Violence against the media and freedom of the press: Evidence from Mexico

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Motivation

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- Most victims worked in small, regional newspapers, covering crime
- Press reports suggest perpetrators are often members of drug-trafficking organizations (DTO's)
- Mexico not at war and journalists are seldom killed in cross-fire (Syria, Iraq). Also not a one-time event (Malta) $\longrightarrow$ ideal setting to study this type of censorship

Motivation

[1] Own translation

Motivation

> *In the Spring of 2010, it came to our attention that there was a spokesman for organized crime. In the coming days a reporter –on behalf of this individual– scheduled a meeting with a group of colleagues. They warned us about who called the meeting and what would happen if we didn't attend [...] The spokesman explained the new rules: no one publishes material without approval by the "boss"; no one is allowed to ignore phone calls from them; no one can refuse to accept bribes [...]*

(Valdez, 2016)[1]

[1] Own translation

Motivation

[2] Own translation

Motivation

Censorship

We still haven't shaken the fear that we had at one point, that's to say there are many things that could be investigated but that aren't.

[2] Own translation

Motivation

Censorship

> *We still haven't shaken the fear that we had at one point, that's to say there are many things that could be investigated but that aren't.*

Backlash

> *If they call us to tell us what to do, or what not to publish, we're going to publish it twice over and we're also going to write that they called us to tell us not to publish it.*

(Ralley, 2014)[2]

[2] Own translation

EneasMx, “A march held after the death of Rubén Espinosa”

Research questions

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- How does the murder of a journalist change coverage of targeted outlets?

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- Are there spillover effects for the press at large?

Literature

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Media bias and censorship

- Government advertising: di Tella and Franceschelli 2011
- Private financial incentives: Beattie, Durante, and Knight 2017; Reuter and Zitzewitz 2006; Gentzkow and Shapiro 2010
- Editorial standards in Mexico: Ramírez Alvarez 2017

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Externalities and costs of drug violence in Mexico

- Economic costs of violence: Robles, Calderón, and Magaloni 2013; Murphy and Rossi 2017; Ashby and Ramos 2013
- Displacement: Basu and Pearlman 2017; Aldeco, Jurado and Ramírez 2019

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Media repression

- Violence against the press: Holland and Rios 2017
- Legal reforms: Stanig 2015
- Imprisonment: Pan and Siegel 2019

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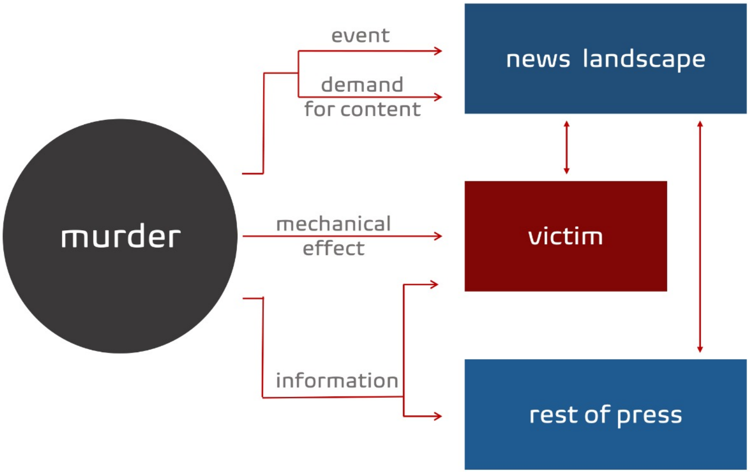
- Event-studies exploiting the precise timing of killings to study the direct and indirect effects on news reporting
- Exploits text content to study changes in tone
- Census data, diff-in-diff and triple-diff exercises looking at demographics to estimate long-run effects on occupation choice and migration decisions


murder
event
demand
for content
mechanical
effect
information
news landscape
victim
rest of press

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- *When* does it arise?
  - Short-run vs. long-run effects

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4. Decrease in number of journalists in dangerous states (*deterrence*)

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3. Average content from targeted outlets becomes more negative with a stronger emphasis on violent aspects of organized crime (*backlash*)
4. Decrease in number of journalists in dangerous states (*deterrence*)
5. Journalists that follow the victim on Twitter decrease their publishing more (*deterrence*)

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2. General population homicides from the National Statistics Office (INEGI)
3. Date, place of murder and up to 4 affiliations for each of the killed 104 journalists (CPJ & Article 19)

Press coverage

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2. 1.8 million tweets from 76 victimized outlets (out of 103, 2009-2017)
3. 5 million tweets from top 200 journalists (2009-2017)

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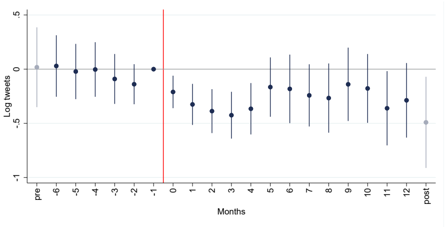
Direct effects of murder

$$
\begin{aligned}
y_{msot} &= \gamma_o + \gamma_{sM} + \sum_{k=-6}^{12} \beta_k \times monthsSinceKilling_{ot} \\
&+ \delta \times x_{msM} + \beta_{pre} \times Pre_{ot} + \beta_{post} \times Post_{ot} + \epsilon_{msot}
\end{aligned}
$$

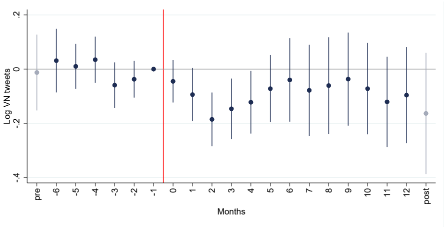
- y_{msot}: outcome for outlet o, in municipality m, state s and time period t
- x_{mst}: log homicides in the past 30 days
- Pre, $Post$: indicator variables for pre 6 months, post 12 months, respectively
- Robust standard errors clustered by outlet

Overall violence | Coverage of attacks/interest

Direct effects on volume of tweets



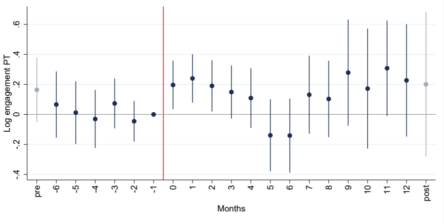
(a) All tweets



(b) Tweets about violence

Robustness: timing Robustness: Google CSE

Direct effects on engagement



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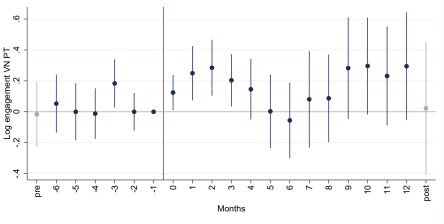
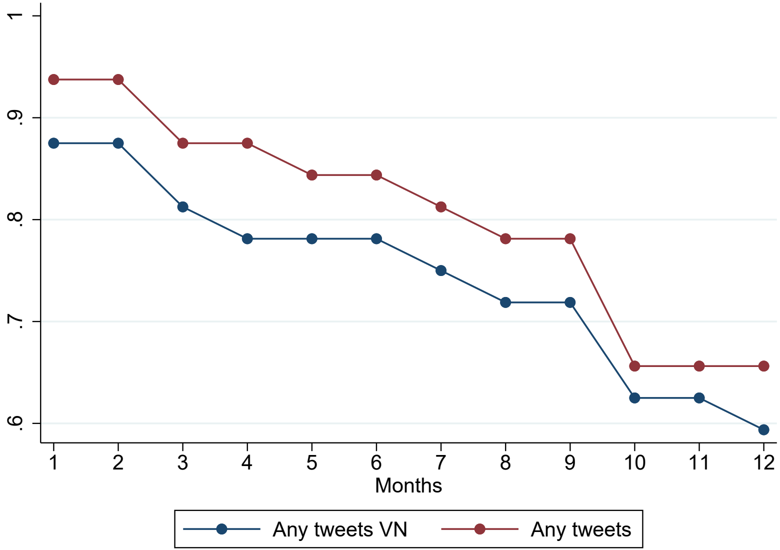


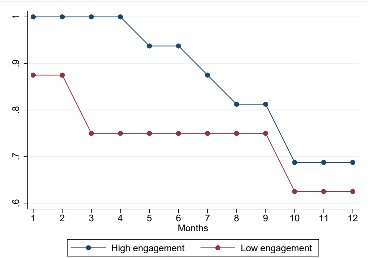
(b) Tweets about violence

Attacks and survival rates

survival(k): fraction of victimized outlets that published *a* tweet *k* months and onward after the attack



Direct effects on volume of tweets



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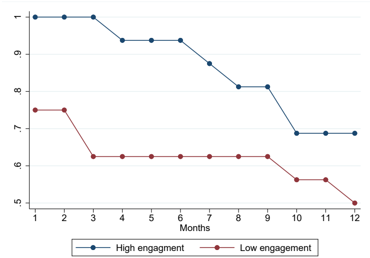


(b) Tweets about violence

Are non-victimized journalists affected by the killing?

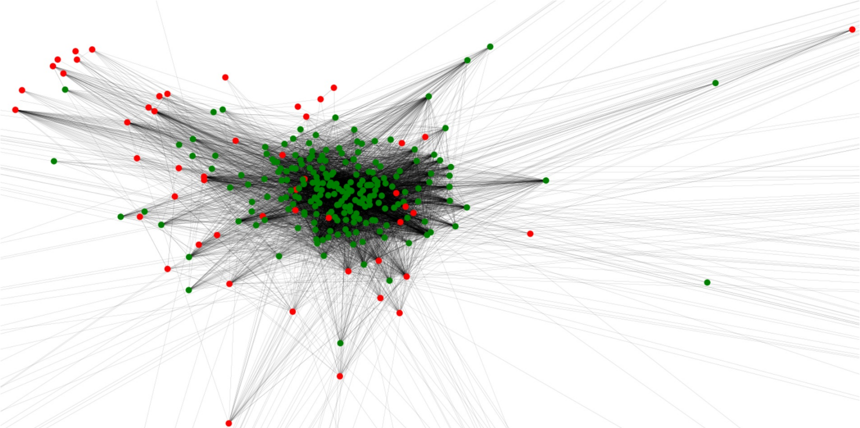
indirect effect of journalists' killings:

$$y_{isft} = \sum_{k=-6}^{12} \beta_k \times monthsSinceKilling \times friend \times inState_{isft} + \lambda_i + \lambda_{sM} + \lambda_{fM} + \epsilon_{isft}$$

$$\begin{aligned}
y_{isft} &: \text{(log) number of tweets for journalist } i \text{ in the 30-day window} \\
monthsSinceKilling_{isft} &: \text{event-time dummies counting periods since `friend'} \\
&\quad \text{in same state of i was victimized} \\
\lambda_i &: \text{user fixed effects} \\
\lambda_{st} &: \text{state} \times \text{calendar-month fixed effects} \\
\lambda_{ft} &: \text{`friend'} \times \text{calendar-month fixed effects}
\end{aligned}$$

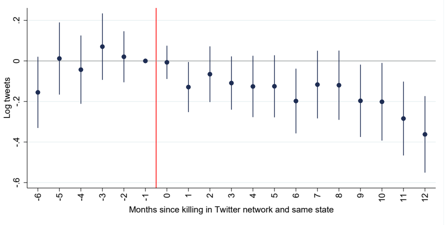
Robust standard errors clustered by journalist

Twitter network of selected accounts



Note: The figure shows a partial Twitter network for the accounts in our dataset. Red nodes represent victimized outlets and green nodes are journalists. An edge is drawn between two nodes if either of the accounts follows the other.

Network effects: journalists in same state and network



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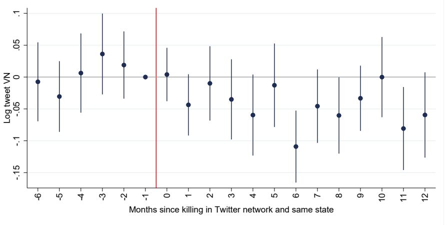

(b) Tweets about violence

Long-run effects of violence on occupational choice

Difference in differences

$$y_{ist} = \alpha + \beta \times violence_s \times post_M + \gamma_t + \gamma_s + \varepsilon_{ist} \qquad (1)$$

- $y_{ist} = 1$ if individual i in state s reported in Census t (2010, 2015) that he/she was a journalist
- $violence_s$: number of journalists killed/indicator for any journalist killed between 2010 and 2015
- Sample: workers with codes "close" to journalist: accountants, researchers, psychologists, artists and performers

Demographics Migration

Long-run effects of violence on occupational choice

Table: Relationship between violence against journalists and share of journalists

	(1)	(2)	(3)	(4)
post x	-0.0009*		-0.0010**	
Nr. MW murd.	(0.0004)		(0.0005)	
post x		-0.0087***		-0.0100***
Any. MW murd.		(0.0030)		(0.0034)
post x	-0.0001	0.0000	-0.0005	-0.0003
log hom.	(0.0014)	(0.0016)	(0.0014)	(0.0016)
N	117673	117673	101421	101421
N-clusters	32	32	32	32
State FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Only wage earners	no	no	yes	yes

Notes: Outcome is an indicator equal to one if individual reports being a journalist. Standard errors clustered at the state level in parenthesis. Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01.

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Measuring changes in tone

- Consider 180 days before/after attack
- Predict whether tweet/article was published before or after attack based on text content
- Estimate Multinomial Inverse Regression framework (**MNIR**; Taddy, 2013), a supervised machine learning model (conceptually, similar to a LASSO regression)

framework

Intuition

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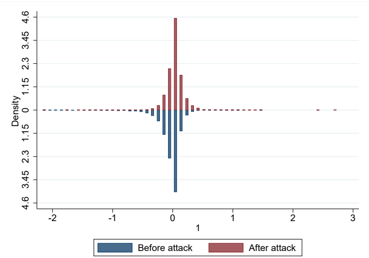
5. Identify words that predict change by looking at coefficients (nr. 1), and relative frequencies

Changes in content



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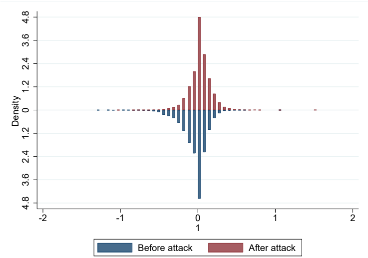
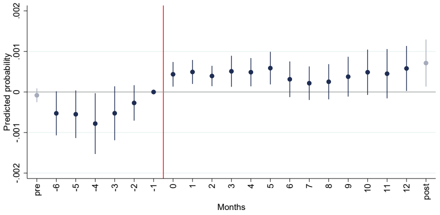


(b) Violent tweets

Changes in content



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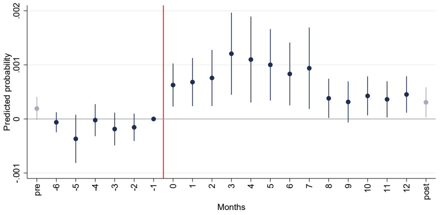
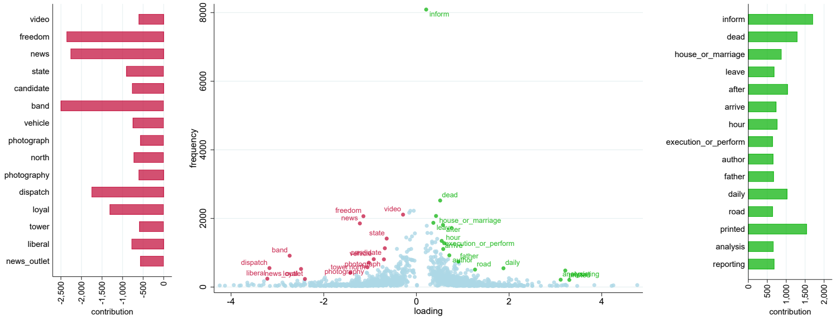


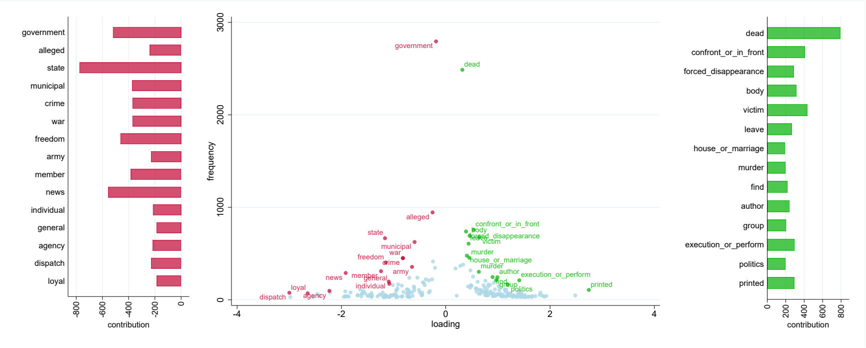
(b) Violent tweets

Words that drive change in tone (All)



Terms that drive change in tone: consider words with $\phi_j \neq 0$. Run PLS of y on $\hat{x}$. Define *contribution* $\equiv \hat{\lambda} \times \hat{x}$

Words that drive change in tone (violent)



Polarity

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Concluding remarks

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Concluding remarks

- The murder of journalists in Mexico leads to a chilling effect with large reductions in Twitter activity by affected outlets
- Fewer journalists work in dangerous states in the long-run
- Mechanical effects: smaller outlets experienced larger declines in publishing
- Behavioral responses: journalists "closer" to victims reduced their twitting relative to other
- Some evidence of permanent changes in tone

Thank you!

References I

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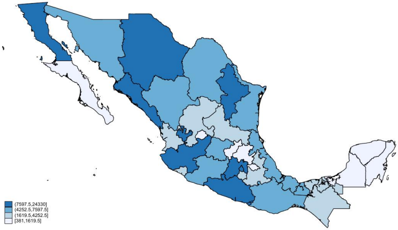
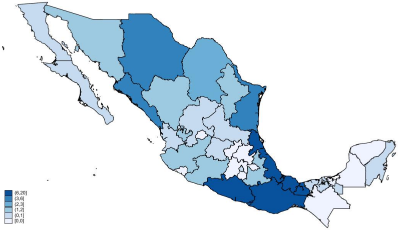
Appendix

Homicides across space

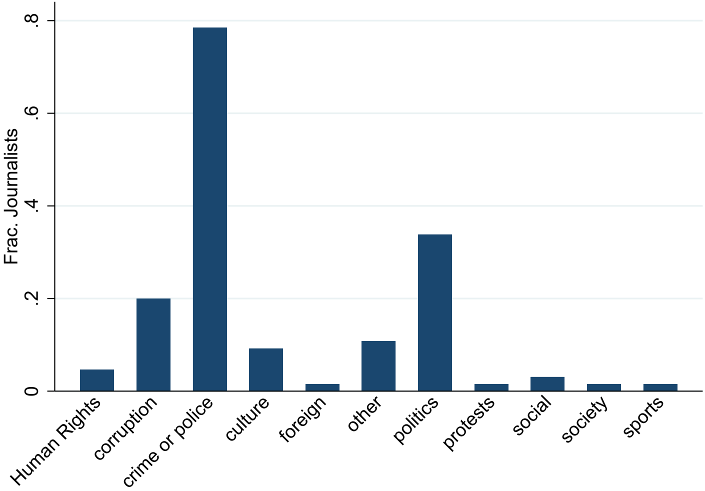


(a) Total homicides



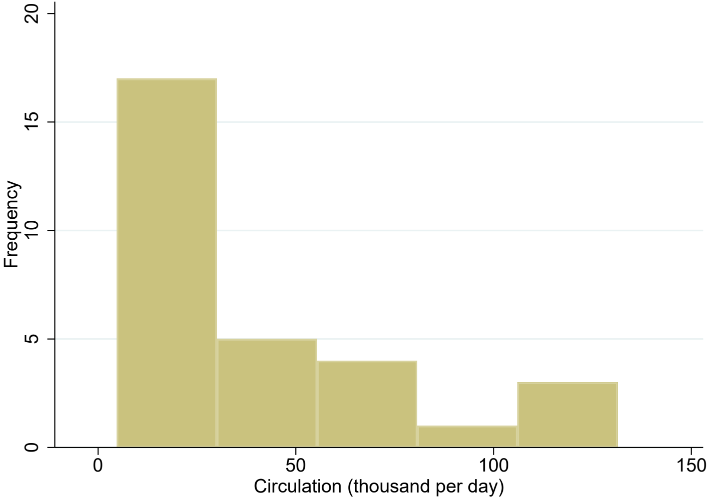
(b) Journalists murdered

Subjects covered by murdered journalists



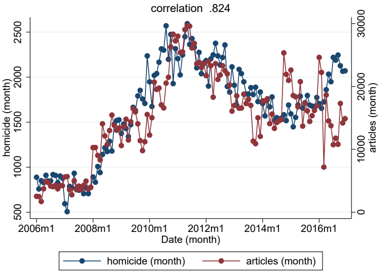
Source: Committee to Protect Journalists (CPJ)

Daily circulation of VO

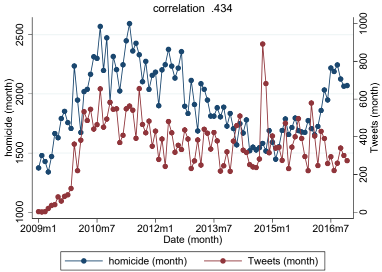


$$N = 30$$

Homicides in the country and coverage of violence



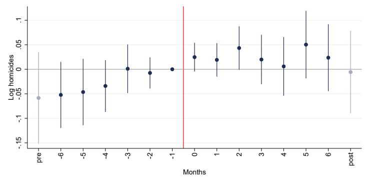
(a) Articles with violent content



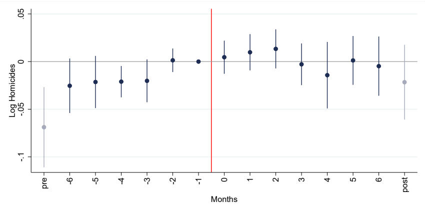
(b) Tweets with violent content

Total *net* homicides around an attack

$$homicides_{set} = \gamma_{se} + \gamma_t + \sum_{k=-6}^{6} \beta_k \times monthsSinceKilling_{set}$$
$$+ \beta_{pre} \times Pre_{set} + \beta_{post} \times Post_{set} + \epsilon_{set}$$



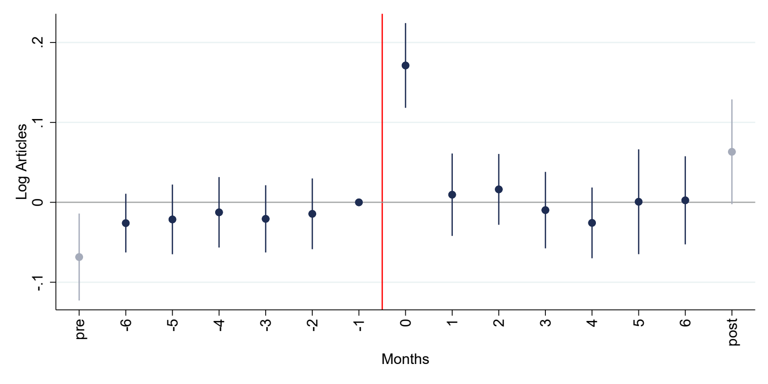
(a) State of aggression



(b) Municipality of outlet

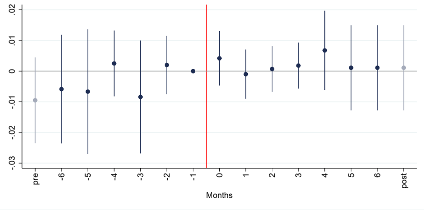
Direct Effects

Mentions of municipalities in the national press

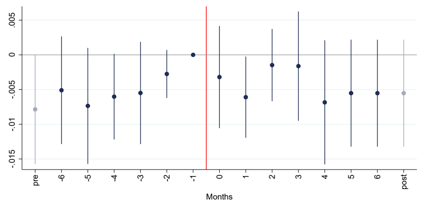


Direct Effects

Mentions of cartels before/after murder (national press)



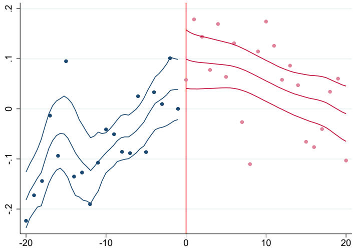
(a) Sinaloa Cartel



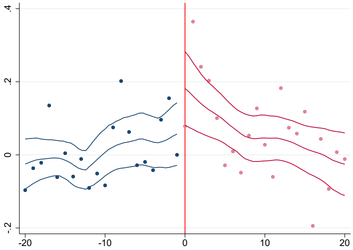
(b) Jalisco New Generation Cartel

Note: dependent variable is log + 1 mentions of municipalities *and* criminal organization

Google searches



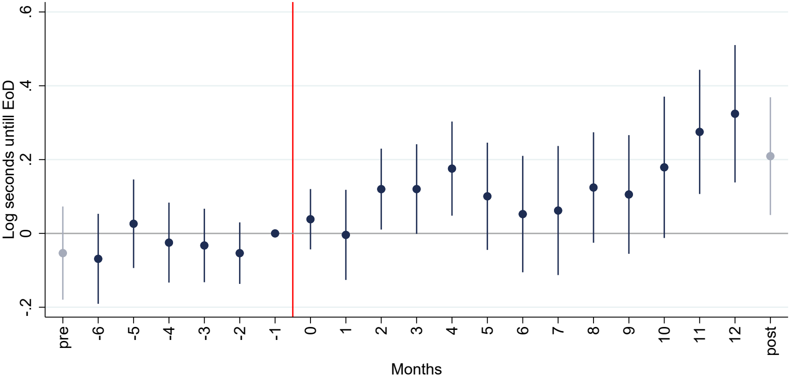
(a) *Murder*



(b) *Journalist*

Direct Effects

Robustness check: timing of tweets



Higher values = more seconds elapsed till end-of-day = tweets earlier in the day = fewer tweets

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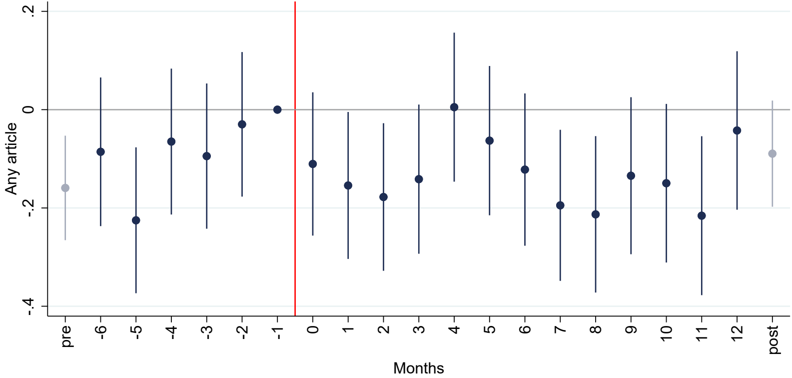
Robustness check: articles (from Google CSE)



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Long-run effects of violence on demographic characteristics

Triple differences

$$\begin{aligned} y_{isto} = \alpha + \beta_0 \times violence_s \times post_t + \beta_1 \times violence_s \times journalist_o \\ + \beta_2 \times journalist_o \times post_t + \beta_3 \times violence_s \times journalist_o \times post_t \\ + \gamma_o + \gamma_t + \gamma_s + \varepsilon_{ist} \end{aligned} \tag{2}$$

- y_{isto}: outcome for individual i in state s, census t (2010, 2015) and occupation o
- $journalist_o$: indicator variable for journalist

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Long-run effects of violence on demographic characteristics

Table: Relationship between violence against journalists and census outcomes

	(1) School yrs	(2) Married	(3) Kids	(4) Age	(5) Urban	(6) Male	(7) Income
post x Nr. MW killed x journ.	-0.0355	-0.0104**	-0.0106**	-0.0191	-0.0026**	0.0035	-0.0215***
	(0.0342)	(0.0047)	(0.0040)	(0.0798)	(0.0010)	(0.0038)	(0.0071)
post x log hom. x journ.	-0.1123	-0.0188	-0.0277	0.3898	-0.0011	-0.0231	0.0349
	(0.1123)	(0.0328)	(0.0336)	(0.4736)	(0.0088)	(0.0247)	(0.0569)
N	117673	117673	117673	117673	117673	117673	101421
N-clusters	32	32	32	32	32	32	32
State FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the state level in parenthesis.
Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01.

Effects of violence on migration of journalists

$$\begin{aligned} y_{hst} &= \alpha + \beta \times X_{hst} + \gamma \times hom_{hst} + \delta \times homjourn_{st} \\ &+ \zeta \times homjourn_{st} \times journ_{hst} + \epsilon_{hst} \end{aligned}$$

- y: indicator for net/out migration of household h in state s and census t
- X: individual controls; household type, size, age group, marital status, indigenous, education attainment
- *hom*: log homicides
- *homjourn*: number of journalists killed
- *journ*: indicator for journalist occupation

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Effects of violence on migration of journalists

Table: Relationship between violence and inflows/outflows

	(1) Inflows	(2) Inflows	(3) Inflows	(4) Outflows	(5) Outflows	(6) Outflows
log hom.	-0.0045	-0.0028	-0.0025	0.0043	0.0023	0.0029
	(0.0057)	(0.0072)	(0.0071)	(0.0029)	(0.0056)	(0.0053)
Any MW killed	-0.0106	-0.0006	-0.0000	0.0025	0.0060	0.0060
	(0.0064)	(0.0037)	(0.0039)	(0.0042)	(0.0038)	(0.0036)
Journ. x any MW killed	-0.0178	-0.0173	-0.0157	0.0138	0.0142	0.0146
	(0.0139)	(0.0110)	(0.0129)	(0.0118)	(0.0109)	(0.0114)
Log avg. wages	0.0014*	0.0008	0.0008	-0.0030	-0.0102**	-0.0087
	(0.0008)	(0.0008)	(0.0007)	(0.0034)	(0.0039)	(0.0056)
N	2041370	2041370	2041370	2333526	2333526	2333526
State FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	No	Yes	Yes	No	Yes

Notes: Standard errors clustered at the state level in parenthesis.
Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01.

MNIR framework

Predict probability of term based on word count of tweet and post-attack:

$x_i \sim MN(q_i, m_i)$ with $q_{ij} = \dfrac{e^{\eta_{ij}}}{\sum_{l=1}^{p} e^{\eta_{il}}}$,

where $\eta_{ij} = \alpha_j + \phi_j y_i$

- x_i bag-of-words representation document i
- $y_1 = 1$ if document i published after attack
- term j
- p total terms
- LASSO penality assures that some $\phi_j = 0$

MNIR framework

Compute the **Sufficient Reduction** (SR): "index" that captures relevant information

$z_i \equiv x_i' \times \Phi$

Project SR to the unit interval (**Forward regression**)

$y_{oi} = \gamma_o + \gamma_m + \beta \times z_{oi} + \epsilon_{oi}$

Perform event study using predicted probability

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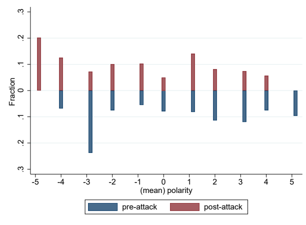
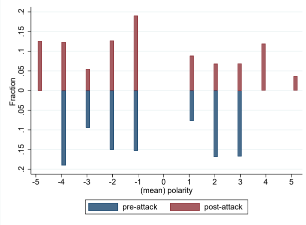
Polarity

Figure: Distribution of terms by polarity



(a) All tweets



(b) Violence tweets

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Violent tweets keywords I

1. cartel
2. *narco*
3. violence
4. homicide
5. death
6. body
7. threat
8. justice
9. alleged
10. accuse
11. criminal
12. assassin
13. kidnap
14. forced disappearance

Violent tweets keywords II

15. victim
16. convict
17. drug
18. government
19. corrupt
20. police
21. military
22. general attorney
23. torture
24. conflict
25. war
26. *Chapo*
27. investigation
28. impunity

Violent tweets keywords III

29. crime
30. ties to
31. arrest
32. member of
33. confrontation
34. injured

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