Online Appendix for: Media Attention and Bureaucratic Responsiveness

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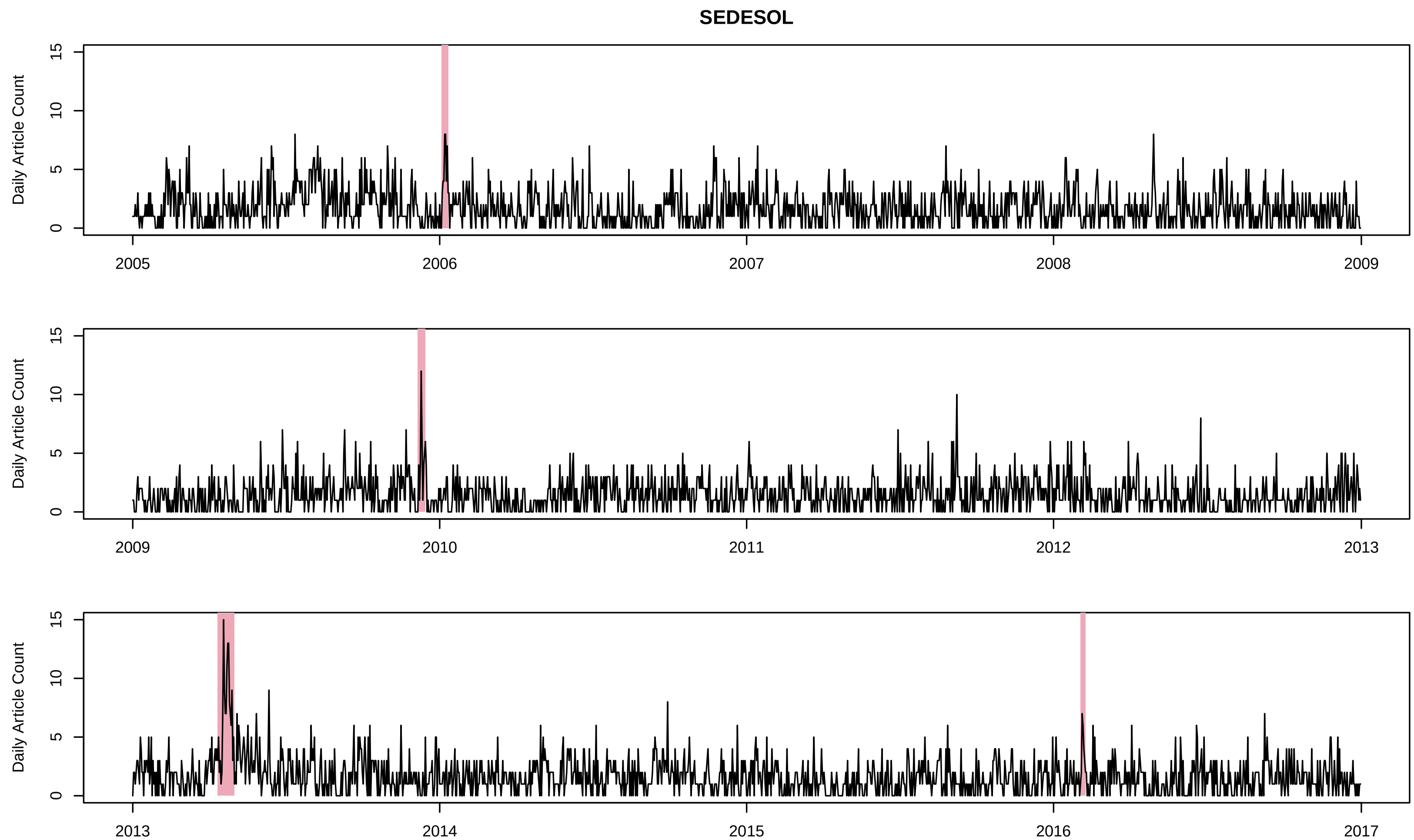
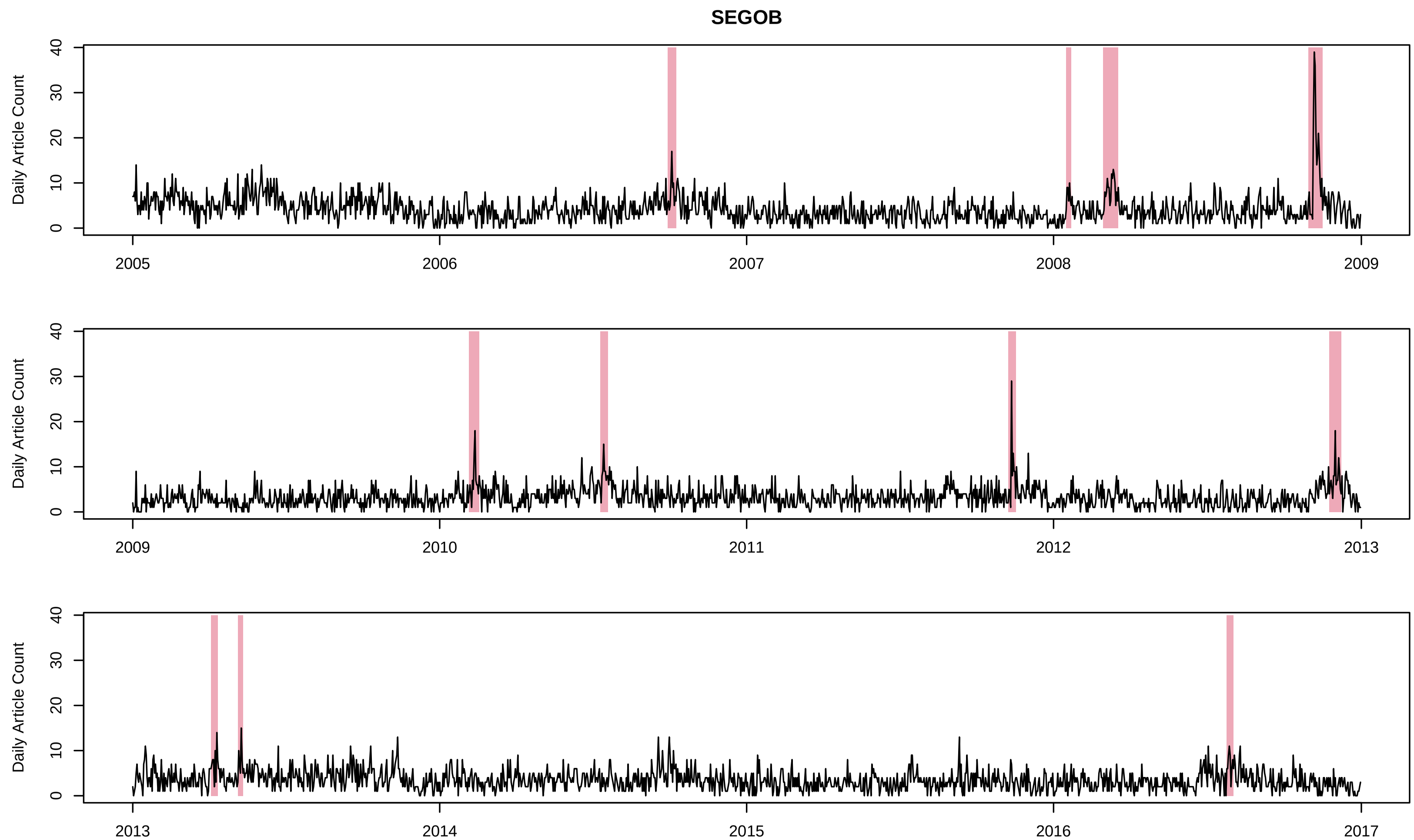


Figure A-1: Daily time series of news article mentions for Secretaría de Desarrollo Social (Ministry of Social Development), along with highlighted periods that the anomaly-detection algorithm identifies as anomalies after the removal of trend and seasonality components.



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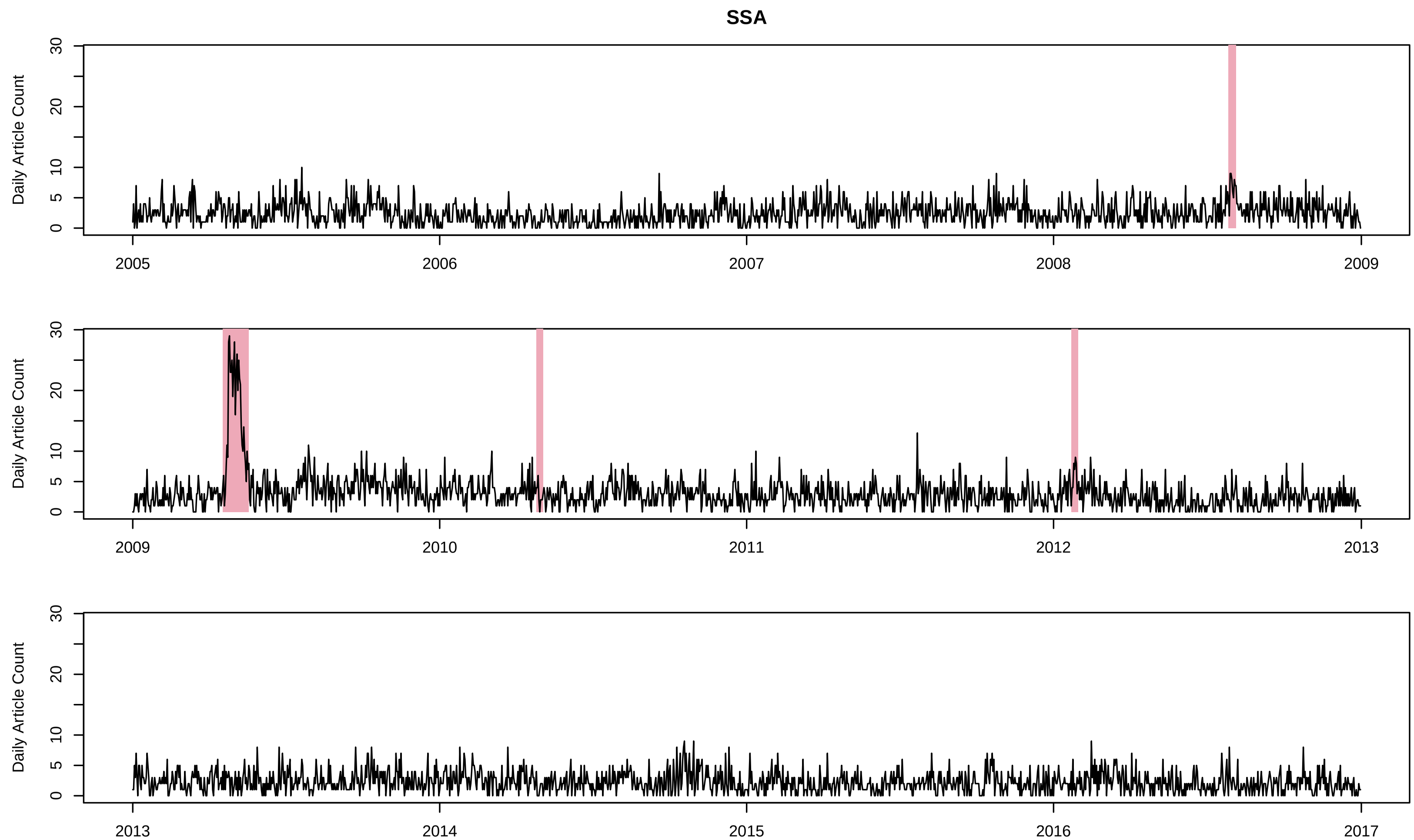

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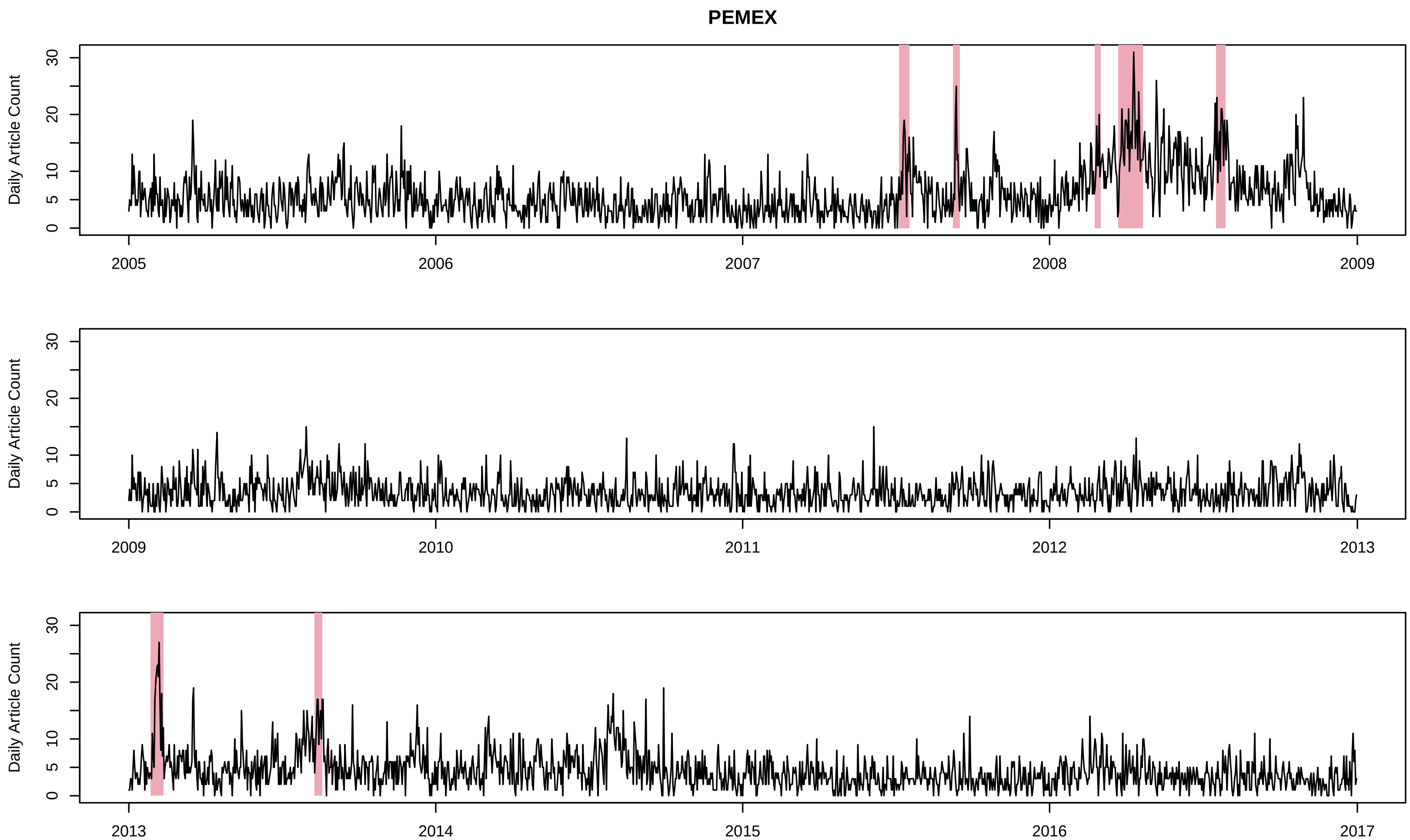

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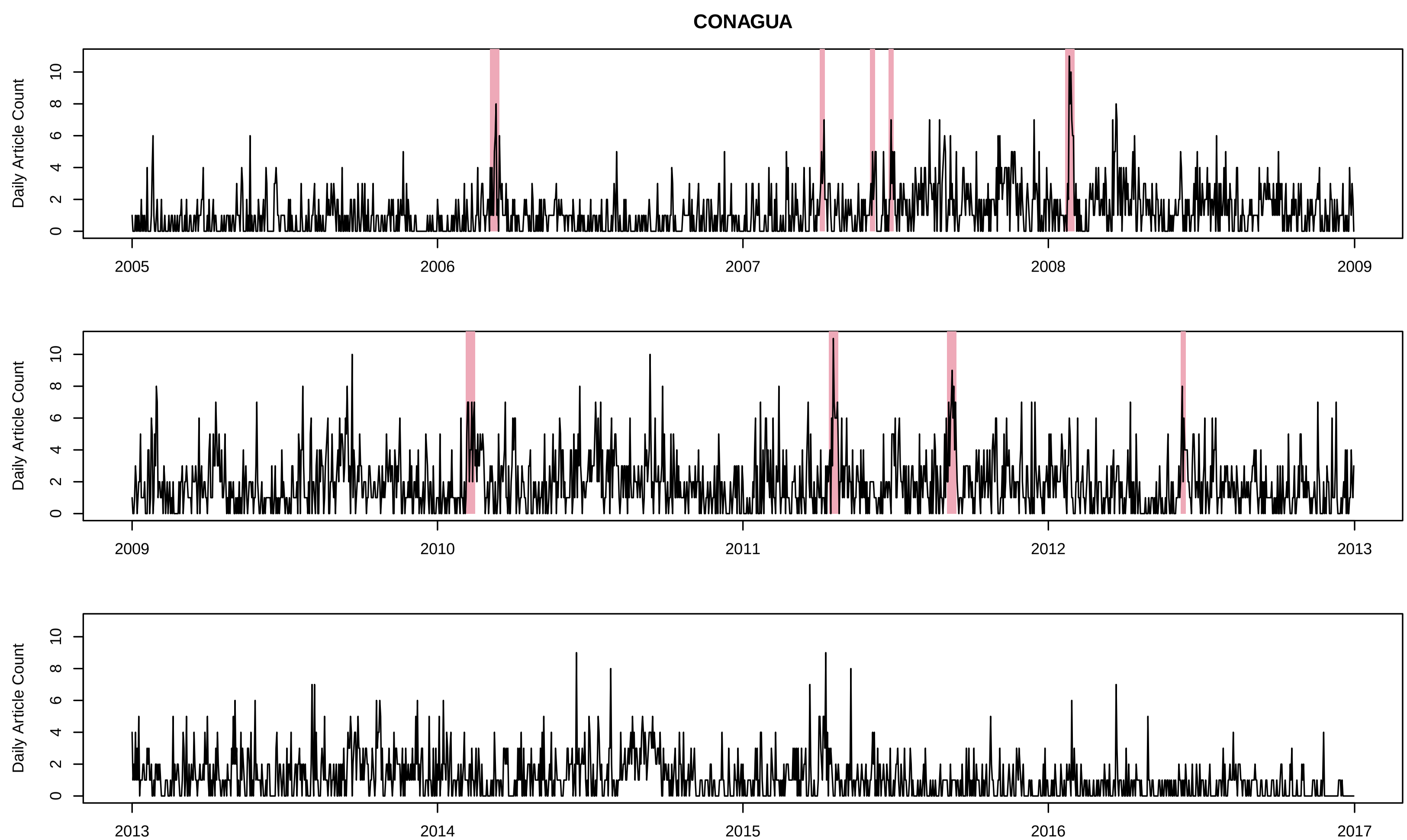

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B Media Anomaly Detection

B.1 Classical Decomposition Model Definition

In this work, newspaper data is represented as time series, which can be described as combinations of different components. A common way to represent a time series is through the classical decomposition model (**?**). Our implementation is based on the *statsmodel* python package. Formally, let X_t represent a time series. We can describe this time series as a realization of the process:

$$X_t = f(M_t, S_t, R_t) \tag{1}$$

where M_t is a function that varies in one direction (increasing or decreasing) known as **trend component**, S_t is a function that varies periodically known as **seasonal component**, and R_t is the **residual component** that represents random variations in the series.

The contributions of these different components can be represented as an additive model. Formally, we can define X_t as:

$$X_t = M_t + S_t + R_t \tag{2}$$

This model assumes that variations in the series are linear. In other words, changes over time are constant and the magnitude of seasonal fluctuations does not vary with the level of the time series.

B.2 Steps to Decompose a Time Series

The decomposition of times series is a useful abstraction that can help to understand the underlying elements of the data being analyzed. This process can be achieved in four steps, as described below.

B.2.1 Estimating the Trend

The first step is to estimate the trend component M_t. There are several ways that can be used, but two of the most common are:

- Estimate the trend by fitting a regression.
- Estimate the trend by using smooth functions, such as moving averages or exponential smoothing.

This step will result in an estimated trend $\hat{M}_t$. In our application, we use moving averages (MA) to model the trend. One thing to notice is that there are two ways to employ moving averages. The first is by using a two-sided moving average, which considers values centered at t. In other words, both past $(t-1, t-2, ...)$ and future $(t+1, t+2, ...)$ observations for M_t are considered in calculating the moving average. The other alternative is to use a one-sided MA, which instead employs a MA derived from *only* the past *or* future series, as defined above. In our application, we only use past values on t. That is, we employ the one-sided past values MA approach to estimate the trend, which prevents data leakage.

B.2.2 Removing the Trend

After estimating the trend $\hat{M}_t$, we remove it from the original time series X_t, resulting in a de-trended series X_t'. For an additive decomposition, this is done by subtracting $\hat{M}_t$ from the series.

$$X_t' = X_t - \hat{M}_t$$

B.2.3 Estimating the Seasonality

After removing the trend, the next step is to estimate the seasonality $\hat{S}_t$. This can be achieved using different methods. We use a simple method, which is often used to remove seasonality: we average the elements of the detrended series using a week as our time frame of interest, and remove the weekly seasonality from our detrended time series X_t' in this fashion. Weekly time units were selected for our considerations of seasonality given the (multi-day, but less than month-long) anomaly durations in our data, and given the broader aggregations employed throughout our paper.

B.3 Estimating the Residuals

The last step is to estimate the residuals, which can be achieved by removing the seasonality term from the detrended series X_t'. In our application, we remove the seasonality by subtracting it from the de-trended series:

$$\hat{R}_t = X_t' - \hat{S}_t$$

We then apply the G-ESD procedure to $\hat{R}_t$ as explained in the main text of the manuscript.

C Media Anomaly Coding Guidelines

Below are the guidelines developed to guide the two expert coders (two authors of this study) in coding each media anomaly. Following the below guidelines, each coder assigned a preliminary set of codes to every single anomaly. The two coders then discussed each of these individually, and reconciled on agreed codes and categorizations where they had initially disagreed. As all coders assessed every anomaly, both individually and then together, measures of inter-coder reliability are not relevant in this context.

Coding media attention anomalies:

We have identified periods of unusually high media attention to Mexican government ministries and agencies. These periods, which we call anomalies, are defined by an anomalously high number of articles mentioning the ministry/agency, its abbreviation, or the title of the Secretary.

We wish to assess what these anomalies are "about." Some may be corruption scandals, while others may be bursts of attention to policy announcements, officials being appointed or resigning, external crises, or things going wrong but without accusations of corruption by officials. Other anomalies could simply reflect periods where nothing out of the ordinary happened, but a few different "ordinary" mentions of an agency in the same week simply led to an anomaly being detected anyway.

The following describes the procedure for qualitatively reading and interpreting all anomalies.

1. In the spreadsheet, note the anomaly number (in the filename) and the relevant ministry or agency (at the top of the file).

2. Read the top ten articles for each anomaly, and consider the words distinctive to the anomaly (at the top of each document).

    - Note that these articles are a selection of all articles that mention the reference agency, during the period of the anomaly in question. They are selected on the basis of the frequency of words "distinctive" to the anomaly. However, bear in mind that some of these articles may nonetheless be "ordinary" news coverage that simply happens during the anomaly period, and not necessarily to the issue or event that instigated the unusually high degree of media attention. Additionally, bear in mind that these top ten articles are not in chronological order, and may NOT include the "first" article that instigated the anomaly. For instance, imagine a major investigative report of corruption in a major ministry, that is followed by a week of intense media attention to that ministry. That initial report may not actually appear as one of these top ten articles, but our reading of the ten articles can nonetheless look for the common thread that makes this period of attention distinctive. Lastly, note also that some articles are editorials, rather than reporting. We are still interested in these, as editorials discussing a major issue are indications of that issue's importance!

3. Write a short description (roughly one sentence) for each anomaly.

   - What appears to be the event or issue that is receiving unusually high media attention for this agency or ministry? Look for the common theme that appears in at least several of the articles and suggests that something out of the ordinary took place. For example, "explosion in Pemex Tower" or "resignation of the Secretary" or "human rights abuses in Chiapas" or "accusations of irregular spending" or "technical failures in passport system."
   - Be careful to focus only on the attention relevant to the specific reference agency/ministry, particularly in cases where only part of the article is relevant (or the article talks about multiple different ministries). It can also be useful to rely on Google searches to help fill in the details. For example, if I see many of the ten articles mention the resignation of the Secretary, or a new policy announcement, but I want to confirm the context surrounding these, I may search some of these terms or names on Google to see if I can get more context about what happened (but being careful to ensure that I am learning about something that matches the timeframe of the anomaly in question).

- If the top ten articles are not sufficiently clear, the additional articles (in order of the frequency of distinctive words) should be consulted for additional information to inform interpretation of the anomaly theme.

4. Categorize the issue or event into one of the following categories.

   - No clear theme: This pertains to cases where no clear theme is present, and instead the articles comprise media attention to a diversity of more minor or ordinary events or issues, none of which would merit anomalous media attention on their own, but rather simply happened to coincide in time.
     - Note: In most cases, this should only be coded if no more than any two of the top ten articles pertain to any same event or issue. If three or more articles pertain to the same event or issue, that suggests this issue should be categorized as below, unless the coder's judgement suggests otherwise. In many cases, it will be useful to refer to additional articles beyond the "top ten" during the anomaly.
   - Policy: Media attention to new policy announcements, policy changes, or the policy output of the agency. This category includes the ordinary activities of the agency, which may receive anomalous attention due to a particularly high profile episode (e.g. for INM the arresting of a large group of migrants).
     - Note: Except in unusual cases, this should be specific to the agency in question.
     - Note also that policy should not normally be coded alongside "government failure" for the same event, as failure by definition pertains to policy output. A category of failure thus "trumps" policy, except in cases where policy and government failure pertain to distinct dimensions of the same event, such that the policy dimension would likely have received high media attention even absent the failure.
   - Personnel: Media attention to personnel changes, especially to Secretaries or other agency heads being appointed or leaving office.

- Note: Except in unusual cases, this should be specific to the agency in question.

- External: Media attention to events or forces external to the agency in question but that affect its decisions. This is something that "happens to" the agency. These may be unexpected shocks but may also be ongoing, such as an economic crisis or a drought.

- Government failure: Media attention to negative consequences of official decisions, to mismanagement (without any reporting of corruption or patronage), or to abuses committed by street-level government agents (such as police or military).
  - Note: Except in unusual cases, this should be specific to the agency in question. This theme should not be coded for failures that are clearly the responsibility of some other entity, without even an "enabling" role of the agency in question.

- Corruption: Media attention to corruption, patronage, or other wrongdoing by politicians or officials.
  - Note: Corruption should be categorized even where it may not have been committed directly by officials of the relevant agency. For instance, if the agency is in the news because of corruption allegations regarding the Secretary's previous role at a different organization, this should still be coded as "corruption" as it is highly likely to bring corruption-related scrutiny to the agency in question as well.
  - Note that investigations of corruption by an investigatory body should normally be categorized as "Policy" for that agency, except where the investigatory body itself may be considered to have enabled the corruption in question, or to have limited investigations, for political purposes.

- In some cases, an anomaly cannot be clearly assigned to just one category; or an event or issue clearly pertains to two different categories. In such cases, an anomaly should also be assigned a second category. You can discuss this if useful in the "notes" field. An example might be a minister being dismissed because of a corruption scandal. Or, reporting of government failure that also involves accusations of corruption. If you are not sure which of two categories ought to be the "primary" one, break the tie by emphasising the one further down the list above — that is, category E trumps category D, and so on.

- In some cases, an anomaly appears to capture two distinct anomalous events that took place at the same time, but each of which would likely warrant intense media attention on their own. Where clearly warranted, and supported with additional reading of articles beyond the top ten, categories relevant for this second event can be recorded. In such cases, the theme and notes fields should note both and explain the relevant reasoning. A secondary event should only be assigned if at least three articles appear to pertain, and if the event in question is clearly something that took place during the anomaly period, rather than being an ongoing issue or process that was likely receiving just as much attention prior to anomaly onset. In cases of potential secondary events, it may be useful to rely on Google searches for additional context.

5. Separately, code whether or not the event exposes the agency substantial controversy or negative attention. By definition, a category of "government failure" or "corruption" will receive a 1 here by default. However, this variable is particularly important to note for the other categories, where, for instance, some policy changes are relatively innocuous whereas others are highly controversial and likely to expose the agency to substantial scrutiny. Or, similarly, some personnel changes clearly "look bad" for the agency given the circumstances of departure, even if the context does not necessitate the assignment of an additional category of corruption or government failure.

D Additional Example Media Anomalies with Codings

Entity	**Year**	**Description**	**Theme**	**Negative**
CONAGUA	2006	Mexico City hosts World Water Forum.	Policy	0
SEMARNAT	2008	National Reforestation Day with goal of planting 5 million trees.	Policy	0
IMPI	2010	Legal dispute over trademark for name of Chivas football team.	Policy	0
COFEPRIS	2014	Launch of new nutritional label guidelines identifying healthy foods.	Policy	0
SRE	2006	Controversy over Mexico City Sheraton Hotel expelling Cuban diplomats in accordance with US law but in violation of Mexican law.	Policy + External	1
PEMEX	2008	Debates over energy sector reform proposals.	Policy	1
SCT	2010	Controversy and court cases over Televisa winning contracts for cell phone frequency.	Policy + Corruption	1
IMSS	2013	Proposals to raise payroll deductions for social security.	Policy	1

Table D-1: Example media anomalies and codings for Policy category.

Entity	Year	Description	Theme	Negative
SENER	2006	New Secretary announced as Calderon enters office.	Personnel	0
SHCP	2006	New budget proposal and new Secretary announced as Calderon enters office.	Personnel + Policy	0
SAGARPA	2009	New Secretary announced.	Personnel	0
SEDESOL	2009	New Secretary announced.	Personnel	0
SEGOB	2010	New Secretary announced after previous Secretary resigned in opposition to electoral coaliations with PRD.	Personnel	1
COFEPRIS	2011	Pressure from television industry forces Commissioner to resign after introducing new ban on advertising of miracle products.	Personnel + Policy	1
SEGOB	2011	Secretary Blake Mora dies in helicopter crash.	Personnel + External	1
SFP	2015	New Secretary appointed and tasked with investigating potential conflict of interest involving properties of the First Lady and SHCP secretary, with criticism over lack of credibility and limited scope of investigation.	Personnel + Corruption	1

Table D-2: Example media anomalies and codings for Personnel category.

Entity	**Year**	**Description**	**Theme**	**Negative**
SEGOB	2006	SEGOB organizes meetings to resolve dispute between protesters and state government of Oaxaca.	External + Policy	0
SRE	2009	Disputes with other countries over H1N1 influenza epidemic.	External + Policy	0
IMPI	2010	Legal dispute over trademark for name of Chivas football team.	External + Policy	0
COFEPRIS	2016	Considering approval of new generic influenza vaccine amidst shortages.	External + Policy	0
IMSS	2009	H1N1 swine flu epidemic.	External	1
SRE	2010	Criticism over response to Haitian earthquake, including losing track of how many Mexican nationals in the country, and insensitivity in reporting deaths.	External + Gov. Failure	1
PEMEX	2013	Explosion in PEMEX tower leaves 37 dead.	External + Gov. Failure	1
SAGARPA	2013	Mass death of farmed shrimp due to bacteria.	External + Gov. Failure	1

Table D-3: Example media anomalies and codings for External category.

Entity	Year	Description	Theme	Negative
INM	2007	Raid on Cancun nightclub owned by former Argentine spy and accused of prostitution, but staff were tipped off ahead of time.	Gov. Failure	1
SEP	2007	Standardized test results announced later than promised, and abandonment of plan to use them to rank schools.	Gov. Failure + Policy	1
SSA	2009	H1N1 swine flu epidemic, with criticism of Ministry's initial delay in issuing alert, and of steps taken to handle the crisis.	Gov. Failure + External	1
IMSS	2009	Death of 38 children in Hermosillo childcare center fire, contracted out by IMSS to a company with legal violations and accusations of corruption.	Gov. Failure + Corruption + External	1
COFEPRIS	2011	FIFA announces over half of tested football players in recent tournament showed traces of clembuterol steroid from eating contaminated meat.	Gov. Failure + External	1
COFEPRIS	2013	Criticism of response to crisis as 800 tons of imported Russian asbestos being stored in open air in Veracruz.	Gov. Failure + External	1
SRE	2015	New passport system faces technical failure, linked to earlier questionable contracts.	Gov. Failure + Corruption	1
SEDENA	2016	Video released showing military and federal police torturing woman in cartel investigation, and Secretary apologizes for military's conduct.	Gov. Failure	1

Table D-4: Example media anomalies and codings for Government Failure category.

Entity	Year	Description	Theme	Negative
SENER	2006	During presidential debate, AMLO makes accusations of corruption by Calderon when he was SENER secretary involving contracts to his brother-in-law's company.	Corruption	1
SHCP	2007	Former Secretary joins HSBC board of directors, raising concerns over conflict of interest.	Corruption + Personnel	1
CFE	2011	Investigation of corruption by former CFE Director of Operations accused of accepting bribes including a yacht and a Ferarri.	Corruption	1
SAGARPA	2011	Accusations SAGARPA involved in vote-buying in Michoacan governor election.	Corruption	1
SHCP	2014	Accusations of conflict of interest over Secretary purchasing a house from Grupo Higa while running presidential transition.	Corruption	1
IMSS	2015	Introduction of new medicine subsidies, a campaign promise of PVEM, with accusations of electoral misuse.	Corruption + Policy	1
SRE	2015	Accusations of corruption over SRE awarding passport issuance contract to a company making a much more expensive bid.	Corruption	1
SEDESOL	2016	Phone recordings reveal SEDESOL delegate in Quintana Roo misusing funds for electoral purposes.	Corruption	1

Table D-5: Example media anomalies and codings for Corruption category.

E Procedure for Second Empirical Approach: Matched Comparison Groups

Recall that our first analysis approach in the main paper applied a panel fixed-effects approach to weekly-level data aggregations. Although this approach is appealing both for its simplicity and ability to make comparisons over time and across agencies, it also has two shortcomings. First, it aggregates away from our fine-grained data on each individual request and response. Second, some responses during anomaly-exposed weeks may be to requests filed after the onset of the anomalous media attention, and thus potentially endogenous to it. To examine exogenous requests exclusively, our second empirical approach thus focuses on the *queue* of requests that had already been filed, but were still awaiting response, on the eve of each anomaly onset. However, making appropriate comparisons is more difficult in this context, particularly as requests that are "in queue" for longer periods before receiving a response will also have higher exposure to potential media anomalies than will requests that receive rapid responses. Our solution is to compare each request from "exposed" queues with a set of matched comparison requests (on the same topic, and with the same number of days already elapsed in queue) drawn from comparison queues at the same agency but during non-anomaly periods. Our procedure is as follows:

First, for each anomaly, we take the queue of agency requests already received, but still awaiting response on the day prior to anomaly onset. To prevent very large queues from some agencies from overwhelming the results, we cap each queue at 100 requests, and therefore randomly sample 100 requests from queues larger than this.

For each anomaly, we then sample 20 comparison dates (ten each before and after) from a four-year period extending from 2.5 years before anomaly onset, to 2.5 years after, but excluding the six months immediately before and after.[1] We then combine all requests from these comparison dates (only for the same agency) into a pool of potential comparison requests.

Next, we match each individual request from the "exposed queue" with other requests from the

[1]We also exclude any period where the agency is experiencing another media anomaly.

"comparison pool" that are about the same topic, and that have the same number of days elapsed since filing. Thus, an anomaly-exposed request about the environment that had been awaiting response for twelve days will only be compared with other requests filed with the same agency, also about the environment, and also awaiting response for twelve days as of their own "comparison" dates. These date-restricted comparisons, while complex, ensure that our results are not biased by varying exposures among requests with already different times-to-response.

For each request, we measure the number of days *remaining* until response, from either the date of anomaly onset or the comparison date, to be used as one of the dependent variables of the ultimate models (the other being response type). We restrict each comparison group to a constant size of ten requests, sampling with replacement where the groups are larger or smaller than this. Results are based on fixed effect comparisons only *within* these comparison groups, each comprising one anomaly-exposed request and ten comparison requests.

We then repeat the procedure for all anomalies and combine the resulting matched datasets. We model time-to-response and indicators of "bad" response, within comparison groups, as a function of an indicator for anomaly exposure (either in general or for subcategories of anomaly), with or without request-level control variables. As the procedure involves some small sampling variability, repeat the entire procedure 1000 times and average across all results.

By including fixed effects for each comparison group, we automatically account for fixed effects for each anomaly and for each agency. Our main paper thus presents the results from this second approach in full. As mentioned in the main paper at this juncture, we also differentiate the results of this approach by the characteristics of each anomaly, and cluster standard errors by comparison group.

F Panel Fixed Effects Models of Agency-Week Incoming Request Volume

Below we assess the effects of media anomalies on the volume of *incoming* requests received by government agencies, using panel fixed-effects models of weekly request volume (logged). The overall average effect of anomaly exposure is positive and statistically significant, equivalent to 8.4 percent more requests per week. Disaggregation reveals the effects differ by anomaly type. First, differentiating negative from other (positive or neutral) anomalies reveals that the increase in request volume arises solely from negative media attention. Members of the public thus react to negative media scrutiny by making increased demands for information from government agencies, but they do not react in this manner to media attention in general. We then disaggregate negative attention further into media anomalies arising from government failure, corruption, or the remaining category of controversy (those anomalies which we coded as risking substantial negative scrutiny or controversy without being categorized into either the government failure or corruption themes). The results show that neither government failure nor controversy are significantly associated with increased request volume, although the coefficient is larger for government failures. Finally, the fourth model differentiates anomalies only by themes, finding no significant results, but with the largest coefficient again for government failure.

	Model 1	Model 2	Model 3	Model 4
Lagged Request Volume (log)	0.219^{***}	0.219^{***}	0.218^{***}	0.219^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Anomaly Exposure	0.076^{*}			
	(0.080)			
Anomaly Exposure: Negative		0.106^{***}		
		(0.009)		
Anomaly Exposure: Positive/Neutral		-0.035	-0.035	
		(0.765)	(0.765)	
Anomaly Exposure: Gov. Failure			0.099	0.070
			(0.174)	(0.434)
Anomaly Exposure: Corruption			0.034	0.017
			(0.625)	(0.829)
Anomaly Exposure: Controversy			0.181^{***}	
			(0.000)	
Anomaly Exposure: Policy				0.051
				(0.399)
Anomaly Exposure: Personnel				-0.000
				(0.995)
Anomaly Exposure: External				0.033
				(0.655)
N	11924	11924	11924	11924
R^2	0.760	0.760	0.760	0.760

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F-6: Panel fixed-effects models of the logged number of requests received by agency-week. All models include agency fixed effects and week fixed effects. Larger coefficients indicate higher public demand for information. Standard errors clustered by agency. P-values are displayed in parentheses.

G Matched Comparison Group Models: Average Effects of Anomaly Exposure

	Model 1	Model 2	Model 3	Model 4
Dependent Variable:	Time	Time	Type	Type
Anomaly Exposure	-0.020^{***}	-0.016^{***}	0.012^{**}	0.012^{**}
	(0.000)	(0.000)	(0.041)	(0.041)
Request Length (log)		0.105^{***}		0.007^{**}
		(0.000)		(0.037)
Request Readability		0.063		0.051^{**}
		(0.322)		(0.042)
Request Attachment		-0.034^{***}		0.021^{**}
		(0.002)		(0.045)
Request Medium		-0.073		0.040^{*}
		(0.256)		(0.058)
Request Legalism		0.694^{***}		1.108^{**}
		(0.000)		(0.047)
Request Punctuation		0.021		0.127^{**}
		(0.148)		(0.045)
Agency Workload		0.111^{***}		0.016^{**}
		(0.000)		(0.044)
N	82359	82359	82359	82359
R^2	0.448	0.457	0.45	0.453

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table G-7: Linear models of request-level response time and response type, within matched comparison groups. Each anomaly-exposed request from the queue of requests awaiting response on the day before anomaly onset is matched with comparison requests to the same agency, on the same topic, and awaiting response for the same number of days as of sampled comparison dates. Larger coefficients indicate lower government responsiveness. All models include fixed effects for each comparison group. Standard errors clustered by comparison group. P-values are displayed in parentheses.

H Assessing Whether Incoming Request Volume Predicts Anomaly Onset

To assess potential concerns that information requests themselves might trigger anomalous media attention (which would mean that requests filed prior to anomaly onset could not be considered "exogenous"), we conducted an event history analysis of anomaly onset at the agency-day level. In this analysis, observations are agency-days, and the dependent variable is an indicator taking a value of 1 for the day of anomaly onset for a given agency (consistent with standard practice for event history modeling, the sample excludes all anomaly days following the relevant day of onset). The main independent variable of interest is a rolling count of the number of requests received by each agency over the preceding 7 days (and logged as the count is skewed). Thus, as suggested, we seek to assess whether there is an association between requests and the onset of a period of anomalously heightened media attention.

We present four variants of this analysis in the table below, with two alternate ways of including duration-dependence, and with and without different fixed effects. In no model is there any evidence that a higher incoming request volume predicts anomaly onset, and in the simpler models there is even evidence of the opposite (although the non-significance of this after including agency fixed effects suggests that the initial negative relationship is largely an artifact of cross-agency differences in request volume). This offers support for our consideration of pre-anomaly requests as exogenous.

	Model 1	Model 2	Model 3	Model 4
Log(Request Count Preceding 7 Days)	-0.184^{*}	-0.226^{**}	-0.164	-0.262
	(0.080)	(0.032)	(0.255)	(0.119)
Log(Days Since Last Onset)	-0.242^{***}		-0.135	-0.052
	(0.001)		(0.107)	(0.543)
Days Since Last Onset		-0.003^{***}		
		(0.001)		
Days Since Last Onset^2		0.000^{**}		
		(0.012)		
Days Since Last Onset^3		-0.000^{*}		
		(0.056)		
Agency Fixed Effects			X	X
Year Fixed Effects				X
Month Fixed Effects				X
AIC	1642.736	1642.718	1663.484	1659.486
N	82417	82417	82417	82417

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table H-8: Logistic regression models of media anomaly onset. DV is an indicator for the first day of each period of anomalously heightened media attention. Observations are agency-days, excluding anomaly-days (after onset) from the sample. P-values are displayed in parentheses.

I Results for Responses to Personal Data Requests

	Model 1	Model 2	Model 3	Model 4
Lagged Personal Data Request Volume (log)	0.446^{***}	0.446^{***}	0.446^{***}	0.446^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Personal Data Response Volume (log)	0.134^{***}	0.133^{***}	0.133^{***}	0.134^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Anomaly Exposure	0.038			
	(0.399)			
Anomaly Exposure: Negative		0.077		
		(0.113)		
Anomaly Exposure: Positive/Neutral		-0.105^{*}	-0.106^{*}	
		(0.053)	(0.053)	
Anomaly Exposure: Gov. Failure			0.011	-0.120
			(0.918)	(0.204)
Anomaly Exposure: Corruption			0.082	0.105
			(0.339)	(0.233)
Anomaly Exposure: Controversy			0.125^{**}	
			(0.039)	
Anomaly Exposure: Policy				-0.006
				(0.893)
Anomaly Exposure: Personnel				-0.087
				(0.376)
Anomaly Exposure: External				0.152^{**}
				(0.017)
N	11915	11915	11915	11915
R^2	0.826	0.826	0.826	0.826

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table I-9: Panel fixed-effects models of the logged number of responses provided by agency-week, considering only responses to personal data requests. All models include agency fixed effects and week fixed effects. Larger coefficients indicate higher government responsiveness. Standard errors clustered by agency. P-values are displayed in parentheses.