Vote Brokers Replication Paper

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Abstract

Timothy Frye, Reuter and Szakony (2019) examine the voter behavior Russia and Venezuela and find different types of brokers, appeals, and targets have different effects on voter turnout. I successfully replicated all of their results. As a robustness test, I impute missing values in the dataset and find results in line with that of the originally study, but of a smaller magnitude. These results confirm the authors' original findings and suggest that the missing values in their sampled population do not bias the results.

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1 Introduction

I am replicating "Vote Brokers, Clientelist Appeals, and Voter Turnout: Evidence from Russia and Venezuela" by Timothy Frye, Ora John Reuter and David Szakonyi.

2 Literature Review

For this paper I looked at a few papers on voting structure in Russia, as I was able to find less on Venezuela. In "How Capitalism was Built", by Anders Aslund, the literature suggests that in many post soviet countries, voting patterns were heavily influenced by the transition to democracy in instiutions built. In Russia, the case was that there was not enough a big push to transform after communism, and thus the country had to face more difficulties in long term in ensuring fair and free elections. Additionally, in Olga Popova's "Corruption, Voting and Employment Status: Evidence from Russian Parliamentary Elections", Popova finds that controlling for different employment statuses and corruption, people are stil likely to vote differently, and more corruption generally induces people to vote more, which I think is to expected.

3 Paper Overview

For my final replication project, I decided to look at Vote Brokers, Clientelist Appeals, and Voter Turnout: Evidence from Russia and Venezuela, a paper by Timothy Frye, Ora John Reuter and David Szakonyi. The paper looks at two countries, Russia and Venezuela, to what factors, if any, in clientelist exchange. The authors specifically look at the role of brokers and leverage in these two cases. The study uses survey data to explore Russian and Venezuelan brokers and how they perform in monitoring voting.

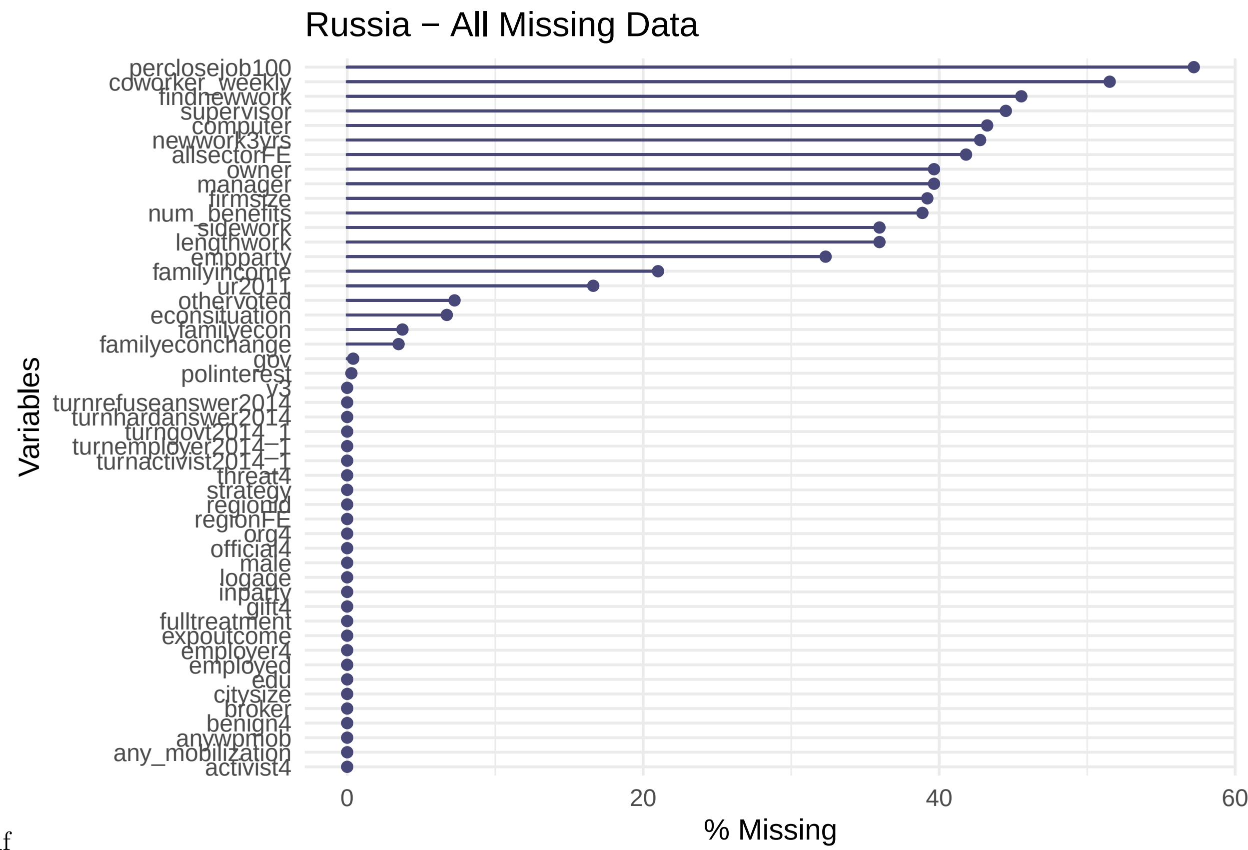
The goal is basically to understand how are monitors pressured by upper management in order to carry out clientelism and skew the voting. To understand this, the authors use a few models, such as difference of means between the different type of brokers and methods of leveraging, in both Russia and Venezuela. They also run fixed effect linear regressions to see what influence the skewing of the voting turnout for a couple of different scenarios, but actually include very few variables in their regression which is strange. The paper also has very specific demographics of the type of individuals they are looking at, which is good because it is specific but might also be a drawback because it limits the scope of the study. This paper ultimately finds that in Russia and Venezuela, different types of brokers and methods can influence voter turnout differently, which seems to be expected.

4 What I was able to replicate

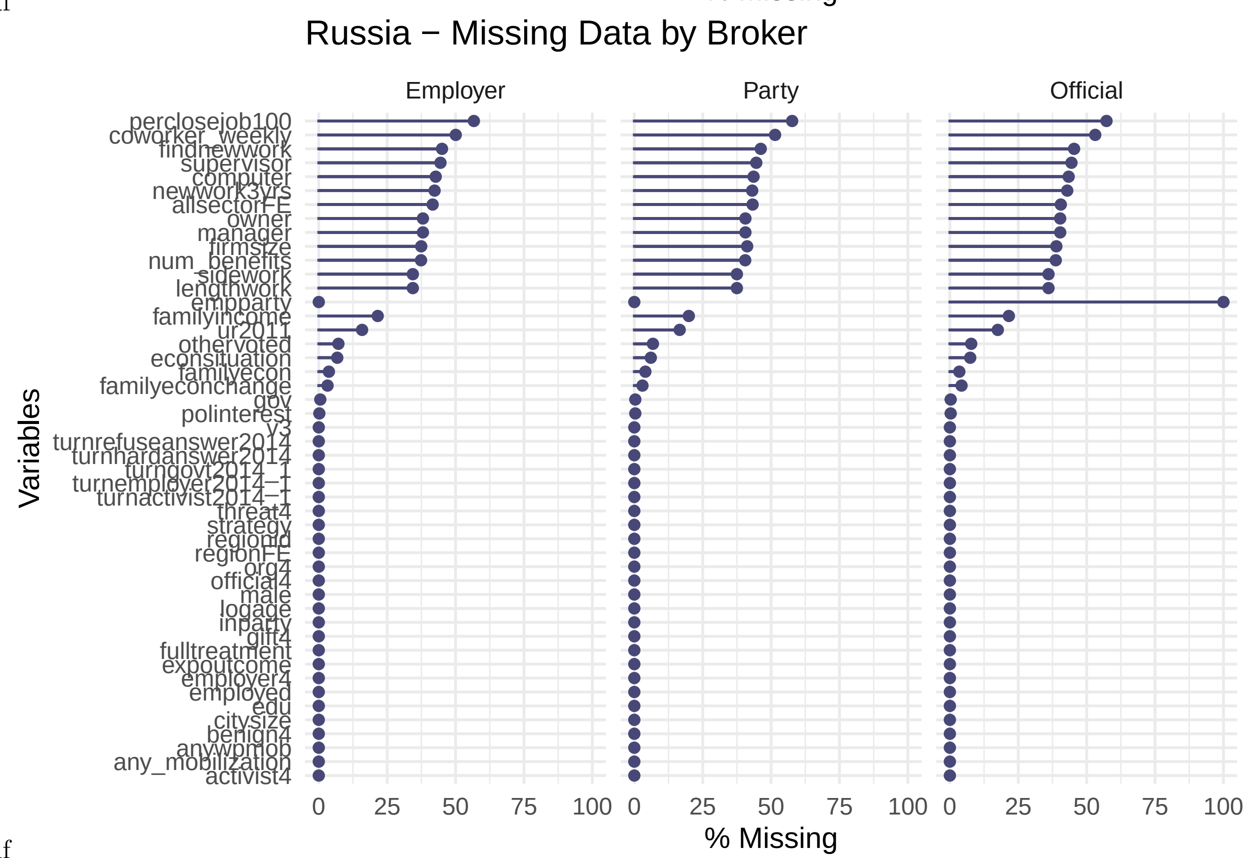
In this paper for the most part I was able to replicate all of the graphics. The tables I couldn't use the old code to make so I hand made them, which I think is not a good idea... I also had an issue combining some of the graphs to have the same legend. I also messed up some of the footnotes on the graphics, and instead used captions. On the regression, the variable order isn't like the original, which I couldn't figure out. Also, I had a lot of trouble getting the exact format from R things like GT to Latex/PDF, so that's why I had to resort to manually doing some things.

5 Extension

For my extension, I decided to look at missing data in the data sets and impute data for the regressions used in table 3. Looking at the tables below, I was able to

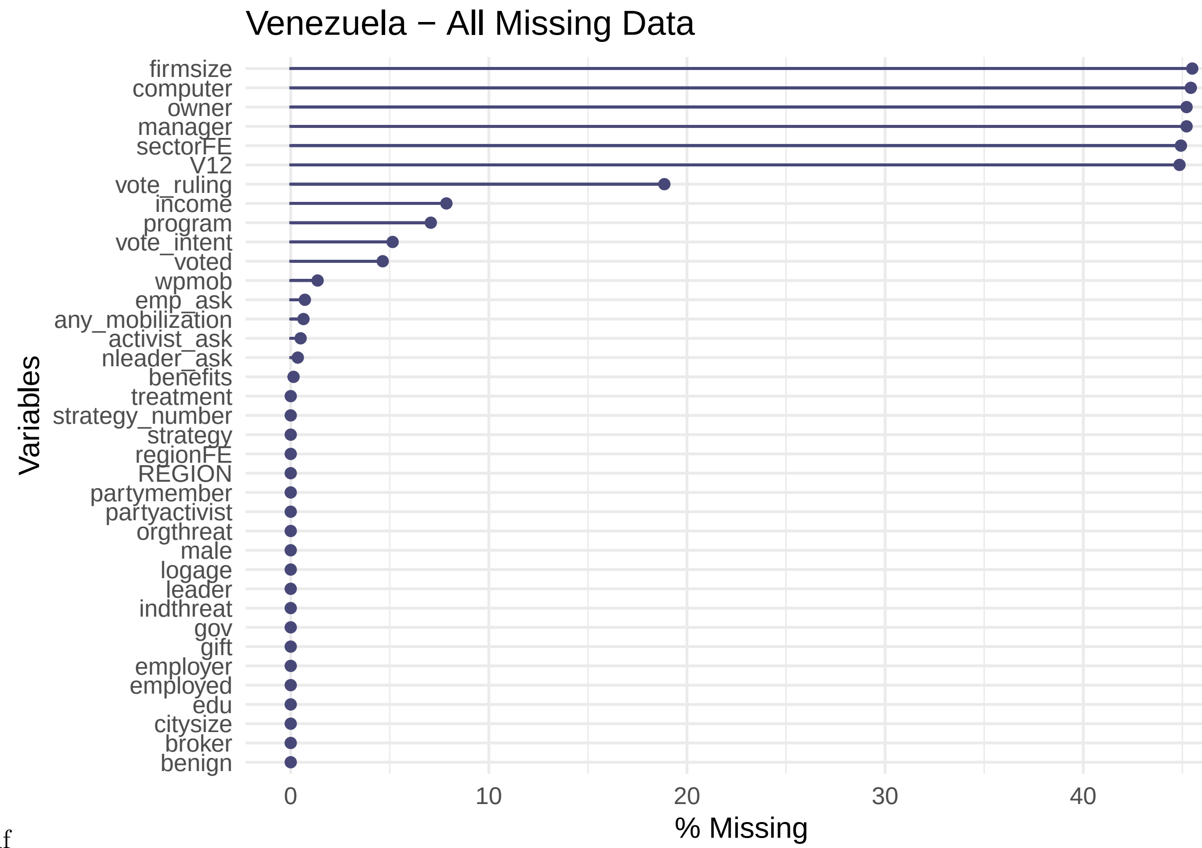


Data Russia-1.pdf

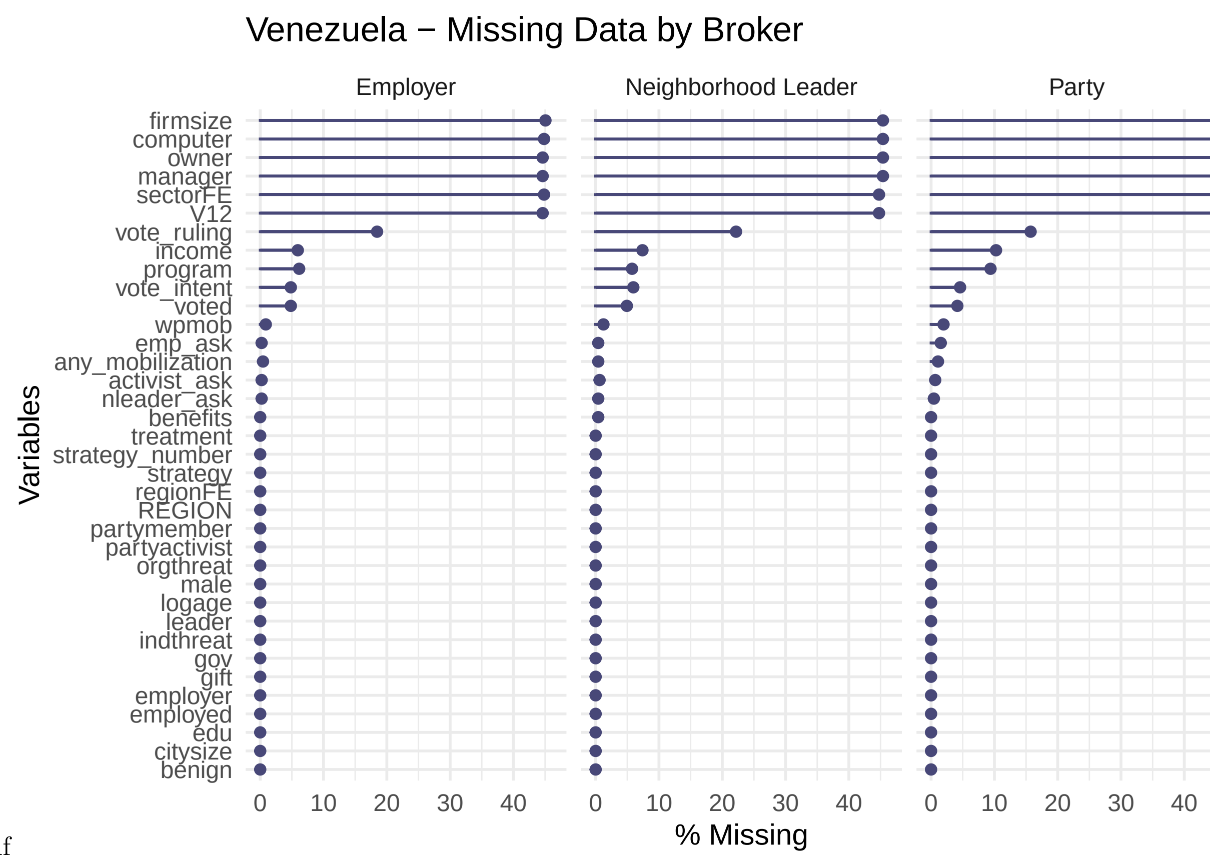


Data Russia-2.pdf

We see that for Russia, there is a lot of data missing for percentclose job, cowoerker_weekly, and findnewwork variables. When we further example data missing by broker, there generally seems to be the same variables missing with the exception being empparty for official, which is missing for 100% of the data.



Data Venezuela-1.pdf



Data Venezuela-2.pdf

We see that for Venezuela, there is a lot of data missing for firmsize, computer, manager, and sector variables. When we further example data missing by broker, there generally seems to be the same variables missing for all of the brokers.

Given that the regression for table 3 uses only data from Russia, I decided to impute the missing values using the mice(), function and re-run the regressions, which can be found in Table 2 of the appendix. When I compare my results with the imputed data and compare it to the original study, I find the same significance and sign of the coefficients, however the magnitude of the coefficients appears to be smaller in general. I think that this just shows the original study is valid and robust, and by being able to not only replicate the data but get very similar results to the original after imputing data, I feel even more confident in the authors' findings.

```
##     anywpmob      turnemployer2014_1 turnactivist2014_1 turngovt2014_1
##  Min.   :0.0000   Min.   :0.00000    Min.   :0.00000    Min.   :0.00000
##  1st Qu.:0.0000   1st Qu.:0.00000    1st Qu.:0.00000    1st Qu.:0.00000
##  Median :0.0000   Median :0.00000    Median :0.00000    Median :0.00000
##  Mean   :0.3361   Mean   :0.02973    Mean   :0.04567    Mean   :0.01832
```

```
##  3rd Qu.:1.0000   3rd Qu.:0.00000    3rd Qu.:0.00000    3rd Qu.:0.00000
##  Max.   :1.0000   Max.   :1.00000    Max.   :1.00000    Max.   :1.00000
##
##     citysize     econsituation   familyeconchange  familyincome
##  Min.   :1.000   Min.   :1.000   Min.   :1.000    Min.   : 1.000
##  1st Qu.:2.000   1st Qu.:3.000   1st Qu.:3.000    1st Qu.: 4.000
##  Median :3.000   Median :3.000   Median :3.000    Median : 7.000
##  Mean   :2.757   Mean   :3.051   Mean   :2.945    Mean   : 6.819
##  3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:3.000    3rd Qu.: 9.000
##  Max.   :5.000   Max.   :5.000   Max.   :5.000    Max.   :14.000
##
##       male            logage          edu           employed
##  Min.   :0.0000   Min.   :2.890   Min.   :1.000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:3.401   1st Qu.:4.000   1st Qu.:0.0000
##  Median :0.0000   Median :3.761   Median :6.000   Median :1.0000
##  Mean   :0.4481   Mean   :3.714   Mean   :5.546   Mean   :0.6403
##  3rd Qu.:1.0000   3rd Qu.:4.025   3rd Qu.:8.000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :4.500   Max.   :8.000   Max.   :1.0000
##
##       gov            firmsize       owner           manager
##  Min.   :0.0000   Min.   :1.00   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:1.00   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :1.00   Median :0.0000   Median :0.0000
##  Mean   :0.1955   Mean   :2.05   Mean   :0.4234   Mean   :0.2721
##  3rd Qu.:0.0000   3rd Qu.:3.00   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :5.00   Max.   :1.0000   Max.   :1.0000
##
##     computer      newwork3yrs        sidework       polinterest
##  Min.   :1.000   Min.   :0.0000   Min.   :0.0000   Min.   :1.000
##  1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:2.000
##  Median :3.000   Median :0.0000   Median :0.0000   Median :3.000
##  Mean   :2.714   Mean   :0.4807   Mean   :0.2593   Mean   :2.755
##  3rd Qu.:4.000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:3.000
```

```
##  Max.   :4.000   Max.   :1.0000   Max.   :1.0000   Max.   :4.000
##
##     inparty      perclosejob100    findnewwork     num_benefits
##  Min.   :1.000   Min.   :0.0000   Min.   :1.000   Min.   :0.000
##  1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:2.000   1st Qu.:0.000
##  Median :1.000   Median :0.0000   Median :3.000   Median :1.000
##  Mean   :1.031   Mean   :0.1111   Mean   :3.424   Mean   :1.787
##  3rd Qu.:1.000   3rd Qu.:0.1000   3rd Qu.:5.000   3rd Qu.:3.000
##  Max.   :3.000   Max.   :1.0000   Max.   :5.000   Max.   :6.000
##
##    supervisor      lengthwork     coworker_weekly  any_mobilization
##  Min.   :1.000   Min.   : 0.500   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:1.000   1st Qu.: 0.500   1st Qu.:0.0000   1st Qu.:0.00000
##  Median :3.000   Median : 2.000   Median :0.0000   Median :0.00000
##  Mean   :2.259   Mean   : 5.494   Mean   :0.3292   Mean   :0.08183
##  3rd Qu.:3.000   3rd Qu.: 7.000   3rd Qu.:1.0000   3rd Qu.:0.00000
##  Max.   :3.000   Max.   :50.000   Max.   :2.0000   Max.   :1.00000
##
##     regionFE       regionid      allsectorFE   turnrefuseanswer2014
##  41     : 553   Min.   : 4.00   10     : 475   Min.   :0.000000
##  55     : 551   1st Qu.:41.00   6      : 427   1st Qu.:0.000000
##  50     : 550   Median :50.00   3      : 412   Median :0.000000
##  63     : 550   Mean   :45.88   7      : 387   Mean   :0.001189
##  4      : 125   3rd Qu.:55.00   12     : 359   3rd Qu.:0.000000
##  5      : 125   Max.   :75.00   21     : 241   Max.   :1.000000
##  (Other):1750                   (Other):1903
##  turnhardanswer2014   expoutcome    strategy      broker       employer4
##  Min.   :0.000000   Min.   :1.000   0:1019   Employer:1434   Min.   :0.0000
##  1st Qu.:0.000000   1st Qu.:2.000   1:1065   Party   :1411   1st Qu.:0.0000
##  Median :0.000000   Median :3.000   2:1086   Official:1359   Median :0.0000
##  Mean   :0.001665   Mean   :2.661   3:1034                   Mean   :0.3411
##  3rd Qu.:0.000000   3rd Qu.:3.000                            3rd Qu.:1.0000
##  Max.   :1.000000   Max.   :5.000                            Max.   :1.0000
```

```
##
##     activist4          official4           gift4            threat4
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :0.000
##  Mean   :0.3356   Mean   :0.3233   Mean   :0.2583   Mean   :0.246
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.000
##
##      benign4            org4            empparty          fulltreatment
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.000   employer_gift: 374
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000   employer_org : 372
##  Median :0.0000   Median :0.0000   Median :1.000   party_org    : 362
##  Mean   :0.2424   Mean   :0.2533   Mean   :0.504   party_gift   : 360
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.000   party_threat : 353
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.000   official_gift: 352
##                                    NA's   :1359    (Other)      :2031
##       ur2011          othervoted            v3           familyecon
##  Min.   :0.0000   Min.   :0.0000   Min.   :1.000   Min.   :1.000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:3.000
##  Median :1.0000   Median :1.0000   Median :1.000   Median :3.000
##  Mean   :0.5797   Mean   :0.5147   Mean   :1.258   Mean   :3.187
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.000   3rd Qu.:4.000
##  Max.   :1.0000   Max.   :1.0000   Max.   :3.000   Max.   :6.000
##
```

6 GitHub

All analysis for this paper be found in the [original paper] (https://www.cambridge.org/core/journals/world-politics/article/vote-brokers-clientelist-appeals-and-voter-turnout-evidence-from-russia-and-venezuela/45FE0BE1216FCD8744B02A82919B328A) and [data verse] (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YSVMS2) My Github repo for this project is located under my username, cpatvakanian. [^1]

```
## Warning in Ops.factor(+citysize + male + logage + polinterest + supervisor + :
## '|' not meaningful for factors

##
## Call:
## glm(formula = is.na(perclosejob100) ~ +citysize + male + logage +
##     polinterest + supervisor + lengthwork + coworker_weekly +
##     edu + gov | factor(strategy) | 0 | regionid, family = binomial,
##     data = subset(rus, employed == 1))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8978  -0.8978  -0.8978   1.4856   1.4856
##
## Coefficients: (1 not defined because of singularities)
##
## (Intercept)
## +citysize + male + logage + polinterest + supervisor + lengthwork + coworker_weekly + edu + gov | fa
##
## (Intercept)
## +citysize + male + logage + polinterest + supervisor + lengthwork + coworker_weekly + edu + gov | fa
##
## (Intercept)
## +citysize + male + logage + polinterest + supervisor + lengthwork + coworker_weekly + edu + gov | fa
##
## (Intercept)
## +citysize + male + logage + polinterest + supervisor + lengthwork + coworker_weekly + edu + gov | fa
##
## (Intercept)
## +citysize + male + logage + polinterest + supervisor + lengthwork + coworker_weekly + edu + gov | fa
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3421  on 2691  degrees of freedom
## Residual deviance: 3421  on 2691  degrees of freedom
## AIC: 3423
##
## Number of Fisher Scoring iterations: 4
```

7 References

I make use of Aslund (2012), Popova (2010), and Frye, Reuter, and Szakonyi (2019).

Aslund, Anders. 2012. *How Capitalism Was Built: The Transformation of Central and Eastern Europe, Russia, the Caucasus, and Central Asia*. 2nd ed. Cambridge University Press. https://doi.org/10.1017/CBO9781139207850.

Frye, Timothy, Ora John Reuter, and David Szakonyi. 2019. "Vote Brokers, Clientelist Appeals, and Voter Turnout: Evidence from Russia and Venezuela." *World Politics* 71 (4): 710–46. https://doi.org/10.1017/S0043887119000078.

Popova, Olga. 2010. "Corruption, Voting and Employment Status: Evidence from Russian Parliamentary Elections." *SSRN Electronic Journal*.

8 Appendix

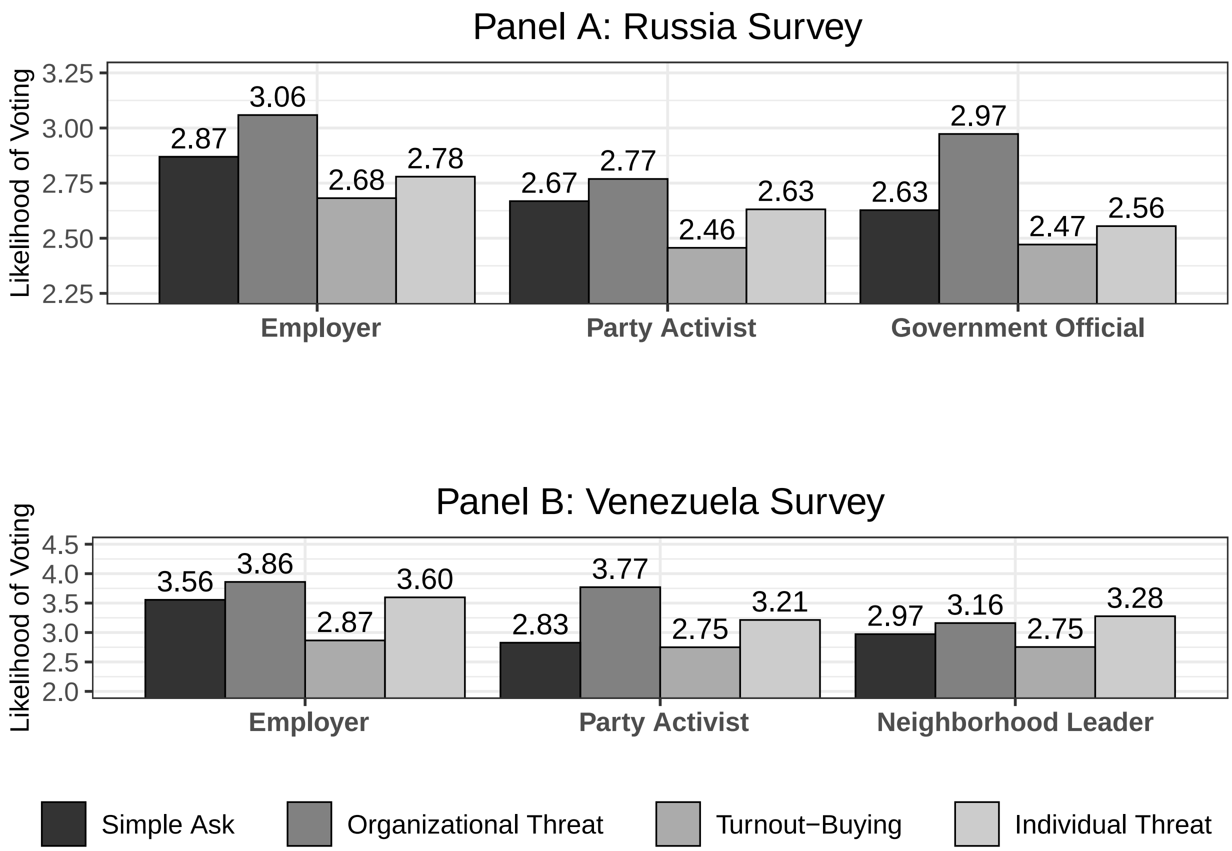


figure 1-1.pdf

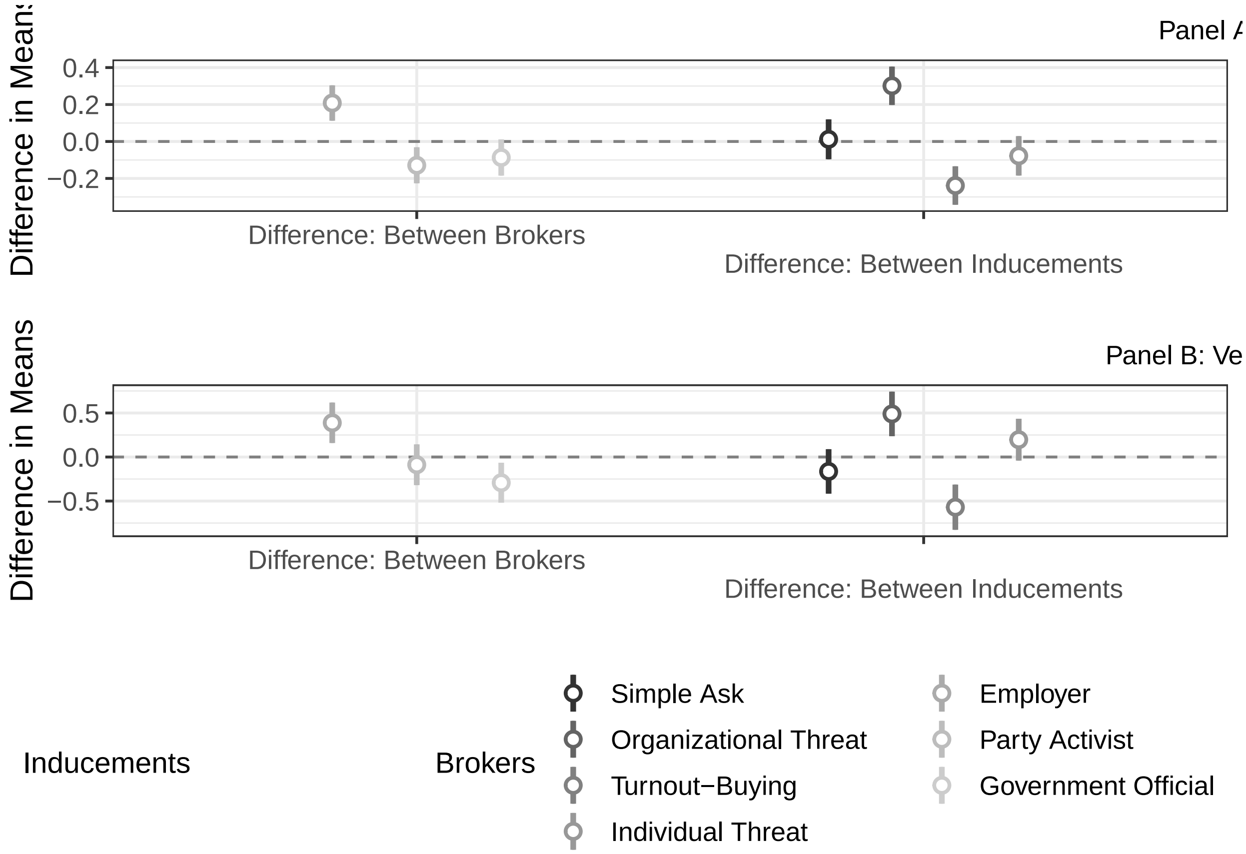


figure 2-1.pdf

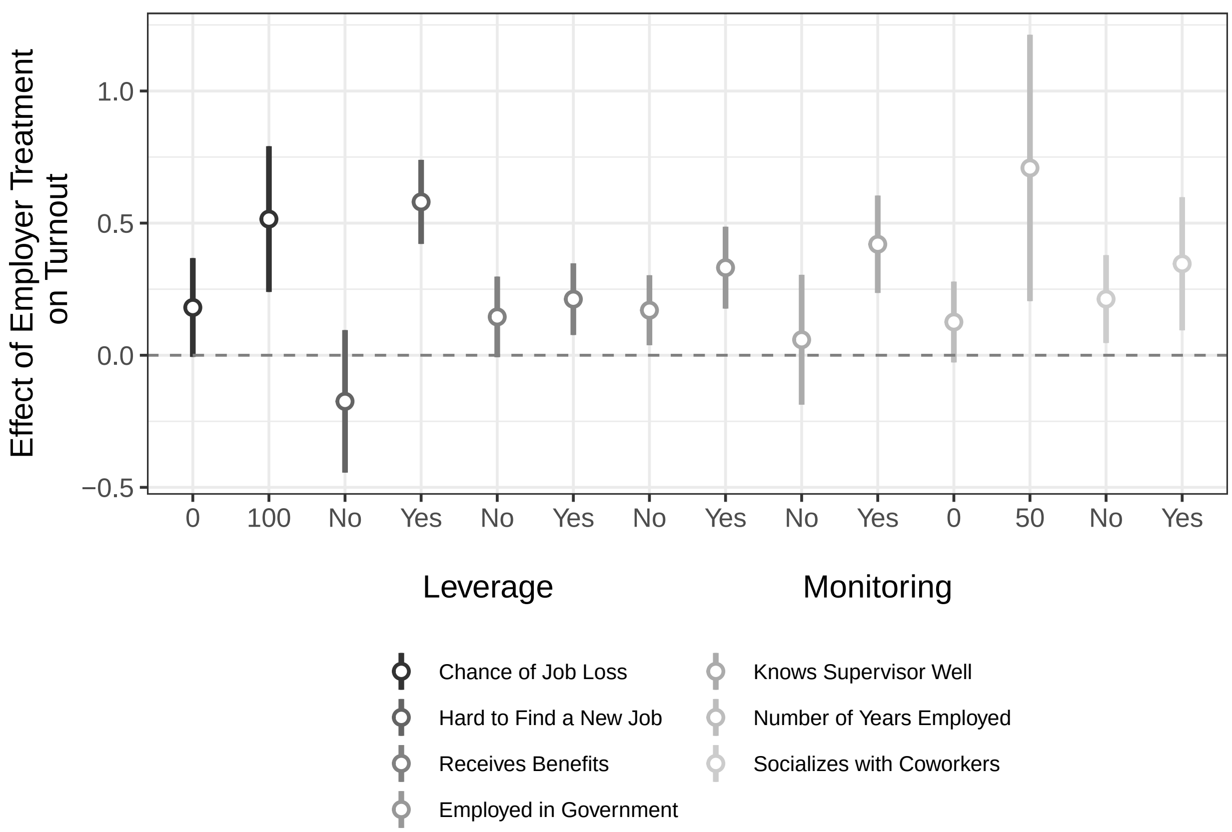


figure 3-1.pdf

Table 1: Survey Coverage

Russian Survey (a)

Broker	Asked You to Vote	Indicates There Will be Negative Consequences For You If You Do Not Vote	Offers You a Gift, Money, or Reward for Voting	Tells You That Your Firm or Org. Will Suffer if Turnout Among Employees is Low
Your Employer	344	344	374	372
A Party Activist	336	353	360	362
A Neighborhood Leader	339	337	352	331

Venezuelan Survey (b)

Broker	Asked You to Vote	Indicates There Will be Negative Consequences For You If You Do Not Vote	Offers You a Gift, Money, or Reward for Voting	Tells You That Your Firm or Org. Will Suffer if Turnout Among Employees is Low
Your Employer	96	132	113	114
A Party Activist	94	133	113	118
A Neighborhood Leader	125	118	120	124

Table 2: Substantive Effects: Predicted Probabilities by Broker Treatment

Probability of Voting (%)

(a)

	Russia	Venezuela
Employer	28.6	54.2
Party Activist	22.5	44.9
Government Official	23.1	
Neighborhood Leader		40.9

Probability of Not Voting (%)

(b)

	Russia	Venezuela
Employer	35.7	24.4
Party Activist	43.5	32.1
Government Official	42.7	
Neighborhood Leader		35.7

Table 1

	Dependent variable:						
	Outcome Respondent Would Vote						
	Leverage					Monitoring	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
empparty:gov				0.166^{**}			
				(0.072)			
empparty:perclosejob100	0.360^{**}						
	(0.167)						
empparty:findnewwork		0.156^{***}					
		(0.038)					
empparty:num_benefits			0.070^{**}				
			(0.036)				
empparty:supervisor					0.119^{**}		
					(0.059)		
empparty:lengthwork						0.012^{**}	
						(0.006)	
empparty:coworker_weekly							0.063
							(0.076)
Observations	1,209	1,532	1,724	1,806	1,567	1,806	1,389

Note: *p<0.1; **p<0.05; ***p<0.01

The outcome variable is the willingness to turnout outcome (five-point scale) from the survey experiment. The sample includes only respondents who received the employer or political party broker treatment. The employer treatment collapses the data along the inducement treatment arm of the factorial design used in the experiment. The sample is limited to only those who are employed. Chance of job loss measures the probability a respondent believes he or she will lose his or her job in the next twelve months. Hard to find a new job uses a five-point scale to capture the likelihood that if he or she were to lose his or her job, a respondent could find a similar one; higher values indicate more difficulty. Receives benefits captures the number of in-kind benefits (health care, education, transportation sub- sidies, etc.) respondents received from their employer. Higher values on the three-point scale used in knows supervisor well indicate better familiarity with one's boss. Number of years employed measures the length of time at one's work. Socializes with coworkers captures whether respondents spend time with colleagues outside work. All models include the constituent terms and basic demographic characteris- tics (gender, age, education, size of settlement, and an indicator for government employment). Models are estimated via ols and cluster errors at the region level.

Table 2

	Dependent variable:						
	Outcome Respondent Would Vote						
	Leverage				Monitoring		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
empparty:gov				0.155**			
				(0.065)			
empparty:perclosejob100	0.252**						
	(0.126)						
empparty:findnewwork		0.087***					
		(0.031)					
empparty:num_benefits			0.057*				
			(0.033)				
empparty:supervisor					0.105**		
					(0.051)		
empparty:lengthwork						0.012**	
						(0.006)	
empparty:coworker_weekly							0.042
							(0.059)
Observations	10,324	10,647	10,839	10,921	10,682	10,921	10,504

Note: *p<0.1; **p<0.05; ***p<0.01

The outcome variable is the willingness to turnout outcome (five-point scale) from the survey experiment. The sample includes only respondents who received the employer or political party broker treatment. The employer treatment collapses the data along the inducement treatment arm of the factorial design used in the experiment. The sample is limited to only those who are employed. Chance of job loss measures the probability a respondent believes he or she will lose his or her job in the next twelve months. Hard to find a new job uses a five-point scale to capture the likelihood that if he or she were to lose his or her job, a respondent could find a similar one; higher values indicate more difficulty. Receives benefits captures the number of in-kind benefits (health care, education, transportation sub- sidies, etc.) respondents received from their employer. Higher values on the three-point scale used in knows supervisor well indicate better familiarity with one's boss. Number of years employed measures the length of time at one's work. Socializes with coworkers captures whether respondents spend time with colleagues outside work. All models include the constituent terms and basic demographic characteris- tics (gender, age, education, size of settlement, and an indicator for government employment). Models are estimated via ols and cluster errors at the region level.

8.1 Regressions with Imputed Data

TABLE 3
EXAMINING MECHANISMS: RUSSIA SURVEY EXPERIMENT[a]

	Outcome: Respondent Would Vote						
	Leverage				*Monitoring*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Employer treatment * Chance of job loss	0.360** (0.167)						
Employer treatment * Hard to find a new job		0.156*** (0.038)					
Employer treatment * Receives benefits			0.070** (0.036)				
Employer treatment * Employed in government				0.166** (0.072)			
Employer treatment * Knows supervisor well					0.119** (0.059)		
Employer treatment * Number of years employed						0.012** (0.006)	
Employer treatment * Socializes with coworkers							0.063 (0.076)
Constituent terms	yes	yes	yes	yes	yes	yes	yes
Demographics	yes	yes	yes	yes	yes	yes	yes
Observations	1209	1532	1724	1806	1567	1806	1389

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

[a]The outcome variable is the willingness to turnout outcome (five-point scale) from the survey experiment. The sample includes only respondents who received the employer or political party broker treatment. The employer treatment collapses the data along the inducement treatment arm of the factorial design used in the experiment. The sample is limited to only those who are employed. *Chance of job loss* measures the probability a respondent believes he or she will lose his or her job in the next twelve months. *Hard to find a new job* uses a five-point scale to capture the likelihood that if he or she were to lose his or her job, a respondent could find a similar one; higher values indicate more difficulty. *Receives benefits* captures the number of in-kind benefits (health care, education, transportation subsidies, etc.) respondents received from their employer. Higher values on the three-point scale used in *knows supervisor well* indicate better familiarity with one's boss. *Number of years employed* measures the length of time at one's work. *Socializes with coworkers* captures whether respondents spend time with colleagues outside work. All models include the constituent terms and basic demographic characteristics (gender, age, education, size of settlement, and an indicator for government employment). Models are estimated via OLS and cluster errors at the region level.

[^1]: [(https://github.com/cpatvakanian/milestone_7)]