Taken at Face Value: Emotion Expression and Protest Dynamics

Ishaan S. Prasad* & Zachary C. Steinert-Threlkeld*

*University of California, Los Angeles

https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660 Content not peer-reviewed by APSA.

Abstract

Understanding the role of emotions in protest is a growing field of research, but existing research does not address the role of emotions once protests start. By applying computer vision models to the expressed emotions of the 37,558 faces in 7,824 geolocated protest images across twelve protest waves in ten countries, this article makes five contributions to the study of emotions and protest. Most importantly, it measures emotions within protest waves, not before them. It also investigates emotions' temporal effects, multiple emotions simultaneously, connects them directly to actual protests, and does so across multiple countries. The results suggest that anger, disgust, fear, happiness, sadness, and surprise occur simultaneously throughout a protest, though happiness peaks on the first day. Emotions sometimes correlate with protest size in unexpected directions, and the coefficient signs differ by country. The most consistent finding is that models without lagged terms outperform those with lags, suggesting emotions and protests covary more than the former causes changes in the latter. *Keywords*: protest, emotions, collective action, social movements, computer vision, machine learning, violence.

Replication data and scripts will be made available upon publication.

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Introduction

Existing research has established that emotions impact protest mobilization (Verhulst and Walgrave, 2009; Pearlman, 2013; Aytaç et al. 2018; Young, 2019), but five gaps remain. First, very little research analyzes emotional mobilization *during* a protest. Second, theory is ambiguous: emotions are instantaneous reactions to events but also proceed mobilization. Third, multiple emotions are rarely considered simultaneously. Fourth, tests of emotions and protest rarely measure actual protest. Fifth, whether or not emotions operate similarly across contexts remains unclear.

This article attempts to fill these gaps by studying expressed emotions in 310,041 geolocated tweets with images, 7,824 of which are protest images containing 37,558 individual faces from twelve protest waves in ten countries. A computer vision model detects protest images and counts faces, while another assigns one of anger, disgust, happiness, neutral, surprise, fear, and sadness to faces. A third model estimates protester and state violence. Images are aggregated to the country-city-day, and two dependent variables, protest size and the percent of faces containing a particular emotion, are developed.

This article complicates the understanding of emotions and protest in several ways. All emotions except for surprise are positively associated with contemporaneous protest size, but when considered simultaneously only anger is. Larger protests are associated with a greater percentage of every emotion: protests are emotional, not dominated by a specific emotion. Differences emerge when comparing contemporaneous and lagged models. Only happiness and surprise are significantly correlated with subsequent protest size, and then with signs opposite of theoretical expectations. Previous protests are only statistically associated with increased angry and disgusted faces. Models with lagged variables also explain less variation in protest size and emotions than contemporaneous models. Finally, emotions' statistical significance varies across protest waves and sometimes switches signs, suggesting that how emotions and protest interact varies by country: emotions matter differently at different times.

Motivation

There exists a growing literature analyzing emotions and contentious politics. This literature describes emotions as affect or reactive, with the latter driving action (Jasper, 1998). In turn, reactive emotions can mobilize or demobilize. Mobilizing reactive emotions such as anger, joy, and pride embolden protesters and bystanders by emphasizing the value of dignity, expanding one's sense of identity, and promoting optimism and risk acceptance. Demobilizing reactive emotions such as fear, sadness, and shame emphasize security, causing individuals to make pessimistic assessments and doubt their individual efficacy. (Pearlman, 2013). Field experiments confirm the mobilizing effect of anger and demobilizing effect of fear (Young, 2019; Young, 2023).

This article starts to fill five gaps in the existing literature. The article's biggest contribution is to study emotions *within* a protest wave. The difficulty of measuring emotions during protests means how they vary within a protest wave has received less consideration. For example, though anger and joy are theorized to mobilize, participant recollections describe joy as *resulting from* mobilizing, not causing it (Zhao, 1998; Pearlman, 2018). Moreover, since reactive emotions are transient by definition, they may vary during a protest. For example, protesters may arrive at a protest feeling neutral but develop anger in response to seeing others express it; certain emotions may therefore result from protest mobilization.

Given the novelty of the first contribution, it is theoretically unclear if emotions and mobilization interact concurrently or with a lag. On one hand, the literature's focus on transitory emotions suggests they affect mobilization as they happen. Yet researchers commonly ask about individuals' emotional state before protesting (Verhulst and Walgrave, 2009; Pearlman, 2013), implying transitory emotions operate on at least a day's lag. This article's research design enables a discriminatory test of these competing expectations.

Third, existing research focuses on singular emotions, yet emotions do not occur in isolation. For example, many first-time protesters report feeling motivated by anger (mobilizing) and powerlessness (demobilizing) to participate (Verhulst and Walgrave, 2009). In Zimbabwe, asking subjects to remember a time they were afraid increases reported fear

https://doi.org/10.33774/apsa-2025-ftqx3 ORCID: https://orcid.org/0000-0002-5122-9660

(demobilizing) but also anger, disgust, and surprise (mobilizing emotions). Since mobilizing and demobilizing emotions occur simultaneously, the net effect of either is not *a priori* clear.

Fourth, existing research rarely directly measure protests. Case studies rely on participants' memory and may suffer from social desirability bias. Experiments on emotions and protest participation use proxies for such as selecting a pro-democracy wristband after the experiment (Young, 2019) or engaging in online discussion (Young, 2023). Studies that connect emotions to political engagement focus on voting (Panagopoulos, 2010), participating in a political campaign (Valentino et al., 2011), or donating to a non-profit organization (Paxton et al., 2020), not protest. These limitations are inherent to the ethical considerations of experiments, whereas this study's use of observational data allows for the observation of emotions *during* protests.[1]

Fifth, the difficulty of measuring emotion means no study analyzes emotion dynamics across multiple events. For example, emotions may play a greater role during protests for public goods than for particularistic ones such as student or labor reforms. We are aware of only one study that analyzes emotions across protests (Verhulst and Walgrave, 2009) and another dynamics during (Zhu et al., 2022). This study's data allows for the analysis of emotions within and across events.

Research Design

Emotions and protest dynamics are studied in the 12 protest waves shown in Table 1. Three criteria drive their selection. First, the issues focus on public goods. Emotions are most likely to affect mobilization for public goods since participants are not motivated by personal benefits. If emotions affect protest dynamics, then they are most likely to do so in protests such as these. Second, they occur before COVID-19 lockdowns, so there is not a concern that wearing face masks affect measurement. Third, countries were selected to ensure geographic and institutional heterogeneity.

Three sets of variables are operationalized, all at the country-city-day level. The raw data are geolocated protest images shared on Twitter; Appendix A describes the data

[1]The closest article of which we are aware is Verhulst and Walgrave (2009). That article asks protest participants to recall their emotions *before* participating.

Table 1

Protest waves described by nation and date ranges.

Protest Wave	Nation	Issue	First Protest	Last Protest
Hong Kong 1	Hong Kong	Democracy	Sep. 18, 2014	Dec. 23, 2014
Venezuela 1	Venezuela	Anti-regime	Oct. 22, 2014	Feb. 10, 2015
Gabon	Gabon	Election	Aug. 23, 2016	Sep. 23, 2016
Korea	Korea	Anti-incumbent	Oct. 19, 2016	Mar. 15, 2017
Venezuela 2	Venezuela	Anti-regime	Dec. 29, 2016	Dec. 17, 2017
Russia	Russia	Anti-corruption	Mar. 12, 2017	Apr. 27, 2017
Spain	Spain	Secession	Aug. 31, 2017	Jan. 01, 2018
Pakistan	Pakistan	Religion	Oct. 31, 2017	Dec. 01, 2017
Hong Kong 2	Hong Kong	Security	Mar. 01, 2019	Dec. 31, 2019
Chile	Chile	Inequality	Oct. 01, 2019	Oct. 30, 2019
Iraq	Iraq	Anti-incumbent	Oct. 25, 2019	Dec. 31, 2019
Lebanon	Lebanon	Anti-austerity	Oct. 26, 2019	Jan. 12, 2020

collection pipeline. First, the number of faces expressing emotions are measured from facial expressions in geolocated protest images from Twitter. Emotions are measured using Python's `Py-Feat` packages while the number of faces is operationalized using a Python implementation of `dlib`. The latter detects more faces than the former, though robustness checks using only `Py-Feat` faces for the protest size estimate show this descrepancy does not change results. The possible emotions are anger, disgust, happiness, neutral, surprise, fear, and sadness.

Figure 1 shows four sample images from Lebanon with expressed emotions labeled. In each figure's right panel, the bar colors correspond to faces, so the longest bar per color is the estimated emotion for that face.

To address concerns about measuring emotions from images, Figure 2 shows the distribution of anger, fear, happiness, neutrality, and sadness by protest and non-protest images as the number of faces changes. (A subset of emotions are shown to reduce figure crowding. Figure A1 shows the distribution of all seven protests by protest and non-protest image.) First, protest photos could exaggerate emotions if emotions make for more appealing photographs. In fact, neutral emotions are the second most common one. Though they appear slightly more common in non-protest than protest images, Figure A1 shows that across

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Figure 1

Sample Images From Lebanon With Expressed Emotion Labels

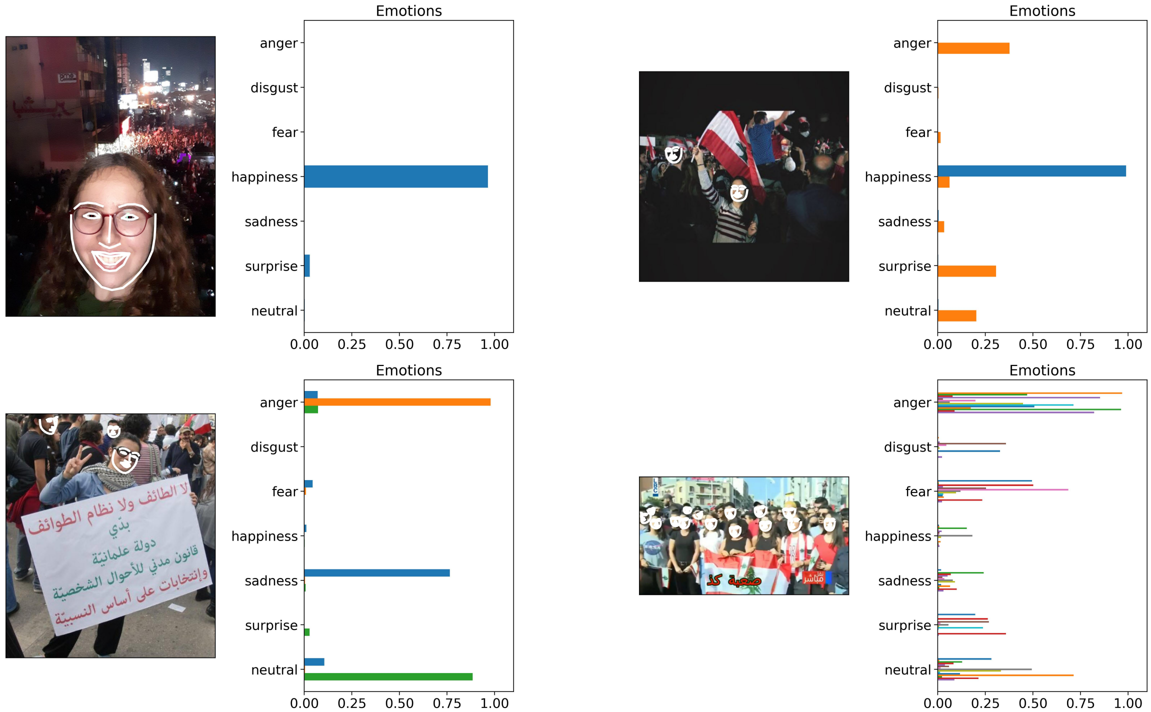
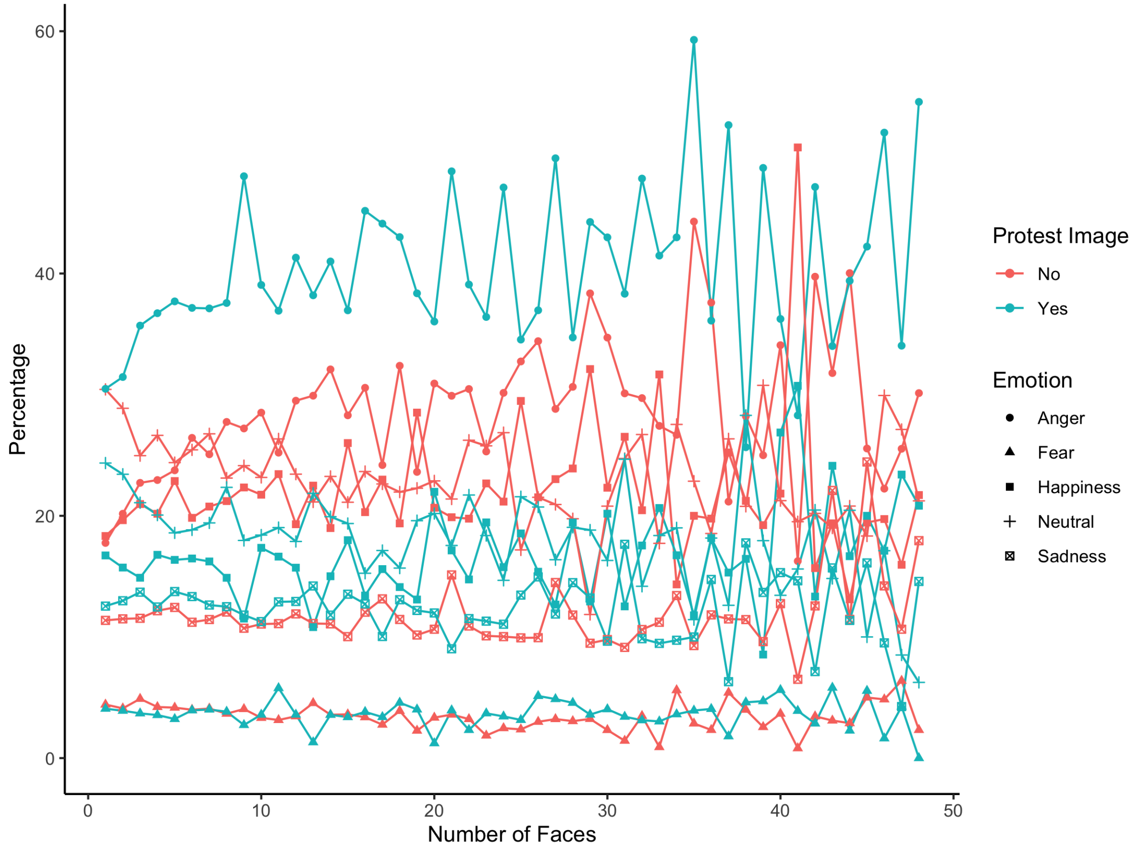


image types they are equally common. Second, protest images could underestimate fear because protesters are running away from police and do not have time to take photographs or do not want to publicize images of fear because they could make protesters look weak. The bottom two lines show that this is not the case: fear is the least common emotion in protest and non-protest images, and they approximately equally common in both. Third, people pose for photographs and may express an emotion not congruent with their emotion at the rest of the protest. If that were the case, however, it is unlikely that the most prevalent emotion for protest images would be anger or the second most common neutral. In fact, anger is the most common emotion until a protest image contains 38 faces, when 28.3% are neutral versus 25.7% express anger. In addition, the second and third images in Figure 1 show that many of the emotions recorded are from faces of individuals *not* posing for photographs and therefore not at risk of introducing measurement error. It could be the case, nonetheless, that most photos of one individual are not representative.

Figure 2

Distribution of Emotions by Image Type and Number of Faces



Second is protest size, the number of protesters per country-city-day, operationalized as the number of faces in protest photos. This operationalization faces two measurement threats. First, images of large crowds make it difficult to count faces, as they become too small for algorithmic detection or others' bodies hide them. Since other research compares this operationalization to protest size estimates from cell phone location records and news article reports and finds it accurately measures protest size (Sobolev et al. 2020), this article's size estimates should also accurately measure protest size. In addition, the protest waves from Steinert-Threlkeld and Joo (2022) and Steinert-Threlkeld et al. (2002) are included in this study, and those articles validated their size using news articles. Second, fake images could distort protest size; manual inspection did not uncover fake images, and other work using geolocated tweets during contentious events also finds no evidence of manipulation (Gohdes and Steinert-Threlkeld, 2024; Walk et al., 2025). Table A1 shows summary statistics for these two sets of variables.

The third set of variables is measures of protester and state violence, again measured from protest images. Steinert-Threlkeld et al. (2022) shows that protester and state violence affect protest violence and postulate that emotions are an intervening mechanism, and others show that state violence triggers emotional reactions (Aytaç, Schiumerini, and Stokes, 2018; Lebas and Young, 2024). These variables are therefore included as controls. They are operationalized using the fine-tuned convolutional neural networks from Steinert-Threlkeld et al. (2022).

Images shared on social media are an ideal source for studying protests and reactive emotions for several reasons. Because reactive emotions are transient, they may be difficult to recall after the fact; images record them, making them available for later study. Protest images are also likely to contain faces, facilitating the measurement of expressed emotion (Scholz et al., 2025). Which participants are featured in an image depends on who takes the picture. When images are from newsarticles, crowds of angry, often violent, individuals are prioritized (Chan and Lee, 1984); social media images come from a wide range of producers, ensuring a more representative sampling of protest participants (Cowart et al., 2016). In addition, the controversy over whether emotions can be measured from facial expressions suggests that, if they can, the effect will be weak, necessitating a the large amount of data social media provide. Appendix B provides a longer discussion about measuring emotions from faces. Previous studies show that estimating protest size produces internally consistent estimates (Sobolev et al., 2020), and the violence models have been validated by human annotators (Steinert-Threlkeld et al., 2022). Finally, taking advantage of social media allows for the creation of of panel data at the country-city-day level, the third literature gap described in the previous section.[2]

Equations 1 and 2 show the two models this article estimates; the unit of analysis is

[2] Verhulst and Walgrave, 2009 measure protests across 8 countries without a temporal component.

city$_i$ on day$_t$. Protest is natural logged, and emotions are the percent of faces containing that emotion. NoEmotion refers to faces detected in a photo but that were not able to have an emotion assigned. Since they contribute to the outcome but not an emotion, they are controlled for. All variables are demeaned, standard errors are city-clustered, and cities are weighted by the number of protest images from them. Lags are to the previous protest, which is not always the previous day; a robustness check shows this decision not affect results.

$$\begin{aligned} Ln(Protesters)_{i,t} =& \beta_0 + \beta_1 Angry\%_{i,t-1} + \beta_2 Disgusted\%_{i,t-1} + \beta_3 Fearful\%_{i,t-1} + \\ & \beta_4 Happy\%_{i,t-1} + \beta_5 NoEmotion\%_{i,t-1} + \beta_6 Sad\%_{i,t-1} + \\ & \beta_7 Surprise\%_{i,t-1} + \tau Dur.Decile_{i,t-1} + \gamma X_{i,t-1} \\ & + \rho Ln(Protesters)_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$Emotion\%_{i,t} = \beta_0 + \tau Dur.Decile_{i,t-1} + \gamma X_{i,t-1} + \rho Ln(Protesters)_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

Each model contributes to addressing the five gaps in the literature. First, emotions are measured during protests, both as an outcome (how they change during a protest) and an input (if they affect protest participation). Second, each model is also estimated without lags, testing whether or not protest and emotions better explain each other contemporaneously or with a lag. Third, the models consider all detectable emotions simultaneously. Fourth, the data sampling strategy ensures protests are directly measured. Fifth, the data contain 105 cities from 12 countries, enabling comparative analysis.

Results

The models shown in Table 2 evaluate the extent to which emotions explain mobilization. The first seven models regress protest size against each emotion individually, and the eighth one uses all emotions, all with a lagged dependent variable and state violence controls. The top half of the table presents the contemporaneous model, the bottom half lagged. To save space, the duration controls are not shown.

The contemporaneous models supports different conclusions than the lagged ones. In the contemporaneous model, every emotion except surprise is positively and statistically

Table 2

Regressing Protest Size Against Emotions

DV: Ln(Total Faces)$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Without Lag:								
Pct. Angry$_{i,t}$	0.5207***							0.1734***
	(0.0430)							(0.0528)
Pct. Disgust$_{i,t}$		0.5574**						0.2344
		(0.2297)						(0.1752)
Pct. Fearful$_{i,t}$			0.2160*					-0.0713
			(0.1144)					(0.0955)
Pct. Happy$_{i,t}$				0.1946***				-0.0934
				(0.0559)				(0.0565)
Pct. No Emo.$_{i,t}$					-0.5474***			-0.5166***
					(0.0299)			(0.0497)
Pct. Sad$_{i,t}$						0.3285***		0.0180
						(0.0727)		(0.0716)
Pct. Surprise$_{i,t}$							0.1660	-0.0927
							(0.1006)	(0.0873)
Perceived State Viol.$_{i,t}$	-0.2941	-0.3457	-0.3693	-0.3507	-0.1581	-0.3662	-0.3440	-0.1564
	(0.2639)	(0.2650)	(0.2687)	(0.2675)	(0.2340)	(0.2752)	(0.2704)	(0.2329)
Perceived State Viol.$^2_{i,t}$	-0.1516	0.0829	0.1010	0.0840	-0.2394	0.1019	0.0752	-0.2898
	(0.4328)	(0.4069)	(0.4112)	(0.4026)	(0.3571)	(0.4239)	(0.4085)	(0.3692)
Photos w/ Police$_{i,t}$	0.0377***	0.0363***	0.0367***	0.0370***	0.0330***	0.0356***	0.0367***	0.0331***
	(0.0038)	(0.0032)	(0.0033)	(0.0035)	(0.0017)	(0.0029)	(0.0032)	(0.0019)
Photos w/ Fire$_{i,t}$	0.0423***	0.0444***	0.0445***	0.0449***	0.0424***	0.0447***	0.0443***	0.0417***
	(0.0060)	(0.0060)	(0.0061)	(0.0060)	(0.0062)	(0.0061)	(0.0061)	(0.0061)
Ln(Total Faces)$_{i,t-1}$	0.0842**	0.0910**	0.0928**	0.0896**	0.0785**	0.0956**	0.0942**	0.0771**
	(0.0371)	(0.0396)	(0.0393)	(0.0396)	(0.0327)	(0.0390)	(0.0394)	(0.0326)
Observations	2,090	2,090	2,090	2,090	2,090	2,090	2,090	2,090
Adjusted R^2	0.43521	0.37988	0.37765	0.38111	0.51580	0.38742	0.37821	0.52569
Within R^2	0.15826	0.07580	0.07248	0.07764	0.27837	0.08704	0.07332	0.29311
With Lag:								
Pct. Angry$_{i,t-1}$	-0.0126							0.0004
	(0.0350)							(0.0506)
Pct. Disgust$_{i,t-1}$		-0.1497						-0.1312
		(0.1201)						(0.1187)
Pct. Fearful$_{i,t-1}$			0.0663					0.0718
			(0.0933)					(0.0957)
Pct. Happy$_{i,t-1}$				-0.1198***				-0.0943*
				(0.0364)				(0.0520)
Pct. No Emo.$_{i,t-1}$					0.0555*			0.0444
					(0.0296)			(0.0522)
Pct. Sad$_{i,t-1}$						0.0916		0.0993
						(0.0654)		(0.0833)
Pct. Surprise$_{i,t-1}$							-0.1055**	-0.0848
							(0.0431)	(0.0545)
Perceived State Viol.$_{i,t-1}$	-0.1257	-0.1307	-0.1240	-0.1377	-0.1410	-0.1246	-0.1301	-0.1572
	(0.2862)	(0.2861)	(0.2836)	(0.2851)	(0.2887)	(0.2838)	(0.2825)	(0.2847)
Perceived State Viol.$^2_{i,t-1}$	0.3668	0.3671	0.3589	0.3776	0.3974	0.3596	0.3665	0.4097
	(0.4939)	(0.4918)	(0.4877)	(0.4890)	(0.4955)	(0.4845)	(0.4876)	(0.4854)
Photos w/ Police$_{i,t-1}$	0.0111***	0.0113***	0.0112***	0.0109***	0.0107***	0.0111***	0.0111***	0.0104***
	(0.0027)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0027)	(0.0026)	(0.0027)
Photos w/ Fire$_{i,t-1}$	0.0089	0.0089	0.0090	0.0085	0.0079	0.0093	0.0088	0.0081
	(0.0076)	(0.0076)	(0.0076)	(0.0076)	(0.0074)	(0.0076)	(0.0076)	(0.0074)
Ln(Total Faces)$_{i,t-1}$	0.1106**	0.1101***	0.1074**	0.1135***	0.1310***	0.1036**	0.1104***	0.1275***
	(0.0440)	(0.0416)	(0.0420)	(0.0416)	(0.0474)	(0.0421)	(0.0414)	(0.0484)
Observations	2,090	2,090	2,090	2,090	2,090	2,090	2,090	2,090
Adjusted R^2	0.35238	0.35263	0.35250	0.35430	0.35349	0.35323	0.35326	0.35687
Within R^2	0.03483	0.03519	0.03500	0.03768	0.03648	0.03608	0.03613	0.04151

City-clustered standard errors in parentheses. Figure A2 shows the duration control results.
Regressions are weighted by number of protest tweets per city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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significantly correlated with protest size, though fear only at a 10% level. Except for sadness and anger, the emotions explain almost the same amount of variation in protest size. Anger explains the most, 15.826%, and sadness the second most, 8.704%. When all emotions are included, however, only anger retains statistical significance. Though emotions in the full model appear to explain 29.311% of the variation in protest size, Model (5) shows that faces with an unclassifiable emotion explain 27.837% of the protest size variation. Overall, only anger appears to explain variation in contemporaneous protest size, though not much.

Lagged emotions explain even less of the variation in protest size, though with some different inferences. All lagged models explain less variation than the contemporaneous equivalents, and the within R^2 in the full model is 14.16% of the contemporaneous model ($\frac{.04151}{.29311}$). Only lagged happiness and surprise are statistically significant on their own, but only lagged happiness is in the full model. It is also negatively correlated, the opposite of theoretical predictions.

Table 3 investigates how emotions respond to protest. The emotions are operationalized as the percent of faces expressing each type of emotion. The top half of the table uses protest size at day t while the bottom half uses protest size at $t-1$.

Table 3 reveals several interesting patterns. For every emotion, contemporaneous protest and state violence explain emotion variation much better than the previous day's. The difference ranges from 12.03 ($\frac{.11078}{.00921}$) for anger to 1.4 ($\frac{.01482}{01058}$) for disgust.[3] In the contemporaneous models, emotions explain anywhere from 12.8% (fear, $\frac{.00685}{.05332}$) to 53.82% (anger, $\frac{.11078}{.20583}$) of the model's variation. These percentages are much lower for the lagged models, with only one within R^2 greater than .01 (disgust). Finally, larger protests are more emotional: the percent of faces with recognized emotions is higher for all emotions while the percent of faces with no recognized emotion is lower. Figure 3 shows that the time within a protest cycle does not consistently explain changes in emotions.

To determine if a particular protest episode drives the results, Table 4 shows the full model from Table 2 rerun by wave.[4] As in Table 2, the contemporaneous models explain

[3]The ratio for undetectable emotions is the highest, 47.95.

[4]Omitted waves did not have enough degrees of freedom.

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Table 3

Regressing The Percent of Faces Expressing an Emotion Against Protest Size

Pct. Faces:	$\text{Angry}_{i,t}$	$\text{Disgust}_{i,t}$	$\text{Fearful}_{i,t}$	$\text{Happy}_{i,t}$	$\text{No Emotion}_{i,t}$	$\text{Sad}_{i,t}$	$\text{Surprised}_{i,t}$
Without Lag:							
Perceived State $\text{Viol.}_{i,t}$	-0.0975	-0.0476***	0.0109	-0.1025	0.3144**	0.0093	-0.0747
	(0.1967)	(0.0171)	(0.0468)	(0.0953)	(0.1550)	(0.1110)	(0.0774)
Perceived State $\text{Viol.}^2_{i,t}$	0.4925	0.0488**	0.0028	0.1297	-0.6984***	0.0083	0.0755
	(0.3421)	(0.0243)	(0.0691)	(0.1653)	(0.2193)	(0.2145)	(0.1121)
Photos w/ $\text{Police}_{i,t}$	-0.0084***	0.0005	-0.0002	-0.0027**	0.0086***	0.0014	-0.0007
	(0.0018)	(0.0004)	(0.0004)	(0.0011)	(0.0025)	(0.0016)	(0.0012)
Photos w/ $\text{Fire}_{i,t}$	-0.0053**	-0.0002	-0.0003	-0.0033**	0.0159***	-0.0033*	-0.0005
	(0.0027)	(0.0004)	(0.0008)	(0.0015)	(0.0043)	(0.0018)	(0.0010)
$\text{Ln(Faces)}_{i,t}$	0.1838***	0.0107***	0.0134***	0.0452***	-0.4138***	0.0537***	0.0214**
	(0.0193)	(0.0028)	(0.0048)	(0.0106)	(0.0381)	(0.0096)	(0.0105)
Observations	2,195	2,195	2,195	2,195	2,195	2,195	2,195
Adjusted R^2	0.20583	0.08037	0.05332	0.07049	0.35850	0.10493	0.07179
Within R^2	0.11078	0.01482	0.00685	0.01519	0.23111	0.02124	0.00964
With Lag:							
Perceived State $\text{Viol.}_{i,t-1}$	-0.1993	-0.0168	0.0217	-0.0509	0.1931	-0.0259	-0.0095
	(0.1532)	(0.0224)	(0.0541)	(0.0856)	(0.1631)	(0.0717)	(0.0594)
Perceived State $\text{Viol.}^2_{i,t-1}$	0.3689	0.0243	-0.0585	0.0559	-0.4035	0.0713	-0.0226
	(0.2888)	(0.0308)	(0.0869)	(0.1276)	(0.2737)	(0.1084)	(0.0860)
Photos w/ $\text{Police}_{i,t-1}$	-0.0035***	-0.0007**	0.0003	-0.0031**	0.0003	0.0033**	-9.43×10^{-5}
	(0.0010)	(0.0003)	(0.0004)	(0.0013)	(0.0033)	(0.0017)	(0.0006)
Photos w/ $\text{Fire}_{i,t-1}$	-0.0036	7.32×10^{-5}	-5.52×10^{-5}	0.0009	-0.0002	4.02×10^{-5}	0.0023
	(0.0025)	(0.0008)	(0.0009)	(0.0025)	(0.0054)	(0.0017)	(0.0017)
$\text{Ln(Faces)}_{i,t-1}$	0.0211*	0.0046*	0.0024	0.0187*	-0.0290	-0.0061	-0.0055
	(0.0106)	(0.0025)	(0.0035)	(0.0095)	(0.0185)	(0.0073)	(0.0057)
Observations	2,090	2,090	2,090	2,090	2,090	2,090	2,090
Adjusted R^2	0.11837	0.09558	0.05121	0.06914	0.17668	0.10077	0.07505
Within R^2	0.00921	0.01058	0.00254	0.00732	0.00482	0.00830	0.00621

City clustered standard-errors in parentheses. Figure 3 shows the duration control results.
Regressions are weighted by number of protest tweets per country-city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

more of the variation of protest size than the lag models, and within waves emotions explain a smaller percentage of variation in the lagged models than the contemporaneous ones. No emotion is statistically significant in every wave or even has the same sign. In the contemporaneous model, $Pct.Angry_{i,t}$ is statistically significant and positive for Hong Kong 2, Korea, and Venezuela 2, and $Pct.Happy_{i,t}$'s significance is negative for Spain but positive for Venezuela 2. In the lagged models, anger works in opposite directions in both Hong Kong waves, fear is negative in Hong Kong but positive in Venezuela 2, and happiness is negative in Chile and Russia.

Appendix C shows three robustness checks that confirm these findings. First, Table A2 shows protest size is estimated as the sum of faces containing emotion, not the sum of all detected faces. Lagged happiness is no longer statistically significant, but its sign is still

Table 4

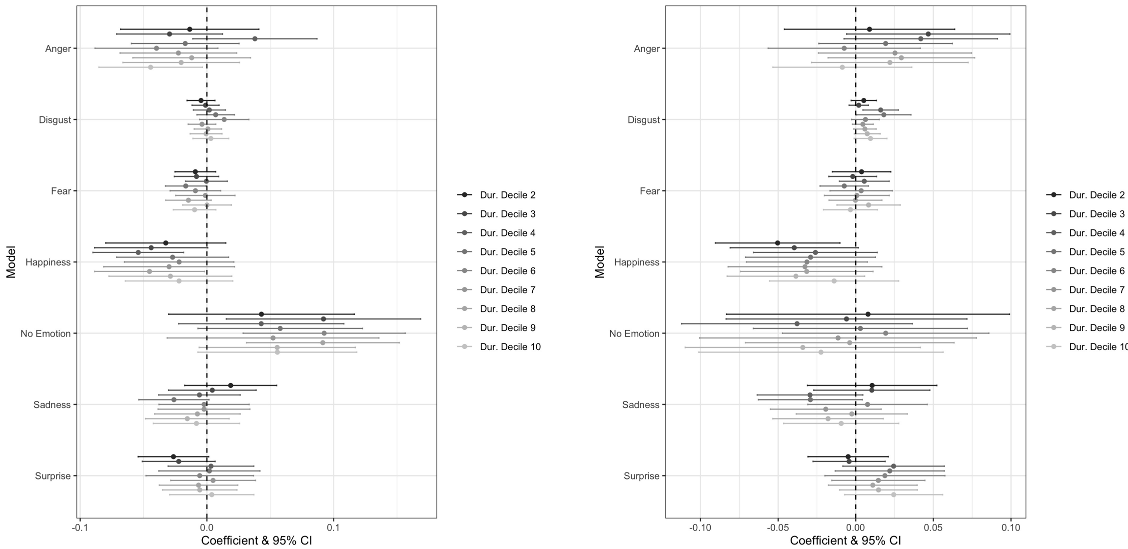
Emotions as IV by Protest Wave

Dependent Variable:	Ln(Faces)$_{i,t}$							
Model:	Chile	Spain	Honk Kong	Hong Kong 2	Korea	Russia	Venezuela	Venezuela 2
Variables								
Pct. Angry$_{i,t}$	0.1367	-0.0969	-0.0619	0.3687**	0.1787*	0.5661	0.1705	0.1687**
	(0.1302)	(0.1989)	(0.2438)	(0.0729)	(0.0824)	(0.3366)	(0.1038)	(0.0126)
Pct. Disgust$_{i,t}$	-0.1396	1.085	0.0688	0.9533	0.1296	1.471	1.019	0.2256
	(0.1763)	(0.9220)	(1.079)	(0.4206)	(0.1820)	(1.030)	(0.7548)	(0.7105)
Pct. Fearful$_{i,t}$	0.1648	0.2928	-0.7982**	-0.0783	-0.0671	0.3910	-0.1059	-0.2450
	(0.3868)	(0.5530)	(0.2155)	(0.1427)	(0.1613)	(0.7353)	(0.3826)	(0.2538)
Pct. Happy$_{i,t}$	-0.1862	-0.4290**	-0.2205	-0.0017	-0.0674	0.1509	-0.1769	0.1031**
	(0.1450)	(0.1655)	(0.3398)	(0.0953)	(0.0745)	(0.1504)	(0.1599)	(0.0052)
Pct. No Emo.$_{i,t}$	-0.5505***	-0.9102***	-0.7869**	-0.2631**	-0.3300***	-0.3975	-0.4482**	-0.5399
	(0.0886)	(0.1879)	(0.2087)	(0.0277)	(0.0575)	(0.2157)	(0.1043)	(0.1420)
Pct. Sad$_{i,t}$	-0.0934	-0.1098	-0.4944	-0.0620	0.5031	0.1818	0.1890	0.0096
	(0.1567)	(0.1564)	(0.2355)	(0.0890)	(0.2602)	(0.1939)	(0.3654)	(0.2921)
Pct. Surprise$_{i,t}$	-0.0010	-0.2860	0.2539	0.2135	0.2059	-0.2736	-0.2693*	-0.3230*
	(0.1924)	(0.2251)	(0.6199)	(0.1622)	(0.3191)	(0.2738)	(0.0873)	(0.0305)
Perceived State Viol.$_{i,t}$	-0.9103	0.1673	-0.4776	-0.2054	-0.6381	1.999**	-1.476	0.2161*
	(0.9284)	(0.3987)	(0.4288)	(0.4258)	(0.4051)	(0.6064)	(0.8944)	(0.0172)
Perceived State Viol.$^2_{i,t}$	0.3737	-0.9442	-0.2922	0.1715	0.7830	-2.938**	1.803	-1.083**
	(2.110)	(0.5554)	(0.5193)	(0.5874)	(0.6022)	(0.9395)	(1.465)	(0.0410)
Photos w/ Police$_{i,t}$	0.1738***	0.0356				0.0255***		0.0694
	(0.0584)	(0.0243)				(0.0034)		(0.0479)
Photos w/ Fire$_{i,t}$	0.0411***	0.0688*	0.1923	0.0318*	0.0112	-0.0046	0.0411***	0.0317*
	(0.0093)	(0.0331)	(0.1066)	(0.0104)	(0.0424)	(0.0283)	(0.0044)	(0.0044)
Ln(Total Faces)$_{i,t-1}$	0.1348**	0.0009	0.0228	-0.0123	-0.0348	0.0595	0.1013	-0.0327
	(0.0560)	(0.0469)	(0.0906)	(0.0594)	(0.0764)	(0.0642)	(0.0874)	(0.0167)
Observations	485	370	87	212	266	107	253	253
Adjusted R^2	0.57243	0.37253	0.53764	0.45650	0.37236	0.67119	0.74482	0.37655
Within R^2	0.40093	0.30224	0.46806	0.43864	0.26747	0.60660	0.41516	0.33969
With Lag:								
Pct. Angry$_{i,t-1}$	-0.1407	-0.0283	-0.2230*	0.3618*	0.1797	-0.2446	0.1404	-0.1670
	(0.1295)	(0.1252)	(0.0899)	(0.0961)	(0.1234)	(0.3449)	(0.2059)	(0.1201)
Pct. Disgust$_{i,t-1}$	0.0873	0.2696	0.8085	-0.3282	-0.3435	-0.8029	-0.3697	-0.6953
	(0.1841)	(0.5943)	(0.8132)	(0.2152)	(0.1992)	(1.050)	(0.2353)	(0.4464)
Pct. Fearful$_{i,t-1}$	0.3093	-0.3867	-0.6368*	0.2212	0.1562	-0.5275	-0.0578	0.3986**
	(0.3282)	(0.3165)	(0.2298)	(0.1386)	(0.1302)	(1.010)	(0.3127)	(0.0301)
Pct. Happy$_{i,t-1}$	-0.2095*	-0.0419	0.1610	0.0563	-0.0262	-0.4462**	0.0527	-0.2002
	(0.1250)	(0.1271)	(0.2770)	(0.0817)	(0.1305)	(0.1812)	(0.1611)	(0.1316)
Pct. No Emo.$_{i,t-1}$	0.0131	0.0388	0.0025	0.1312	0.0471	0.1379	0.2795	-0.0641
	(0.1309)	(0.1859)	(0.1683)	(0.0946)	(0.1098)	(0.1041)	(0.1833)	(0.0230)
Pct. Sad$_{i,t-1}$	0.0809	0.3154	-0.1288	-0.1028	-0.1341	0.1613	0.0285	-0.3686
	(0.1718)	(0.2160)	(0.2542)	(0.1564)	(0.1031)	(0.1344)	(0.3184)	(0.1980)
Pct. Surprise$_{i,t-1}$	0.0565	-0.2251	-0.7222	-0.0013	0.0378	0.2402	0.0471	-0.0819
	(0.1609)	(0.1668)	(0.5894)	(0.0992)	(0.0800)	(0.1440)	(0.2381)	(0.0428)
Perceived State Viol.$_{i,t-1}$	0.1666	0.7235	0.5479	-0.1401	0.7363	-1.567	-0.6087	-0.7739
	(1.024)	(0.5813)	(1.004)	(0.2217)	(0.7695)	(0.9217)	(0.2857)	(0.3019)
Perceived State Viol.$^2_{i,t-1}$	-1.998	-1.213	-0.4040	0.2217	-0.6695	2.845	0.5157	1.669**
	(2.735)	(0.9381)	(1.115)	(0.5266)	(1.069)	(1.520)	(0.6974)	(0.0704)
Photos w/ Police$_{i,t-1}$	-0.4393***	0.0948				-0.0039		0.0061
	(0.0572)	(0.1357)				(0.0071)		(0.0803)
Photos w/ Fire$_{i,t-1}$	0.0031	0.0586	0.1357	0.0209**	0.2913***	-0.0570	-0.0037	-0.0188
	(0.0084)	(0.0328)	(0.0999)	(0.0044)	(0.0315)	(0.0340)	(0.0055)	(0.0034)
Ln(Total Faces)$_{i,t-1}$	0.2125**	0.0255	0.0003	-0.0792**	-0.0025	0.2565*	0.2246	0.0624
	(0.0813)	(0.0870)	(0.1231)	(0.0091)	(0.0881)	(0.1134)	(0.1426)	(0.0162)
Observations	485	370	87	212	266	107	253	253
Adjusted R^2	0.39817	0.17839	0.40394	0.18123	0.20587	0.42880	0.66037	0.14060
Within R^2	0.15678	0.08635	0.31424	0.15433	0.07316	0.31661	0.22161	0.08980

City-clustered standard errors in parentheses. Duration decile controls are included but not shown.
Regressions are weighted by the number of protest images per city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 3

Duration Decile Controls for Table 3.



No lag controls *Lagged controls*

negative. The contemporaneous models still outperform the lagged ones. The anger model now explains half as much of the variation in the outcome as the original model, though the other models' explanatory power is approximately the same. The same results hold when emotions are the outcome, as shown in Table A3. The new operationalization of protest size affects the anger model fit but not the others, and signs and significance are largely the same.

Second, the models are rerun with the original dependent variable but keeping only consecutive protests so that the lagged terms only capture protest the previous day, not the previous protest regardless of how many days have passed. Table A4 presents those results for the protest outcome models and Table A5 and Figure A4 for the emotion outcome models. The results are broadly consistent. Larger protests have a greater percentage of emotive faces. Contemporaneous anger is still the best explained emotion, but lagged emotions explain its variation about as well as they explain the other emotions. In the contemporaneous models, state violence is now statistically significant and still negatively correlated with surprised faces; high levels of state violence negatively correlate with fearful faces but positively does with surprised ones. In the lagged models, the only statistically significant variable is the number of photos containing police. It is negatively correlated with anger, disgust, and happiness. The duration controls remain statistically insignificant except for explaining the percent of happy faces, in which case they are negative and usually statistically significant: happiness peaks on the first day of protests.

Third, `PyFeat` assigns a score per emotion per face, and the model operationalizes emotion as that which receives the highest emotion score. Because there is uncertainty within and across scores, the emotion percents and protest size are re-estimated by summing the emotion scores per country-city-day. Tables A7 and A6 and Figure A5 show these results. Model fit slightly improves compared to Tables A2 and A3, but inference does not.

Discussion

This article contributes to growing research about emotions and protests by providing the first large-scale, cross-national analysis of expressed emotions and protest dynamics. This contribution is possible by applying a series of computer vision models to protest images shared in geolocated tweets from 10 countries and 12 protest waves. Aggregating these estimates to the country-city-day, regression results show that expressed emotions and protest size are most strongly correlated on the same day. In contrast, few expressed emotions at $t-1$ are statistically significantly associated with changes in protest size, suggesting that expressed emotions are not associated with protest mobilization. Anger is the only variable to consistently correlate with protest size, and others that do frequently exhibit variation opposite of theoretical predictions.

One explanation of this article's results could therefore be measurement validity, as the technology to measure expressed emotions from social media data is still emerging. There are known biases in datasets used to train models that estimate facial expressions (Rhue, 2018; Dominguez-Catena et al., 2023), so these results may not accurately measure expressed emotions. Twitter images are also naturalistic whereas existing training data tends to use images taken from similar angles under good lighting, so models trained on them may produce noisier estimates when encountering faces in photos shared on social media.

Not only are the faces in images small, since humans do not consistently interpret the same facial expressions as the same emotions, a computer vision model may also have difficulty consistently estimating emotion. One method for studying this uncertainty is to measure the distribution of a classifier's estimates across emotions. Face expression models generate confidence scores for however many emotions they are trained on, seven in the case of the model for this article. New findings show that analyzing the difference between the log of the highest probability and second highest probability labels recovers 60-70% of mislabeled instances in political stance, ideology, and framing tasks (Farr et al., 2024). Understanding the distribution of emotion confidence scores is therefore a promising avenue for future work.

This article's findings could differ from others' because of compositional change. While the data are panel at the country-city-day, the measured emotions are not: specific faces are not tracked across protests, so individuals expressing emotion at $t-1$ are likely different than those observed protesting at t. By contrast, case studies and experiments measure the same individuals. Relatedly, this article does not and cannot measure the emotions *provoked* in bystanders observing a protest. To capture this dynamic, a machine learning model would need to be trained to estimate the provoked emotion from a protest image, not the emotions expressed in faces in images.

The difficulty of collecting data has limited research to focusing on single countries via experiments or retrospective case studies. That this article finds different results with more data could be due to theoretical underdevelopment or measurement error. As the ability to measure expressed emotions at scale continues to improve, continued development of theory and measurement is required.

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Appendix A

Appendix A: Data Pipeline

To observe expressed emotions at scale, this article starts with a large dataset of tweets that were collected in real time from Twitter's POST statuses/filter endpoint. Other than requiring a tweet contain location information, no filters were used; this collection strategy captures a random sample of $\frac{1}{2}$ to $\frac{1}{3}$ of all geolocated tweets (Steinert-Threlkeld 2018). Next, time and country filters were applied to this collection to return geolocated tweets from country-day combinations encompassing twelve protest waves in ten nations; see Table 1 for these countries and periods. This filtering returns approximately 310,041 geolocated tweets with images containing 620,197 faces. A convolutional neural network trained to detect protests with 85% precision is applied to those images, resulting in 22,292 tweets with protest images that contain 96,857 faces.

Four steps then transform these 96,857 protesting faces into the country-city-day protest dataset the article analyzes. First, faces are detected in each image using `PyTorch` (Paszke et al., 2019). Second, information about each in a photo was analyzed using `PyFeat` (Cheong et al., 2023).[1] The model returns the reactive emotions happiness, anger, surprise, sadness, neutrality, disgust, and fear. Each emotion received a detection score between 0 and 1, and the emotion with the highest detection score per face is kept as that face's emotion.

The third step in the pipeline is location processing. Twitter assigns tweet locations at the level of point of interest, neighborhood, city, state, or country. Tweets with only state or country information are excluded from analysis. The remaining locations are cleaned by removing diacritics, translating city names into English, and manually extracting cities when necessary, e.g. ‘’Beirut’ ’ from ‘’Banque Du Liban’ ’. Finally, tweets are aggregated to the country-city-day level. Protest size is calculated as the sum of faces in protest images,

[1] `PyFeat` was selected because it is the best open source tool in R or Python for estimating reactive emotions from face expressions. Its only packaged competitor is ‘DeepFace’. A less feature rich package in general, ‘DeepFace’ is not appropriate for this project because it does not document its emotion recognition model. It provides only one possible model, and that model's weights are provided by the package creator without documentation. By contrast, `PyFeat` uses a well-known deep learning face expression recognition model, a residual masking network, to estimate the emotions of each face from action units, configuration of facial muscles (Pham et al., 2021; Serengil and Ozpinar, 2020, 2021, 2024).

which other research has found provides accurate undercounts of actual protest size (Sobolev et al., 2020). The seven emotions are operationalized as counts and percentages of protest size per emotion. Table A1 shows summary statistics for the variables. Only cities for which there are protests $\frac{1}{7}$ of the days the country experiences protests are kept, resulting in 7,824 geolocated protest images containing 37,558 faces.

Table A1

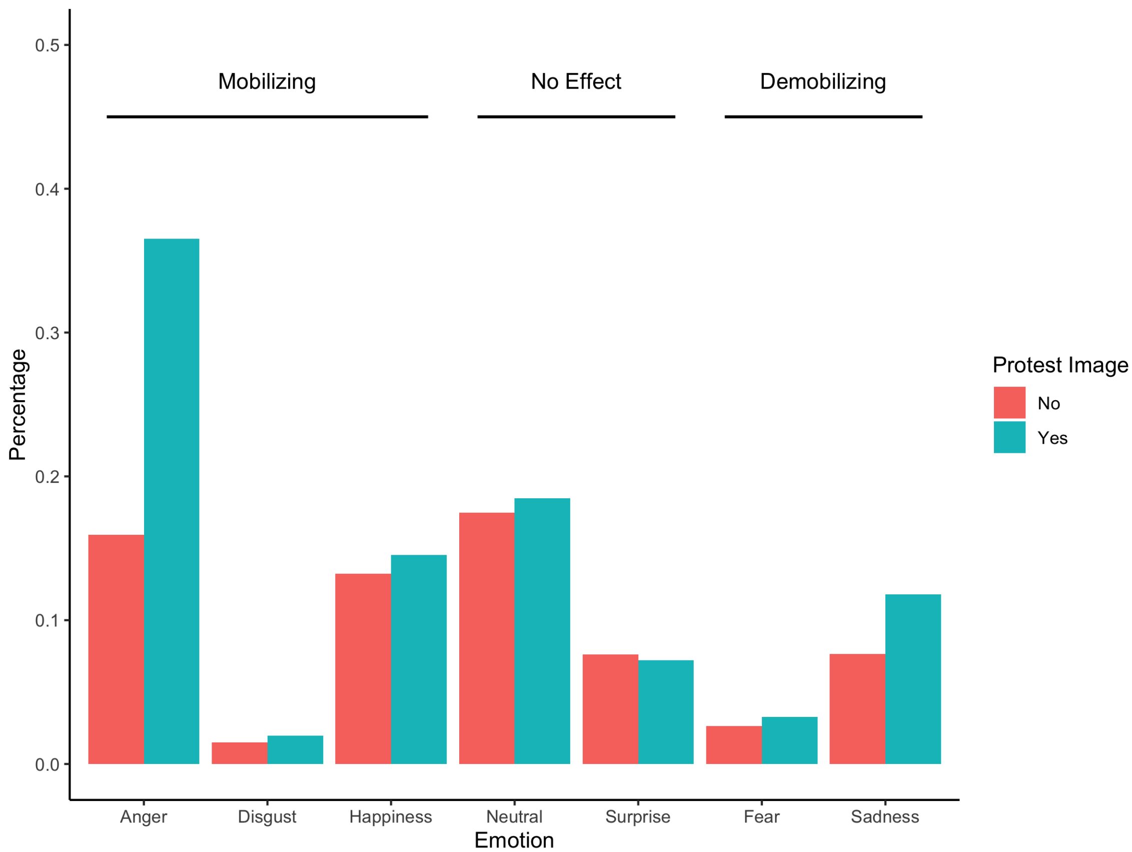
Summary Statistics.

Variable	N	Mean	SD	Min.	Max.
Num. Angry Faces	2,195	5.962	21.508	0	512
Num. Disgusted Faces	2,195	0.397	1.980	0	34
Num. Fearful Faces	2,195	0.552	2.300	0	67
Num. Happy Faces	2,195	2.442	8.072	0	208
Num. Neutral Faces	2,195	3.401	10.580	0	220
Num. Sad Faces	2,195	2.205	7.547	0	201
Num. Surprised Faces	2,195	1.282	4.060	0	98
Num. Total Faces	2,195	17.111	53.562	1	1,332

Figure A1 shows the distribution of the seven emotions this article analyzes. The emotions are grouped by whether theoretical expectations are that they mobilize protesters, have no effect, or demobilize them. In line with other work that finds anger is one of if not the strongest driver of political mobilization, the plurality of faces express anger. The second and third most common emotions are neutral and sadness, respectively. That there are large numbers of faces across emotions that should have different effects provides confidence that any subsequent results are not due to a lack of faces expressing a type of emotion.

Figure A1

Distribution of Emotions, Sorted by Expected Mobilizing Effect



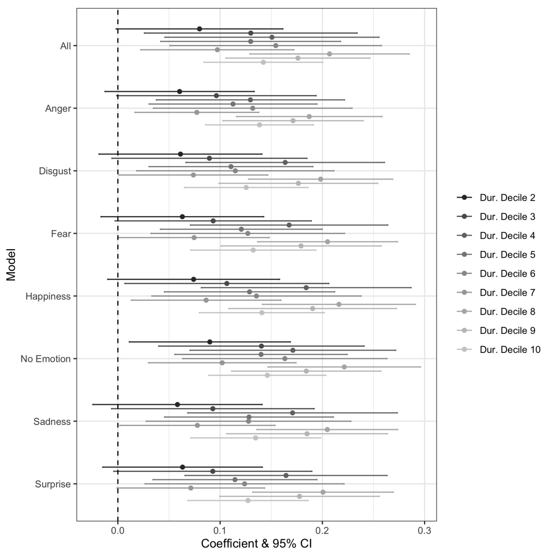
https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660

Appendix B

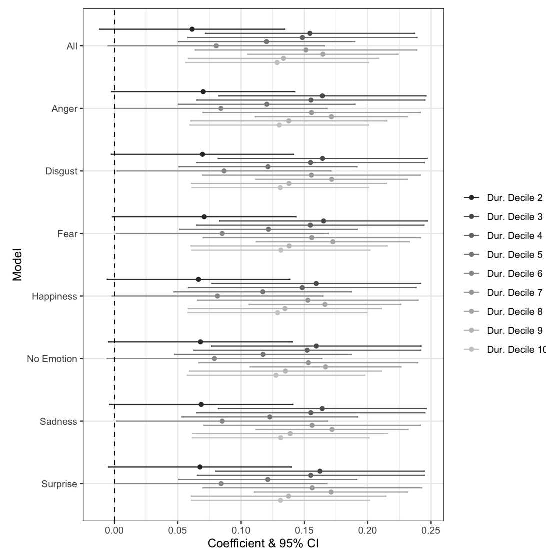
Appendix B: Duration Controls for Table 2

Figure A2

Duration Decile Controls for Table 2.



No lag controls



Lagged controls

Appendix C

Appendix C: Emotions From Facial Expressions

There is a large debate about whether or not reactive emotions are observable using expressions (face muscle patterns), if they are if the same expressions are used across cultures, and if outward expression represents actual internal emotional states. This debate extends at least as far back as Charles Darwin, who argues emotions exist across cultures and species and, at least for humans, share a universality based on muscular contractors (Darwin and Ekman, 1998). The school of thought arguing for measuring emotion expression via facial muscles and the universality of these expressed emotions is most closely associated with the work of Paul Ekman and collaborators. This literature finds that individuals across countries recognize the same emotions when evaluating images designed to avoid culturally specific face arrangements (Ekman et al., 1967; Ekman and Friesen, 1971), and even sixty years ago it faced researchers claiming emotional expression is context dependent. The non-universalist literature in its modern form is most closely associated with the work of Lisa Barrett and collaborators. They contend that universality exists only at a minimal level: rather, how emotions are conveyed varies across cultures and contexts within a culture, facial expressions do not always convey any emotional state, and the same configuration can map to multiple emotional states (Barrett et al., 2019). A standardized dataset of facial images this group created by prompting professional actors to express an emotion exhibits much greater variability in facial expressions than would be expected if the universalists are correct, and when these images are given to other to interpret, the inclusion of descriptive content greatly increases the rate at which the correct emotion is identified, suggesting that face expressions alone do not convey emotion (Le Mau et al., 2021)

The truth is likely in between. For example, though there is variability in emotion interpretation, Le Mau et al. (2021) finds fear, happiness, and surprise are the most uniformly expressed and recognized. Because there is a biological basis for the expression of reactive emotions, there should be some similarity across cultures. The universalist tests rely on images chosen "only for the pure display of a single affect" (Ekman et al. 1967, p. 87), a decision that is scientifically appropriate but is likely to result in facial images dissimilar to what is encountered in everyday politics.

Appendix D

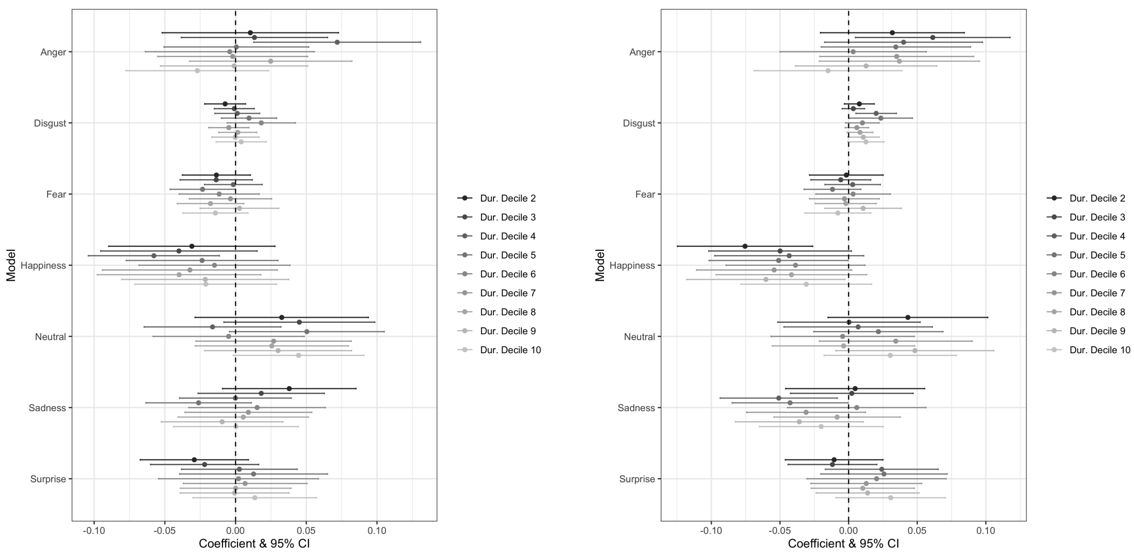
Appendix D Robustness Checks

Protest Size From Only Faces with Emotions

Table A2 re-estimates Table 2 using only faces containing emotions. Table A3 re-estimates Table 3 the same way, and Figure A3 shows the duration controls from those models.

Figure A3

Duration Decile Controls for Table A3.



No lag controls *Lagged controls*

Keep Only Consecutive Protests

Table A4 is the same model as Table 2 and Table A5 is the same as Table 3 restricted to only consecutive protests. Figure A4 shows the duration control results from Table A5.

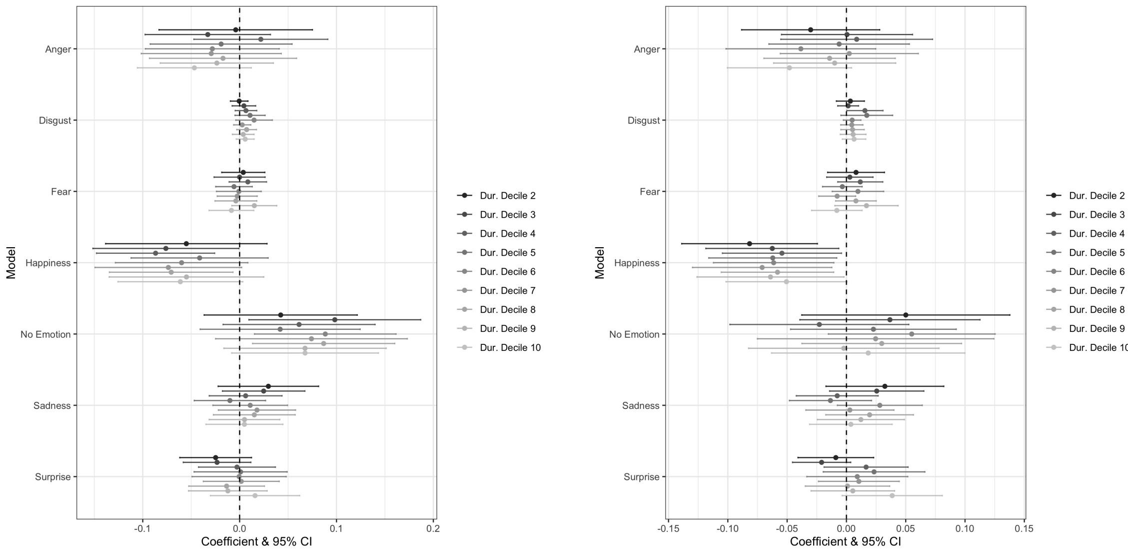
Weighted Emotions

The models in this section calculate emotions per city-day by summing all emotions scores across faces instead of assigning the highest scoring emotion per face as the emotion of that face.

https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660

Figure A4

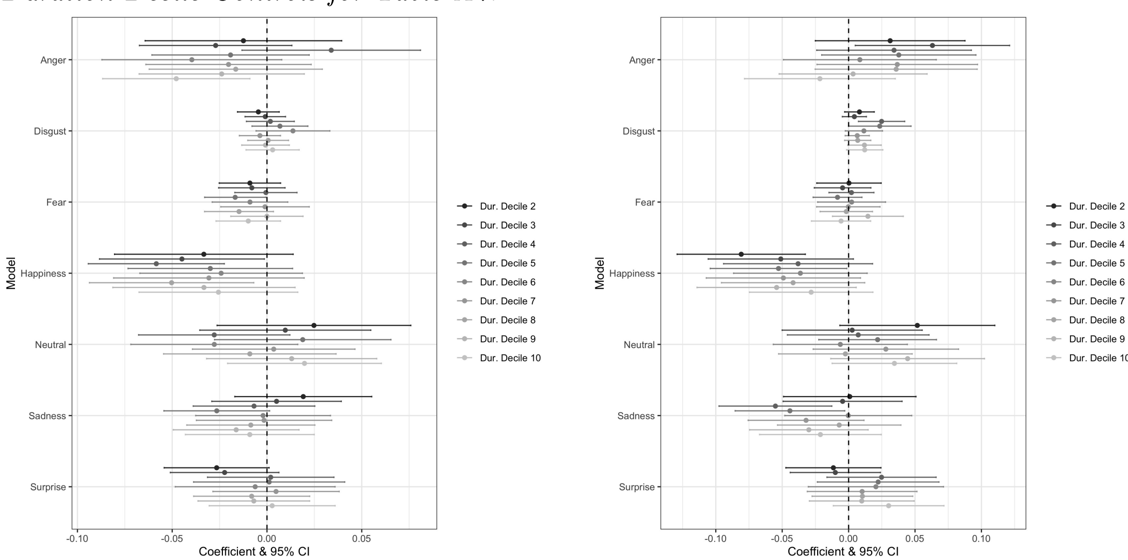
Duration Decile Controls for Table A5.



No lag controls *Lagged controls*

Figure A5

Duration Decile Controls for Table A7.



No lag controls *Lagged controls*

https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660

Table A2

Regressing Protest Size Against Emotions, Only Faces With Emotions

DV: Ln(Faces With Emotion)$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Without Lag:							
Pct. Angry$_{i,t}$	0.4083***						0.3898***
	(0.1023)						(0.1249)
Pct. Disgust$_{i,t}$		0.4789					0.5593
		(0.3927)					(0.4049)
Pct. Fearful$_{i,t}$			-0.1502				-0.0497
			(0.2022)				(0.2034)
Pct. Happy$_{i,t}$				-0.3176***			-0.1562
				(0.1080)			(0.1155)
Pct. Sad$_{i,t}$					0.0388		0.1495
					(0.1462)		(0.1566)
Pct. Surprise$_{i,t}$						-0.2321	-0.0875
						(0.1693)	(0.2024)
Perceived State Viol.$_{i,t}$	-1.227*	-1.209*	-1.227*	-1.244*	-1.234*	-1.257*	-1.225*
	(0.6980)	(0.6875)	(0.6959)	(0.6974)	(0.6971)	(0.6922)	(0.6862)
Perceived State Viol.$^2_{i,t}$	0.5232	0.6624	0.6743	0.6763	0.6845	0.6991	0.5301
	(1.069)	(1.046)	(1.053)	(1.067)	(1.055)	(1.052)	(1.067)
Photos w/ Police$_{i,t}$	0.0826***	0.0807***	0.0810***	0.0802***	0.0809***	0.0810***	0.0813***
	(0.0054)	(0.0046)	(0.0048)	(0.0044)	(0.0048)	(0.0049)	(0.0050)
Photos w/ Fire$_{i,t}$	0.0844***	0.0856***	0.0856***	0.0847***	0.0856***	0.0858***	0.0845***
	(0.0125)	(0.0126)	(0.0126)	(0.0128)	(0.0126)	(0.0126)	(0.0125)
Ln(Faces w/ Emotion)$_{i,t-1}$	0.0770***	0.0780***	0.0793***	0.0812***	0.0794***	0.0785***	0.0769***
	(0.0277)	(0.0278)	(0.0279)	(0.0279)	(0.0278)	(0.0280)	(0.0278)
Observations	1,696	1,696	1,696	1,696	1,696	1,696	1,696
Adjusted R^2	0.36284	0.35549	0.35494	0.35816	0.35477	0.35581	0.36567
Within R^2	0.08457	0.07400	0.07322	0.07785	0.07297	0.07447	0.08863
With Lag:							
Pct. Angry$_{i,t-1}$	0.0375						0.0029
	(0.1035)						(0.1389)
Pct. Disgust$_{i,t-1}$		-0.1760					-0.1900
		(0.3345)					(0.3464)
Pct. Fearful$_{i,t-1}$			0.2677				0.2096
			(0.2443)				(0.2451)
Pct. Happy$_{i,t-1}$				-0.2236**			-0.2071
				(0.0980)			(0.1443)
Pct. Sad$_{i,t-1}$					0.3177*		0.2470
					(0.1820)		(0.2242)
Pct. Surprise$_{i,t-1}$						-0.2502*	-0.2495
						(0.1404)	(0.1657)
Perceived State Viol.$_{i,t-1}$	-0.4036	-0.4098	-0.4040	-0.4246	-0.4158	-0.4078	-0.4491
	(0.8200)	(0.8241)	(0.8178)	(0.8213)	(0.8195)	(0.8108)	(0.8092)
Perceived State Viol.$^2_{i,t-1}$	1.286	1.306	1.300	1.312	1.329	1.290	1.333
	(1.440)	(1.434)	(1.426)	(1.428)	(1.413)	(1.421)	(1.408)
Photos w/ Police$_{i,t-1}$	0.0221**	0.0220**	0.0218**	0.0216**	0.0210**	0.0219**	0.0211**
	(0.0088)	(0.0087)	(0.0088)	(0.0089)	(0.0091)	(0.0086)	(0.0091)
Photos w/ Fire$_{i,t-1}$	0.0146	0.0146	0.0145	0.0146	0.0153	0.0147	0.0152
	(0.0192)	(0.0191)	(0.0191)	(0.0191)	(0.0189)	(0.0192)	(0.0190)
Ln(Faces w/ Emotion)$_{i,t-1}$	0.1416***	0.1433***	0.1431***	0.1390***	0.1430***	0.1407***	0.1381**
	(0.0522)	(0.0522)	(0.0520)	(0.0524)	(0.0525)	(0.0527)	(0.0527)
Observations	1,692	1,692	1,692	1,692	1,692	1,692	1,692
Adjusted R^2	0.33018	0.33020	0.33058	0.33133	0.33194	0.33103	0.33399
Within R^2	0.03266	0.03269	0.03325	0.03433	0.03521	0.03390	0.03817

City-clustered standard errors in parentheses.
Regressions are weighted by number of protest tweets per city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A3

Regressing The Percent of Faces Expressing an Emotion Against Protest Size, Only Faces With an Emotion

Pct. Faces:	$\text{Angry}_{i,t}$	$\text{Disgust}_{i,t}$	$\text{Fearful}_{i,t}$	$\text{Happy}_{i,t}$	$\text{Neutral}_{i,t}$	$\text{Sad}_{i,t}$	$\text{Surprised}_{i,t}$
Without Lag:							
Perceived State $\text{Viol.}_{i,t}$	0.0184	-0.0498**	0.0302	-0.0824	0.0773	0.0569	-0.0505
	(0.2058)	(0.0214)	(0.0535)	(0.1162)	(0.1384)	(0.1388)	(0.1026)
Perceived State $\text{Viol.}^2_{i,t}$	0.3649	0.0446	-0.0366	0.0309	-0.2871	-0.1063	-0.0105
	(0.3630)	(0.0301)	(0.0786)	(0.2070)	(0.2292)	(0.2607)	(0.1448)
Photos w/ $\text{Police}_{i,t}$	-0.0062***	0.0007	0.0002	-0.0010	0.0035***	0.0025	0.0004
	(0.0019)	(0.0005)	(0.0005)	(0.0014)	(0.0011)	(0.0015)	(0.0013)
Photos w/ $\text{Fire}_{i,t}$	-0.0010	1.65×10^{-5}	0.0008	-0.0003	0.0011	-0.0018	0.0011
	(0.0026)	(0.0004)	(0.0011)	(0.0016)	(0.0026)	(0.0021)	(0.0012)
Ln(Faces w/ $\text{Emotion})_{i,t}$	0.0319***	0.0021	-0.0017	-0.0162**	-0.0090	0.0005	-0.0075
	(0.0081)	(0.0017)	(0.0031)	(0.0062)	(0.0066)	(0.0054)	(0.0056)
Observations	1,772	1,772	1,772	1,772	1,772	1,772	1,772
Adjusted R^2	0.10923	0.08428	0.06577	0.07031	0.09495	0.09126	0.07520
Within R^2	0.03302	0.01204	0.00581	0.01213	0.01269	0.00812	0.00867
With Lag:							
Perceived State $\text{Viol.}_{i,t-1}$	-0.2193	-0.0157	0.0329	0.0149	0.1477	0.0136	0.0259
	(0.1505)	(0.0315)	(0.0685)	(0.1180)	(0.1770)	(0.1057)	(0.0725)
Perceived State $\text{Viol.}^2_{i,t-1}$	0.4100	0.0218	-0.0938	-0.0720	-0.1352	-0.0145	-0.1164
	(0.2764)	(0.0452)	(0.1105)	(0.1702)	(0.2948)	(0.1668)	(0.1165)
Photos w/ $\text{Police}_{i,t-1}$	-0.0040***	-0.0009**	0.0005	-0.0035***	0.0042***	0.0037***	4.47×10^{-5}
	(0.0011)	(0.0004)	(0.0007)	(0.0011)	(0.0009)	(0.0011)	(0.0009)
Photos w/ $\text{Fire}_{i,t-1}$	-0.0046**	1.49×10^{-5}	-1.67×10^{-6}	0.0006	0.0012	-0.0002	0.0030
	(0.0020)	(0.0009)	(0.0010)	(0.0028)	(0.0040)	(0.0017)	(0.0019)
Ln(Faces w/ $\text{Emotion})_{i,t-1}$	0.0071	0.0024**	-0.0002	0.0051	-0.0062	-0.0038	-0.0044*
	(0.0053)	(0.0012)	(0.0018)	(0.0042)	(0.0052)	(0.0032)	(0.0025)
Observations	1,696	1,696	1,696	1,696	1,696	1,696	1,696
Adjusted R^2	0.09355	0.09867	0.06467	0.07188	0.09394	0.10632	0.08273
Within R^2	0.01087	0.01250	0.00363	0.00917	0.01004	0.01294	0.00930

City clustered standard-errors in parentheses. Figure A3 shows the duration control results.
Regressions are weighted by number of protest tweets per country-city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4

Regressing Protest Size Against Emotions, Consecutive Protests Only

DV: $\text{Ln(Faces)}_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Without Lag:								
Pct. $\text{Angry}_{i,t}$	0.5389***							0.1661**
	(0.0643)							(0.0768)
Pct. $\text{Disgust}_{i,t}$		0.5178**						0.1738
		(0.2547)						(0.1947)
Pct. $\text{Fearful}_{i,t}$			0.2220					-0.0882
			(0.1542)					(0.1146)
Pct. $\text{Happy}_{i,t}$				0.1898***				-0.1204*
				(0.0692)				(0.0703)
Pct. No $\text{Emo.}_{i,t}$					-0.5887***			-0.5619***
					(0.0337)			(0.0633)
Pct. $\text{Sad}_{i,t}$						0.4173***		0.0637
						(0.1269)		(0.1136)
Pct. $\text{Surprise}_{i,t}$							0.1714	-0.1153
							(0.1395)	(0.1075)
Perceived State $\text{Viol.}_{i,t}$	-0.3481	-0.4579	-0.5014	-0.4650	-0.2708	-0.4930	-0.4431	-0.2577
	(0.3645)	(0.3781)	(0.3882)	(0.3856)	(0.3584)	(0.3792)	(0.3852)	(0.3484)
Perceived State $\text{Viol.}^2_{i,t}$	-0.0474	0.2411	0.2973	0.2477	-0.1478	0.2963	0.1910	-0.1867
	(0.5932)	(0.6150)	(0.6304)	(0.6208)	(0.5705)	(0.6039)	(0.6165)	(0.5644)
Photos w/ $\text{Police}_{i,t}$	0.0357***	0.0345***	0.0349***	0.0352***	0.0312***	0.0331***	0.0348***	0.0311***
	(0.0033)	(0.0029)	(0.0031)	(0.0032)	(0.0020)	(0.0028)	(0.0031)	(0.0020)
Photos w/ $\text{Fire}_{i,t}$	0.0437***	0.0460***	0.0461***	0.0465***	0.0439***	0.0468***	0.0458***	0.0433***
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0065)	(0.0062)	(0.0061)	(0.0065)
$\text{Ln(Faces)}_{i,t-1}$	0.1095**	0.1145**	0.1165**	0.1129**	0.1055***	0.1206**	0.1175**	0.1055***
	(0.0439)	(0.0482)	(0.0476)	(0.0481)	(0.0374)	(0.0478)	(0.0477)	(0.0375)
Observations	1,499	1,499	1,499	1,499	1,499	1,499	1,499	1,499
Adjusted R^2	0.45425	0.40473	0.40323	0.40571	0.53240	0.41562	0.40371	0.54139
Within R^2	0.16179	0.08574	0.08344	0.08725	0.28182	0.10247	0.08418	0.29563
With Lag:								
Pct. $\text{Angry}_{i,t-1}$	0.0092							0.0055
	(0.0451)							(0.0635)
Pct. $\text{Disgust}_{i,t-1}$		-0.1178						-0.0961
		(0.2131)						(0.2064)
Pct. $\text{Fearful}_{i,t-1}$			0.0988					0.0909
			(0.1107)					(0.1271)
Pct. $\text{Happy}_{i,t-1}$				-0.1438***				-0.1231*
				(0.0397)				(0.0636)
Pct. No $\text{Emo.}_{i,t-1}$					0.0838**			0.0499
					(0.0376)			(0.0627)
Pct. $\text{Sad}_{i,t-1}$						-0.0027		0.0001
						(0.0768)		(0.0882)
Pct. $\text{Surprise}_{i,t-1}$							-0.1541**	-0.1405
							(0.0725)	(0.0911)
Perceived State $\text{Viol.}_{i,t-1}$	0.2473	0.2405	0.2449	0.2267	0.2120	0.2453	0.2162	0.1802
	(0.3850)	(0.3891)	(0.3861)	(0.3894)	(0.3927)	(0.3860)	(0.3836)	(0.3915)
Perceived State $\text{Viol.}^2_{i,t-1}$	-0.4739	-0.4630	-0.4716	-0.4330	-0.4015	-0.4684	-0.4303	-0.3669
	(0.6454)	(0.6507)	(0.6430)	(0.6547)	(0.6592)	(0.6457)	(0.6411)	(0.6497)
Photos w/ $\text{Police}_{i,t-1}$	0.0062	0.0062*	0.0062*	0.0059	0.0056	0.0062*	0.0064*	0.0059
	(0.0038)	(0.0036)	(0.0037)	(0.0037)	(0.0036)	(0.0037)	(0.0035)	(0.0036)
Photos w/ $\text{Fire}_{i,t-1}$	0.0025	0.0025	0.0025	0.0020	0.0011	0.0025	0.0024	0.0012
	(0.0076)	(0.0076)	(0.0076)	(0.0076)	(0.0074)	(0.0076)	(0.0076)	(0.0075)
	(0.0517)	(0.0518)	(0.0528)	(0.0509)	(0.0509)	(0.0512)	(0.0523)	(0.0538)
$\text{Ln(Faces)}_{i,t-1}$	0.1372**	0.1401***	0.1374***	0.1442***	0.1691***	0.1388***	0.1404***	0.1624***
	(0.0539)	(0.0511)	(0.0518)	(0.0513)	(0.0575)	(0.0515)	(0.0512)	(0.0585)
Observations	1,499	1,499	1,499	1,499	1,499	1,499	1,499	1,499
Adjusted R^2	0.37202	0.37211	0.37224	0.37430	0.37405	0.37201	0.37351	0.37687
Within R^2	0.03551	0.03565	0.03585	0.03901	0.03863	0.03549	0.03779	0.04295

City-clustered standard errors in parentheses.
Regressions are weighted by number of protest tweets per city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660

Table A5

Regressing The Percent of Faces Expressing an Emotion Against Protest Size, Consecutive Protests Only

Pct. Faces:	$Angry_{i,t}$	$Disgust_{i,t}$	$Fearful_{i,t}$	$Happy_{i,t}$	No $Emotion_{i,t}$	$Sad_{i,t}$	$Surprised_{i,t}$
Without Lag:							
Perceived State $Viol._{i,t}$	-0.2027	-0.0367*	0.1070	-0.0841	0.2766	0.0719	-0.1714*
	(0.2167)	(0.0195)	(0.0733)	(0.1167)	(0.2428)	(0.1050)	(0.0945)
Perceived State $Viol.^2_{i,t}$	0.5875	0.0360	-0.1676*	0.0940	-0.7626*	-0.1041	0.3660**
	(0.3705)	(0.0299)	(0.0921)	(0.2073)	(0.4033)	(0.1601)	(0.1759)
Photos w/ $Police_{i,t}$	-0.0070***	0.0005	-0.0004	-0.0024**	0.0072***	0.0021	-0.0003
	(0.0015)	(0.0004)	(0.0006)	(0.0011)	(0.0023)	(0.0016)	(0.0010)
Photos w/ $Fire_{i,t}$	-0.0036	-0.0001	-0.0006	-0.0034**	0.0140***	-0.0048**	0.0006
	(0.0025)	(0.0003)	(0.0009)	(0.0014)	(0.0041)	(0.0019)	(0.0013)
$Ln(Faces)_{i,t}$	0.1588***	0.0099***	0.0106*	0.0388***	-0.3681***	0.0555***	0.0164
	(0.0215)	(0.0030)	(0.0057)	(0.0112)	(0.0380)	(0.0130)	(0.0123)
Observations	1,527	1,527	1,527	1,527	1,527	1,527	1,527
Adjusted R^2	0.21223	0.13071	0.09611	0.09172	0.37418	0.14179	0.10174
Within R^2	0.09534	0.01402	0.00964	0.02074	0.22241	0.03012	0.01346
With Lag:							
Perceived State $Viol._{i,t-1}$	-0.1252	-0.0273	0.0231	-0.0301	0.0762	0.0918	-0.0397
	(0.1468)	(0.0246)	(0.0585)	(0.0933)	(0.2490)	(0.0866)	(0.0778)
Perceived State $Viol.^2_{i,t-1}$	0.1743	0.0398	-0.0690	-0.0497	-0.2003	-0.0824	0.0076
	(0.2495)	(0.0396)	(0.1079)	(0.1468)	(0.4579)	(0.1478)	(0.1323)
Photos w/ $Police_{i,t-1}$	-0.0036***	-0.0006*	4.75×10^{-5}	-0.0038***	0.0023	0.0032	5.89×10^{-5}
	(0.0011)	(0.0004)	(0.0004)	(0.0014)	(0.0046)	(0.0024)	(0.0007)
Photos w/ $Fire_{i,t-1}$	-0.0029	-0.0001	-0.0004	-0.0002	0.0010	-0.0010	0.0029
	(0.0024)	(0.0007)	(0.0010)	(0.0028)	(0.0054)	(0.0016)	(0.0021)
$Ln(Faces)_{i,t-1}$	0.0175	0.0043	-0.0001	0.0177	-0.0221	-0.0083	-0.0079
	(0.0135)	(0.0032)	(0.0050)	(0.0107)	(0.0232)	(0.0073)	(0.0079)
Observations	1,499	1,499	1,499	1,499	1,499	1,499	1,499
Adjusted R^2	0.13750	0.13246	0.09570	0.09173	0.19947	0.13412	0.10412
Within R^2	0.00811	0.01068	0.00790	0.01492	0.00599	0.01199	0.01487

City clustered standard-errors in parentheses. Figure A4 shows the duration control results.
Regressions are weighted by number of protest tweets per country-city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A6

Regressing Protest Size Against Weighted Emotions

DV: Ln(Faces With Emotion)$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Without Lag:							
Pct. Angry$_{i,t}$	0.5496***						0.5448***
	(0.0818)						(0.0985)
Pct. Disgust$_{i,t}$		0.4318					0.5909
		(0.3570)					(0.3752)
Pct. Fearful$_{i,t}$			-0.4604**				-0.2663
			(0.1774)				(0.1824)
Pct. Happy$_{i,t}$				-0.2236**			-0.0048
				(0.1101)			(0.1146)
Pct. Sad$_{i,t}$					-0.1582		0.0517
					(0.1337)		(0.1335)
Pct. Surprise$_{i,t}$						-0.3137*	-0.0832
						(0.1633)	(0.1833)
Perceived State Viol.$_{i,t}$	-1.275*	-1.239*	-1.249*	-1.276*	-1.257*	-1.300*	-1.247*
	(0.6810)	(0.6642)	(0.6742)	(0.6758)	(0.6708)	(0.6683)	(0.6630)
Perceived State Viol.$^2_{i,t}$	0.5674	0.7330	0.7373	0.7563	0.7393	0.7820	0.5426
	(1.052)	(1.005)	(1.013)	(1.026)	(1.008)	(1.015)	(1.035)
Photos w/ Police$_{i,t}$	0.0798***	0.0775***	0.0779***	0.0772***	0.0783***	0.0776***	0.0792***
	(0.0047)	(0.0040)	(0.0041)	(0.0038)	(0.0043)	(0.0042)	(0.0046)
Photos w/ Fire$_{i,t}$	0.0764***	0.0785***	0.0787***	0.0779***	0.0782***	0.0786***	0.0767***
	(0.0125)	(0.0126)	(0.0126)	(0.0128)	(0.0126)	(0.0126)	(0.0125)
Ln(Faces w/ Emotion)$_{i,t-1}$	0.0770***	0.0780***	0.0793***	0.0812***	0.0794***	0.0785***	0.0769***
	(0.0277)	(0.0278)	(0.0279)	(0.0279)	(0.0278)	(0.0280)	(0.0278)
Observations	1,696	1,696	1,696	1,696	1,696	1,696	1,696
Adjusted R^2	0.37603	0.35881	0.35995	0.36006	0.35873	0.36019	0.37842
Within R^2	0.09985	0.07501	0.07666	0.07681	0.07490	0.07700	0.10330
With Lag:							
Pct. Angry$_{i,t-1}$	-0.0194						-0.0879
	(0.0831)						(0.1167)
Pct. Disgust$_{i,t-1}$		-0.0292					-0.0919
		(0.2818)					(0.2922)
Pct. Fearful$_{i,t-1}$			0.2998				0.1919
			(0.2552)				(0.2499)
Pct. Happy$_{i,t-1}$				-0.2477**			-0.2741*
				(0.1003)			(0.1414)
Pct. Sad$_{i,t-1}$					0.3217**		0.2022
					(0.1605)		(0.2012)
Pct. Surprise$_{i,t-1}$						-0.1818	-0.2404
						(0.1390)	(0.1562)
Perceived State Viol.$_{i,t-1}$	-0.4602	-0.4636	-0.4624	-0.4862	-0.4633	-0.4689	-0.4946
	(0.7733)	(0.7756)	(0.7690)	(0.7741)	(0.7718)	(0.7642)	(0.7602)
Perceived State Viol.$^2_{i,t-1}$	1.355	1.351	1.350	1.362	1.367	1.345	1.399
	(1.336)	(1.334)	(1.327)	(1.327)	(1.313)	(1.323)	(1.301)
Photos w/ Police$_{i,t-1}$	0.0203**	0.0204**	0.0202**	0.0200**	0.0191**	0.0204**	0.0185**
	(0.0083)	(0.0081)	(0.0081)	(0.0083)	(0.0086)	(0.0080)	(0.0087)
Photos w/ Fire$_{i,t-1}$	0.0129	0.0129	0.0126	0.0128	0.0133	0.0129	0.0130
	(0.0165)	(0.0165)	(0.0165)	(0.0165)	(0.0162)	(0.0166)	(0.0164)
Ln(Faces w/ Emotion)$_{i,t-1}$	0.1452***	0.1443***	0.1459***	0.1407***	0.1470***	0.1421***	0.1452***
Observations	1,692	1,692	1,692	1,692	1,692	1,692	1,692
Adjusted R^2	0.33932	0.33931	0.33993	0.34123	0.34150	0.33988	0.34406
Within R^2	0.03509	0.03507	0.03597	0.03788	0.03827	0.03590	0.04200

City-clustered standard errors in parentheses.
Regressions are weighted by number of protest tweets per city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

https://doi.org/10.33774/apsa-2025-ftqx3 **ORCID:** https://orcid.org/0000-0002-5122-9660

Table A7

Regressing The Percent of Faces Expressing a Weighted Emotion Against Protest Size

Pct. Faces:	$\text{Angry}_{i,t}$	$\text{Disgust}_{i,t}$	$\text{Fearful}_{i,t}$	$\text{Happy}_{i,t}$	$\text{Neutral}_{i,t}$	$\text{Sad}_{i,t}$	$\text{Surprised}_{i,t}$
Without Lag:							
Perceived State $\text{Viol.}_{i,t}$	-0.0410	-0.0447***	0.0145	-0.0772	0.0165	0.0250	-0.0654
	(0.1944)	(0.0169)	(0.0469)	(0.0946)	(0.1133)	(0.1115)	(0.0783)
Perceived State $\text{Viol.}^2_{i,t}$	0.4188	0.0447*	-0.0022	0.1026	-0.0954	-0.0125	0.0647
	(0.3439)	(0.0239)	(0.0689)	(0.1630)	(0.1830)	(0.2146)	(0.1121)
Photos w/ $\text{Police}_{i,t}$	-0.0098***	0.0005	-0.0003	-0.0037***	0.0009	0.0011	-0.0011
	(0.0019)	(0.0004)	(0.0004)	(0.0012)	(0.0015)	(0.0015)	(0.0012)
Photos w/ $\text{Fire}_{i,t}$	-0.0059**	-0.0002	-0.0004	-0.0042***	-0.0033	-0.0035*	-0.0007
	(0.0025)	(0.0004)	(0.0008)	(0.0015)	(0.0027)	(0.0018)	(0.0010)
$\text{Ln(Faces)}_{i,t}$	0.0939***	0.0052***	0.0065***	0.0308***	0.0453***	0.0268***	0.0128***
	(0.0083)	(0.0010)	(0.0018)	(0.0045)	(0.0054)	(0.0040)	(0.0045)
Observations	2,195	2,195	2,195	2,195	2,195	2,195	2,195
Adjusted R^2	0.24933	0.08226	0.05447	0.08543	0.11230	0.11206	0.07529
Within R^2	0.15948	0.01686	0.00806	0.03103	0.05316	0.02903	0.01338
With Lag:							
Perceived State $\text{Viol.}_{i,t-1}$	-0.2480	-0.0162	0.0413	-0.0024	0.2128	-0.0103	0.0229
	(0.1580)	(0.0355)	(0.0665)	(0.1293)	(0.1772)	(0.1048)	(0.0777)
Perceived State $\text{Viol.}^2_{i,t-1}$	0.4529	0.0211	-0.1090	-0.0459	-0.2276	0.0162	-0.1077
	(0.2828)	(0.0508)	(0.1032)	(0.1815)	(0.2927)	(0.1640)	(0.1283)
Photos w/ $\text{Police}_{i,t-1}$	-0.0042***	-0.0012***	0.0006	-0.0040***	0.0047***	0.0043***	-0.0002
	(0.0012)	(0.0004)	(0.0007)	(0.0010)	(0.0009)	(0.0012)	(0.0008)
Photos w/ $\text{Fire}_{i,t-1}$	-0.0040*	-0.0002	-0.0002	0.0004	0.0010	-0.0001	0.0031
	(0.0022)	(0.0009)	(0.0009)	(0.0029)	(0.0040)	(0.0018)	(0.0020)
$\text{Ln(Faces)}_{i,t-1}$	0.0080	0.0030**	-0.0007	0.0057	-0.0075	-0.0023	-0.0063**
	(0.0058)	(0.0015)	(0.0018)	(0.0047)	(0.0055)	(0.0037)	(0.0030)
Observations	1,696	1,696	1,696	1,696	1,696	1,696	1,696
Adjusted R^2	0.10056	0.09284	0.06272	0.07413	0.10047	0.10274	0.08667
Within R^2	0.01108	0.01358	0.00405	0.00938	0.01184	0.01163	0.00934

City clustered standard-errors in parentheses. Figure A5 shows the duration control results.
Regressions are weighted by number of protest tweets per country-city-day.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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