Close Elections, Campaign Contributions, and Financial Deregulation

December 1, 2021

Kyung Woong Koh[1]

Abstract

This paper builds upon Igan and Mishra (2014) on vote switches towards financial deregulation by US legislators. I measure the effect of close elections on US legislators on switching their votes towards financial deregulation in Congress bills. I aim to distinguish between vote switches towards financial deregulation because of voters' general interests (especially after the Global Financial Crisis of 2007) versus the financial industry's special interests and the industry's campaign contributions and lobbying expenditures towards legislators in close elections.

Keywords Campaign Contributions, Close Elections, Financial Deregulation, Global Financial Crisis

JEL codes D72

Powered by Econ-ARK

The paper is the author's 2nd year paper for fulfillment to the PhD in Economics program at Johns Hopkins University, and also for Professor Christpher Carroll's Computational Methods course. I thank Professors Laurence Ball and Filipe Campante for comments and advice, and Deniz Igan and Prachi Mishra for sharing their data.

[1]Contact: kkoh8@jhu.edu, Department of Economics, Johns Hopkins University, Baltimore, MD 21218.

1 Introduction

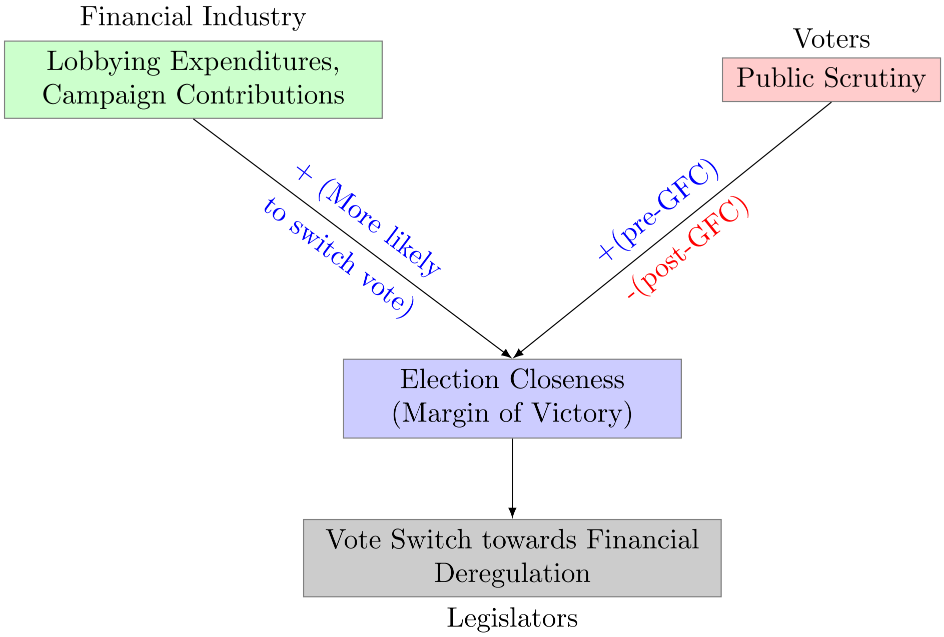

Figure 1 Two Channels in which Legislators in Close Elections Switch their Votes Toward Financial Deregulation

How do legislators in close elections vote differently on financial deregulation compared to legislators in sure elections? I use data from Igan and Mishra (2014) to answer this question.

2 The Problem

I aim to answer part of a wider question of whether legislators, in their legislative activities, are influenced by lobbying and campaign contributions from private interests. Take the Finance, Insurance, and Real Estate (FIRE) industry as an example. As FIRE firms wish to increase the amount of loans that they can make to consumers, they may try to influence legislators to change their stances (and hence votes) towards financial deregulation that allows more lending activities. An ideal study would have multiple bills of the same type of financial regulation, such that we can identify which legislators switch their votes or co-sponsorship towards financial deregulation. In the case of votes, a legislator would initially vote against financial deregulation in an earlier reincarnation R of a bill group B, then vote for financial deregulation in a later reincarnation of the same bill group B. In the case of co-sponsorship, a legislator would initially not co-sponsor an earlier reincarnation, then co-sponsor a later reincarnation.

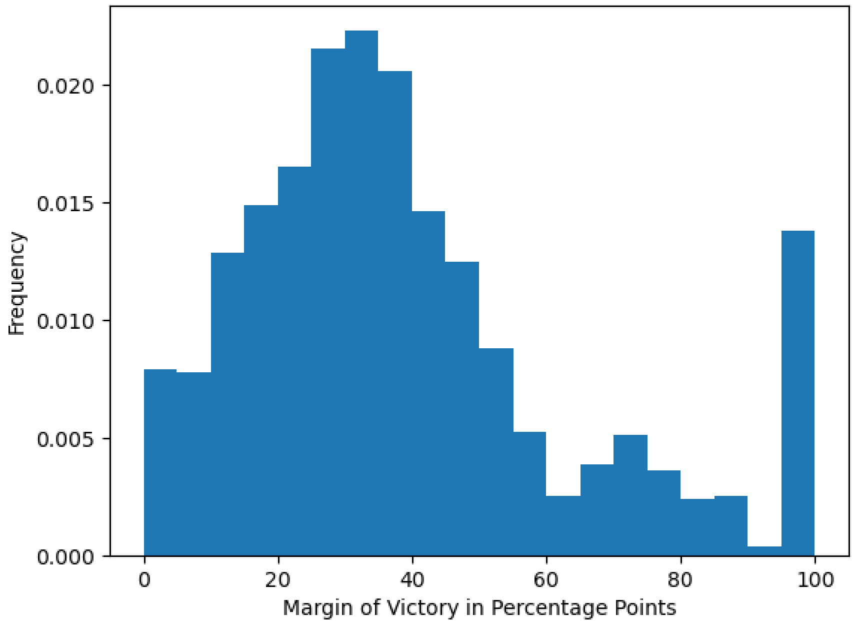

Figure 2 Histogram of Legislators' Past Margin of Victory

Igan and Mishra (2014) look at the case of U.S. Congressional legislators from 1999 to 2006. To do so, they focus on aggregate lobbying expenditures by the FIRE industry on six groups ($B = 1, 2, \ldots, 6$, in total composed of 47 bills. They set as their dependent variable a dummy variable on whether the Congressional legislators' voting records or bill co-sponsorship status *switched* towards financial deregulation (i.e. easing lending activities to consumers).

Igan and Mishra (2014) argue that their results, that lobbying expenditures make legislators more likely to switch their votes towards financial deregulation, is a correlational result and therefore cannot be taken as causation from either of these reasons. I attempt to provide at least a partial answer by introducing new variables, including one for whether a legislator has been in or will be facing a close election. I also include other variables to support the regression strategies that can differentiate between voters' public scrutiny and the financial industry's special interests.

The next step is to identify variation in the general interest of voters on financial (de)regulation. There are several possible ways of doing this.

1. I would extend the existing dataset of Igan and Mishra (2014), from 1999 to 2006, to the Global Financial Crisis (GFC) starting in 2007 and beyond. Given the perceived increase in voters' general interests against financial deregulation after the GFC, the changes in general interest allow me to identify their effect on

Table 1 Definition of the Main Dependent Variable, Vote Switch towards Deregulation

Value of S_{iBR}	Voted for deregulation in Bill B, R	Voted against deregulation in Bill B, R
Voted for deregulation in Bill $B, R-1$	0	0
Voted for deregulation in Bill $B, R-1$	1	0

legislators switching their vote towards financial deregulation, and thus the effect of special interests on legislators' votes as well.

2. I would include a measure of "media congruence" as named by Snyder and Stromberg (2010). Media congruence is defined as the geographical alignment between local news markets and congressional districts. Intuitively, if a congressional district is more geographically aligned with the local news markets, then the legislator representing that district may be covered by the local newspapers more closely than otherwise. The greater public scrutiny incentivizes legislators to vote more on behalf of his/her district voters and less on behalf of special interests such as the FIRE industry. Snyder and Stromberg (2010) include a dataset with an index of media congruence for all Congressional districts from 1984 to 2006.

2.1 Setup

3 Variables

3.1 Dependent Variable

3.2 Election Closeness

Compared to the original Igan and Mishra (2014) paper, I add the new variable of "Election Closeness" as the main focus of this paper. I define "election closeness" for each legislator i and bill BR, denoted as X_{iBR}, as the degree to which the legislator has faced (past) or will face (future) a close election. Note the two possible ways of looking at election closeness: through the past election(s) of the legislator, or to the (immediately next) future election of the legislator. Meanwhile, the measure of future election closeness

Past election closeness is defined simply, in this paper, as the percentage margin of victory of the legislator in the last election before a vote on a bill BR. I denote this variable as X^P_{iBR}. As a concrete example, assume that legislator A won his/her last election with 49,000 votes against the runner-up, who got 47,000 votes in a congressional election of a total of 100,000 votes, and that the remaining 4,000 votes all went to third-party, independent, and write-in votes. In this case, legislator A's margin of victory is $(49,000 - 47,000)/100,000 = 2\%$. There are two important characteristics of this variable: first, X^P_{iBR} must necessarily be greater than zero, as the legislator must have won at least one more vote than the runner-up. Second, X^P_{iBR} is the same across all bills BR during the same congress C, as legislator i has only one value of past election closeness at any given congress C and all the bills therein.

Ideally, future election closeness may be defined as the expected margin of victory in the next (future) election of the legislator. I denote this variable as X^F_{iBR}. The future expected margin of victory of an as-of-yet undecided election can be proxied by results of election polls. Since most future congressional elections at any given electoral cycle have at least one polling result, and in most cases more than one, X^F_{iBR} can differ across bills BR even in the same congress C.

3.3 Original Variables

4 Regressions

4.1 Regression A

Concretely, I write Regression A1 as:

$$\begin{aligned} S_{iBR} &= \beta_1 L_{BR} + \beta_2 X^P_{iBR} + \beta_3 (L_{BR} \times X^P_{iBR}) \\ &\quad + \alpha F_{BR} + \gamma T_{BR} + s_i \times t_c + v_B \times t_c + \mu_R \times t_c + \varepsilon_{iBR} \end{aligned} \tag{1}$$

5 Results

See results in Appendix.

6 Conclusions

References

IGAN, DENIZ, AND PRACHI MISHRA (2014): "Wall Street, Capitol Hill, and K Street: Political Influence and Financial Regulation," *Journal of Law and Economics*, 57, 1063–1084.

Appendices

Dep. Variable:	sw_p	**R-squared:**	0.094
Model:	OLS	**Adj. R-squared:**	0.094
Method:	Least Squares	**F-statistic:**	445.1
Date:	Tue, 21 Dec 2021	**Prob (F-statistic):**	3.77e-275
Time:	12:20:17	**Log-Likelihood:**	-1546.4
No. Observations:	12875	**AIC:**	3101.
Df Residuals:	12871	**BIC:**	3131.
Df Model:	3		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.0674	0.027	-2.487	0.013	-0.120	-0.014
log_contributions_FIRE	0.0083	0.002	3.626	0.000	0.004	0.013
bill_complexity	0.0306	0.001	23.294	0.000	0.028	0.033
tight	-0.1466	0.005	-29.261	0.000	-0.156	-0.137

Omnibus:	5961.604	**Durbin-Watson:**	2.326
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	23918.430
Skew:	2.391	**Prob(JB):**	0.00
Kurtosis:	7.661	**Cond. No.**	140.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Dep. Variable:	sw_p	**R-squared:**	0.094
Model:	OLS	**Adj. R-squared:**	0.094
Method:	Least Squares	**F-statistic:**	268.2
Date:	Tue, 21 Dec 2021	**Prob (F-statistic):**	1.14e-273
Time:	12:20:17	**Log-Likelihood:**	-1543.7
No. Observations:	12875	**AIC:**	3099.
Df Residuals:	12869	**BIC:**	3144.
Df Model:	5		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.0347	0.053	0.655	0.513	-0.069	0.138
log_contributions_FIRE	-4.741e-05	0.004	-0.011	0.991	-0.009	0.009
mov_past	-0.0023	0.001	-2.094	0.036	-0.004	-0.000
mov_contr_int	0.0002	9.42e-05	1.990	0.047	2.82e-06	0.000
bill_complexity	0.0306	0.001	23.301	0.000	0.028	0.033
tight	-0.1467	0.005	-29.283	0.000	-0.157	-0.137

Omnibus:	5957.868	**Durbin-Watson:**	2.327
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	23882.919
Skew:	2.389	**Prob(JB):**	0.00
Kurtosis:	7.656	**Cond. No.**	1.20e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.2e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Dep. Variable:	sw_p	**R-squared:**	0.113
Model:	OLS	**Adj. R-squared:**	0.113
Method:	Least Squares	**F-statistic:**	334.6
Date:	Tue, 21 Dec 2021	**Prob (F-statistic):**	1.61e-204
Time:	12:20:17	**Log-Likelihood:**	-1466.4
No. Observations:	7892	**AIC:**	2941.
Df Residuals:	7888	**BIC:**	2969.
Df Model:	3		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.0180	0.010	-1.760	0.078	-0.038	0.002
congruence_dc	0.0384	0.014	2.724	0.006	0.011	0.066
bill_complexity	0.0432	0.002	22.356	0.000	0.039	0.047
tight	-0.1396	0.007	-19.690	0.000	-0.154	-0.126

Omnibus:	2920.422	**Durbin-Watson:**	2.384
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8395.412
Skew:	2.014	**Prob(JB):**	0.00
Kurtosis:	6.051	**Cond. No.**	19.6

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

References

IGAN, DENIZ, AND PRACHI MISHRA (2014): "Wall Street, Capitol Hill, and K Street: Political Influence and Financial Regulation," *Journal of Law and Economics*, 57, 1063–1084.