The effects of economic sanctions on political unrest in Iran

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Broad economic sanctions disrupt economic exchange.

Purpose is behavioral modification, regime change, or simply "demonstration of resolve" (Hufbauer et al., 2007).

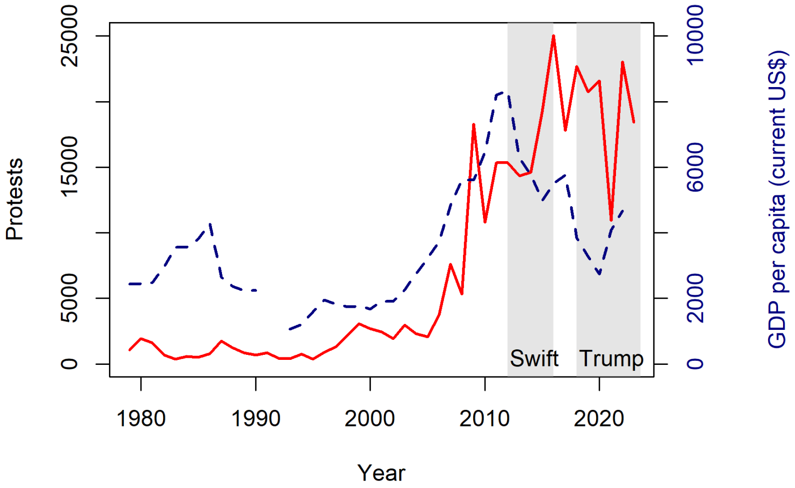
Intended mechanism starts with trade disruption

- creates discontent with current policy or regime
- decreases tax revenue, further increases discontent
- discontent increases demand for behavioral or regime change

Works this way?

- trade can be diverted
- can increase focus on domestic production
- cost of discontent can be ∞
- can harm citizens in target country
- can strengthen support for current policy and regime

INTRO - IRAN CONTEXT



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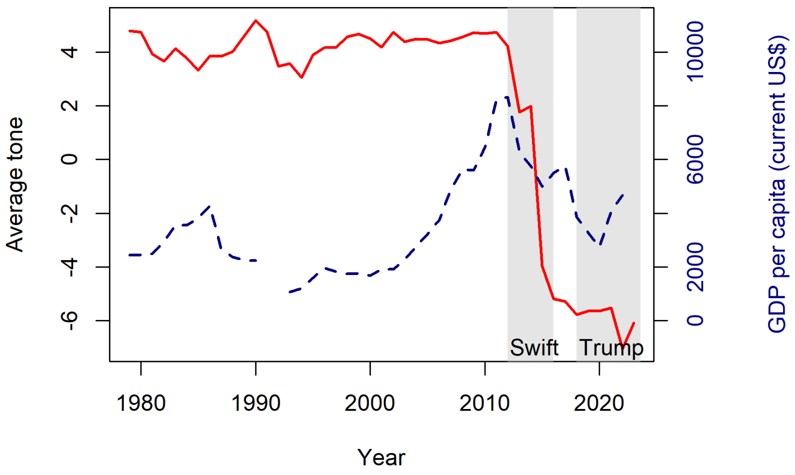


INTRO - METHODOLOGY

Study built around two primary data sets: 1. confidential household data from Iranian Statistical Office; 2. protest data from GDELT.

Household data has detailed expenditure information on items that fall under: food, clothing, housing, and education. Covers 314388 households, 1158 items, from 2008 until 2018, amounting to 29 million household-item-month observations.

Use household data to examine differential effects of sanctions. Focus on differential effects of 3 sanction regimes: 2012 Obama/Swift; 2016 sanction relief; 2018 Trump reimposition.

Outcomes: number of demonstrations, tone, nature (women's rights e.g.)

INTRO - FINDINGS

Findings are VERY preliminary, but...

removal of sanctions due to JCPOA: tone of protests more negative – protests luxury activity?

reimposition of sanctions in 2018: more protests, but less negative women's rights protests most prevalent after removal of sanctions – women's rights protests luxury activity?

still developing data/narratives

INTRO - CONTRIBUTION

Draca, Garred, Stickland and Warrinnier, 2023:

- examine bluntness of sanctions
- show evidence that (TSE) stock returns of key actors (IRGC and Supreme Leader Ali Khamenei) decreases

Gold, Hinz, and Valsecchi, Working Paper, 2023:

- examine differential subnational effects of 2014 economic sanctions on Russia
- evidence shows vote share for Putin increased by more in affected regions

Crozet and Hinz, Working Paper, 2023:

- examine differential subnational effects of 2014 countersanctions against France (by Russia)
- shows vote share for far right (pro Russia) parties increased by more in affected regions

BACKGROUND - POLITICAL SYSTEM

	ELECTED INSTITUTIONS	APPOINTED BY ELECTED INSTITUTIONS	UNELECTED INSTITUTIONS
ELECTORATE	PARLIAMENT	GUARDIAN COUNCIL (like upper house)	HEAD OF JUDICIARY
	PRESIDENT	CABINET	ARMED FORCES
	ASSEMBLY OF EXPERTS (88 Mujtahids)	SUPREME LEADER	EXPEDIENCY COUNCIL

BACKGROUND - TIMELINE

1996	U.S. Iran Sanctions Act
2006	UN Resolution 1737
2007	EU Regulation 423
2007	U.S. sanctions Qods Force
2010	Comprehensive Sanctions Act
2010	EU Regulation 961
2011	NDAA targets finance
2012	**EU Regulation 267/2012**
2012	**Expanded sanctions**
2013	Executive order with IFCA sanctions
2015-2016	**Joint Plan of Action and lifting of sanctions**
2018	**Trump reinstates sanctions**

BACKGROUND - SANCTION REGIMES

- March 2012 (SWIFT):
  - Iran excluded from SWIFT;
  - US: companies shipping Iranian oil sanctioned;
  - EU: embargo on Iranian oil imports

Obama quote: “Because of our efforts, Iran is under greater pressure than ever before. . . Few thought that sanctions could have an immediate bite on the Iranian regime. They have, slowing the Iranian nuclear program and virtually grinding the Iranian economy to a halt in 2011. Many questioned whether we could hold our coalition together as we moved against Iran’s Central Bank and oil exports. But our friends in Europe and Asia and elsewhere are joining us. And in 2012, the Iranian government faces the prospect of even more crippling sanctions.”

BACKGROUND - SANCTION REGIMES

- January 2016 (OBAMA LIFTS SOME SANCTIONS)
  - ban on Iran–US trade financial transactions remain; sanctions on automotive sector of Iran;
  - Iran can trade luxury goods aircrafts;
  - UN: sanctions and US secondary sanctions lifted;
  - EU: ban on purchases of oil, gas from Iran lifted; Iranian banks readmitted to SWIFT;
- November 2018 (TRUMP REIMPOSES US SANCTIONS)
  - transactions with Iran in luxury goods, aircraft;
  - petroleum-related transactions with Iran;
  - transactions by foreign banks with Iran's Central Bank;
  - countries have to cut oil purchases from Iran for maintaining exemptions.

DATA - HOUSEHOLDS

Household Expenditure and Income Survey, 1387–1399 (2008–2018), conducted by Statistical Center of Iran

Purpose: measure average income ($\rightarrow$ individual level) and expenditures ($\rightarrow$ hh level) at municipality and province level

Multi–state sample design: full sample consisting of all private rural and urban households of Iran, 3–stage cluster sampling method with strata:

1. census areas selected
2. urban and rural blocks selected
3. households sampled, samples evenly distributed over months of year

Face-to-face interviews (responses cannot have legal consequences)

DATA - HOUSEHOLDS

Observe expenditures on: food, tobacco, clothing, housing, furniture, health, transport, communication, leisure, education, etc.

Income: salary from employment in private and public sector, self-employed income, miscellaneous income, non-monetary income (e.g., value of home production)

Altogether, 314388 households, 1158 items, from 2008 until 2018, amounting to 29 million household-item-month observations.

SUMMARY STATISTICS

Table: **Summary statistics for household data.**

	Mean	SD	Min	Max	N
total expenditures (IRR)	789,856.90	13,493,412.64	0.00	8700000000.00	29682673
total expenditures (current USD)	18.76	320.51	0.00	206650.83	29682673

Notes:

[1] Unit of observation is defined by the household, the product, and the survey wave. Sample covers 314388 distinct households, 1158 distinct products, from 2008 to 2018 inclusive.

[3] IRR references Iranian rials. 42225 rials can be exchanged for $1 U.S. as of 30 May 2024.

SUMMARY STATISTICS - TOP ITEMS

Mean	SD	Min	Max	N	Description
1.17	1.52	.0096	1350	3469145	Vegetables (ND)
2.03	2.91	.0024	470.4	1868671	Fruit (ND)
4.89	10.87	0	1584	1784821	Bread and cereals (ND)
2.20	3.48	.012	1092	1580965	Milk, cheese and eggs (ND)
1.10	2.52	.0072	652.8	1378946	Other appliances, articles and products for personal care (ND)
.96	1.25	0	288	1267180	Food products n.e.c. (ND)
1.68	2.79	.0024	1008	980667	Sugar, jam, honey, chocolate and confectionery (ND)
7.82	14.08	.0288	1920	909223	Meat (ND)
3.70	7.18	.0072	960	702220	Passenger transport by road (S)
4.97	5.53	.018	360	673015	Telephone and telefax services
7.69	14.07	0	1680	589359	Garments (SD)
1.31	1.77	0	264	555339	Mineral waters, soft drinks, fruit and vegetable juices (ND)

Notes:

[1] Unit of observation is defined by the household, the product, and the survey wave. Sample covers 314388 distinct households, 1158 distinct products, from 2008 to 2018 inclusive.

[2] ND refers to non-durable. S to services.

EXPOSURE MEASURE

Use household data in pre-Swift period to measure exposure of shahrestans (counties) to sanctions. Assume exposure of each household h is given by

$$exp_{hc} = \sum_{j=1}^{n} s_{jhc} \left[\frac{m_j - x_j}{m_j + x_j} \right]$$

where $c =$ municipality, $j =$ 4-digit COICOP tradable, $n =$ number of tradables.

- $s_{jhc} = \frac{e_{jhc}}{e_{hc}}$, e_{jh} is household expenditure on tradable j,
- x_j is exports of tradable j, m_j is imports of tradable j.

Aggregate household exposure to shahrestan

$$\overline{exp}_c = \sum_{h=1}^{H_c} exp_{hc} / H_c$$

Figure: **Quantile plot for the three exposure measures.**

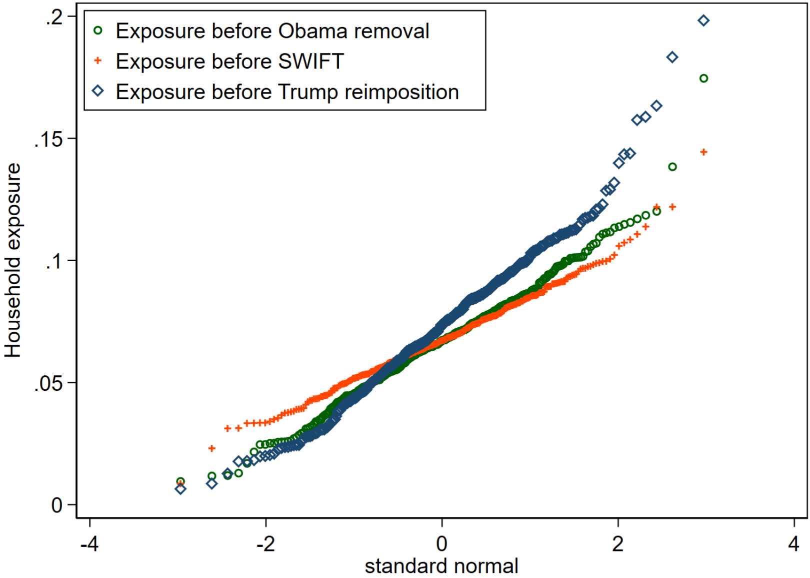
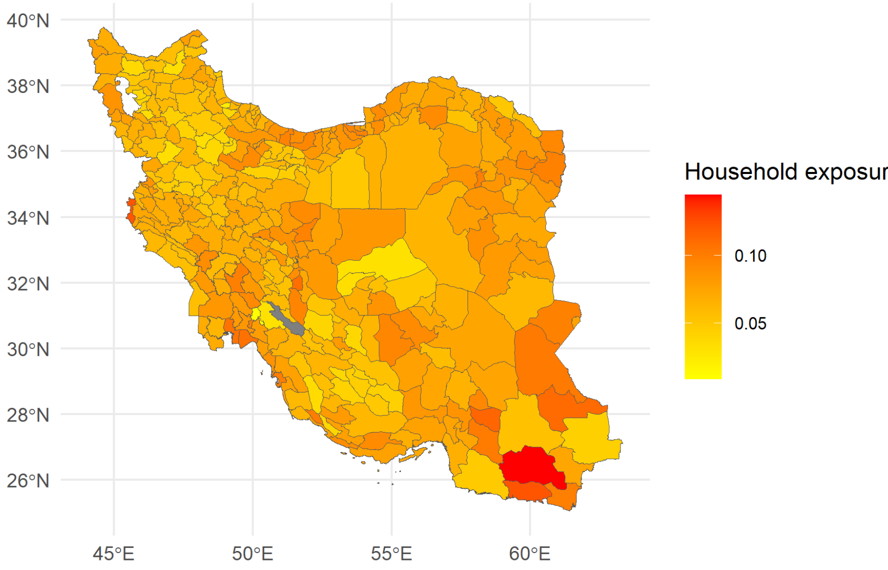


Figure: **Household exposure by municipality.**



GDELT: Global Database of Events, Language, and Tone

- Automated collection using key words, the internet and predetermined scores
- Updated every 15 minutes
- 300 different types of political events
- Sourcing, including hundreds of thousands of traditional media stories, translated from over 100 languages
- Dynamic source, changes daily, without oversight

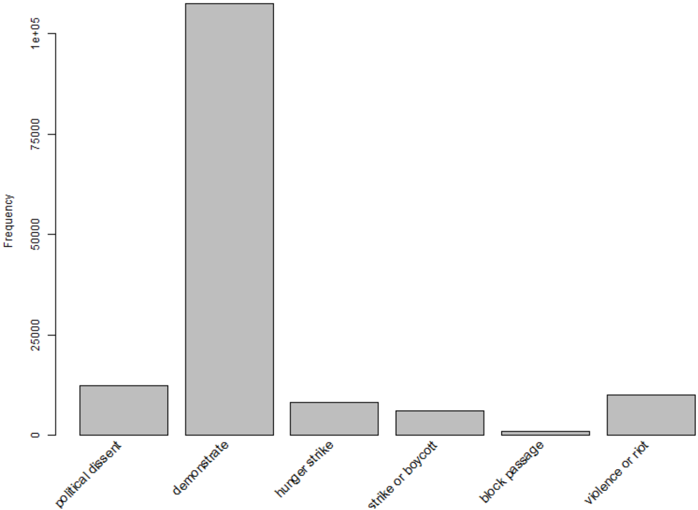
GDELT PROTEST DATA

Event identification and collation based on newspaper articles and websites, e.g., tribune.com.pk, en.trend.az, www.arabnews.com, globalnews.ca, etc.

Classifies demonstrations:

- "political dissent"
- "demonstrate"
- "hunger strike, strike or boycott"
- "block passage"
- "violence or riot"

Figure: **Protest categories.**



“AVERAGE TONE”

average tone of demonstration = positive word share (“wonderful”, “delightful”, “fantastic”) minus – negative word share share (“awful”, “terrible”, “horrific”)

Ranges between -100 (extremely negative) and +100 (extremely positive).

Let’s us distinguish b/w demonstration and “protest”

Hassan Rouhani Victory Celebrations Fill Tehran's Streets As Iranians Embrace New Reformist President (PHOTOS)

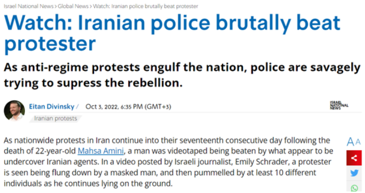
LOOK: Iranians Celebrate New Reformist President

Jun 15, 2013, 05:24 PM EDT

LEAVE A COMMENT

Reformist candidate Hassan Rouhani won Iran's presidential election on Saturday, garnering hope among the country's moderate and liberal youth for democracy and significant change. Thousands of citizens took to the streets in Tehran, flashing victory signs and shouting, "Long live Rouhani!" in celebration of their new leader. Check out these photos of excited Iranians rallying around their president-elect.

Figure: Example one.



Israel National News > Global News > Watch: Iranian police brutally beat protester

Watch: Iranian police brutally beat protester

As anti-regime protests engulf the nation, police are savagely trying to supress the rebellion.

Eitan Divinsky / Oct 3, 2022, 6:35 PM (GMT+3)

Iranian protests

As nationwide protests in Iran continue into their seventeenth consecutive day following the death of 22-year-old Mahsa Amini, a man was videotaped being beaten by what appear to be undercover Iranian agents. In a video posted by Israeli journalist, Emily Schrader, a protester is seen being flung down by a masked man, and then pummelled by at least 10 different individuals as he continues lying on the ground.

Figure: Example two.

Rank	Actors	Frequency	Rank	Actors	Frequency
1	IRAN vs	16429	51	IRAN vs UNITED KINGDOM	632
2	IRANIAN vs	6437	52	PROTESTER vs POLICE	630
3	IRAN vs IRAN	5955	53	IRAN vs TEHRAN	621
4	IRANIAN vs IRAN	3997	54	IRAN vs SCIENTIST	610
5	vs IRAN	3814	55	AMERICAN vs	609
6	IRAN vs UNITED STATES	2977	56	UNITED STATES vs IRANIAN	577
7	UNITED STATES vs IRAN	2218	57	ISRAEL vs	576
8	IRAN vs IRANIAN	2018	58	IRANIAN vs ISRAEL	565
9	TEHRAN vs	2001	59	STUDENT vs IRAN	559
10	vs IRANIAN	1696	60	IRAN vs SYRIA	542
11	IRAN vs ISRAEL	1527	61	SYRIA vs IRAN	528
12	IRAQ vs IRAN	1468	62	AMERICAN vs IRAN	523
13	PROTESTER vs IRAN	1413	63	POLICE vs IRAN	520
14	IRANIAN vs IRANIAN	1355	64	PAKISTAN vs IRAN	513
15	IRAN vs REGIME	1338	65	IRAQ vs	511
16	REGIME vs	1245	66	IRANIAN vs GOVERNMENT	510
17	IRAN vs AMERICAN	1220	67	IRAN vs LEBANON	504
18	IRAN vs ISLAMIC	1173	68	IRAN vs PAKISTAN	503
19	IRAN vs IRAQ	1140	69	ISRAELI vs IRAN	495
20	UNITED STATES vs	1127	70	WORKER vs	491
21	GOVERNMENT vs	1111	71	IRANIAN vs THE US	485
22	PROTESTER vs	1059	72	IRANIAN vs IRAQ	484
23	ISLAMIC vs	1047	73	IRAQI vs IRANIAN	482
24	IRAN vs GOVERNMENT	1042	74	ISRAEL vs IRANIAN	481
25	IRAN vs POLICE	1015	75	IRAN vs PRESIDENT	477
26	ISLAMIC vs IRAN	1015	76	PRISONER vs	477
27	ISRAEL vs IRAN	983	77	IRANIAN vs BRITISH	475
28	IRANIAN vs UNITED STATES	957	78	IRAN vs MILITARY	473
29	IRAN vs PRISON	937	79	UNITED KINGDOM vs IRAN	452
30	IRAN vs PRISONER	906	80	SAUDI ARABIA vs IRAN	446
31	IRAN vs SAUDI ARABIA	876	81	LEBANON vs IRAN	443
32	TEHRAN vs IRAN	871	82	IRANIAN vs POLICE	440
33	PRISON vs IRAN	850	83	SUICIDE BOMBER vs IRAN	440
34	PRISON vs	811	84	WASHINGTON vs IRAN	440
35	PROTESTER vs IRANIAN	[illegible]	85	THE US vs IRANIAN	[illegible]

"PROTEST TYPE"

From 2013 onwards, GDELT includes a url source. The url includes the title of the article. Can use text from url to classify protests into types:

- Economic protests
  - urls with words "price","rising-price","high-price","inflation","currency","-rial","unemployment"
- Social protests
  - urls with words "hijab","rape","execution"

Table: **Descriptive statistics.**

	(1) count	(2) mean	(3) sd	(4) min	(5) max
Protests	68485	4.12	50.81	0.00	4707.00
Average tone	13052	-1.78	5.57	-25.00	16.33
Economic protests	68485	0.01	0.43	0.00	76.00
Hijab protests	68485	0.02	0.73	0.00	127.00
Execution protests	68485	0.06	2.07	0.00	461.00
Rape protests	68485	0.01	0.25	0.00	19.00

Notes:

[1] Unit of observation is municipality by month and year.

Figure: **Protests by municipality.**

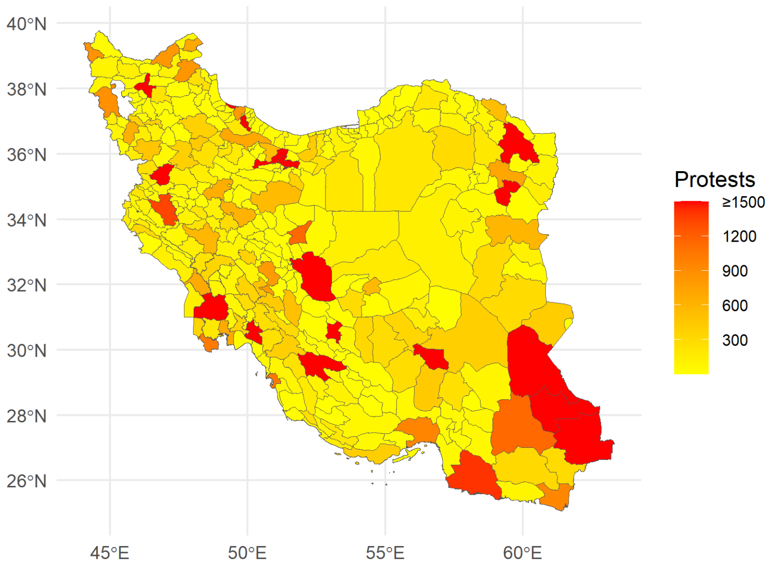


Figure: **Average tone by municipality.**

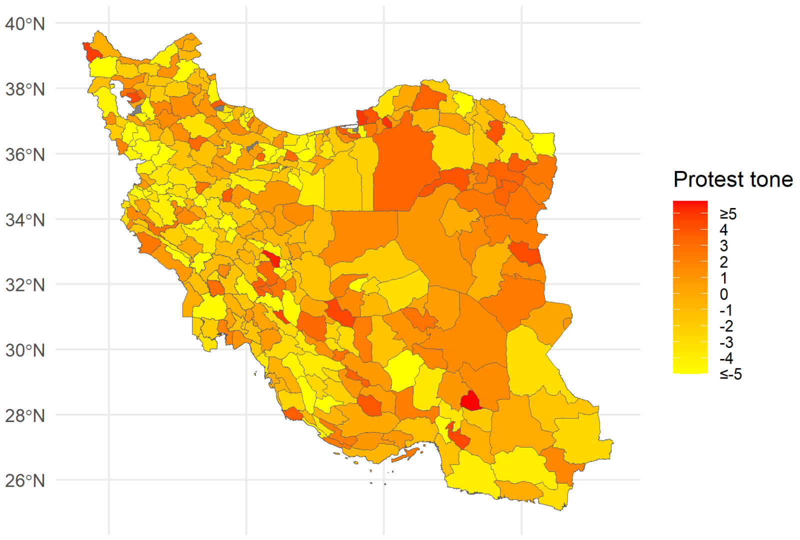


Figure: **Import-export relative price by municipality.**

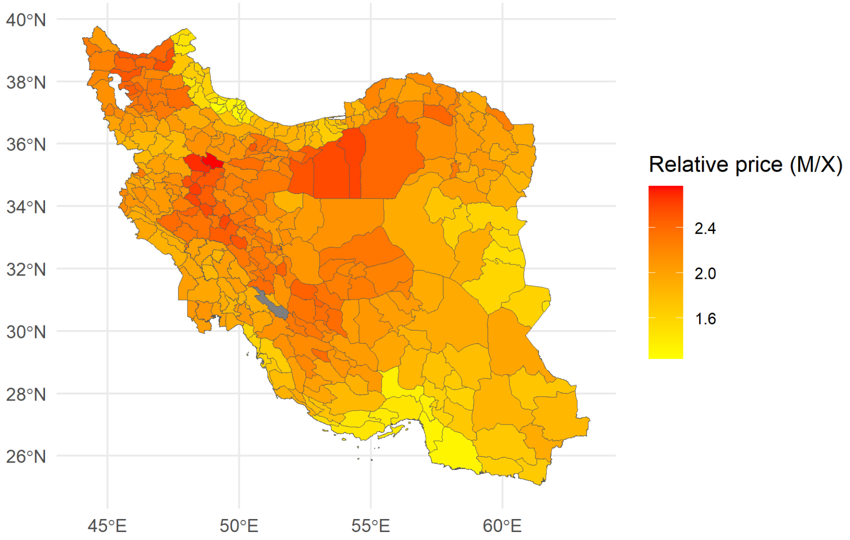
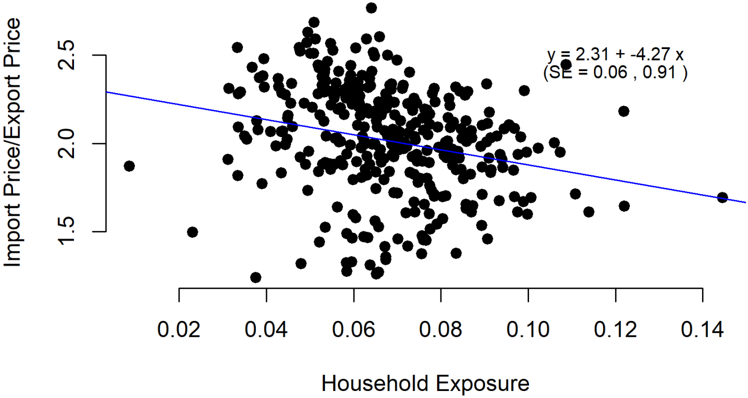


Figure: **Exposure against relative price by municipality.**



BASELINE SPECIFICATION

We estimate

$$y_{ct} = \alpha_c + \beta \overline{exp}_c post_t + \gamma_{s(c)t} + e_{ct}$$

where

- $c = sharestan(county), s(c) = state, t = year - month$
- y_{ct} is protest outcome (number, tone, type)
- $post_t$ equals 1 after sanction regime change
- $\overline{exp}_c$ is average exposure of households in sharestan c in terms of expenditures on tradables.

Table: **Baseline regressions.**

	(1) Protests≥ 1	(2) Tone ≤ 0
HH exposure $\times$ Swift	-0.304	0.147
	(0.371)	(0.525)
Observations	31844	18918
HH exposure $\times$ Obama	-0.109	0.892
	(0.709)	(0.013)
Observations	26571	17781
HH exposure $\times$ Trump	0.807	-4.184
	(0.016)	(0.000)
Observations	11757	2978
Dep Var Mean	0.19	0.11

Notes:

[1] Unit of observation is municipality by month and year.

[2] Dependent variables are binary.

[3] All regressions include fixed effects for the municipality and month-year combination.

[5] Standard errors are clustered on the province. *p* values in parentheses.

Table: **Exposure by Net Imports and Net Exports.**

	(1) Protests≥ 1	(2) Tone ≤ 0	(3) Protests≥ 1	(4) Tone ≤ 0
HH exposure $\times$ Swift	-0.304	0.147		
	(0.371)	(0.525)		
HH exposure (net imports) $\times$ Swift			-0.411	0.111
			(0.187)	(0.680)
HH exposure (net exports) $\times$ Swift			-0.981	-0.018
			(0.116)	(0.972)
Observations	31844	18918	31844	18918
R^2	0.387	0.870	0.388	0.870
HH exposure $\times$ Obama	-0.109	0.892		
	(0.709)	(0.013)		
HH exposure (net imports) $\times$ Obama			-0.130	1.238
			(0.667)	(0.000)
HH exposure (net exports) $\times$ Obama			0.685	-1.397
			(0.185)	(0.009)
Observations	26571	17781	26571	17781
R^2	0.418	0.765	0.418	0.766
HH exposure $\times$ Trump	0.807	-4.184		
	(0.016)	(0.000)		
HH exposure (net imports) $\times$ Trump			0.680	-1.593
			(0.112)	(0.123)
HH exposure (net exports) $\times$ Trump			0.407	5.102
			(0.653)	(0.008)
Observations	11757	2978	11757	2978
R^2	0.474	0.752	0.474	0.772

Discussion

Results very preliminary. Need further vetting.

But results from Trump reimposition are interesting to us. Raises questions about mechanism.

Reactance? Pressuring people into accepting a view can cause them to adopt or strengthen the contrary view.

Working on getting data to learn more about this (wvs, confidential political attitude surveys). As a first pass...

Table: **Effects of sanctions on economic protests.**

	Economic protests$\geq$ 1
HH exposure $\times$ Obama	0.082
	(0.154)
Observations	26571
HH exposure $\times$ Trump	-0.012
	(0.711
Observations	11757

Table: **Effects of sanctions on women's rights protests.**

	Women's rights protests$\geq$ 1
HH exposure $\times$ Obama	0.109
	(0.155)
Observations	26571
HH exposure $\times$ Trump	-0.082
	(0.027)
Observations	11757