Political Funding after *Citizens United*: Who Benefits From Independent Spending?

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Abstract. This paper uses a two sided matching model to simulate the market for political funding. Effects of lifting independent spending restrictions as a result of the 2010 Supreme Court case *Citizens United v. FEC* - and thus the introduction of corporate and labor interests into political funding - are examined. In particular, estimation of parameters for matching complementarities is carried out using the Maximum Score Estimator. These parameters are then used to simulate differences in matching, had independent funding not been allowed in the market.

1 Introduction

The relationship between Political Action Committees (PACs) and Political Candidates has been central in the heated debate about the place of money in politics. In particular, the controversial 2010 Supreme Court case *Citizens United v. FEC*, which broadened the avenues for political funding, is often pointed to as the culprit for the recent explosion of money in American politics.

The consequences of *Citizens United v. FEC* have led to the introduction of independent spending by corporate and labor interests. A full examination of the policy surrounding political funding is out of the scope of this paper, however Klumpp et al. (2016) [4] note that in general, *Citizens United* has led to a wide array of options for corporations and unions to affect political speech.

In this context, I seek to model the process of funding for political candidates within the transferable utility framework. In particular, I'm interested in examining the effects of introducing indirect funding - for example, in the form of attack ads - upon outcomes in the market between candidates and committees. Some research questions I seek to answer in this paper are as follows: How has the broadening of independent spending has changed funding along party lines? What is the extent to which certain subsets of legislators have gained or lost from this funding?

To answer these questions, two datasets were jointly used. Data from FollowTheMoney.org, and the associated National Institute on Money In Politics, is the primary resource used to obtain data for political contributions and independent expenditures. The website uses financial disclosures to tie independent expenditures to political candidates. The other dataset used is Historical Congressional Legislation and District Demographics 1972-2014 [1], which contains characteristics of members of the House of Representatives. A wealth of information is available, including which committees legislators are a part of, the race and sex of each legislator, median incomes of constituencies, etc. After cross referencing these datasets, a subset of 153 House members from the 2012 election are considered.

At the time of writing, this is the only work examining political funding through matching, as well as the first paper to apply transferable utility matching to politics.

2 Previous Work

A variety of literature exists regarding funding in politics. In a similar vein of considering *Citizens United*, Klumpp et al. (2016) [4] construct a differences-in-differences model to estimate the effects of the Supreme Court case on the probability of certain political parties winning. Since in certain states campaign finance laws were almost unchanged by the case, while in others the laws were dramatically changed, the historical structure lent itself to such an examination. They found that the effects *Citizens United v. FEC* were positive for Republicans.

The literature on matching for politics is sparse; however, some previous works which dealt with similar models for fundraising exist in the venture capital (VC) matching literature.

One such example is Sørensen (2007) [7]. In this paper, a structural two-sided matching model is estimated using a Bayesian estimation procedure. The dataset used contains two endogenous variables - whether the company had an IPO, and the matching indicators between VCs and companies. Important information for controlling company characteristics and market characteristics is also included within the dataset. Several different measures of investor experience are included; for example, the basic measure considered is years of experience for all individuals in the firm, but this is broken down further into experience in particular industries and within different stages of the VC process. Thus, models are fit with each of these different measures. Evidence is found supporting the conclusion that more experienced investors make better investments.

However, the previous paper doesn't use any transferable utility concepts. In particular, the structure of their model is such that the error term across matches is independent; this rules out that some firm-VC pairs are more productive for certain matches than others. In Fox et. al. (2012) [3], an application of matching to the VC market is presented which differs in several key areas. First, the model estimated uses transferable utility concepts. In addition, the idea of *unobserved complementarities* is introduced, and a model is fit with an estimation procedure for such unobservables.

3 Model Description

I now describe the modeling framework. Each candidates can be supported by more than one donor, and each donor often supports many Candidates. Thus, the many-to-many matching framework is appropriate.

Within this framework, a finite set of political contributors, $P = \{1, 2, ..., P\}$ is to be matched to a finite set of candidates, $C = \{1, 2, ..., C\}$. Let each P have a type θ, and each C have a type ψ. These types need not be scalar; an example of types are characteristics of individuals or contributors - whether a candidate is an incumbent, how many prolific a contributor is, etc. Additionally (as we are in the many-to-many framework), define a quota for each side; let q_i, $1 \leq i \leq P$, to be the maximum number of candidates contributor i can support, and let q_j, $1 \leq i \leq C$, be the maximum number of contributors that can donate to candidate j.

Now, denote a match as (p, c). If match (p, c) is formed, a transfer τ takes place. Then, an assignment $A = \{\{(p_1, c_1), ...(p_i, c_j)\}\}$ selects at most q_i candidates for each committee, and at most q_j committees for each candidate; that is, in the P by C assignment matrix A, at most q_i elements are nonzero for each column, and at most q_j elements are nonzero for each row.

Thus, let each direct contributor and indirect spender be indexed i, and each candidate be indexed by j. Letting α_{ij} be the value that a candidate adds to a political action committee, and γ_{ij} be the value a contributor or spender adds to a candidate, and τ to be the transfer from a committee to a candidate, we can now describe the payoff functions. The payoff functions for a contributor (π^S) and candidate (π^C) can be described as:

$$\pi^P(i, j) = \alpha_{ij} - \tau_{ij}$$

$$\pi^C(i, j) = \tau_{ij} + \gamma_{ij}$$

Then, let the total production for a candidate and committee pair be denoted as

$$f(i,j) = \alpha_{ij} + \gamma_{ij}$$

A necessary condition for equilibrium stability is, for committees i, a and candidates j, b:

$$f(i,j) + f(a,b) \geq f(a,j) + f(b,i)$$

Our optimal solution, then, is

$$\max \sum_{p,c} w_{\langle p,c \rangle} \cdot f_{\langle p,c \rangle}$$

Where $w_{\langle p,c \rangle}$ is 1 if match $\langle p,c \rangle$ forms and 0 otherwise.

Now, the question becomes how to compute these production values, since the valuations each candidate and contributor have aren't observable. The following model of production is a specification over observable characteristics, which form interaction terms. Then, we model production as:

$$\begin{aligned} f_{\langle p,c \rangle} = & \pm \beta_{\text{Party}} \text{SUP\_IND}_p \cdot \text{PARTY}_c + \beta_{\text{Experience}} \text{NUM\_CANDS}_p \cdot \text{YRS\_EXP}_c \\ & + \beta_{\text{Efficacy}} \text{WIN\_\%}_p \cdot \text{PASS\_\%}_c + \beta_{\text{Power}} \text{FUND\_\%}_p \cdot \text{BILL\_PASS\_\%}_c \\ & + \beta_{\text{Incumbent}} \text{NUM\_CANDS}_p \cdot \text{INCUMB}_c \end{aligned} \tag{1}$$

There is a possible effect for YRS_EXP of also being an incumbent; since it is likely that the effect of having 1 or more previous terms is different than that of 0 previous terms, a dummy interaction for Incumbency is also included. A further description of each variable in Equation 1 is included in Table 1.

Given a method of estimating production, we want to find the equilibrium assignment. Since the equilibrium solution has a solution that maximizes total welfare, we can solve a linear program maximizing overall production to find the optimal assignment.

Table 1. Variable Descriptions

Variable	Market Side	Description
SUP_IND	Contributors	$\frac{\text{\# Republicans Supported}}{\text{Total \# candidates}} - .5$
PARTY	Candidates	Party of the candidate; 1 for Republican, -1 for Democrat
NUM_CANDS	Contributors	Total # of candidates a contributor donated to
YRS_EXP	Candidates	Number of terms a candidate has served
WIN_%	Contributors	How many candidates a contributor supported won
PASS_%	Candidates	Candidate efficacy; % of bills a candidate sponsored that passed
FUND_POW	Contributors	Fund power; % of overall funding a particular fund spends
CAND_POW	Candidates	Power of the committees the candidate serves on; 1-4
INCUMB	Candidates	1 if candidate is incumbent else 0

Then, the setup for the linear program for many-to-many matching is:

$$\begin{aligned} \max \quad & \sum_{p,c} w_{\langle p,c\rangle} \cdot f_{\langle p,c\rangle} \\ \text{subject to} \quad & \sum_{c} w_{\langle p,c\rangle} \leq q_p, \quad p = 1, ..., P \\ & \sum_{p} w_{\langle p,c\rangle} \leq q_c, \quad c = 1, ..., C \\ & w_{\langle p,c\rangle} \geq 0, \forall p, c \end{aligned}$$

As before, $w_{\langle p,c\rangle} = 1$ if match $\langle p, c\rangle$ forms and 0 otherwise.

4 Dataset Description

In this paper, political donations are investigated using data from the National Institute on Money In Politics [1], and a dataset on characteristics of legislators within the House of Representatives [1]. Due to lack of a common ID, as well as differing standards in storing candidate names and congressional districts, a subset of the data with 153 Candidates and 6484 Contributors was selected. For Contributors, two types exist: direct contributors, of which there are 6419, and the remaining 67 indirect spenders. Note also that the first data contains

[1] https://www.followthemoney.org/

Table 2. Data Summary

Variable	Market Side	Count	Mean (Std.)	Min	Max
SUP_IND	Contributors		0.136 (0.394)	0.500	-0.500
PARTY	Candidates	100(R), 53(D)	0.3071 (0.954)	-1	1
NUM_CANDS	Contributors		10.599 (33.230)	1	685
YRS_EXP	Candidates		4.48 (4.08)	0	15
WIN_%	Contributors		0.878 (0.177)	0.012	1.00
PASS_%	Candidates		4.499 (8.982)	0	48
FUND_POW	Contributors		1.351e-5 (1.313e-4)	1.037e-11	0.007
CAND_POW	Candidates		1.092 (0.948)	0	4
INCUMB	Candidates	119(Inc), 34(New)	0.778 (0.417)	0	1

all political donations, including to candidates who lost, whereas the data on characteristics of legislators naturally only includes candidates who won.

What follows is a brief description of the United States legislature. The U.S. has a *bicameral* legislature, in that it is separated into two houses - the House of Representatives, and the Senate. Here, only legislators from the lower house - the House of Representatives - are considered. Within each house, there are committees which legislators serve on during their terms. Some of these committees are more powerful than others, which makes information on the committees valuable as a proxy for the "power" of a candidate. This is the measure of candidate power used in equation 1.

The following data was aggregated for candidates: the Party of each candidate (1 for Republican, -1 for Democrat), Years Experience (for all non-incumbents, this is 0), Sponsored Bill Percentage, the sum of Committee Power for each committee the candidate sat on, and whether the candidate was an incumbent.

On the donor side, a support index, which is (% of republicans a candidate supports) $-.5$ (ranging from -.5 to .5, such that the effect of a contributor being on the same side of the political spectrum as a candidate has gives positive production), number of candidates supported, the number of candidates supported that won their elections, and the percentage of overall funding a committee had (inclusive of indirect funding).

See Table 2 for summaries of important quantities within the data, and Table 3 for a breakdown of how funding differs within different subsets of the data.

Table 3. Funding Breakdown. Note that some sums and averages for subsets may not be representative.

Variable	Subset	Direct Funding Sum (Avg)	Indirect Funding Sum (Avg)
Overall		\$110,233,527 (\$1659)	\$25,940,985 (\$18358)
Party	Democrat	\$34,032,443 (\$1,651)	\$12533540 (\$68,117)
	Republican	\$76,201,084 (\$1,663)	\$13,407,444 (\$10,909)
Sex	Male	\$94,197,839 (\$1,669)	\$25,153,360 (\$18,855)
	Female	\$16,035,687 (\$1,602)	\$787,624 (\$9,969)
Race	Not Black or Hispanic	\$103,692,746 (\$1,657)	\$25940840 (\$18,397)
	Black	\$6,540,781 (\$1712)	\$93.65 (\$93.65)
	Hispanic	\$1,498,900 (\$1489)	\$50 (\$25)

5 Estimation Procedure

The estimation method used here is a maximum score estimator, proposed by Fox (2007) [2]. The set of conditions specified in Appendix 1 are sufficient such that the estimator set identifies β, and are also sufficient for set consistency of the estimator.

An intuitive explanation of the estimator follows. Note that in a competitive equilibrium in matching markets, social welfare is maximized; thus, other allocations have (weakly) lower social welfare. One way to measure this is at how many points the local production value for market participants is maximized - that is, considering a match within a market, checking whether the agents within that match have their production maximized relative to their production from participating in other matches.

Then, consider a committee, i, and candidate j, which could be matched to a different committee, a, and candidate, b, than proposed previously. The matching maximum score inequality based on these matches is, using the production model defined in equation 1:

$$f(i,j) + f(a,b) \geq f(i,b) + f(a,j)$$

For a specific vector β in the production function, our estimator has the following objective function.

$$\sum_{a,b \in Z, i,j \in Z'} \left(I\left[X'(\theta_i, \psi_j) \cdot \beta + X'(\theta_a, \psi_b) \cdot \beta \geq X'(\theta_i, \psi_b) \cdot \beta + X'(\theta_a, \psi_j) \cdot \beta \right] \right)$$

Note that the set of empirical matches within the dataset is denoted Z, while the set of alternate matches Z' is set by the researcher. $X(\theta_p, \psi_c)$ refers to a match between contributor p with characteristics θ_p and candidate c with characteristics ψ_c. Also, $I[]$ is the indicator function, specifying whether the inequality is satisfied or not for specific $\{a, b, i, j\}$. We optimize the objective over a set of β vectors to identify the coefficients specified in equation 1.

To optimize this objective function, a blackbox optimization routine called differential evolution is used. A simple implementation of the differential evolution optimization procedure does the following:

Algorithm 1: Differential Evolution

```
Parameters: Objective function F, Population P, Max iterations N
Randomly initialize candidates x_p , p = 1...P;
for i = 1...N do
    select a, b, c from x_p randomly;
    construct v = a + (b − c)/2;
    randomly swap components between x and v to get v';
    if F(v') > F(x) then
        x ← v' end
    end
    return x
```

See Storn and Price (1997) [6] for more context, as well as Mezura-Montes et al. 2006 [5] for more advanced variants of the algorithm. The specific implementation used here is part of the *BlackBoxOptim* Julia package.

In the context of this paper, estimation of model coefficients proceeded as follows. The empirical assignment seen in the dataset was used, and a subset of inequalities chosen. Then, parameters were estimated using the differential evolution algorithm described above, with the maximum score estimator as the objective function F. A variety of tuning parameters for the algorithm were used, to balance computational feasibility with estimation accuracy.

6 Monte Carlo Estimator study

In order to test the optimization and estimation procedure, Monte Carlo simulations are performed for four different market sizes: 25, 60, 125, and 250. First, a true parameter vector β is chosen - this is used to generate the data. Then, for each of these market sizes, a simple procedure is followed:

1. Sample from distributions to obtain simulated observables (X) for candidates and committees
2. Generate fake production values, $X'\beta + \epsilon$, using the true β
3. Solve for the optimal assignment using a linear program
4. Using the maximum score estimator and differential evolution, estimate $\hat{\beta}$
5. Repeat 1-4 1000 times, then compute Bias, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE)

The dataset generation procedure is as follows. Consider a simple one-to-one matching, with N candidates on each side. Then, N values are drawn from beta distributions. Once these data are generated, the $N \times N \times K$ matrix X is created by computing the elementwise multiplication of each drawn vector.

Across the different market sizes, bootstrap confidence intervals are also constructed; for each market size, N values are randomly sampled with replacement from one side of the market (call this side C). The corresponding assignments on the other side of the market (call this P), of which there are $N' \leq N$ are also selected - such that a new assignment $A = \{C_1, P_1\}...\{C_N, P'_N\}$ is selected. Then, parameters are estimated with this simulated assignment, and the process is repeated 1000 times. From these 1000 parameter draws, a $100(1-\alpha)\%$ percentile confidence interval, $[q_{\alpha/2}, q_{\alpha/2}]$, is constructed. This is repeated a number of times for each market size, and the coverage percentage - the amount of times the confidence interval contains the true parameter - is then calculated.

See Table 4 for the Monte Carlo study results.

Table 4. Monte Carlo Results

# Agents	Inequalities	Bias	MSE	RMSE	Coverage %
25	300	1.213	652.944	25.553	100
60	1770	0.8004	11.2628	3.3560	100
125	7750	0.3256	3.0012	1.7324	100[2]
250	31125	-2.318	162.153	1.732	100[3]

7 Counterfactual Analysis

As discussed in previous sections, an important question surrounding political funding has been how policy has affected who gets funding. As such, in this section, a market with no independent spending is simulated. The process for this analysis starts from the previous section; using estimates for model parameters, $\hat{\beta}$, the $C \times P$ production matrix $M = X' \cdot \hat{\beta}$ is constructed. With production values for candidates and contributors we can now compute equilibria to the assignment problem. Now, the linear programs to solve the original assignment, as well as the assignment where independent spending isn't allowed, are presented.

$$\begin{aligned}
\max \quad & \sum_{p,c} w_{\langle p,c \rangle} \cdot f_{\langle p,c \rangle} \\
\text{subject to} \quad & \sum_{c} w_{\langle p,c \rangle} \leq q_p, \quad p = 1, ..., P \\
& \sum_{p} w_{\langle p,c \rangle} \leq q_c, \quad c = 1, ..., C \\
& w_{\langle p,c \rangle} \geq 0, \forall p, c
\end{aligned}$$

Note that the quotas q_p and q_c are those found empirically.

Let $P_{ind} \subset P$ be the set of donors that are independent spenders. Then, the alternate linear program setup is:

$$\begin{aligned}
\max \quad & \sum_{p,c} w_{\langle p,c \rangle} \cdot f_{\langle p,c \rangle} \\
\text{subject to} \quad & \sum_{c} w_{\langle p,c \rangle} \leq q_p, \quad \forall p \in \{P \setminus P_{\text{ind}}\} \\
& \sum_{c} w_{\langle p,c \rangle} \leq 0, \quad \forall p \in \{P_{\text{ind}}\} \\
& \sum_{p} w_{\langle p,c \rangle} \leq q_c, \quad c = 1, ..., C \\
& w_{\langle p,c \rangle} \geq 0, \forall p, c
\end{aligned}$$

Differences between specifications are presented in Table 5. In general, the specifications aren't as dissimilar as expected. This can most likely be attributed

[2] Only 5 iterations due to computational reasons.

[3] Only 5 iterations. Confidence intervals for low numbers of agents were extremely wide, but became increasingly thin; with more iterations, it is likely we would see lower coverage.

Table 5. Counterfactual Results

Variable	**Original**	**Counterfactual**
Matching Value %	100	96.8
# Matches	32049	31958
Funding Lost	N/a	$1,073,758
Total Donation %	100	86.9

to the low number of Independent Spending donors in relation to the number of overall donors.

In order to further analyse the differences in contributions, the change in funding between assignments is computed for each candidate. What follows is a brief exploration of the differences among funding for when independent spending is allowed versus when it isn't.

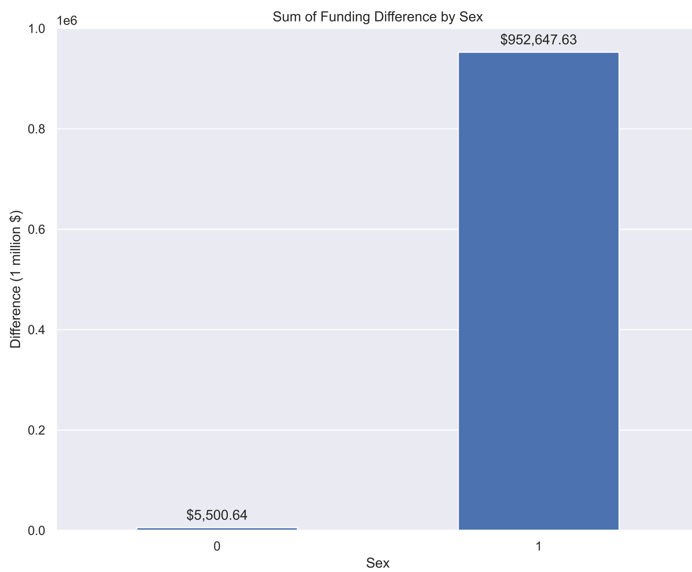

Fig. 1. Resulting funding differences by Sex. On the left is Female and on the right is Male.

Figure 1 shows the difference in funding by Sex. As Indirect Spending is largely oriented toward Males, this result matches intuition. Figure 2 shows simulated differences in funding across party lines. This result is more difficult to explain; one possibility is that, since more Republicans are incumbents in this market (70 Republican incumbents vs. 49 Democratic), they are a more desirable candidate to sponsor and thus are more easily able to find different sources of funding.

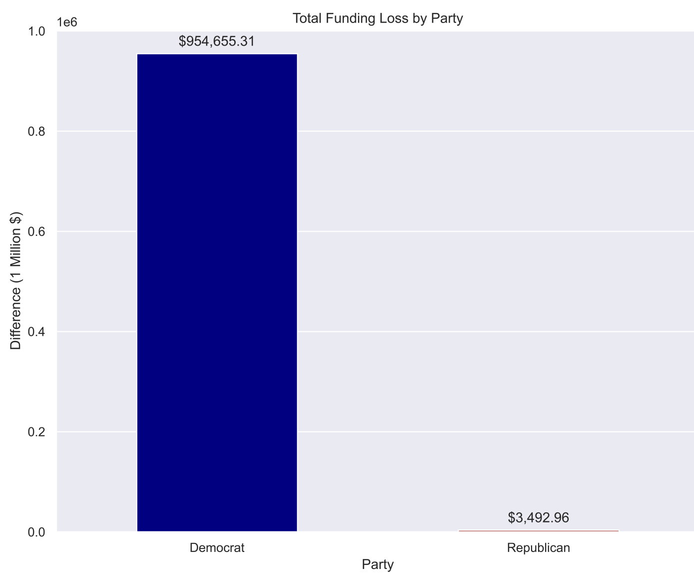

Fig. 2. Average Funding Difference by Party

8 Conclusions

In this paper, we examined the effects of *Citizens United* on political funding. In general, the counterfactual analysis didn't show dramatic differences. This can be attributed to a number of factors - the low number of Independent Spenders overall (though they contribute relatively more, on average), as well as using a smaller number of candidates in comparison to the complete market. This can also partly be attributed to disclosure laws; a large amount of independent spending goes unreported due to lax Federal regulations.

In further explorations, I would seek to include a larger amount of candidates, as well as use more recent political funding data that has a larger amount of independent spending. Datasets with candidate characteristics for the U.S. Senate would also be an interesting topic to look into, as political races for these positions are more contested, and thus the level of funding is elevated.

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