Petitions, political participation, and government responsiveness

Petitions, Political Participation, and Government Responsiveness

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Abstract

Private citizens have used petitions to address and make demands from political leaders for centuries. Similar to other democratic institutions, a petition's effectiveness is determined largely by participation of other citizens. Yet, participation itself is a function of expectations about government responsiveness to the petition, suggesting a "chicken and egg" problem. This paper studies the effect of government responsiveness on citizen participation in petitions in the United Kingdom, where the government is obligated to officially and publicly respond to petitions that receive a threshold number of signatures. We first develop a theoretical model, which reveals that the structure of the system implies a bunching strategy for identifying the effect of government responsiveness on citizen participation. Applying the strategy, we estimate that the government's commitment to respond to citizens caused an increase of at least 84% and as much as 115% in petitions that crossed the threshold, and provide evidence that petitioners mobilize other citizens to reach this threshold using social media platforms such as Twitter. Using methods from Natural Language Processing (NLP) together with detailed elections data, we show that petitions are primarily an instrument of the political right.

JEL: D72, D78

Keywords: Political participation, Government responsiveness, Petitions, Protest, Text analysis, Bunching, Structural estimation.

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1 Introduction

The events of recent years have revealed liberal democracy to be much more fragile and reversible than was imagined even thirty years ago, at the purported "end of history."[1] Greater centralization of power in the hands of a few, increased perceived distance between government elites and "the people," and diminished trust in and willingness to accept the results of elections are all symptoms of a widespread and much lamented pattern of "democratic backsliding." In this political climate, institutions that serve as a conduit for citizen preferences and information to political leaders play a crucial role; it is much more difficult for decision makers to make decisions against the will of the people when that will is common knowledge.

In this paper, we study one such institution, petitions.[2] Our setting is the United Kingdom (UK), which has had a petition system through which citizens can advocate for political change for hundreds of years. Our primary line of inquiry is the relationship between citizen participation in petitions and government responsiveness to citizen demands expressed by the petition. Citizen political participation in political institutions is fundamental in shaping societal outcomes. In principle, mass participation allows decision makers to aggregate citizen information and preferences and make decisions that reflect the will of the citizenry.[3] However, as in the case of boycotts, demonstrations, elections and other mass expressions of citizen demands, the incentive to participate is at least in part determined by the possibility that the government will respond in some way. A citizen who expects her government to

[1]In an influential article, Fukuyama (1989) famously argued that the events of the last decades of the 20th century were evidence of the "end of history" in the sense that the world had come to the "endpoint of mankind's ideological evolution and the universalization of Western liberal democracy."

[2]Petitions are widely regarded as an important form of protest as a means to influence political decision makers and even predate elections as democratic institutions in many countries. For theoretical and empirical evidence on the importance of petitions and protests see, e.g., Battaglini, Morton and Patacchini (2021); Enikolopov, Makarin and Petrova (2020); Battaglini (2017); Cantoni et al. (2019); Manacorda and Tesei (2020).

[3]This partly motivates the immense scholarly effort spent in understanding why individuals turnout to vote in elections. See Levine and Mattozzi (2020) for an example of recent work in economics. Cancela, João and Geys, Benny (2016) is a useful recent survey of the political science literature on voter turnout.

ignore a protest, regardless of the number of participants, is less likely to participate than one who expects her government to respond.

While this question is fundamental in political economy, identification of the causal effect of government responsiveness on the incentive to participate has been elusive. This is due mainly to challenges associated with identification. While responsiveness may affect the incentive to participate, if governments tend to be more responsive to larger protests, then the reverse is also true - larger protests are more likely to engender a government response, confounding identification. To identify the effect of responsiveness, we exploit a unique institutional feature of the UK's current petition system, in which private citizens may write, post, and sign petitions on any subject. Specifically for our purposes, the government is committed to officially and publicly responding to petitions that receive at least 10,000 signatures. It is this threshold feature of the institutional design and the exogenous variation it generates that is the focus of the present work.

We first develop a simple model of *mobilization* where a petitioner observes initial public reaction to her petition and then decides how much costly *mobilization effort* to exert in order to attract additional signatures. The key feature of the model is the government commitment to a response once a signature threshold is reached. As the petitioner has a preference for government response, this results in a discontinuous increase in the mobilization effort. The prediction of the theoretical model is unambiguous: If the petitioner observes that initial signatures are close enough to the threshold, she is willing to exert a higher mobilization effort to gain signatures than she would in a counterfactual scenario with no threshold. In the data, we should then expect to observe a spike in the number of petitions just above the threshold.

The model combined with the threshold feature of the UK petition system implies a bunching identification strategy in the vein of Kleven and Waseem (2013). Specifically, under the assumptions of the model there exists a clear window of petitions in which petitioners exert a higher than baseline level of effort in order to reach the threshold relative to petitions outside the window, and the counterfactual distribution of signatures in the absence of the threshold can thus be identified. We can then compare the factual and counterfactual distributions to uncover the effect of the government's commitment to respond to participation in the petition system.

We face an additional challenge that studies using bunching in the context of income tax thresholds, for example, do not. Kleven and Waseem (2013) and Kleven (2016) suggest that one boundary of the bunching window can be determined visually and then the other obtained through an iterative process. This is not an option in our setting because the mobilization technology is imprecise: randomness in the mobilization technology results in imprecise targeting of the threshold; individuals can not put in just enough effort to reach the 10,000 signature cutoff. We thus exploit our theoretical model to place further restrictions on the data, which yield upper and lower bounds on the bunching window, and obtain estimates for each possible window.

We find that the government's commitment to a response threshold leads to a substantial and statistically significant increase in the number of petitions just to the right of the threshold. In particular, we find that the threshold rule caused an increase of between 84-115% petitions in the bunching region relative to the counterfactual scenario, and that these effects are significant at the 1% level. The results suggest that the prospect of government response is a strong incentive to participate, and that government *commitment* to simply respond to citizen concerns (with no promise of policy change) is a significant driver of citizen engagement. Moreover, the tight link between our model and the identification strategy allows us to obtain structural estimates of two key parameters in our model: citizens' utility value of government responsiveness and the effectiveness of the political mobilization technology.

Our story hinges on the concept of "mobilization effort." Canvassing for signatures, for example, is a well-recognized method of mobilization effort in the case of petitions.[4] We can not observe this effort directly in the data, so that providing direct evidence that more effort

[4]See Carpenter and Moore (2014) for evidence in the case of anti-slavery petitions.

does indeed generate more signatures is difficult. To provide indirect evidence, however, we tracked a set of petitions daily from their infancy, while also collecting information on Twitter activity related to the petitions. Social media (and Twitter in particular) is known to be an important channel through which petitioners and their supporters generate interest in petitions.[5] We show that petitions that are discussed on Twitter receive substantially higher increases in signatures on the day they are discussed than petitions that do not. Given we have a panel of petitions over time, this can not be explained by popular petitions being more likely to receive Twitter attention and being more likely to be signed, as we control for petition fixed effects.

Finally, we study the *politics* of the petition system. It is clearly not the case that even the most democratic of institutions are used equally by individuals on the political left and right. For example, voter turnout for an election may skew left if there are more options, or more appealing options, for left wing voters than there are for those on the right, or if electoral laws disproportionately disenfranchise (however indirectly) one group of voters.[6] The petition system is an interesting case study in this light, as it is very much a political "free market," with low and equal costs of participation to individuals across the political spectrum. This allows us to cleanly examine whether and how one side of the ideological spectrum uses the petition system systematically more than the other.

To do so, we must first be able to classify petitions as either "Left" or "Right" in orientation. Since ideological orientation of a petition is not known to us *a priori*, we use methods from Natural Language Processing (NLP) to classify the petitions in our sample. As we observe signatures by petition at the level of electoral constituency, we construct a set of petitions that are popular in constituencies that are Conservative party strongholds (and not popular elsewhere) and a set of petitions that are popular in constituencies that

[5] The UK Parliament's Petitions Committee uses Twitter as its main channel to engage with the public on petitions being discussed in the House of Commons Asher, Bandeira and Spaiser (2017).

[6] It has long been argued, for example, that voter ID laws in the United States disproportionately suppress turnout on the left.

are Labour party strongholds (and not popular elsewhere), and label these as "Right" and "Left" respectively. Together, these comprise our training sample of petitions. We then apply the Naive Bayes Multinomial classification model to classify the remaining petitions. We then show that right-leaning constituencies participate in petitions that represent their own preferences at a much higher rate than left-leaning constituencies do, consistent with the idea that petitions are more an instrument of conservative politics. We then apply our bunching strategy to petitions labelled "right" and "left" separately and find also that more right-wing petitions are pushed across the threshold relative to the counterfactual than are left-wing petitions. Interestingly, however, our structural estimates suggest that left-wing mobilizers have greater reach than their counterparts on the right do.

Related literature.

While there is a large literature on how citizen political participation affects government responsiveness,[7] the reciprocal direction, which we study in our paper, is under-explored. A notable exception is is Trucco (2017) who runs a randomized field experiment and identifies direct casual evidence of how the improvement in government responsiveness affects citizen demands for public goods. Specifically, Trucco (2017) shows that a stronger government responsiveness to demands for repairs of sidewalks in Buenos Aires increases the likelihood that citizens request such repairs, and that the increase comes from the broader participation in the communities, driven by the change in citizens' beliefs about government responsiveness to their concerns.[8]

Our study is complementary in the sense that we also identify citizen participation in political institutions as a result of government commitment to respond to citizen participation. Where our study deviates from Trucco (2017) (in addition to the obvious difference

[7] Besley and Burgess (2002) develop a framework where more informed citizenship improves government responsiveness. The key theme is the dependance of citizens' informativeness on well-functioning mass media and institutional transparency (see also Strömberg (2004)). More recently, Chen, Pan and Xu (2016) show that citizens' demands translate into government responsiveness even in an authoritarian context such as China.

[8] Other studies on the perception of government responsiveness, and its effect on citizens participation and the quality of governance include Banerjee et al. (2011),Giné and Mansuri (2018) and Bayan (2021).

in methodology) is that in our setting there is no commitment on the part of the government to make a material change, only to communicate a verbal response. Furthermore, as we have access to petition text and the electoral data, our framework allows us to identify heterogeneity in the effect of government response by ideological orientation.

The effect of organizational responsiveness to political participation is studied in Hager et al. (2021). They analyze, using an RCT, how a change in responsiveness of a political party to its members changes the engagement of those members in political campaigns. Specifically, if the party members believe that the responsiveness to their concerns increases, their political engagement improves. This also relates to Hirschman (1970) who first discussed the idea how organizational deterioration decreases engagement of its members and leads to an organizational exit.

We also contribute to the empirical literature on the determinants of participation in public protest. In recent years, several studies seek to understand how increased social connectivity affects protest participation, for example through the diffusion of mobile phones (Manacorda and Tesei 2020), or through the expansion of social networks (Zhuravskaya, Petrova and Enikolopov 2020; Enikolopov, Makarin and Petrova 2020). Cantoni et al. (2019) study the role of beliefs about others' participation on a potential protestor's own decision. On one hand, if there is a "strength in numbers," the decision to turnout to protest may be complementary to beliefs about others' turnout decisions. But on the other, if protest participation is viewed in the same light as contributing to a public good, beliefs may be strategic substitutes. In the context of the July 2016 anti-authoritarian protests in Hong Kong, Cantoni et al. (2019) find that the latter is the case.

However, the main point of any protest, whether it is a boycott, demonstration, or petition is to get the attention of decision makers and hopefully create change. At the same time, little is known about the effect of decision maker responsiveness to protest on the decision to turnout to protest. We provide (to the best of our knowledge) the first causal evidence on this question, albeit in a specific context, using a novel identification strategy.

Finally, petitions and protests are useful to policy makers because they are a channel through which citizens can convey private information about optimal policy. Battaglini, Morton and Patacchini (2021) theoretically and experimentally evaluate how the informational value of a petition depends on connectivity (information sharing properties) within social groups (see also Battaglini (2017)).[9] Our results suggest that threshold rules such as the one in the UK system generate more information for decision makers by increasing citizen participation in protest.

2 A simple model of mobilization

An agent derives utility from the popularity of her petition. Suppose that the agent observes the initial public reaction to her petition, measured by a number of initial signatures s_0. The agent then exerts effort $e \geq 0$ to probabilistically increase the number of signatures on the petition. In particular, if effort e is exerted, then the resulting number of total signatures is

$$s = s_0 + e + \epsilon, \ \epsilon \sim U[0, a]$$

where a denotes the reach of the agent's mobilization technology. For example, a could reflect the breadth of the agent's social media network. The agent pays private cost $\frac{e^2}{2}$ for exerting effort e.

Motivated by the UK system, we assume there exists an exogenous threshold $\bar{s} > 0$ such that the agent derives a fixed benefit $\theta > 0$ if $s \geq \bar{s}$. The benefit derives from an anticipated response by the government to petitions that reach this threshold. The agent's payoff is

$$u_P = \alpha s + \theta \mathbb{1}_{s \geq \bar{s}} - \frac{e^2}{2}, \ \alpha > 0$$

where α is a given parameter which measures the (marginal) benefit from an additional

[9] A complementary literature studies information aggregation properties of elections, see Feddersen and Pesendorfer (1997).

signature.

The parameter a is stochastic. We assume that while a is determined before the agent decides on her effort, the agent does not observe a at the time of her choice. For instance, the agent might not know the details about the extent of her social media reach, and therefore might not know how exactly her social media activity translates into additional signatures.

We make some assumptions on the distribution of a which are imposed mainly for tractability and could be relaxed.

Assumption. The parameter a is distributed according to a full-support $f(a)$ with:

1. $E[a] < \sqrt{\frac{\theta}{2}}$, and
2. $\max(a) \leq \sqrt{2\theta}$.

2.1. Analysis We make the following two observations.

Observation 1: In the absence of a threshold, the agent's expected payoff is $\alpha\left(s_0 + e + \frac{E[a]}{2}\right) - \frac{e^2}{2}$. Using the first-order approach we obtain the corresponding optimal choice: $e_0^* = \alpha$. This is the *minimal* effort in our setting, whatever the initial level of signatures s_0.

Observation 2: There exists a *marginal buncher*, i.e., a type of the agent who observes $s_0 \equiv s_m < \bar{s}$ such that she is indifferent between exerting the baseline effort $e_0^* = \alpha$ (with no chance of reaching $\bar{s}$) and a strictly higher effort e_1 in order to reach $\bar{s}$.

Assume for the moment that if s_m exerts $e_1 > e_0$ (to be determined below) then she reaches $\bar{s}$ with probability 1. For this to be true, the effort e_1 must be equal to the distance $\bar{s} - s_m$: in this case $\bar{s}$ is reached even under $a = 0$. Below we derive parameter range for which this holds.

The marginal buncher s_m satisfies the indifference condition:

$$\alpha\left(s_m + e_0^* + \frac{E[a]}{2}\right) - \frac{(e_0^*)^2}{2} = \alpha\left(s_m + e_1^* + \frac{E[a]}{2}\right) + \theta - \frac{(e_1^*)^2}{2}.$$

Using $e_0^* = \alpha$ and $e_1^*(s_m) = \bar{s} - s_m$ in the above indifference condition, we obtain a simple expression for the marginal buncher:

$$s_m = \bar{s} - \alpha - \sqrt{2\theta}.$$

The corresponding optimal effort for s_m is $e_1^* = \bar{s} - s_m = \alpha + \sqrt{2\theta}$.

In the next step we need to ensure that none of the agent types $s_0 < s_m$ has an incentive to exert effort above the baseline effort $e_0^* = \alpha$. Note, first, that if an agent with $s_0 < s_m$ does exert a higher effort $e_1' > e_0^*$ and expects to attain $\bar{s}$ with probability strictly within $(0,1)$, her expected payoff is

$$\alpha\left(s_0 + e_1' + \frac{E[a]}{2}\right) + \frac{s_0 + e_1' + E[a] - \bar{s}}{E[a]}\theta - \frac{(e_1')^2}{2}$$

where the agent believes that he reaches $\bar{s}$ with probability $\frac{s_0+e_1'+E[a]-\bar{s}}{E[a]}$ (this is the expected area of the density above $\bar{s}$). Using the first-order approach we obtain $(e_1')^* = \alpha + \frac{\theta}{E[a]}$. To prevent the agent type $s_0 < s_m$ from exerting higher effort, we need to ensure that

$$\alpha\left(s_0 + e_0^* + \frac{E[a]}{2}\right) - \frac{(e_0^*)^2}{2} > \alpha\left(s_0 + (e_1')^* + \frac{E[a]}{2}\right) + \frac{s_0 + (e_1') + E[a] - \bar{s}}{E[a]}\theta - \frac{((e_1')^*)^2}{2},$$

which implies $s_0 < \bar{s} - E[a] - \alpha - \frac{\theta}{2E[a]}$. In other words, we need to ensure that

$$\bar{s} - E[a] - \alpha - \frac{\theta}{2E[a]} < \bar{s} - \alpha - \sqrt{2\theta}$$

$$2E[a]^2 < \theta.$$

Assumption: $2E[a]^2 < \theta$.

In the Appendix, we also analyze the case $2E[a]^2 > \theta$ showing that qualitative results remain the same.

Finally, consider the effort choice for the agent types $s_0 > s_m$. First, note that for $s_0 \in [\bar{s} - \alpha, \bar{s})$ the optimal effort is α with which $\bar{s}$ is reached with probability 1.

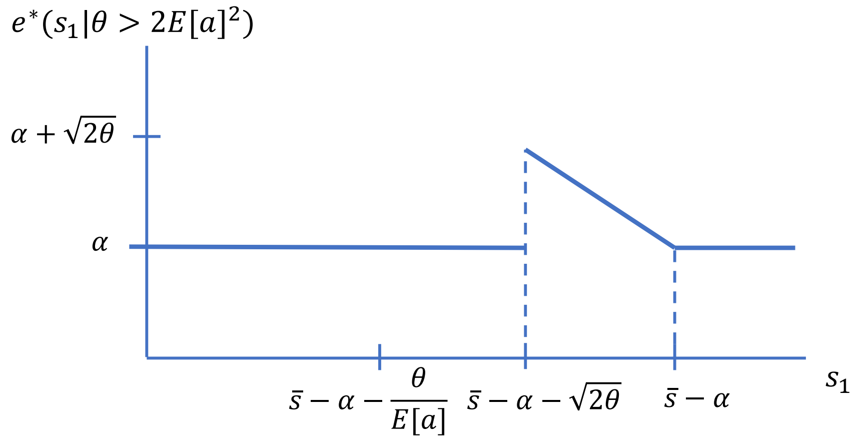


Figure 1: Optimal effort as a function of s_0 under the restriction $\theta > 2E[a]^2$.

We only need to obtain the optimal effort for the types $s_0 \in (s_m, \bar{s} - \alpha)$. If the effort is such that $Pr(s \geq \bar{s}) = 1$, then it must be true that $e^*(s_0) = \bar{s} - s_0$. Suppose not, and suppose that under $e^*(s_0)$, $Pr(s \geq \bar{s}) \in (0, 1)$. Then the first-order condition yields $e^* = \alpha + \frac{\theta}{E[a]}$. But this implies that the minimal probability of being above $\bar{s}$ is $\frac{s_m + e^* + E[a] - \bar{s}}{E[a]} = 1 + \frac{\theta}{E[a]^2} - \frac{\sqrt{2\theta}}{E[a]}$. However, $1 + \frac{\theta}{E[a]^2} - \frac{\sqrt{2\theta}}{E[a]} < 1$ if $\theta < 2E[a]^2$, a contradiction to our assumption $\theta > 2E[a]^2$. Therefore, for $s_0 \in (s_m, \bar{s} - \alpha)$ it cannot be that the effort results in $Pr(s \geq \bar{s}) \in (0, 1)$. Finally, recall that for all $s_0 \in [s_m, \bar{s} - \alpha)$ exerting $e^* = \alpha + \sqrt{2\theta}$ yields a higher expected payoff for the agent than the baseline effort e_0^*. But then, for $s_0 \in (s_m, \bar{s} - \alpha)$, it must be true that the optimal effort is $\bar{s} - s_0$.

We conclude that the optimal effort function under $2E[a]^2 < \theta$ is

$$e^*(s_0) = \begin{cases} \alpha & \text{if } s_0 < \bar{s} - \alpha - \sqrt{2\theta} \text{ or } s_0 \geq \bar{s} - \alpha, \\ \bar{s} - s_0 & \text{if } s_0 \in [\bar{s} - \alpha - \sqrt{2\theta}, \bar{s} - \alpha). \end{cases}$$

This function is illustrated in Figure 1.

Note that the "additional area" under the density function related to the increase in optimal effort above α, is $\frac{1}{2}(\sqrt{2\theta})^2 = \theta$.

3 Data and Context

We observe the universe of petitions submitted to the UK online petition system at https://petition.parliament.uk/ from it's inception in 2011 up to May of 2022. Petitions which are not "rejected" by the system[10] are open for signatures for six months. For each petition, we observe the title and the text of the petition, the date the petition opened and closed as well as the number of signatures the petition received. We observe signatures at the level of electoral constituency. In Figure 2 we present an example of what a posted petition in the UK system looks like online.

To illustrate the range of topics that appear in the petitions, in Figure 3 we plot the frequency distribution of the grams found most commonly in the petitions in the sample. We have plotted the frequency after cleaning (stemming) the text. We see that a large fraction of petitions contain the grams "UK," "peopl" (people) and "govern" (government) but that topics as varied as Brexit (EU, referendum), animal rights ("anim," "dog") and healthcare and government services ("health," "servic") are well-represented. In the Appendix we provide an alternative representation of the most frequent words in the petitions in form of a Wordcloud.

The key institutional feature of the UK system that we exploit is the 10,000 signature cutoff. Petitions which reach 10,000 signatures before 6 months passes *must* receive an official public response from the government on the petitions website. There is no commitment to change policy, but the government must verbally address the concerns of the petitioner and her signatories. Petitions that cross the 10,000 signature threshold are also more likely to be debated in parliament.[11] If citizens do value a government response (and a response alone, not a change in policy) and are able to mobilize for signatures, we should see a spike in the

[10] Petitions may be rejected for a number of reasons, but the most common reason is that the subject of the petition is already covered by an existing petition in the system. Other reasons include incoherence, abusive language, etc.

[11] Petitions that reach 100,000 signatures must be formally debated, while petitions that pass 10,000 are simply more likely to be debated. There are relatively few petitions that receive 100,000 signatures.

Figure 2: Petition Example

Petition

Increase the state pension to £19,760 a year (£380 a week)

The Government should raise the state pension to match the yearly equivalent of the national living wage (NLW). The NLW is rising to £9.50 an hour (i.e. £19,760 a year for F/T 40h per week), which we are told is needed to live, yet pensioners are expected to live on a state pension of £7,376 a year.

More details

The state pension is not enough to live on. All people regardless of standing are supposed to be looked on as equal, this is clearly not the case.
Most people have paid into the state pension through national insurance contributions during their working life.
Most pensioners live active lives and have to pay the same bills as others have to find money for but are expected to do it on less than half the income of those on the national living wage, this is unacceptable.
Level up and treat everyone the same, this is the right thing to do.

Sign this petition

46,732 signatures

Show on a map 100,000

Figure 3: Gram Frequencies across all Petitions

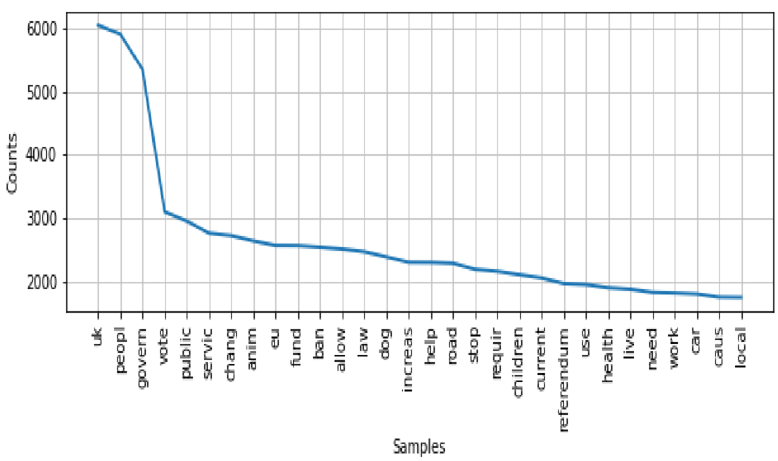
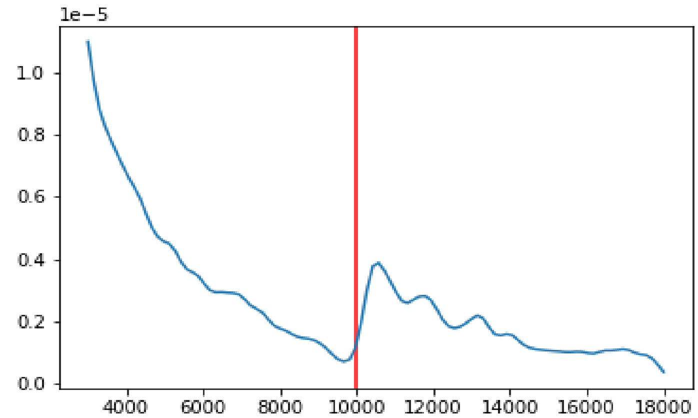


Figure 4: Bunching at the 10000 Cutoff



distribution to the right of the 10,000 cutoff. In Figure 4 we plot the raw density (using a Gaussian kernel) of the distribution of signatures around the 10,000 signature cutoff. There is a clear evidence of bunching: the distribution is in decline approaching the cutoff, and then jumps just to the right of it.

In Table 1 we present simple regressions of (the log of) signatures on constituency characteristics at the level of constituency-election year-petition to get a sense of correlations between participation and various political and demographic features of the constituencies. We restrict the sample to petitions in the neighborhood of the 10,000 signature threshold: ones that received between 5000 and 15,000 signatures, which leaves us with nearly 600,000 observations. In all regressions we include Petition fixed effects. We do not include election year fixed effects as these are absorbed by petition effects (petitions are specific to an election period) and we also do not include constituency fixed effects as many of these characteristics vary little if at all between the two election periods in the data. Our aim here is not to identify a causal effect but to understand how constituency characteristics correlate with participation in petitions.

First, it is clear that all the constituency characteristics matter for explaining signatures, and all estimated relationships are statistically significant, almost all at the 1% level. We

Table 1: Signatures and Constituency Characteristics The unit of observation is constituency-election year-petition. Standard errors clustered at the level of constituency. p-values in parentheses.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
turnout	2.108							0.457
	(0.000)							(0.049)
Conservative share		0.654						0.608
		(0.000)						(0.000)
Labour share			-0.108					0.512
			(0.084)					(0.000)
post-secondary educ				0.628				0.487
				(0.000)				(0.000)
no education					-1.986			-0.708
					(0.000)			(0.000)
white emp. rate						1.771		0.806
						(0.000)		(0.000)
non-white/white popn							-0.076	-0.090
							(0.000)	(0.000)
Petition FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	595,495	595,495	595,495	586,942	580,637	586,942	382,689	378,863
Rsquared	0.305	0.303	0.305	0.304	0.312	0.306	0.275	0.306

focus on the column 8, where all variables are included together. Among the three election variables, vote shares for the two main political parties are the most important. We see that constituencies that vote for the Conservative party are more likely to sign petitions than are ones that support Labour, though political support for both parties is associated with more participation in petitions. Post-secondary education strongly predicts participation in petitions, while constituencies with a high fraction of individuals with less than high school education participate less. Finally, as many petitions are populist in nature and the e-petition itself is often viewed as a vehicle for populist politics (Wright 2015) we include measures of the white employment rate and the ratio of non-white to white population, the latter a measure of local immigration levels. White employment is strongly and positively associated with petition participation, while a larger presence of immigrants is not. Altogether the results suggest that participation in petitions is predicted by participation in elections, especially in support of the Conservative party, as well as higher levels of education and employment and lower levels of immigration.

3.1. How do Petitioners Mobilize Our model and identification strategy rely on the notion that petitioners and their supporters *mobilize* others to sign their petitions. While traditionally, petitioners mobilized by physically canvassing for signatures (Carpenter and Moore 2014), social media plays a key role in mobilization for e-petitions. Specifically, petitioners and their supporters use Twitter to encourage individuals to sign petitions that are near the 10,000 signature threshold. In Figure 5 we display a couple of examples of mobilization efforts for petitions dealing with very different issues. It is clear from these that petitioners and their core supporters are aware of the threshold rule and they use the rule to motivate individuals to sign. It is also evident that other platforms such as YouTube and Whatsapp also play a role in mobilization.

To provide more rigorous evidence that petitioners can mobilize and that mobilization matters for signatures, we tracked petition signature changes *daily* from July 25th 2022 to

Figure 5: Mobilization via Twitter

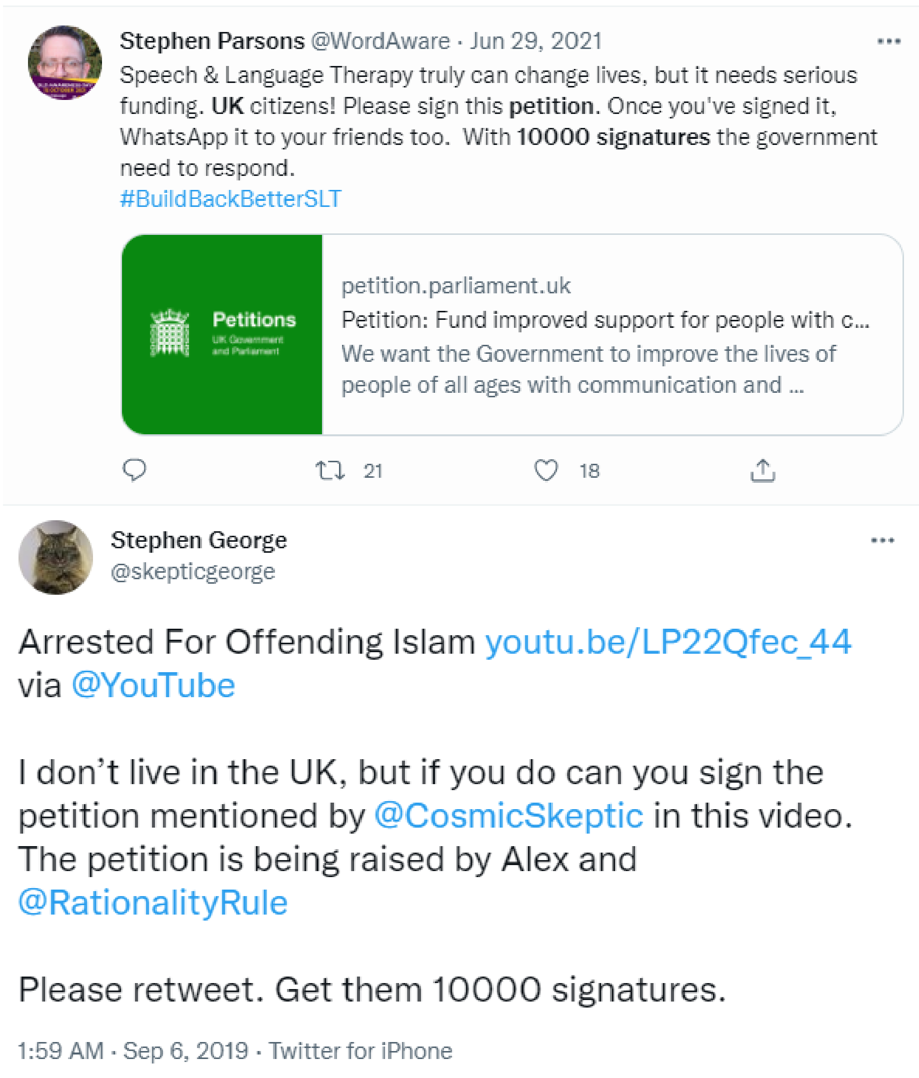
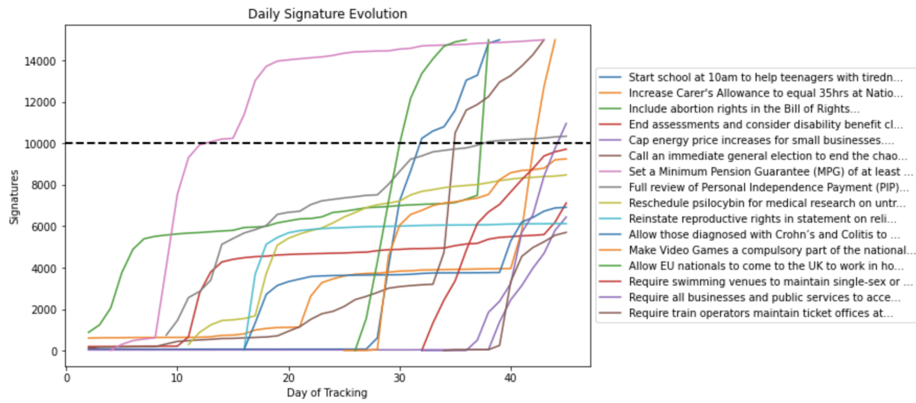


Figure 6: Signatures over Time



September 07, 2022, [12] and linked these to tweets about the petitions. In total, we were able to observe the daily signature evolution of 1606 petitions, a small subset of which crossed the 10,000 signature threshold while we were monitoring them. In Figure 6 we present the evolution of a subset of petitions that we tracked – the ones that we observed from their infancy and reached at least 5000 signatures while we were tracking them.

We consider regressions of the following form:

$$\Delta(s)_{pt} = \beta_0 + \beta_1 tweet_{pt} + \omega_p + \delta_t + e_{pt} \tag{1}$$

where:

$$\Delta(s)_{pt} = signatures_{pt} - signatures_{pt-1} \tag{2}$$

is the change in the number of signatures between days $t-1$ and t and $tweet_{pt}$ is an indicator variable that takes the value of 1 if petition p was tweeted about on date t. ω_p and δ_t represent petition and date fixed effects respectively. β_1 then tells us the number of additional signatures a petition gets on a given date when there is Twitter activity about the petition on that date. Including ω_p helps us control for the fact that popular petitions will tend to

[12]With the passing of Queen Elizabeth II on September 08, 2022, all petition activity was paused until a later date (eventually determined to be September 22, 2022).

Table 2: Signature Growth and Mobilization on Twitter The unit of observation is petition-date. Standard errors clustered at the level of the petition. p-values in parentheses. Estimated on the sample of petitions that we tracked between July 25 and September 07, 2022.

	(1)	(2)	(3)
$tweet_{pt}$	270.569	270.148	157.317
	(0.000)	(0.000)	(0.002)
Observations	57,512	57,512	57,512
Rsquared	0.015	0.015	0.122
Date FE	NO	YES	YES
Petition FE	NO	NO	YES

get more signatures as well as more twitter activity. Including δ_t helps us to control for the possibility that on certain dates (i.e., weekends and holidays) individuals are more likely to both sign petitions and be active on twitter.

In Table 2 we present estimates of different specifications of Equation 1. The richest specification in column 3 implies that Twitter activity on date t increases the number of signatures the petition receives between date $t-1$ and t by 157 signatures. The effect is significant at the 1% level. While these estimates are only suggestive, they illustrate a robust relationship between twitter activity and petition signatures, that would justify the decision to mobilize.

4 Identification and Estimation

We argue now that the model presented above together with the threshold rule in the petition system imply a bunching identification strategy for recovering the effect of government responsiveness on citizen political participation. We exploit the discontinuity in incentives at the signature threshold to construct an identification strategy that generally follows Kleven and Waseem (2013) and Kleven (2016), with some important modifications. The idea is to compare the observed (factual) distribution of signatures under the threshold policy with the counterfactual distribution of signatures that would exist in the absence of a threshold rule. While the former is straightforward to estimate using raw signature data, the latter requires that some assumptions in the signature generating process are satisfied. In particular, the following three Bunching Assumptions (BA) must hold (see Kleven (2016)):

BA1. There is a clear theoretical bunching window.

BA2. The bunching is all in one direction.

BA3. There is not missing mass *everywhere* to left of the cutoff.

Our theoretical model establishes that assumptions BA1-BA3 hold. Formally, letting s_m denote the *marginal buncher* and s_1 denote the signatures received in the first stage, before any mobilization effort is exerted, individuals with $s_1 < s_m$ choose a level of "baseline" level of effort α such that there is no chance of reaching the threshold $\bar{s}$ in the second stage. Individuals with initial signatures s_0 such that $s_0 \in (s_m, \bar{s})$ choose a mobilization effort that reaches the threshold number of signatures with certainty. Individuals with $s_0 \geq \bar{s}$ choose the same level of effort as those with $s_0 < s_m$. Our model then clearly predicts that:

1. There is a clear window for bunching - the range of initial signatures $s_0 \in (s_m, \bar{s})$.
2. The bunching is all in one direction, upwards - all individuals exert *positive* effort.
3. Not all individuals bunch - individuals with initial signatures $s_0 < s_m$ exert a baseline effort that is lower than the effort exerted in the bunching window, and reach the threshold with 0 probability.

These are the main assumptions that allow us to use data from *outside* the bunching window to estimate what the signature distribution *would have* looked like inside the window – the counterfactual distribution.

The procedure given in Kleven (2016) to estimate the counterfactual signature distribution is as follows. In the first step, we group petitions into bins by the number of total signatures received. Index bins by j, and let s_j be the number of signatures on petitions in bin j and c_j represent the count of the number of petitions in bin j. Let s_U and s_L respectively be the upper and lower bounds of the bunching window. We then estimate the equation:

$$c_j = \sum_{i=0}^{p} \beta_i (s_j)^i + \sum_{i=s_L}^{s_U} \gamma_i \mathbf{1}\left[s_j = i\right] + \nu_j \tag{3}$$

The sum $\sum_{i=0}^{p} \beta_i (s_j)^i$ is a polynomial of order p in signatures,[13] while $\sum_{i=s_L}^{s_U} \gamma_i \mathbf{1}\left[s_j = i\right]$ are a series of indicators of bins inside the bunching window $[s_L, s_U]$. The estimated counterfactual distribution of signatures in bin $j \in [s_L, s_U]$ is $\hat{c}_j = \sum_{i=0}^{p} \hat{\beta}_i (s_j)^i$.

The key issue here is that s_L and s_U are not known to the researcher. The marginal buncher is not observable, and while in some applications the bunching window can be determined by inspection of the raw data, in our case this is unrealistic. Specifically, there is uncertainty in the signature generation process: a petition writer can not exert the precise amount of effort that would take her petition to precisely the cutoff point and not beyond. For example, the petition writer has little control over how much her initial Tweet about a petition is re-tweeted and shared etc. There is significant randomness in this process and a mobilizer in our setting faces uncertainty in the number of signatures generated, for a given level of mobilization effort. So we begin by explaining the iterative process in Kleven and Waseem (2013), where the authors treat one limit of the bunching window as observable in the data, and then discuss how we extend it to deal with our application.

In the case of notches, the missing mass on one side of the threshold should be equal

[13] While high order polynomials are typically preferable, bunching methods are typically applied to administrative data, so that there are a large number of observations outside the bunching window. While the petition data set is not small, it is not large enough to precisely estimate a polynomial of very high order. We keep p at 4 in our estimation, but provide results in the appendix for alternative polynomial specifications.

to the extra mass on the other. Kleven and Waseem (2013) use this insight in an iterative procedure to select the bunching window. Specifically, let the missing mass to the left of the cutoff be given by M and the excess mass due to bunching to the right of the cutoff be given by B, and let the bunching window be given by $[s_L, s_U]$ such that $s_L < \bar{s} < s_U$. Suppose that s_U is known, and that we initially guess $s_L^0 \simeq \bar{s}$. We then estimate a counterfactual count of signatures $\hat{c}_j^0$ for every bin j in the window $[s_L^0, s_U]$ and then have an initial estimate of the missing mass, $\hat{M}^0$ and the excess bunching mass, $\hat{B}^0$. Since we guessed $s_L^0 \simeq \bar{s}$, we will have $\hat{M}^0 < \hat{B}^0$. We then decrease our guess of s_L to $s_L^1 < s_L^0$, re-estimate a counterfactual count of signatures $\hat{c}_j^1$ for every bin j in the window $[s_L^1, s_U]$ and check if $\hat{M}^1 = \hat{B}^1$. If it is, we stop, and we have the bunching window, if not we continue until $\hat{M}^k = \hat{B}^k$.

This approach requires knowledge of s_U, which is the case in the application that Kleven and Waseem (2013) consider. In our case, given the uncertainty in signature generation in response to mobilization, we can not credibly claim to know s_U, so we take a different approach. Specifically, we iteratively search for s_U, where, at each guess of s_U we repeat the above process. The result will be a set of pairs, $\{(s_L^n, s_U^n), n = 1, ..., N\}$, one for each of the N guesses of s_U. For each such pair (s_L^n, s_U^n) it will be the case that $\hat{M}^n = \hat{B}^n$. We can then restrict the set of feasible pairs using the constraints on the data implied by our model as follows.

We first make the following observations:

1. $|s_U - \bar{s}| = a$, the realized width of the distribution of ε, the noise in the signature mobilization process. This is because s_U is the highest point that a buncher can reach, which occurs when the buncher gets the highest value of the shock - this is the realized value of a.

2. $|\bar{s} - s_L| = \sqrt{2\theta}$. This is because the lower bound s_L is the smallest number of total signatures that a buncher would reach *in the absence of the threshold* $\bar{s}$; with the threshold, the effort discontinuously increases leading to a missing mass just above the

point s_L:

$$s_L = s_m + e_0^* = \bar{s} - \alpha - \sqrt{2\theta} + \alpha = \bar{s} - \sqrt{2\theta} \tag{4}$$

which implies $|\bar{s} - s_L| = \sqrt{2\theta}$.

3. Combining the first two observations we get:

$$|\bar{s} - s_L| - |s_U - \bar{s}| = \sqrt{2\theta} - a. \tag{5}$$

which is positive given the assumptions in the model of mobilization above.

This then gives us a second restriction, and any candidate pair (s_L^n, s_U^n) must satisfy:

1. $M^n = B^n$

2. $|\bar{s} - s_L| > |s_U - \bar{s}|$.

Finally, we also assume that in the absence of a threshold rule, the distribution of signatures is decreasing over the domain $[s_L - \epsilon, s_U + \epsilon]$ for some $\epsilon > 0$. The Figure 4 clearly supports this assumption, as the signature distribution appears to be decreasing everywhere away from the bunching areas around the threshold. There is no reason to expect bumps in the distribution in the absence of bunching incentives.

These assumptions significantly reduce the feasible set of pairs (s_L, s_U). However, we still do not have point identification of the bounds of the window, and we thus report estimates at the two extremes of the feasible set. Define the feasible set of pairs as S^{feas}. Notice that each possible s_U^n in the set S^{feas} implies a different value of a, and the implied value of a is increasing in s_U. So let s_U^{max} be the largest s_U in the set S^{feas} and let s_U^{min} be the smallest. Let the associated lower limits of the bunching window be given by s_L^{max} and s_L^{min}. The restrictions 1 and 2 imply that the largest feasible window is given by s_L^{max}, s_U^{max} and the smallest feasible window is s_L^{min}, s_U^{min}. We obtain estimates for each of these windows.[14]

[14]We search over a large grid of possible values of s_U.

Further, we also obtain estimates of the structural parameters implied by each of these windows as:

$$\begin{aligned} a^{max} &\equiv s_U^{max} - \bar{s} \\ a^{min} &\equiv s_U^{min} - \bar{s} \end{aligned}$$

and

$$\begin{aligned} \theta^{max} &= \frac{|\bar{s} - s_L^{max}|^2}{2} \\ \theta^{min} &= \frac{|\bar{s} - s_L^{min}|^2}{2} \end{aligned}$$

In Figure 7 we present the factual and counterfactual signature distributions associated with the bunching windows $[s_L^{min}, s_U^{min}]$ and $[s_L^{max}, s_U^{max}]$ respectively. The gap between the factual and counterfactual distributions to the right of the threshold suggests that the government's commitment to respond did result in a significant shift in behavior. Citizens mobilize to push petitions over the threshold and receive government response.

The effect of the threshold rule is formally given by (Kleven and Waseem 2013):

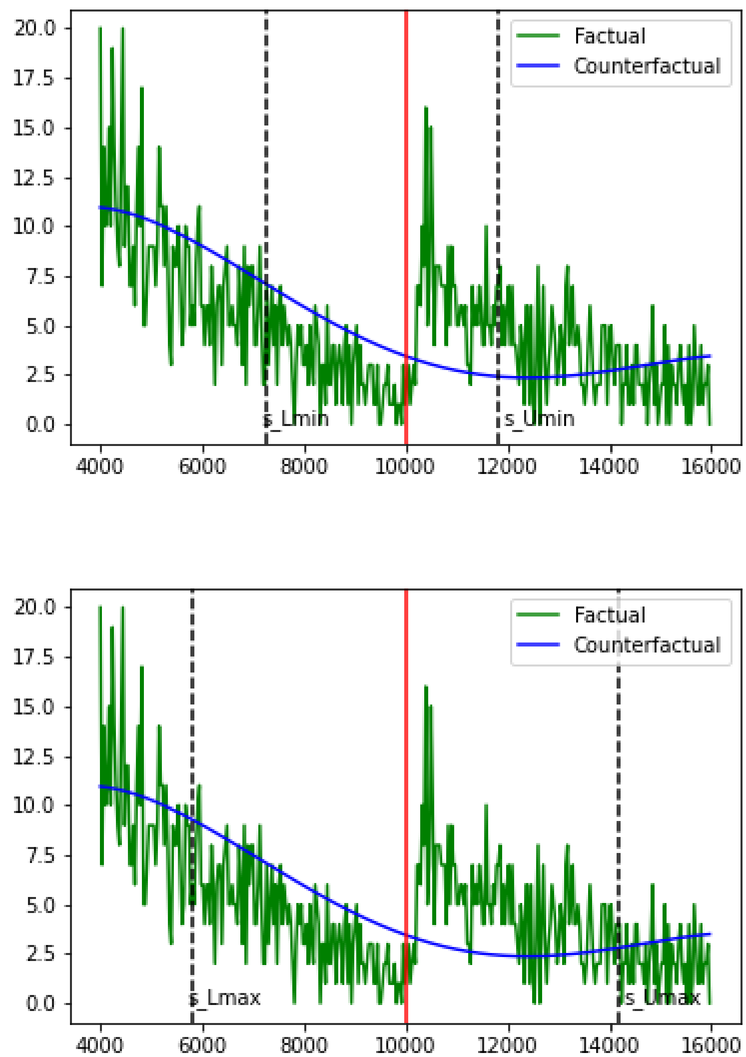
$$\hat{E} = \sum_{j=10,000}^{s_U} (c_j - \hat{c}_j) \tag{6}$$

That is, the sum of the difference between the factual and counterfactual signature counts in the region of excess mass M. This is the total number of petitions pushed above the threshold as a result of the governments commitment to respond. In Table 3 we present our baseline results for each extreme of the feasible set of bunching windows.

As noted in Figure 7, to obtain the estimates we assume a polynomial of order 4 for the counterfactual.[15] Standard errors are calculated using the bootstrap method of Chetty

[15] In the Appendix we present results for a polynomial of order 3, as a robustness check. The results are

Figure 7: Factual vs Counterfactual Signature Distributions estimated with window $[s_L^{min}, s_U^{min}]$ (Top) and $[s_L^{max}, s_U^{max}]$ (Bottom)



1 Counterfactual distribution estimated using a 4th order polynomial.

2 Bins have a width of 40 signatures.

3 In top panel $(s_L, s_U) = (7264, 11820)$ and in bottom panel $(s_L, s_U) = (5802, 14166)$

4 Petitions that were rejected by the government or received less than 3000 signatures were not included.

Table 3: Baseline Estimates

	$\hat{E}$	% increase	Implied $\hat{a}$	Implied $\hat{\theta}$
Minimum Window	175.922	115%	1820	3742848
$(s_L, s_U) = (7706, 11922)$	(10.242)			
Maximum Window	273.197	84%	4166	8811602
$(s_L, s_U) = (5224, 14540)$	(17.675)			

1 Standard errors estimated using bootstrap procedure recommended by Chetty et al. (2011). See appendix for details.

et al. (2011). See the appendix for details on standard error calculation. The estimates suggest that the promise of response with 10,000 signatures resulted in a massive increase in citizen participation in the petition system at either extreme of the bunching window. In column 1 we present our estimated effect $\hat{E}$ as defined in Equation 6. Not surprisingly the effect is larger in the case of the wider window, but we need to compare this to the number of petitions that would lie in the bunching region in the counterfactual scenario. We do this in column 2 and find that the increase in petitions in the bunching region is between 84 and 115%. The effects are significant at the 1% level. In columns 3 and 4 we present the implied estimates of a and θ respectively. Not surprisingly, given their definition, the estimates of these parameters are very sensitive to the size of the window. Interpreting the parameter magnitudes becomes more meaningful in the following section, where we perform this exercise for different types of petitioners separately, and can compare magnitudes across the different groups.

5 The Politics of Petitions

In Table 1 above we showed that petition signatures are strongly positively correlated with vote share of the Conservative party across UK electoral constituencies. This is perhaps not

qualitatively similar though larger in magnitude.

surprising, as petitions represent a form of *direct democracy*, which political parties of the ideological right tend to systematically support relative to their left wing counterparts. In this section we leverage data on election outcomes to drill down further into the politics of petitions. Specifically, we use detailed elections data together with Natural Language Processing (NPL) methods to classify petitions as ones favored by left wing voters and ones favored by right wing voters. Then, given the knowledge of whether a petition is "right" or "left" wing in nature, we first study how ideological leaning at the (time-varying) level of constituency is associated with support for the different type of petition. We find that constituencies that lean right are systematically more likely to support right wing petitions than constituencies that lean left are to support left wing petitions. Finally, we then study mobilization behavior separately for each class of petition using our bunching strategy.

We first describe the details of the classification procedure, and then provide results. For further details on the classification approach, see the online appendix.

5.1. Procedure We use supervised machine learning methods to classify petitions as either "Right" (R) or "Left" (L) as follows. First we define a subset of UK parliamentary constituencies as Conservative and Labour *strongholds*.[16] The idea is to select constituencies with a *permanently* large share of partisan voters on each side of the political spectrum. We then label the petitions that are popular in Conservative strongholds but not popular in Labour strongholds as "R" petitions and label petitions that are popular in Labour strongholds but not Conservative ones as "L" petitions. We then use these labelled petitions as our training data, which we use to build our classification model, and then classify the remaining petitions.

The first step is to define what a stronghold is. We define a Conservative party stronghold to be one where the minimum vote share received by the Conservative party over the election periods in the sample is above some level vc^*, and we define a "Labour" party stronghold to

[16] The Conservative party is the mainstream right wing party in the UK while the Labour party is the mainstream left wing party.

be one where the minimum vote share received by the Labour party over the election periods in the sample is above some level vl^*. We allow for the possibility that $vc^* \neq vl^*$.[17] Our approach is to find the minimum vote share in each constituency over all the election periods in the sample for each party, and then select the top 25 constituencies for each party: vc^* is the vote share in the 25th constituency in the Conservative list and vl^* is the vote share in the 25th constituency in the Labour list.

We find $vc^* = 0.561$ and $vl^* = 0.55$. For comparison's sake, the median vote share for the Conservative party across constituency-years is 0.367 is and the median vote share for the Labour party is 0.286. So a constituency whose *minimum* vote share over the elections in the sample was 0.561 is considerably more Conservative party leaning than the median (and similar for Labour). Then, for each set of stronghold constituencies, we select the F most frequently signed petitions (per captia) in these constituencies. Denote these sets of petitions as $\mathcal{P}_C(F)$ and $\mathcal{P}_L(F)$. There will be some petitions common to both of these sets – some petitions are massively popular and signed by individuals across the political spectrum. Moreover, if (say) L voters are more likely to sign petitions than other voters, then L voters in C strongholds who sign a given petition at a high rate can make the petition appear popular to C voters when in fact it is not. So we refine our partisan petition sets as follows:

$$\begin{aligned}\mathcal{P}^*_C(F) &= \mathcal{P}_C(F) \setminus \mathcal{P}_L(F)\\ \mathcal{P}^*_L(F) &= \mathcal{P}_L(F) \setminus \mathcal{P}_C(F)\end{aligned}$$

That is, Conservative petitions are ones that are popular in Conservative strongholds and not Labour strongholds and vice versa. These petitions together comprise the training set which we use to classify the remaining petitions. [18]

[17] This is because there are multiple parties in the electoral system, and the vote is split differently on the left and right of the spectrum over time.

[18] F is a key choice at our discretion. There is a trade off in this choice. A large F means a bigger training sample and model construction that is less prone to overfitting. But given the nature of the election and

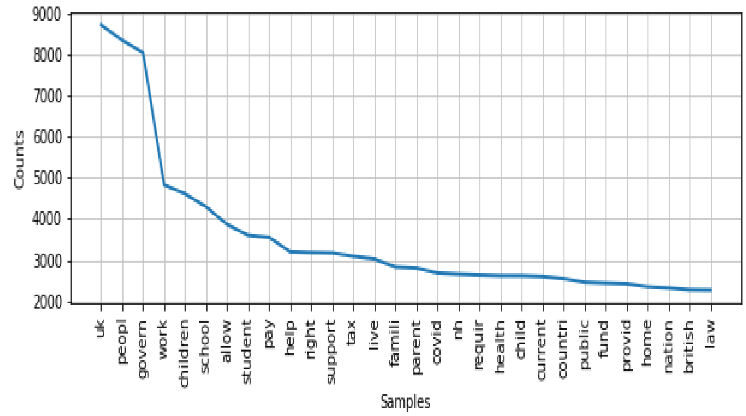
The second step is to build a classification model, taking the training data as an input. First we vectorize the text of the petitions using TF-IDF, which assigns a numeric value to each n-gram in each petition. n-grams which occur frequently in a given petition but infrequently across all petitions receive a high TF-IDF score. With the text vectorized, we apply Naive Bayes Multinomial classification models to classify petitions.[19] Let the vector of tf-idf scores for petition p be given by $\mathbf{Z}_p$. This vector is as long as the number of grams. Let Y_p be a binary variable that indicates whether a petition is "right wing" or not. We observe Y_p for all petitions in our training data. So we fit the model using the set of observations on $(Y_p, \mathbf{Z}_p)$ in the training data.

5.2. Classification Results In Figures 8 and 9 we plot the frequency distribution of the grams found most commonly in petitions classified by the model as "L" and "R" respectively. The grams "UK," "government" and "people" are most common in both groups, but we see a big departure between the two groups after these three. Petitions classified as "Left" include grams such as "work, student, pay, help, support" among others within the top category, while petitions classified as "Right" feature "public, eu, fund, ban, law" in their respective top category. It is reassuring that phrases we expect to be associated with the political left appear in petitions we classify as "Left" and similarly on the right. Using k-fold cross validation applied to our training sample, we classify correctly at a rate of 82.3%. We provide

petition data, having an "F" too large will result in misclassification in constructing the training sample. The reason is that the further down the list of most popular petitions we go in each type of constituency, the more likely we are to select idiosyncratic petitions (for example, highly "local" ones that are only popular in a few constituencies). Note as well, the size of the training set does not monotonically increase in F. That is because we only keep the set of petitions that are uniquely popular in L strongholds and the set of petitions that are uniquely popular in C strongholds. As we increase F, though we are adding more popular petitions to draw from, we are also increasing the likelihood that petitions that were uniquely popular to L or C at smaller values of F are no longer so. To be totally rigorous, we consider a range of F and then pick the value of F that yields the best accuracy score. Checking over a grid of values for F, ranging from 500 to 3000, we find that $F = 900$ yields the best accuracy of 82.3% (result of k-fold cross validation applied to the training data). At $F = 900$ we end up with 430 petitions in the training set, 215 of each "L" and "R". The model then classifies 52% of the petitions in the test sample as "R" and 48% of petitions as "L".

[19] Another option we have considered is Logistic regression. There are a few reasons we have chosen Naive Bayes instead. First, Logistic regression places relatively strong parametric restrictions on the data. Second, Naive Bayes is preferable when the training set is not especially large. Third, Naive Bayes is preferable when the data may be "unbalanced" in the sense that there are many more of one type of class (L or R) than the other. The second and third considerations are especially important in our application.

Figure 8: Gram Frequencies in Petitions Classified as "Left"



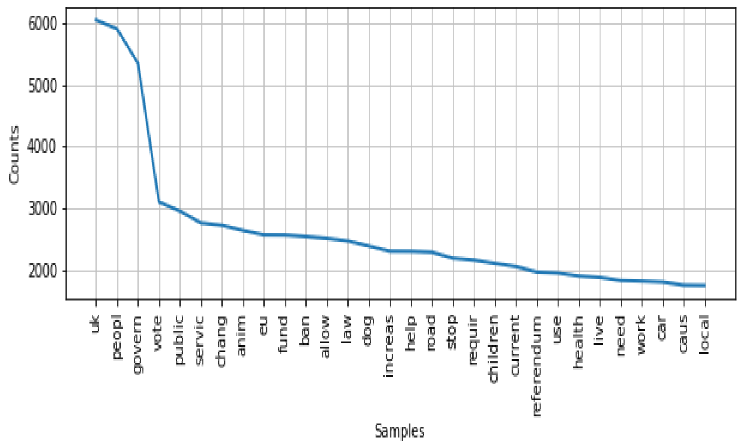
further evidence on the validity of our classification approach in the following subsection.

5.3. Ideological Leaning and Petition Support In this subsection we study how ideological leaning translates into support for petitions in general and right and left wing petitions separately. To do so, we consider regressions of the form:

$$y_{ce} = \alpha + \rho RLean_{ce} + \gamma_c + \delta_e + \eta_{ce} \tag{7}$$

where c indexes constituency and e indexes the election period. y_{ce} is a measure of petition signatures in constituency c during period e (total, left, or right) and $RLean_{ce}$ measures the "right leaning-ness" of constituency c in election period e: the difference between vote shares for the conservative and labour party in the national election that occurs **at the beginning** of period e in constituency c. γ_c and δ_e capture constituency and election period effects

Figure 9: Gram Frequencies in Petitions Classified as "Right"



respectively.

The coefficient of interest here is ρ. While we are reluctant to attach a strong causal interpretation to our estimates of ρ, we note that:

1. $RLean_{ce}$ is predetermined relative to y_{ce} - it is an outcome from election day, at the beginning of period e, while y_{ce} accumulates throughout period e.

2. We include constituency level fixed effects so that estimates of ρ can not be confounded by constituencies being both more permanently conservative in nature and more likely to sign petitions.

Estimates of equation 7 with different signature outcomes are in Table 4.

Table 4: Ideological Leaning and Petition Signatures Standard errors clustered at the level of the petition. p-values in parentheses.

	(1) Total	(2) Total	(3) Total	(4) Total	(5) Right	(6) Left	(7) Right	(8) Left	(9) Right	(10) Left
$RLean_{ce}$	0.109	1.910	0.097	0.108	0.862	-0.264	0.883	-0.253	0.940	-0.168
	(0.011)	(0.000)	(0.003)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
$Turnout$									0.603	0.866
									(0.381)	(0.227)
Constituency FE	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Election Period FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	YES	NO	NO	YES	YES	YES	YES
Observations	1599	1599	1599	1024	1599	1599	1024	1024	1024	1024
R-squared	0.009	0.370	0.928	0.934	0.789	0.989	0.801	0.988	0.802	0.988

In columns 1-4 we study how ideological leaning explains total petition signatures. In the fourth column, once we include constituency and election effects as well as time-varying constituency characteristics (the demographic variables in table 1), we see that a shift in vote share of 10 percentage points from Labour to Conservatives results in a 1.3% increase in total signatures on petitions. While modest economically, the estimated effect is significant at the 1% level. This suggests that more conservative leaning constituencies experience greater participation in petitions.

Once we split petition signatures into right and left, we get a clearer picture of what drives this result. In columns (7) and (8), where we include all fixed effects and controls, we see that a 10 percentage point swing towards the conservatives is associated with an 8.8% increase in signatures on right-wing petitions - almost one for one. By contrast, a 10 percentage point swing towards Labour is associated with only a 2.6% increase in signatures on left-wing petitions. Again, both estimates are significant at the 1% level. So the result in column 4 for total signatures is explained primarily by conservative-leaning constituencies participating heavily in right-wing petitions.

In the final two columns we include voter turnout as a control variable to ensure our estimated effects of ideological leaning are not confounded by electoral participation. Voter turnout is another measure of political engagement and is likely correlated with petition signatures, and it is also likely that turnout is associated with ideological leaning. We see that turnout is positively associated with more of both types of signature, but more importantly that there is no change in the qualitative results in columns 7 and 8. If anything, the difference between the effects of ideological leaning on left and right petition signatures grows wider. While the results in these columns are even stronger than in columns 7 and 8, we hesitate to label these as our "favoured specification" as relative vote shares can be an outcome of turnout (or vice versa) depending on the model of electoral participation one has in mind.

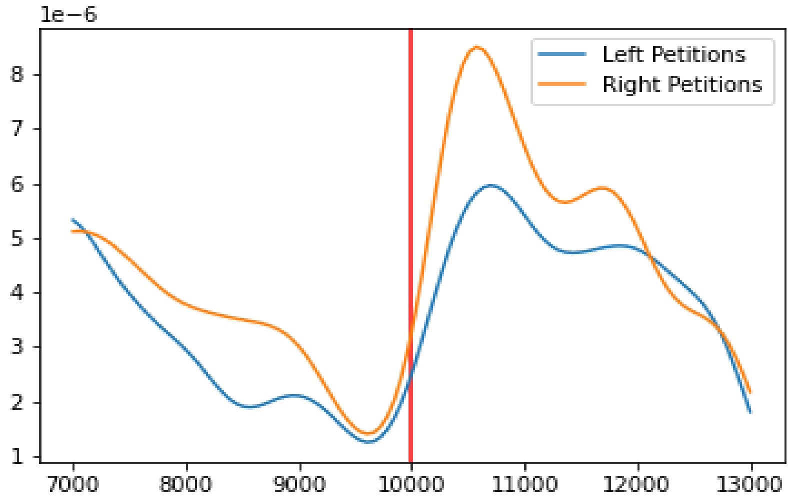
Altogether, the results suggest that right-leaning constituencies participate in petitions that represent their own preferences at a much greater rate than left-leaning constituencies do. Note as well that these results validate further our classification exercise - we would be concerned if right leaning constituencies were as likely to support L petitions as left leaning constituencies. Note that the results here are not mechanically a function of our classification however - our stronghold constituencies that we used to create our training sample numbered only 25 each, while there are over 600 electoral constituencies in total.

These results immediately raise the question of how different the bunching behavior is across the two ideological groups. If conservative voters are far more likely to participate in ideologically right wing petitions than labour voters are to participate in ideologically left wing petitions, is it also the case that bunching in response to the threshold is more prevalent on the right as well? In Figure 10 we plot the raw distribution of signatures on right and left wing petitions around the threshold. Visually, it indeed appears that bunching is more pronounced for right wing petitions. We check this rigorously by repeating our bunching estimation for each type of petition separately. We follow the exact same procedure as described in the Estimation section above, but separately for the subsample of petitions that are classified as "L" and "R."

In Figure 11 we present the factual and counterfactual signature distributions associated with the bunching windows $[s_L^{min}, s_U^{min}]$ and $[s_L^{max}, s_U^{max}]$, for petitions classified as "R," and in Figure 12 we do the same for petitions classified as "L," while in Table 5 we present the bunching estimates for the two subsamples of R and L petitions.

The effect of government response implies an 83-133% increase in petitions in the bunching area for R petitions and a 71-100% increase for L petitions. Not surprisingly given Figure 10 above, the estimated effect is larger for R petitions. However, the bunching window is estimated to be larger for L petitions than for R petitions, which in turn implies that α and θ are both larger for L petitions. Taking our model seriously, this suggests that mobilization technology is more effective for L petitioners and preference for government response

Figure 10: Bunching at the 10000 Cutoff - Left vs Right Wing Petitions

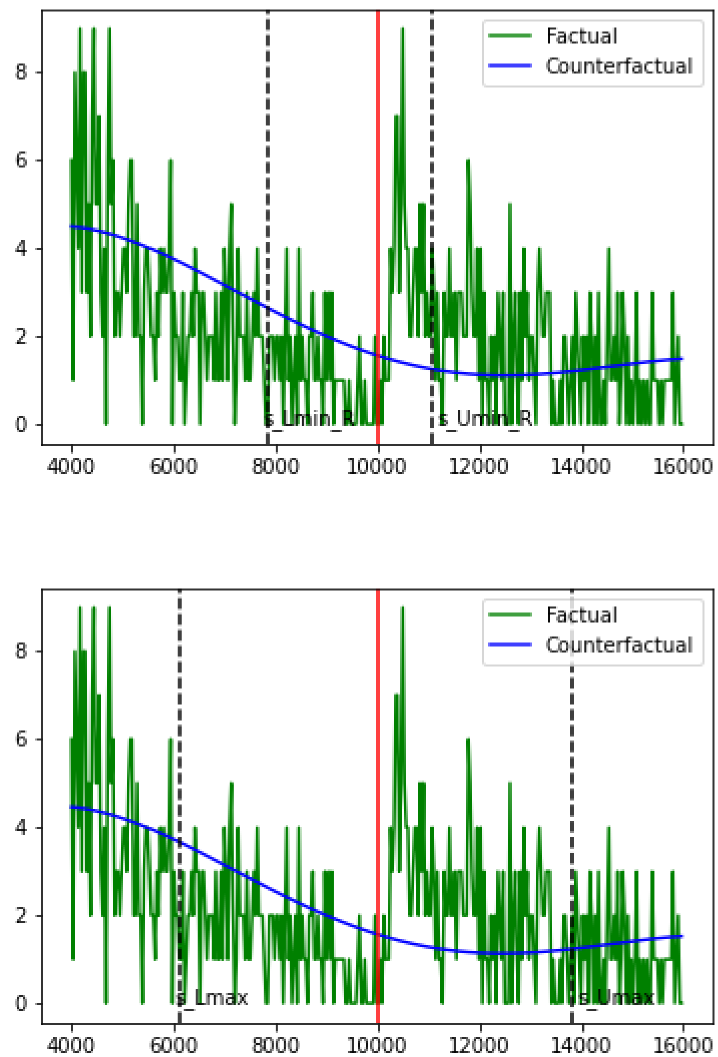


bunching.png

is also higher among L petitioners. However the bunching effect is larger for R petitions in spite of this, because the increase in signatures is larger *relative to the counterfactual* for R petitioners than it is for L petitioners.

We can only speculate given the data at hand, but the results here are consistent with a more precise mobilization technology for right wing voters. For example, if right wing voters generate signatures by physical canvassing and (literal) word of mouth instead of using social media, while left-wing voters did the opposite, we would observe the patterns that we see here. In any case, while it is tempting to draw strong conclusions from these results, we should also note that the Conservative party held government throughout the period of our sample, perhaps making response more valuable to Conservative as opposed to Labour voters.

Figure 11: Factual vs Counterfactual Signature Distributions estimated with window $[s_L^{min}, s_U^{min}]$ (Top) and $[s_L^{max}, s_U^{max}]$ (Bottom): R petitions



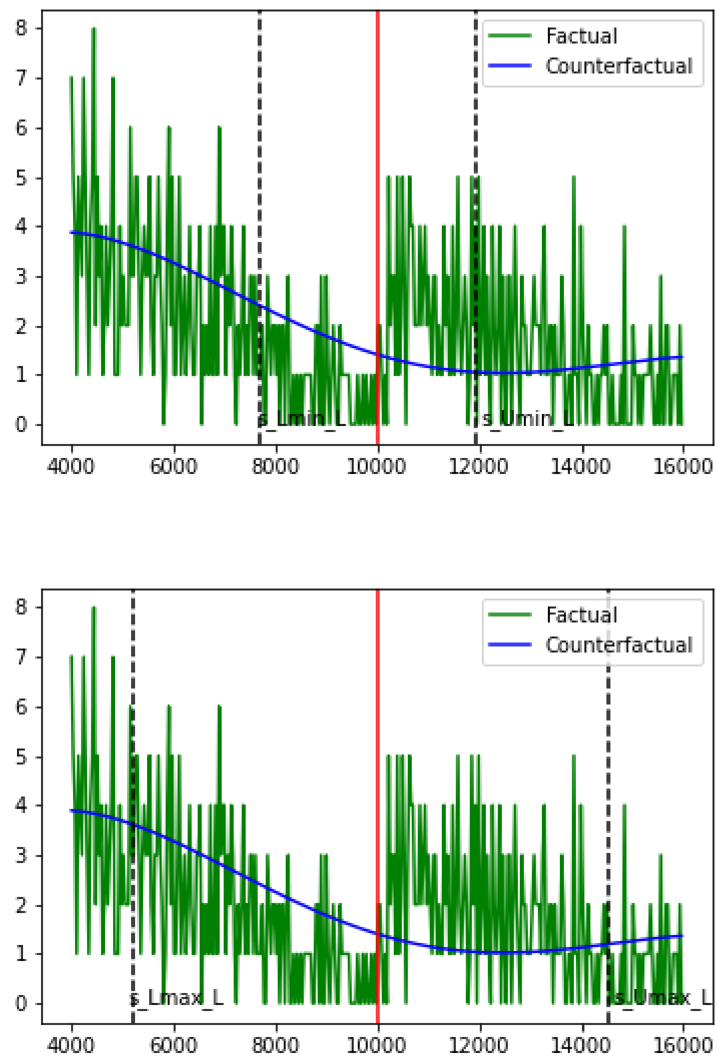
1 Counterfactual distribution estimated using a 4th order polynomial.

2 Bins have a width of 40 signatures.

3 In top panel $(s_L, s_U) = (7842, 11072)$ and in bottom panel $(s_L, s_U) = (6108, 13826)$

4 Petitions that were rejected by the government or received less than 3000 signatures were not included.

Figure 12: Factual vs Counterfactual Signature Distributions estimated with window $[s_L^{min}, s_U^{min}]$ (Top) and $[s_L^{max}, s_U^{max}]$ (Bottom): L petitions



1 Counterfactual distribution estimated using a 4th order polynomial.

2 Bins have a width of 40 signatures.

3 In top panel $(s_L, s_U) = (7706, 11922)$ and in bottom panel $(s_L, s_U) = (5224, 14540)$

4 Petitions that were rejected by the government or received less than 3000 signatures were not included.

Table 5: Heterogeneous Bunching

	$\hat{E}$	% increase	Implied $\hat{a}$	Implied $\hat{\theta}$
R Petitions				
Minimum Window	59.445	133%	1072	2328482
$(s_L, s_U) = (7842, 11072)$	(3.209)			
Maximum Window	116.134	83%	3826	7573832
$(s_L, s_U) = (6108, 13826)$	(10.862)			
L Petitions				
Minimum Window	67.197	100%	1922	2631218
$(s_L, s_U) = (7706, 11922)$	(5.095)			
Maximum Window	106.900	71%	4540	11405088
$(s_L, s_U) = (5224, 14540)$	(9.765)			

6 Conclusion

Petitions are a centuries-old political instrument, through which political leaders can remain aware of preferences and information dispersed across the citizenry. Relative to protests and public demonstrations, which can be more noisy in the sense that protestors show up to a protest for a host of unobservable reasons, petitions can deliver a clear and articulate message to policy makers about the will of the people. Relative to elections, which are infrequent and in most cases result in far less than perfect representation of the electorate, petitions present an opportunity for continuous information flow to decision makers from citizens any where on the political spectrum, *de facto* enfranchised or not. In a time where many observers are concerned for the future of democracy, petitions have the potential to keep citizens engaged with the mainstream political system, and leaders and the governed well connected, limiting the possibility of democratic backsliding.

We exploit a unique signature threshold rule in the UK e-petition system to study how government responsiveness affects citizen political participation. Specifically, to the extent that citizen participation is motivated by the possibility of the government responding to citizen demands, the signature threshold creates a discontinuity in incentives. Petition writers who produce petitions that receive a number signatures in the neighbourhood of the threshold have extra incentive to mobilize other citizens to sign the petition, move across the threshold, and receive the promised response from the government.

Guided by a theoretical model of mobilization, we develop a bunching strategy for identifying the effect of government responsiveness on citizen participation. Applying the strategy to our data set of nearly 158,000 UK petitions, we find that the prospect of government response causes an increase in the number of petitions that cross the signature threshold by between 84-115%. Tracking petitions and signature mobilization on Twitter at the daily level, we provide robust evidence that day-to-day increases in signatures are indeed driven by mobilization efforts of petition writers and their followers. Finally, using methods from Natural Language Processing combined with detailed electoral district level data, on signatures and voting behaviour, we show that the effect of government responsiveness on participation is largely driven by petitions with a right-wing political orientation.

While our results come from a specific context, we argue that the effects we recover in this paper are an important first step to answering a general and important question in political economy. Little is known about how the potential for government responsiveness motivates protest, demonstration, boycotts, etc., in part because it is difficult to identify. We have presented, to the best of our knowledge, the first causal evidence on this question.

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Online Appendix of:

Petitions, Political Participation, and Government Responsiveness

Arvind Magesan, and Dimitri Migrow

A Calculation of Standard Errors

We use the residual resampling bootstrap approach of Chetty et al. (2011) to calculate standard errors for our estimates $\hat{E}$. Specifically, from the estimation of Equation A.1 we recover a set of regression residuals $\hat{\nu}_j$. From this set we can sample with replacement repeatedly. For sample k, for example, we obtain

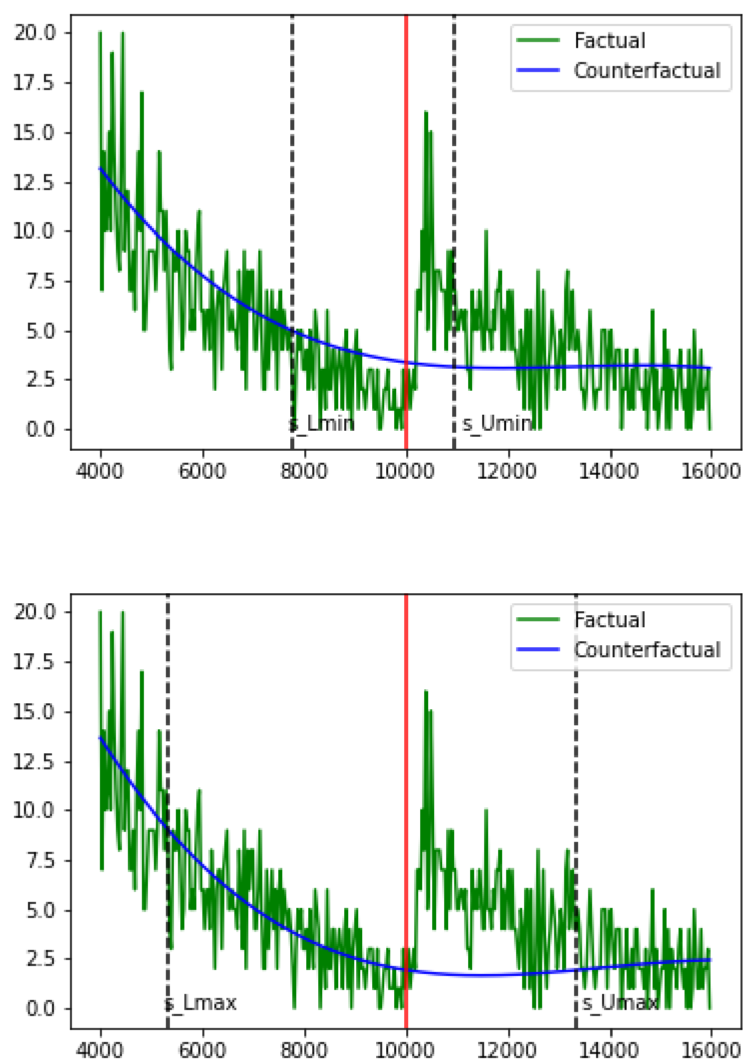
$$\hat{c}_j^k = \sum_{i=0}^{p} \hat{\beta}_i (s_j^k)^i + \sum_{i=s_L}^{s_U} \hat{\gamma}_i \mathbf{1}\left[s_j = i\right] + \hat{\nu}_j^k \tag{A.1}$$

We then have a sample $\{\hat{c}_j^k, s_j^k\}_{j=1}^N$, with which we can obtain an estimate $\hat{E}^k$, We repeat this M times to obtain a distribution of $\hat{E}$. The standard deviation of this distribution is our calculated standard error.

B Robustness to Polynomial Order

Here we repeat the exercise we carried out to obtain baseline estimates, but now use a polynomial of order 3. In Figure B.1 we present the factual and counterfactual signature distributions associated with the bunching windows $[s_L^{min}, s_U^{min}]$ and $[s_L^{max}, s_U^{max}]$ respectively, and in Table B.1 we present the estimated effects.

Figure B.1: Factual vs Counterfactual Signature Distributions estimated with window $[s_L^{min}, s_U^{min}]$ (Top) and $[s_L^{max}, s_U^{max}]$ (Bottom)



1 Counterfactual distribution estimated using a 4th order polynomial.

2 Bins have a width of 40 signatures.

3 In top panel $(s_L, s_U) = (7774, 10970)$ and in bottom panel $(s_L, s_U) = (5326, 13350)$

4 Petitions that were rejected by the government or received less than 3000 signatures were not included.

Table B.1: Baseline Estimates

	$\hat{E}$	% increase	Implied $\hat{a}$	Implied $\hat{\theta}$
Minimum Window	100.352	107%	970	2477538
$(s_L, s_U) = (7774, 10970)$	(5.407)			
Maximum Window	347.599	200%	3350	10923138
$(s_L, s_U) = (5326, 13350)$	(32.399)			

C Classification

In this section we describe in detail the steps taken to classify petitions.

C.1. Pre-processing Cleaning the text of the petitions is an important pre-processing step. We did the following:

1. Make all petition text lower case.
2. Remove all punctuation.
3. Remove all non-alpha numeric characters.
4. Remove all numbers.
5. Remove all words that appear 2 or less times in the entire sample of petitions (this gets rid of "noise").
6. Remove "stop words."
7. Stemming - it would be efficient to treat words like "child" and "children" as the same token. "Stemming" removes the stem of words.

While another common step is to remove very short words (these typically do not provide much context) we do not want to lose words like UK, NHS, GYM etc. So we try to include as many short words as possible in the stopword list and do not use word length as a criteria for exclusion.

C.2. tf-idf The "TF" stands for "Text Frequency" and the "IDF" stands for "Inverse Document Frequency." Term frequency is simple - for every word/bigram in each petition (document), the term frequency is simply the fraction of the time the term appears in the petition. The inverse document frequency is the (log of the) inverse of the fraction of petitions (documents) in which the phrase appears. Specifically, let p index petitions and $\mathcal{P}$ represent the full set of petitions, and let t index a unigram or bigram of text. Then:

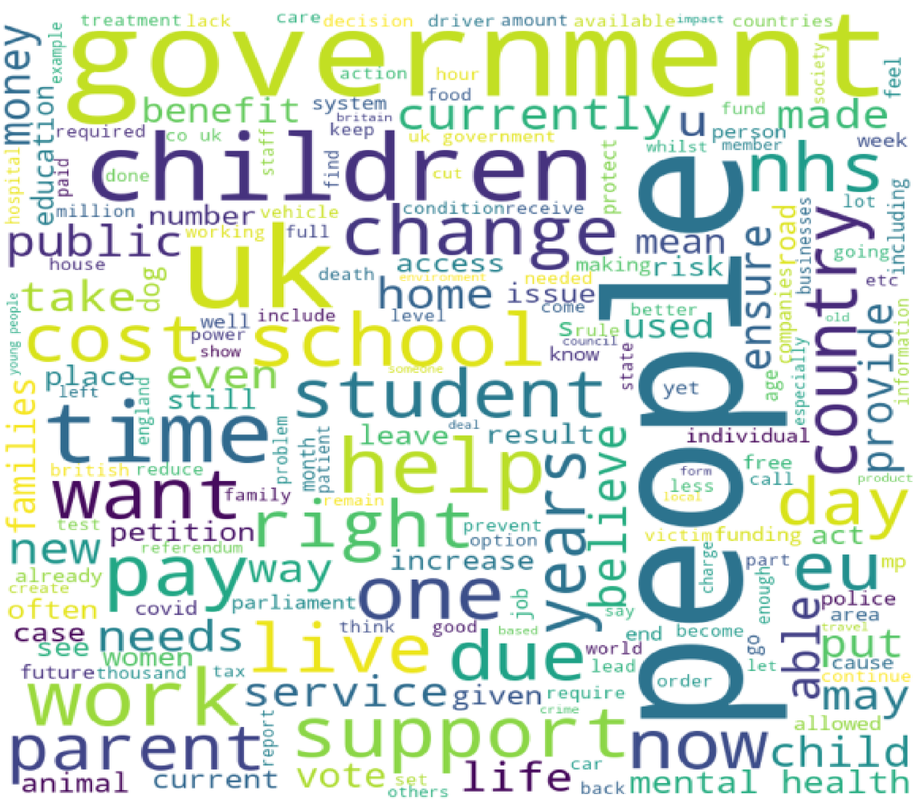
$$\begin{aligned} tf(t,p) &= \frac{f_{t,p}}{\sum_{t' \in p} f_{t',p}} \\ idf(t,\mathcal{P}) &= \ln \frac{|\mathcal{P}|}{|\{p \in \mathcal{P} : t \in p\}|} \end{aligned}$$

and:

$$tfidf(t,p,\mathcal{P}) = tf(t,p) idf(t,\mathcal{P})$$

So grams with a high tf-idf score for a given petition are ones that occur frequently in that petition and not so frequently in other petitions.

Figure C.2: Wordcloud related to all petitions in the sample.



Model analysis: $\theta < 2E[a]^2$

As before, the first-order approach yields $e_0^* = \alpha$ and $e_1^* = \alpha + \frac{\theta}{E[a]}$.

We continue with the following two observations. First, if $s_1 \in [\bar{s} - \alpha, \bar{s}]$, then exerting effort α brings s over the threshold $\bar{s}$ with probability 1. In this case, using the first-order approach, the optimal effort is simply α.

Second, consider $s_1 \in (\bar{s} - \alpha - \frac{\theta}{E[a]}, \bar{s} - \alpha)$. In the following we show that in this range for s_1 the optimal effort is exactly $\bar{s} - s_1$.

First, if P exerts effort $e^* > \bar{s} - s_1 > \alpha$, then the probability of being above $\bar{s}$ is always 1. But then, any effort $e' \in (\bar{s} - s_1, e^*)$ is better than e^* for the following reason. First, note that under both e' and e^*, $\text{Prob}(s \geq \bar{s}) = 1$. Recall than *conditional* on a fixed probability for $s \geq \bar{s}$, the improvement arises the closer is the effort to the level α. Thus we cannot have $e^* > \bar{s} - s_1$.

Second, suppose that the level of effort is strictly below $\bar{s} - s_1$. But then, one of the two cases must occur.

Case 1: $\text{Prob}(s \geq \bar{s}) \in (0, 1)$ and so is dependent on effort. But then it is optimal to increase the effort to the level $\alpha - \frac{\theta}{a} > \bar{s} - s_1$, a contradiction to the above claim above that the optimal effort cannot exceed $\bar{s} - s_1$.

Case 2: $\text{Prob}(s \geq \bar{s}) = 0$. In this case, the optimal effort is α, where $\alpha < \bar{s} - s_1$, and the corresponding expected payoff is $\pi_1 \equiv \alpha(s_1 + \alpha + \frac{E[a]}{2}) - \frac{\alpha^2}{2}$. On the other hand, when exerting the effort $\hat{e} = \bar{s} - s_1$, the expected payoff is $\pi_2 \equiv \alpha(s_1 + \hat{e} + \frac{E[a]}{2}) + \theta - \frac{(\hat{e})^2}{2}$. The difference in expected payoffs is

$$\pi_2 - \pi_1 = \theta - \frac{1}{2}(\bar{s} - s_1 - \alpha)^2.$$

Note that because we are looking at the range $s_1 \in (\bar{s} - \alpha - \frac{\theta}{E[a]}, \bar{s} - \alpha)$, it must be that

$\bar{s} - s_1 - \alpha < \frac{\theta}{E[a]}$. But then, $\theta - \frac{1}{2}(\bar{s} - s_1 - \alpha)^2 > \theta - \frac{1}{2}\left(\frac{\theta}{E[a]}\right)^2$ where we also note that

$$\theta - \frac{1}{2}\left(\frac{\theta}{E[a]}\right)^2 > 0 \iff 2E[a]^2 > \theta.$$

Then, the inequality $\theta - \frac{1}{2}\left(\frac{\theta}{E[a]}\right)^2 > 0$ implies that $\theta - \frac{1}{2}(\bar{s} - s_1 - \alpha)^2 > 0$. Thus, the inequality $\pi_2 > \pi_1$ means that for $s_1 \in (\bar{s} - \alpha - \frac{\theta}{a}, \bar{s} - \alpha)$ the optimal effort cannot be strictly lower than $\bar{s} - s_1$.

As a result, we conclude that under the restriction $2E[a]^2 > \theta$, the optimal effort for $s_1 \in (\bar{s} - \alpha - \frac{\theta}{E[a]}, \bar{s} - \alpha)$ has to be exactly $\bar{s} - s_1$, which guarantees reaching the threshold $\bar{s}$ with probability 1.

Before obtaining the optimal effort function, we now consider the minimal threshold s_m at which P is indifferent between exerting effort e_1^*, and exerting the effort e_0^* (both e_1^* and e_0^* have been obtained above). We solve the indifference condition

$$\alpha\left(s_1 + e_0^* + \frac{E[a]}{2}\right) - \frac{(e_0^*)^2}{2} = \alpha\left(s_1 + e_1^* + \frac{E[a]}{2}\right) + \frac{s_1 + e_1^* + E[a] - \bar{s}}{E[a]}\theta - \frac{(e_1^*)^2}{2},$$

which implies

$$s_m = \bar{s} - \alpha - E[a] - \frac{\theta}{2E[a]}.$$

For the following we assume

$$s_m < \bar{s} - \alpha - \frac{\theta}{E[a]} \iff \theta < 2E[a]^2.$$

Then, under the parameter restriction $\theta < 2E[a]^2$ the optimal effort function becomes:

$$e^*(s_1|\theta < 2E[a]^2) = \begin{cases} \alpha & \text{if } s_1 < s_m \text{ or } s_1 \geq \bar{s} - \alpha, \\ \alpha + \frac{\theta}{E[a]} & \text{if } s_1 \in [s_m, \bar{s} - \alpha - \frac{\theta}{E[a]}), \\ \bar{s} - s_1 & \text{if } s_1 \in [\bar{s} - \alpha - \frac{\theta}{E[a]}, \bar{s} - \alpha). \end{cases}$$

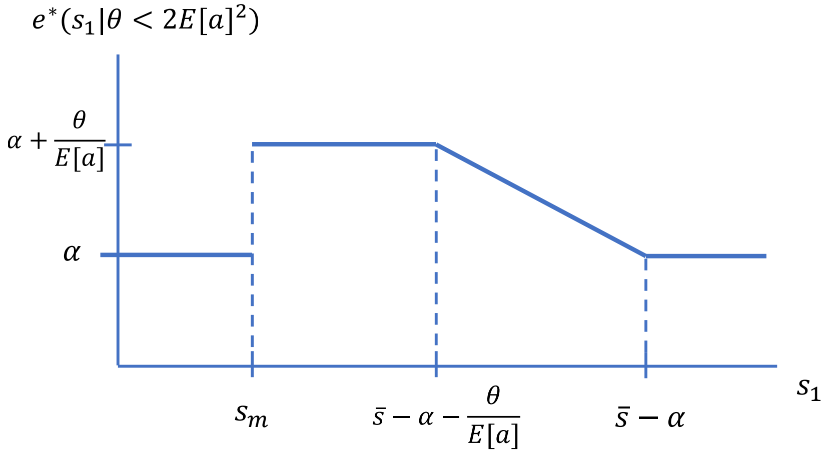


Figure C.3: Optimal effort as a function of s_1 under the restriction $\theta < 2a^2$.

See Figure C.3 for the illustration.