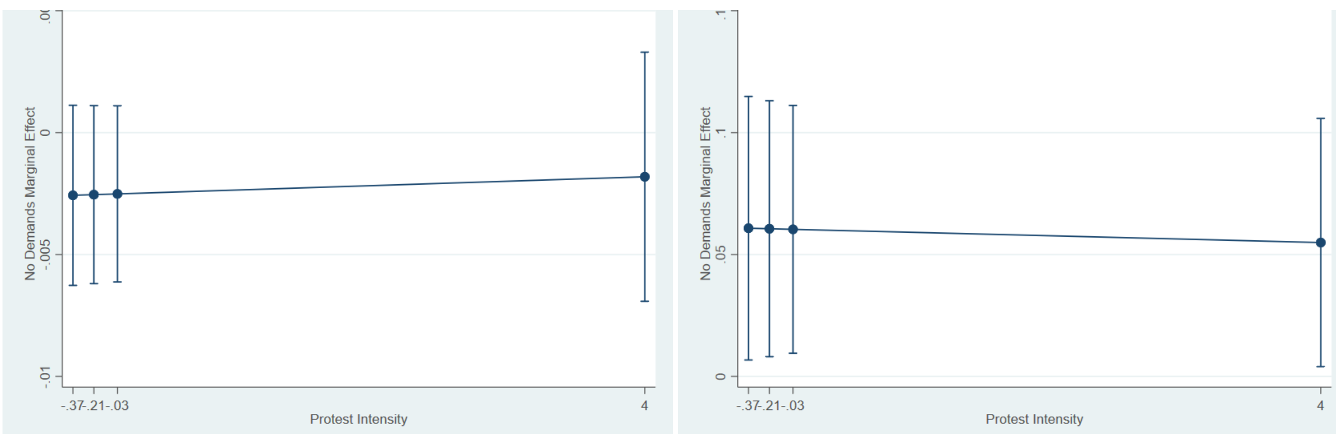


Figure 22: Total marginal effect of *No Demands* index on the share of pork barrel spent in a certain municipality (left) and on the share of pork barrel spent in a certain municipality that is related to protests (right)): selected subsample of pork barrel that has a municipality identifier.

Noise index –.

Table 17: **Effect of protests on legislators' behavior**

	Pork Barrel (% R$ total spent mun)			Pork Barrel (% R$ protests mun)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post*Twitter Intensity Index	-0.000343		-0.00597	0.00210		0.00104
	(0.00101)		(0.00581)	(0.0180)		(0.0485)
Post*Twitter Noise Index		-0.0346**	-0.0343**		-0.0262	-0.0301
		(0.0137)	(0.0138)		(0.108)	(0.109)
Post*Twitter Noise Index*Twitter Intensity Index			-0.00641			0.0318
			(0.00488)			(0.0427)
Observations	209,478	59,468	59,468	209,478	59,468	59,468
Adjusted R-squared	0.559	0.585	0.585	0.329	0.369	0.369
Number of periods	2 years	2 years	2 years	2 years	2 years	2 years
Mean Dep. Var.	0.20	0.20	0.20	0.71	0.71	0.71
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator-municipality FE	Yes	Yes	Yes	Yes		

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t and municipality m. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity in municipality m. The higher the index, more exposure to the protests the legislator had. $TwitterNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity in municipality m. The higher the index, more noise to protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

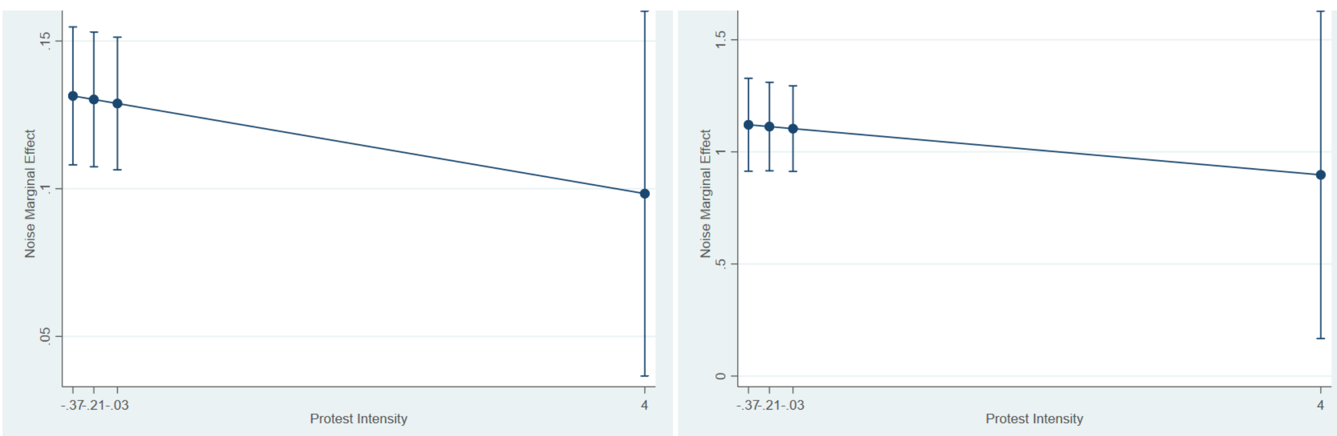


Figure 23: Total marginal effect of *Noise* index on the share of pork barrel spent in a certain municipality (left) and on the share of pork barrel spent in a certain municipality that is related to protests (right)): selected subsample of pork barrel that has a municipality identifier.

I Effective accountability – only cities that had protest registered: *No Demand* index.

No demands index –.

Table 18: **Effect of Protests on Legislators' Behavior**

	Pork Barrel (%)			Presence in Plenary		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Legislator Intensity Index	-2.727***		6.625*	-0.428		-2.150
	(0.770)		(3.656)	(0.405)		(3.760)
Post x No Demands Index		-10.31***	-9.276**		-0.372	1.793
		(3.513)	(3.596)		(0.410)	(3.807)
Post x Leg. Intensity Ind. x Leg. No Dem. Index			-0.873			-0.238
			(0.900)			(0.444)
Observations	928	928	928	21,767	21,767	21,767
Adjusted R-squared	0.660	0.675	0.677	0.226	0.226	0.226
Number of periods	2 years	2 years	2 years	43 weeks	43 weeks	43 weeks
Number of legislators	322	322	322	513	513	513
Mean Dep. Var. pre-protest	51	51	51	98	98	98
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Legislator FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' performance. Observation unit is performance variable of legislator d at time t. In this table only twitter indexes for municipalities that had protests in real life were used when computing legislator indexes. Each column presents the result of an OLS regression where the dependent variable is listed in the column. *Post* is a dummy indicating periods after the protests and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoDemandIndex$ is an index reflecting twitter activity with no clear demands in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

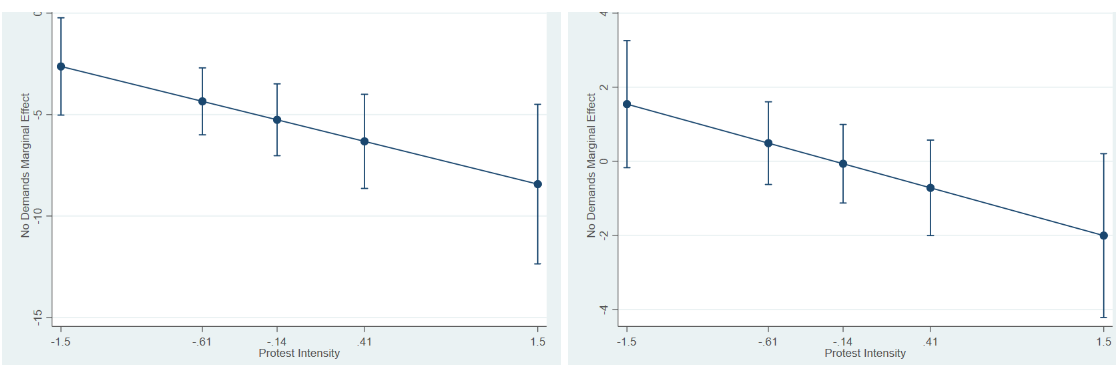


Figure 24: Marginal effect of *No Demand Index* for the subsample of municipalities that have registered a protest in real life.

J Vote share – alternative measure of vote share: how much of deputy Y votes came from Municipality X

No Demand Index –.

Table 19: **Effect of protests on legislators' vote share, municipality level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.920**	-1.004**	-1.113***	-1.115***
	(0.375)	(0.395)	(0.418)	(0.418)
Election x Twitter Intensity Index		-0.0997*		-0.115*
		(0.0557)		(0.0589)
Election x Twitter No Demand Index			0.104*	0.100*
			(0.0600)	(0.0605)
Election x Twitter Int. Index x Twitter No Dem. Index				0.00748
				(0.0279)
Observations	264,120	174,576	105,774	105,774
Adjusted R-squared	0.972	0.972	0.972	0.972
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	.27	.27	.27	.27
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and *TwitterIntensityIndex* is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. *TwitterNoDemandIndex* is an index reflecting twitter activity with no clear demands - i.e, how diffuse were protesters demands - in municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

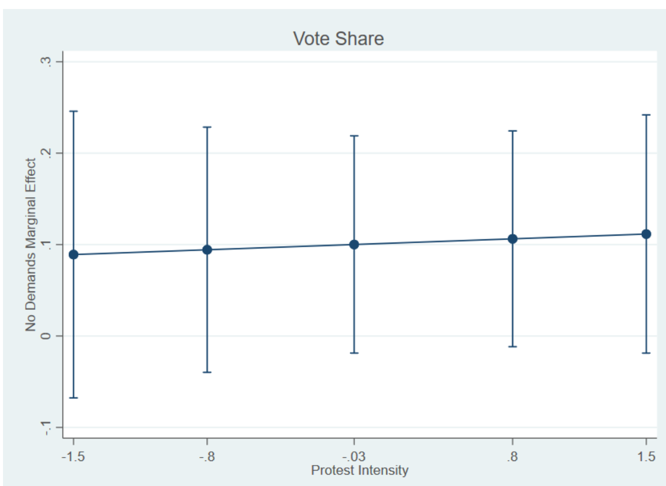


Figure 25: Total marginal effect of *No Demands* on legislators vote share at the municipal level.

Noise Index –.

Table 20: **Effect of protests on legislators' vote share, municipality level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.920**	-1.004**	-0.582***	-0.638***
	(0.375)	(0.395)	(0.166)	(0.169)
Election x Twitter Intensity Index		-0.0383*		-0.194**
		(0.0557)		(0.513)
Election x Twitter Noise Index			-0.688***	-0.676***
			(0.254)	(0.255)
Election x Twitter Int. Index x Twitter Noise Index				-0.798*
				(0.434)
Observations	264,120	174,576	49,746	49,746
Adjusted R-squared	0.972	0.972	0.972	0.972
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	1.11	1.11	1.11	1.11
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity at municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

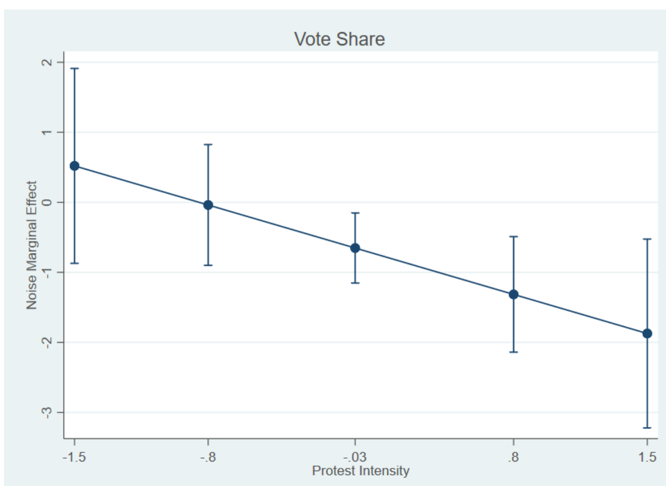


Figure 26: Total marginal effect of *Noise* on legislators vote share at the municipal level.

K Vote share – municipal level data: *No Demands* index.

Table 21: **Effect of protests on legislators' vote share, municipality level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.151***	-0.158***	-0.172***	-0.173***
	(0.0190)	(0.0207)	(0.0226)	(0.0227)
Election x Twitter Intensity Index		-0.0383*		-0.0395*
		(0.0228)		(0.0238)
Election x Twitter No Demand Index			0.00681	0.00656
			(0.0207)	(0.0217)
Election x Twitter Int. Index x Twitter No Dem. Index				-0.00146
				(0.0131)
Observations	264,120	174,576	105,774	105,774
Adjusted R-squared	0.762	0.786	0.815	0.815
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	1.11	1.11	1.11	1.11
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoDemandIndex$ is an index reflecting twitter activity with no clear demands - i.e, how diffuse were protesters demands - in municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

Figure 27: Total marginal effect of *No Demands* on the vote share of legislators at the municipal level.

L Vote share – legislator level data

No Clear Demand index –.

Table 22: **Effect of protests on legislators' vote share, legislator level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.329***	-0.328***	-0.341***	-0.325***
	(0.0744)	(0.0740)	(0.0748)	(0.0738)
Election x Legislator Intensity Index		-0.149**		-0.207***
		(0.0705)		(0.0734)
Election x Legislator No Demands Index			0.200**	0.185**
			(0.0778)	(0.0771)
Election x Leg. Intensity Ind. x Leg. No Dem. Ind.				-0.180*
				(0.101)
Observations	732	732	732	732
Number of legislators	366	366	366	366
Mean Dep Var	1.86	1.86	1.86	1.86
Adjusted R-squared	0.050	0.059	0.052	0.068
Legislator FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes. Observation unit is vote share variable of legislator d at at elections t. *Election* is a dummy indicating 2014 elections and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoDemandIndex$ is an index reflecting twitter activity with no clear demands in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more diffuse protests demands the legislator had. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

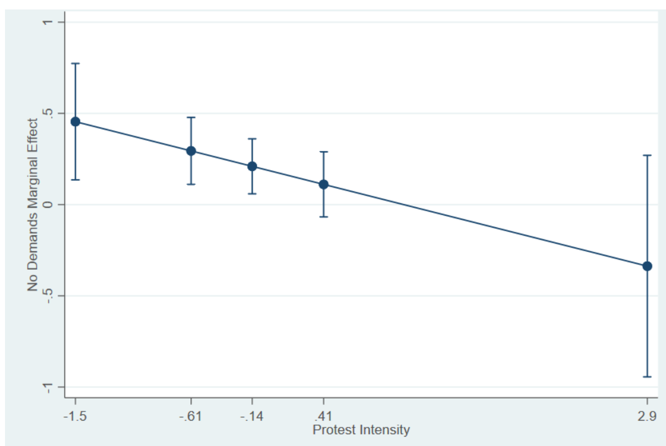


Figure 28: Total marginal effect of *No Demands* on the vote share of legislators at the legislator level.

Noise index –.

Table 23: **Effect of protests on legislators' vote share, legislator level**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.329***	-0.328***	-0.331***	-0.323***
	(0.0744)	(0.0740)	(0.0746)	(0.0728)
Election x Legislator Intensity Index		-0.149**		-0.237***
		(0.0705)		(0.0776)
Election x Legislator Noise Index			0.0891	0.0950
			(0.0859)	(0.0853)
Election x Leg. Intensity Ind. x Leg. Noise Ind.				-0.145
				(0.0924)
Observations	732	732	732	732
Number of legislators	366	366	366	366
Mean Dep Var	1.86	1.86	1.86	1.86
Adjusted R-squared	0.050	0.059	0.052	0.068
Legislator FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes. Observation unit is vote share variable of legislator d at at elections t. *Election* is a dummy indicating 2014 elections and $LegislatorIntensityIndex$ is an index reflecting how intense was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population. The higher the index, more exposure to the protests the legislator had. $LegislatorNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity in the legislator's electorate municipality of residence, weighted by municipality population We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator and time fixed-effects. Standard errors are clustered by legislator and displayed in brackets.

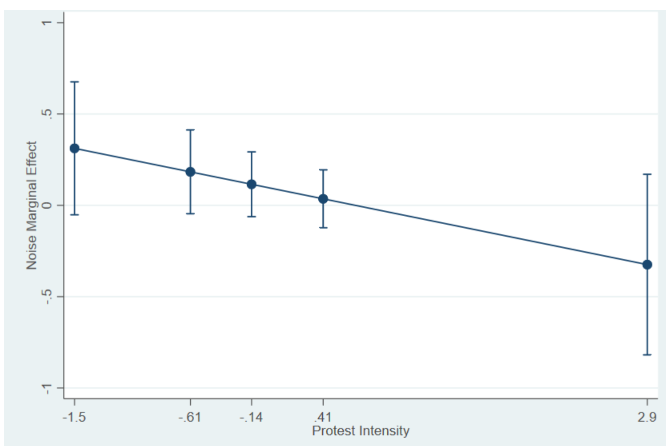


Figure 29: Total marginal effect of *Noise* on the vote share of legislators at the legislator level.

M Vote share – municipal level, only cities that had protests.

No Demand Index –.

Table 24: **Effect of protests on legislators' vote share, municipality level: only municipalities that experienced a real life protest.**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.206***	-0.216***	-0.206***	-0.219***
		(0.203)		(0.205)
Election x Twitter Intensity Index		-0.682***		-0.720***
		(0.0181)		(0.148)
Election x Twitter No Demand Index			0.000282	-0.0172
			(0.0636)	(0.0691)
Election x Twitter Int. Index x Twitter No Dem. Index				0.209
				(0.239)
Observations	26,344	25,160	23,924	23,924
Adjusted R-squared	0.870	0.871	0.870	0.871
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	1.11	1.11	1.11	1.11
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. This is a sub sample composed of municipalities that experienced real life protests. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoDemandIndex$ is an index reflecting twitter activity with no clear demands - i.e, how diffuse were protesters demands - in municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets. We consider only municipalities that experienced real life protests.

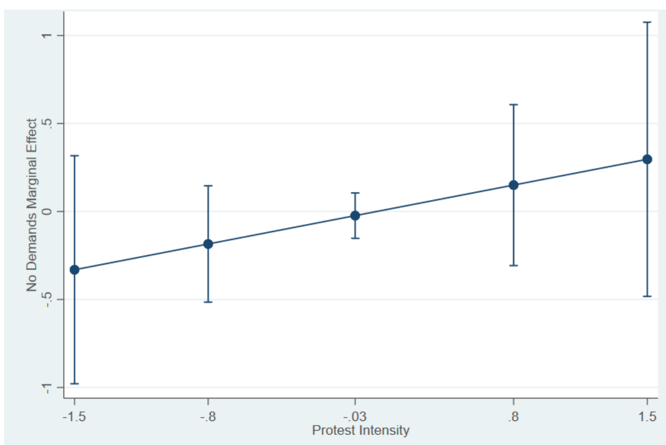


Figure 30: Total marginal effect of *Noise* on the vote share of legislators at the legislator level when there are protests registered in real life accordingly to G1 news portal.

Noise Index –.

Table 25: **Effect of protests on legislators' vote share, municipality level: only municipalities that experienced a real life protest.**

	Vote Share (%)			
	(1)	(2)	(3)	(4)
Election	-0.206***	-0.216***	-0.132**	-0.0957
	(0.0332)	(0.0357)	(0.0550)	(0.0594)
Election x Twitter Intensity Index		-0.682***		-0.379*
		(0.203)		(0.194)
Election x Twitter Noise Index			-0.0650**	-0.0996**
			(0.0321)	(0.0421)
Election x Twitter Int. Index x Twitter Noise Index				-0.531**
				(0.212)
Observations	26,344	25,160	18,948	18,948
Adjusted R-squared	0.870	0.871	0.870	0.871
Number of periods	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366
Mean Dep. Var. pre-protest	1.11	1.11	1.11	1.11
Legislator-municipality FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. This is a sub sample composed of municipalities that experienced real life protests. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity at municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets. We consider only municipalities that experienced real life protests.

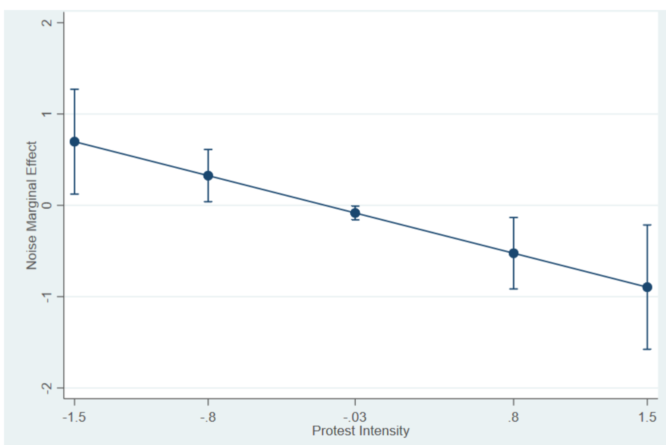


Figure 31: Total marginal effect of *Noise* on the vote share of legislators at the legislator level when there are protests registered in real life accordingly to G1 news portal.

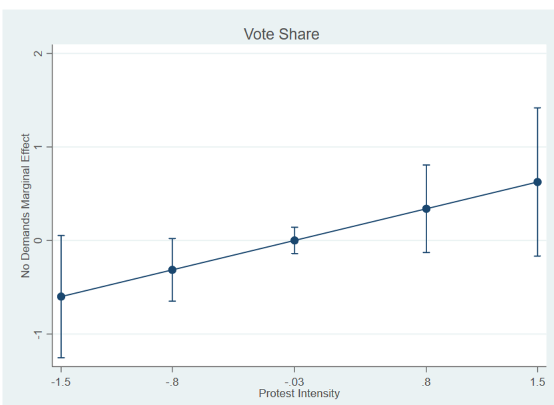
N Vote share – municipal level, only cities that had protests by G1, split by performance levels.

No Demand Index –.

Table 26: **Effect of protests on legislators' vote share, municipality level: only municipalities that experienced a real life protest.**

	Vote Share (%)							
	Pork Barrel				Presence in Plenary			
	below md	**above md**	**below md**	**above md**	**below md**	**above md**	**below md**	**above md**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Election	-0.268***	-0.176***	-0.273***	-0.177***	-0.246***	-0.194***	-0.250***	-0.196***
	(0.0676)	(0.0317)	(0.0682)	(0.0318)	(0.0434)	(0.0403)	(0.0435)	(0.0407)
Election x Twitter Intensity Index	-0.794***	-0.565***	-0.832***	-0.606***	-0.667***	-0.691***	-0.701***	-0.731***
	(0.293)	(0.187)	(0.300)	(0.188)	(0.233)	(0.236)	(0.239)	(0.238)
Election x Twitter No Demand Index			-0.0422	0.0126			-0.0157	-0.0193
			(0.0914)	(0.0752)			(0.0802)	(0.0854)
Election x Twitter Int. Index x Twitter No Dem. Index			0.00915	0.408*			0.135	0.255
			(0.290)	(0.242)			(0.269)	(0.274)
Observations	11,454	13,706	10,834	13,090	10,178	14,982	9,626	14,298
Adjusted R-squared	0.872	0.870	0.871	0.869	0.861	0.877	0.859	0.877
Number of periods	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366	366	360	360	366
Mean Dep. Var. pre-protest	1.26	.95	1.26	.95	1.12	1.04	1.12	1.07
Legislator-municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoDemandIndex$ is an index reflecting twitter activity with no clear demands - i.e, how diffuse were protesters demands - in municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets. We consider only municipalities that experienced real life protests and split between relative performance (above/below median) on pork barrel and presence in plenary.



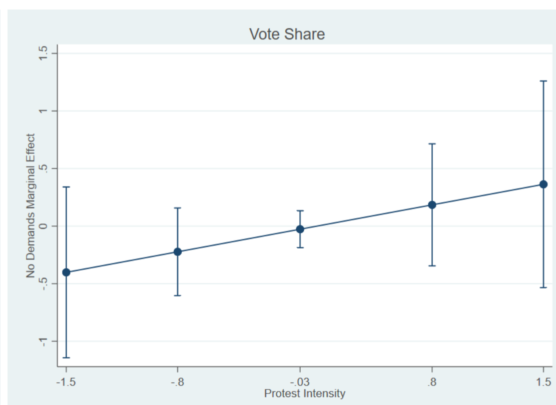


Figure 32: Total marginal effect of *Noise* on legislators vote share at the municipal level when there are protests registered in real life accordingly to G1 news portal for above the median on pork barrel (left) and presence (right).

Noise Index –.

Table 27: **Effect of protests on legislators' vote share, municipality level**

	Vote Share (%)							
	Pork Barrel				Presence in Plenary			
	below md	**above md**	**below md**	**above md**	**below md**	**above md**	**below md**	**above md**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Election	-0.268***	-0.176***	-0.0996	-0.0904*	-0.246***	-0.194***	-0.0436	-0.131*
	(0.0676)	(0.0317)	(0.0956)	(0.0517)	(0.0434)	(0.0403)	(0.0710)	(0.0720)
Election x Twitter Intensity Index	-0.794***	-0.565***	-0.409	-0.343**	-0.667***	-0.691***	-0.192	-0.482*
	(0.293)	(0.187)	(0.291)	(0.164)	(0.233)	(0.236)	(0.252)	(0.248)
Election x Twitter Noise Index			-0.139**	-0.0713*			-0.170***	-0.0519
			(0.0637)	(0.0415)			(0.0549)	(0.0495)
Election x Twitter Int. Index x Twitter Noise Index			-0.610**	-0.441**			-0.684**	-0.440*
			(0.287)	(0.212)			(0.277)	(0.233)
Observations	11,454	13,706	8,502	10,446	10,178	14,982	7,574	11,374
Adjusted R-squared	0.872	0.870	0.870	0.872	0.861	0.877	0.849	0.881
Number of periods	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections	2 elections
Number of legislators	366	360	360	366	366	360	360	366
Mean Dep. Var. pre-protest	1.26	.95	1.26	.95	1.12	1.04	1.12	1.07
Legislator-municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the protests on legislators' vote share, considering the total of valid votes cast at municipality m. This is a sub sample composed of municipalities that experienced real life protests. Observation unit is vote share variable of legislator d at municipality m at elections t. *Election* is a dummy indicating 2014 Elections and $TwitterIntensityIndex$ is an index reflecting how intense was twitter activity at municipality m. The higher the index, more intense was protest activity measured at twitter. $TwitterNoiseIndex$ is an index reflecting how noisy - i.e, how diffuse were protesters demands - was twitter activity at municipality m. We standardized the indexes to have mean = 0 and standard deviations = 1 in order to facilitate interpretation. All regressions include time and legislator-municipality fixed-effects. Standard errors are clustered by legislator and displayed in brackets. We consider only municipalities that experienced real life protests and split between relative performance (above/below median) on pork barrel and presence in plenary.

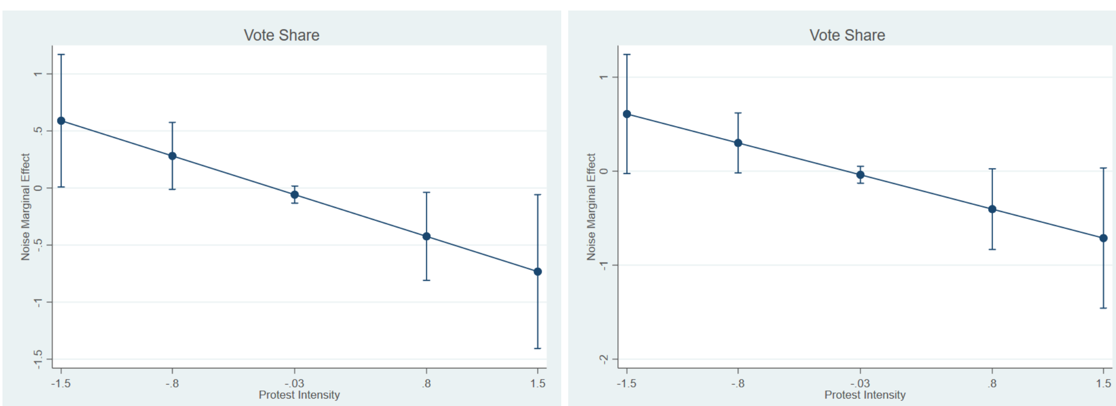


Figure 33: Total marginal effect of *Noise* on legislators vote share at the municipal level when there are protests registered in real life accordingly to G1 news portal for above the median on pork barrel (left) and presence (right).

O Proofs

Proof of Proposition 1

Proof. Fix $\mu = \Pr(\omega = 1) \in (0, 0.5)$ and $a = 1$ the action protesters would prefer the government to choose. The protesters will choose the fourthuple $(q_0^L, q_1^L, q_0^H, q_1^H)$ of probabilities:

	$\pi(s=0\|\omega,L)$	$\pi(s=1\|\omega,L)$
$\omega=0$	$1-q_0^L$	q_0^L
$\omega=1$	$1-q_1^L$	q_1^L

	$\pi(s=0\|\omega,H)$	$\pi(s=1\|\omega,H)$
$\omega=0$	$1-q_0^H$	q_0^H
$\omega=1$	$1-q_1^H$	q_1^H

Table 28: Signal structure for low and high types of government.

The choice of the fourthuple $(q_0^L, q_1^L, q_0^H, q_1^H)$ is such that the expected payoff of protesters is maximized. Recall that the protesters only receive payoff of 1 when $a = 1$ and the government delivers $a = 1$ whenever $\Pr(\omega = 1|s') > 0.5$. Therefore, the protesters will solve this system of four inequalities $\Pr(\omega = 1|s' = 0, \tau = H) \geq \frac{1}{2}, \Pr(\omega = 1|s' = 1, \tau = H) \geq \frac{1}{2}, \Pr(\omega = 1|s' = 0, \tau = L) \geq \frac{1}{2}, \Pr(\omega = 1|s' = 1, \tau = L) \geq \frac{1}{2}$. We will use Baye's rule for the updates. Let's start with the high type of government, recalling that the type of government and the true state of the world are independent. Let's start with $s' = 1$ recalling that for the high type of government, $s' = 1$ can only happen when $s = 0$, since there is no noise in the communication channel:

$$\begin{aligned}
\Pr(\omega = 1|s' = 1, \tau = H) &= \frac{\Pr(s' = 1|\omega = 1, \tau = H)\Pr(\omega = 1)}{\Pr(s' = 1)} \geq \frac{1}{2} \\
&= \frac{q_1^H \mu_0}{q_1^H \mu_0 + q_0^H (1 - \mu_0)} \geq \frac{1}{2} \\
\frac{\mu_0}{1 - \mu_0} &\geq \frac{q_0^H}{q_1^H} \qquad (12)
\end{aligned}$$

Now let's assume $s' = 0$:

$$\begin{aligned}
\Pr(\omega = 1|s' = 0, \tau = H) &= \frac{\Pr(s' = 0|\omega = 1, \tau = H)\Pr(\omega = 1)}{\Pr(s' = 0)} \geq \frac{1}{2} \\
&= \frac{(1 - q_1^H)\mu_0}{(1 - q_1^H)\mu_0 + (1 - q_0^H)(1 - \mu_0)} \geq \frac{1}{2} \\
\frac{\mu_0}{1 - \mu_0} &\geq \frac{1 - q_0^H}{1 - q_1^H} \qquad (13)
\end{aligned}$$

First, note that the likelihood ratio delivered by the inequality 12 is inconsistent with the inequality delivered by 13. However, since the payoff of the protesters is increasing in q_0^H and q_1^H, we find that the solution of this problem is given by $q_1^H = 1$ and with 12 holding with equality, which delivers $q_0^H = \frac{\mu_0}{1-\mu_0}$.

Now we have to find the optimal solutions for the case in which the government is low type. We start with $s' = 1$. Now, since $\tau = L$, $s' = 1$ because there was no noise and so $s = 1$ or because there was noise and $s = 0$. Recall that the noise process is independent of the type of the government and of the state of the world and note that and $\Pr(s' = 1|\omega = 1, \tau = L)\Pr(\omega = 1) = (\Pr(s' = 1|\omega = 1, \tau = L, s = 1) + \Pr(s' = 1|\omega = 1, \tau = L, s = 0))\Pr(\omega = 1)$ $\Pr(s' = 1) = (\Pr(s' =$

$1|\omega = 1, \tau = L, s = 1) + \Pr(s' = 1|\omega = 1, \tau = L, s = 0)) \Pr(\omega = 1) + (\Pr(s' = 1|\omega = 0, \tau = L, s = 1) + \Pr(s' = 1|\omega = 0, \tau = L, s = 0)) \Pr(\omega = 0)$.

$$\Pr(\omega = 1|s' = 1, \tau = L) = \frac{\Pr(s' = 1|\omega = 1, \tau = L) \Pr(\omega = 1)}{\Pr(s' = 1)} \geq \frac{1}{2}$$

Using the definitions for $\Pr(s' = 1|\omega = 1, \tau = L)$ and for $\Pr(s' = 1)$ from above and the fact that the payoff of the protesters is increasing in q_0^L and q_1^L, with simple algebra we find that the optimal probabilities are $q_1^L = 1$ and $q_0^L = \frac{\mu_0 - \epsilon}{(1-\mu_0)(1-2\epsilon)}$. For q_0^L to be a probability we require that (i) $\mu_0 > \epsilon$ and $\epsilon < 0.5$ or (ii) $\mu_0 < \epsilon$ and $\epsilon > 0.5$. Since $\epsilon < 0.5$ is not only the most intuitive assumption – a small error – but also the only one that matches the equilibrium we are describing here, we follow with (i).

Since we have the fourthuple $(q_0^L, q_1^L, q_0^H, q_1^H)$, we can go back and compute the posteriors for all types of government. With simple algebra we find the posteriors mentioned in Proposition 1. □