WWS 404 C05: Money and Influence in Policymaking

Dr Zhao Li

A Flood of Ama-Zoning: Political Changes, Campaign Contributions, and Voter Participation in California

Misha Tseitlin

15 May 2020

This paper represents my own work in accordance with University regulations.

Up in the Cloud(s): An Introduction

One of the first dictums any economist learns is that "there's no such thing as a free lunch." However, while an economist may spend years just to prove such a core concept, the American politician knows it all too well from their own experience. Simply, elections in the US are expensive—a politician could always use more money to finance their campaigns. Through political donations, the American political system allows individuals to vocalise preferences and affect outcomes. The more contested an election, the more exigent finances become for electoral success: individual contributions particularly contribute the marginal dollar (Ansolabehere, de Figueiredo, and Snyder 2003).

California provides a particularly relevant landscape to examine such trends. The state has spent years pushing forward various democratic reforms—from open primaries to independent redistricting—in order to increase the competitiveness and transparency of elections. At the same time, it is home to one of the largest and fastest growing industries in the US over the past few decades: the tech sector and the cream of the crop—Amazon, Microsoft, Facebook, Apple, and Google—that are often referred to as "Big Tech". The state also exemplifies the growing interlink between corporate and political interests: Apple and Google both have had recent construction projects in Santa Clara County, leaving their mark on the municipality. Previously, Google had a longstanding motto: "don't be evil." Since removed from its corporate code of conduct's preface, many technologists have noticed a conflict between such a slogan and their bottom line, all while striving to do the right thing (Montti 2018, Tiku 2019, Exclusive 2020).

To examine those assumptions, we will look at how corporate campaign contributions, particularly from the technology sector and especially from Big Tech, drive trends of political participation in California. Political participation, in this case, will be analysed from metrics of voting and individual political contributions. Technology companies claim to strive for social good and occasionally do provide direct and indirect benefits, yet they have undeniably altered the landscape of communities across California and the San Francisco—Bay Area in particular. Trends in demographics, affordability, transparency, and policy have all been touched in some way by these changes, in turn affecting how people seek to engage with their political representatives.

This paper will look at a variety of mechanisms for such corporate influence. On one hand, corporations could have trickle-down participation effects by increasing community wealth. On the other hand, corporations could crowd-out individual contributions or minimise consideration of community political interests. Finally, the agnostic middle ground may prevail: corporations could be entirely independent from drivers of individual political behaviour. Unfortunately, trends are not nearly so reducible, though corporate contributions broadly limit individual political participation. There are two specific trends: (1) tech employee contributions (especially from Big Tech employees) and overall corporate contributions are associated with more individual contributions and less voting; and (2) corporate tech donations have the opposite effect. To understand why, we must dig deeper.

Rising Tides: What We Know

Though it may appear straightforward to look at the relationship between individual and corporate contributions, the interaction of the two is far from a settled question. For one, corporate contributions make up a miniscule portion of independent campaign expenditures. These contributions in particular are driven by heterogeneity in political beliefs of key decision-makers, who are more adventurous and ideological in their individual contributions (Bonica 2016a). This ideological impact has been studied in corporate access-seeking Political Action Committees (PACs), where individual political preferences directly affect contributions to said PACs: more importantly, it demonstrates employee political awareness about the contribution behaviour of their employers (Li 2018). Despite more recent, targeted cutting-edge research, overcounts of individual contributions and undercounts of PAC spending are likely driven by the age-old phenomenon of bundling, where interest groups arrange and take credit for a bundle of individual campaign contributions. Along with the immeasurable nature of dark money in politics and the prevalence of PACs, this empirical analysis will face similar constraints to many others in the field (de Figueiredo and Garrett 2005). Additionally, partisan politics plays a notable role in corporate contributions, as corporate PACs from industries susceptible to political volatility direct their contributions to respond to polarisation (M. Barber and Eatough 2019). The actual gains to corporations more broadly are unclear, with evidence both for and against impacts to the bottom line from political donations (Jayachandran 2006, Fowler, Garro, and Spenkuch 2019). Regardless of the economic gains, technology companies in particular have long been playing both sides of the aisle, though they have had a longstanding preference to their liberal roots (Abramoff 2011). As tech companies increasingly find their way from California to DC, political clout can increasingly affect federal contracts, public perception, and the bottom line (Nix and Capaccio 2020).

When looking at the motivations behind individual giving, Bonica and others stress ideological factors, which is in line with the consumption theory on contributions and bolstered by the apparent substitution between charity and political donations (Petrova et al. 2020). On the other hand, donors have been found to respond more to personal business interests, implying that giving is an investment towards individual economic interests (M. J. Barber, Canes-Wrone, and Thrower 2017).

Though we understand the effect of both types of contributions and participation in isolation, occasionally looking at their effects on other phenomena in tandem, the direct causal relationship is more uncertain. One hypothesis may be that individuals, increasingly concerned with corporate governance, may care more about their own work's impact in, say, a machine learning project for the US military than any individual congressperson's legislative role or less significant vote. However, previous work shows no trade-offs between individuals' political participation in private governments like community associations and the broader political process (Gordon 2003). Though this is an imperfect analogy, it suggests that individuals' motivation to participate in the political process are relatively inelastic.

The motivation behind all political decisions can come down to a rudimentary model: an actor's ability to participate (or can otherwise be described as the cost to participation, which includes the counterfactual opportunity costs) is evaluated in relation to the perceived gains from participation. The interaction between these terms is modified by an elasticity parameter: the lower the elasticity, the further an individual will seek to participate relative to their limited means and other associated costs.

We already know that individuals' evaluation of losses and gains follows a complicated behavioural circuitry that makes direct quantitative comparisons difficult (Kahneman and Tversky 1979). Additionally, though individuals within a singular city may have some shared interests, such as the furthering of a job-providing industry, heterogeneity in personal preferences is difficult to capture and can stem from a variety of factors including race, economic status, and political affiliation. Corporate contributions broadly reflect attitudes about the gains from contributions as well as a community's outward focus. Similar trends drive behaviour for both ideological and economical models of contributions. Ultimately, the inelasticity of contribution alongside a variety of practical causal factors for individual giving suggests a more complicated behavioural-sociological picture.

Controlling for ideology, income, race, and other socioeconomic factors, contributions may give rise to several potential effects. Corporate contributions could increase individual apathy about the political process: no one wants to throw away their money on a seemingly broken system where they feel disenfranchised. Simultaneously, the perception of homogeneity within communities suppresses voter turnout, despite reforms like open primaries. Instead, as tech companies grow, the currency of political engagement increasingly becomes income—a persistent trend in California, where even local lobbying of the state government becomes an increasingly common and effective extension to more traditional political avenues (Payson 2019). Out-of-district contests may be more ample fodder for the donations of savvy relocated technologists and the natives that they displaced, giving them more bang for buck (Baker 2016). The converse effect of corporate money may stifle turnout by decreasing race competitiveness (Stockemer 2015). Simultaneously, remaining locals may increase grassroots political participation as a response; though the Bay Area has some tradition of such mobilisation, particularly a few large cities, such trends are far from the state-wide norm (Robinson 1995). However, technology corporations also create an omnipresent omen of growing American corporatism. In providing a common enemy to local communities, they can galvanise political action among the same populations that have been priced out of other ways to participate. These broader behavioural and sociological questions warrant more qualitative work and could be supplemented with further research on out-of-district and out-of-state contributions from the same contribution dataset used in this research. This work only notes increasing divergence and inequality in Californian municipalities as well as diverging incentives and effects among corporations and their employees.

Particularly, individual relationships towards technology companies and relevant political issues can be modulated through an awareness factor—how informed communities are about Big Tech's impacts. This can stem from community dialogue in media publications or social networks, and would warrant future work on individual information exposure and processing (Coppock, Guess, and Ternovski 2016). Community attitudes and broadly contrarian traditions (e.g. the liberally bohemian San Francisco and the "woke" Oakland, birthplace of the Black Panthers) may also drive different schema for political engagement and reactions to the newfound presence of tech corporations (Brabazon 2014). San Francisco has seen wilful corporate ventures into the political arena in an effort to proactively alter labour, housing, transit, and taxation to benefit technology corporations while acting against the broader public interest (McNeill 2016): these are likely to galvanise political participation in voting while pricing locals out of the money-based political marketplace. Communities may better empathise with their neighbours—the overworked and liberal workforces that generate these companies' profits—and limit their backlash to employee political behaviour.

Various other minor factors could be at play: educated technologists are more likely to be politically informed and engaged, while a contrarian backlash can engender opposite effects among local communities. Also, the well-discussed crowd-out effect, both from corporate donations as well as from the voting patterns of their employees, could cause further disenfranchisement among average Californians. There is a decisive certainty on the far-reaching impacts of the tech sector on the average resident: economic output, increased employment, consumer spending, tax payments, presence in local job forums, news, city (or other levels of) government meetings, and social media. The precise way that these shape local attitudes towards political involvement remains unclear.

Simply, this analysis does not measure the relative strength of the investment or consumption model, which could be analysed through metrics like using data on federal and state transfers to municipalities but is left as an unanswered question for future researchers. This paper will measure the chilling effects of, or suppression of participation from, Big Tech contributions and that of their (and other technologist) employees on individual contributions and voting. Effects can be differentiated based on their spread and magnitude, by using the number and amounts of different subsets of contributions respectively. A full explanation warrants taking a few steps back to start from the methodological beginnings and the data.

Silicon Valley's Favourite: Framework for Analysis

The data used in the empirical analysis came from three sources, leading to the generation of three separate datasets via cleaning in R. The core contribution data came from the Database on Ideology, Money in Politics, and Elections (DIME), which has data for all even-numbered election years from 1980 to 2018 (Bonica 2016b). Using latitude and longitude values (which had varying confidence) that originated from self-reported address, individual contributions were grouped and summarised by census place. These usually correspond to cities in California, due to the nature of incorporated communities in the state, and include more specificity for unincorporated areas in smaller Census Designated Places (CDP). This, of course, begs the question of omitted variable bias (OVB) and systematic trends in the observed data: omissions either come from unintentional error or deliberate dissemblance. However, the results show nothing particularly concerning (Table 4).

The grouped data contained information exclusively on campaign contributions and the area of each CDP: this includes both contributor and recipient information, summarised both by quantity and amount. The controls include ideology of both contributors and recipients, through Bonica's CF score, as well as their party. Contributions can also be subset by corporate and individual contributors, as well as PAC recipients. Fuzzy string search using Levenshtein distance[1] generated indicators for individual occupations (whether they were a technologist, programmer, and engineer) and employers (Big Tech is of interest in this case). For corporate donors, an indicator determined whether the donation was from a Big Tech corporation: Apple, Facebook, Microsoft, Amazon, and Google/Alphabet. These were all summed, along with all other contribution variables of interest and controls, by CDP.

The second dataset was the Statewide Database (SWDB) for redistricting in California, which included data on elections from 1996 to 2018 though data is only

[1] Our indicators used only distances of 1 or less for a tighter string search.

accessible from 2002 to 2018 (McCue n.d.). All even-numbered “Statement of Vote” data on all voting turnout for general elections, including absentee and in-person votes, by-precinct was used, as well as the conversion from precinct to 2010 census tract and block. These census block and tracts were converted to census place and then merged with the DIME data to create the second dataset (or data subset). This dataset only gives us information about the number of voters who turned out and registered.

The third source of data was the American Communities Survey (ACS) single-year demographic estimates, which go from 2006 to 2018 (Social Explorer n.d.). These were also included in the final regression for the third dataset, and included controls about population, density, economic welfare, commute times, housing, age, race, and nationality. Importantly, these are only for cities with 60 000 people or more, possibly leading to a skew with the exclusion of more rural and less corporate parts of the state. Omitted groups may either be small and urban, and thus represented by included larger cities, or large and rural: the latter case is characterised low voting and contributions (by less wealthy residents and small, local businesses), potentially causing underestimates of the effects of larger and more typical businesses.

A reader might ask why such an analysis was constrained to California, rather than including Washington—where Amazon and Microsoft call home. Why exclude Oracle, Cisco, and IBM (all older Silicon Valley companies) while including out-of-state presences? For one, the presence Amazon and Microsoft have in the Bay Area is undeniable: by no means do they have the kind of footprint Google and Apple might have, but they certainly contribute to, and are a part of, the newest wave of technological innovation and dominance. This newest wave of tech qualitatively would appear to be systematically different in its reach, profitability, and independence—unlike its more aged Valley peers. A simple constraint is cross-state effects and regulations become harder to process when taking into account the political currents not just in Sacramento, but in Olympia as well. The heterogeneity of a big state like California, as well as the ever-greater reach of Big Tech provides ample ground for analysis rather than stratified rural/urban divides in Washington that are less gradual as a side effect of the state's size.

However, before moving on to the regression strategies, we much acknowledge the inconsistencies in data. Specifically, voter registration and turnout exceed ACS population for every CDP in the sample. This could be a result of both systematic error in ACS and SWDB data. In the 2010 census, no California county had more than 74% response, with some response rates around 20%. California's population is majority non-white, 45% renting, 27% foreign-born, 18% low-income, and with 87% internet connectivity: all of these are risk factors for undercounting and likely contribute to these effects (Census 2020 Hard to Count Map n.d.). On the other hand, alphabetically split precincts, the lack of subprecinct geography, and general "unexplained inconsistency or incomplete maps" may also play a role in SWDB inaccuracies (Statewide Database | Precinct Conversion Diagrams n.d.). Verification of the following findings can come from looking at other sources of voting data, like the Secretary of the State of California's biannual voter registration reports (though these require either OCR software or manual labour to convert from PDF into workable data).

Political participation is measured in two ways—voter participation and individual contributions—each of which is measured in different ways. Specifically, contributions are tabulated by-census place (henceforth referred to as by-city) both in terms of aggregate amounts and counts. Means and percentages could also be generated, but the former contains only as much information as its constituent two variables, giving less meaningful results about the relative effect on counts and amounts. Percentages and ratios were excluded because they have a direct trade-off (i.e. any increase in % individual contributions implicitly means a decreased % corporate contributions) and are more likely to run into problems of collinearity and spurious regression results. Voter participation, on the other hand was measured in absolute voter turnout and registration numbers (not percentages) as well as the number of turnout relative to registration.

The methodology in this paper always maximises the original variables without opting for linear combinations. The justification for this follows from confounding effects: we want to more clearly be able to separate distinct effects for each variable of interest (for example, number and amount of contributions of a given type give us more information about where the causality is coming from than a mean or ratio). A larger and more significant effect that comes from number of contributions would indicate a bottom-up effect in contributions; a converse finding would stress the importance of income, amount, and wealth as the driver for contributions. This is also true when considering controls for population, the total amount of contributions, and etc. Their inclusion as controls and the supplementary year fixed effects (though interaction terms would be helpful as a future extension to clarify this effect) could soak up most of the deterministic trend and OVB and look simply at the causal relationships between the variables of interest. The sole exception here is the voter turnout rate, as this metric allows us to view interacting trends in voter registration and turnout. Turnout rate responds positively to a logarithmic transformation on the regressors of interest, though this could result from either characteristics of the overall relationship or just the relevant subsample of cities with nonzero donations: logarithmic transformation mark zero values (85% of the original sample) as missing or null data. Future exploration of per-capita specifications may yield differing results. As mentioned, the inclusion and consideration of interaction terms for a variety of variables was not explored and warrants further analysis.

The data was analysed in Stata with a standard OLS panel regression, the functional form of which can be specified as follows:

$$Particip_{i,t} = \beta_0 + \beta_1 Corp\ Contrib_i + \beta_2 Tech_i + \ldots + W'_i \cdot \Gamma + \alpha_i + \lambda_t + u_i \text{ (Eq 1)}$$

In Equation 1, i is the unit effect, in this case by city; W is the vector of controls in later regressions; α is the city fixed effects (FE); λ is the time fixed effect; and finally, u_i is the error term. The coefficients represent the magnitude of the effect of corporate contributions (with separate coefficients on number and amount of corporate contributions by city for 2 variables), technology indicators (6 variables that include number and amount of contributions by big tech, their employees, and technologists), and other variables of interest on the endogenous variables against a null hypothesis of no relationship (i.e. that the relationship is 0). For datasets 1 and 2, controls are simply DIME values for overall contributions, the ideology of recipients and contributors, and the nature of recipients (PAC or candidate). Dataset 3 adds dozens of demographic controls, selecting 52 variables for income, housing, and other relevant socioeconomic factors. The errors in this case are clustered by-unit, or by-city, to produce proper estimates of the relationship. Though turnout rate might beget a panel logit or probit regression, the inability to cluster errors leads to too many concerns about unreasonably small confidence bands.

For the third dataset, the wide nature of the ACS data provides 292 potential regressors to include as controls in the full regression. A big data technique known as Lasso (least absolute shrinkage and selection operator) helps to reduce this number due to its unique shrinkage factor that excludes less predictive variables from the regression. Though our data is in a panel structure and lasso cannot incorporate unit fixed effects, it is nonetheless robust to panel standard errors (Medeiros and Mendes 2016).

$$S^{Lasso}(\beta; \lambda_{Lasso}) = \sum_{i=1}^{n}(Particip_i - \beta_1 X_{1i} - \ldots - \beta_k X_{ki})^2 + \lambda_{Lasso} \sum_{j=1}^{k} |\beta_j| \text{ (Eq 2)}$$

The aforementioned equation 2 is a minimisation for $S^{Lasso}(b; \lambda_{Lasso})$ where λ_{Lasso} is the shrinkage parameter and the βs are coefficient values from a standard OLS. Xs here represent the ACS demographic parameters. When implemented, participation metrics were de-meaned and all potential exogenous regressors were normalised to minimise magnitude biases in variable selection.

The presence of deterministic trends in the data are not as concerning, as they represent an aspect of the behaviour of the trends of the interest; such questions are more relevant in the context of predictive analytics. Future work could build on these findings by looking at regression discontinuity, as such discussions are omitted in this analysis.

Going South: Data Perspectives

Promising results in the following regression analysis illustrate the complicated nature of influences on political participation. First, one important nuance to note is that tech sector variables are subsets of total individual and corporate contributions, with the former for employees and the latter for their employers. Thankfully this nuance does not impede interpretations particularly: positive values on technology coefficients would signify a neutral or slightly positive effect (as each additional contribution for the endogenous variable is also included in exogenous contribution terms), while negative or even zero values correspond to a chilling effect. Turnout rate represents the effects of trends on voter turnout divided by voter registration, otherwise described as voter "follow-through": the amount of people that commit to voting who actually do so. This a particularly good proxy for election day apathy or inaccessibility.

Table 1: Means and Standard Deviations for Variables of Interest

Dataset	(1)	(2)	(3)
Contents	Contributions 1980-2018	Voting and Giving 2002-18	Full Data 2006-18
# Corporate Contributions	42.44 (435.6)	59.11 (547.7)	461.3 (1 723)
$ Corporate Contributions	141 657 (3 012 000)	233 780 (3 953 000)	2 120 000 (13 950 000)
# Big Tech Contributions	2.392 (46.95)	3.926 (61.73)	34.14 (219.7)
$ Big Tech Contributions	1 700 (32 889)	2 659 (42 294)	18 553 (100 757)
# Big Tech Employee Contributions	14.6 (194.2)	25.02 (255.7)	230.3 (878.2)

$ Big Tech Employee Contributions	3 816 (71 308)	6 346 (93 853)	44 766 (211 526)
# Tech Employee Contributions	150.3 (1 471)	256.0 (1 931)	2 208 (6 606)
$ Tech Employee Contributions	48 129 (1 758 000)	79 056 (2 316 000)	397 686 (1 556 000)
# Individual Contributions	1 225 (11 686)	2 037 (15 340)	16 914 (52 944)
$ Individual Contributions	363 458 (4 948 000)	559 561 (6 433 000)	4 156 000 (19 570 000)
Voter Registration	–	537 259 (1 592 000)	2 173 000 (2 897 000)
Voter Turnout	–	344 818 (987 195)	1 361 000 (1 830 000)
Voter Turnout Rate	–	0.653 (0.163)	0.627 (0.155)
# Total Contributions	1 332 (12 267)	2 194 (15 083)	18 158 (55 162)
$ Total Contributions	814 329 (11 650 000)	1 273 000 (15 180 000)	10 500 000 (50 520 000)
Population	–	–	180 654 (363 569)

Looking at the summary statistics across data, contributions increase substantially as time progresses (and the number of observations shrinks). The only exception is voter turnout rate, where bigger cities may actually have less voter follow-through. There is more variance among the variables of interest with the exception of the amount of tech employee contributions, which are actually more homogenous in later years, signalling the growing ubiquity of technologists across the larger Californian cities (Table 1). Global contributions often have negative minimum values, which represent refunds from recipients or amendments to previous filings.

Among the control variables of interest, a strong rightwards skew appears in the data, with maximum values for all contribution types in the hundreds of millions (except for big tech employees and corporations who only give in the millions as a maximum). The exceptions are CF score variables, which are slightly more symmetrically distributed, but still right skewed because of the heavy liberal nature of California. For interpretation, greater CF score means more conservative ideologies, ranging from -3.5 (very liberal) to 4.2 (very conservative) (Table S5). Originally, standard deviations of CF score by city were included to record heterogeneity of political ideology by city, but they shrunk the regression set. Not all contributors and candidates have CF scores, with less common contributors and recipients most likely to be left out, giving us a bias towards big-name candidates and contributors.

For the second dataset, mean values of variables increase across the board, except for CF scores, where both mean variables become more liberal and the difference between them shrinks: with growing documentation of political polarisation in the US, this is unsurprising. A much greater variation appears in the number of registered voters compared to the ones who turned out, with turnout rates going from 9% to significantly above 100% (Table S8). Post-2006 large cities (the entirety of dataset 3) no longer have any turnout rates above 1, indicating that in larger, urban areas there is less likely to be cross-place registration and voting as well as precinct mapping issues.

In the final dataset, means for contributions and voters increase substantially, with negative contribution values only for the number of individual technology contributions. Not a single zip code lacks a technologist contributor, showing the ubiquity of technology in the post-2006 economic state of California. As expected, the smallest city has 61 628 inhabitants. Various variables lack good interpretations, like the move-in variables that have a shockingly small maximum value indicating the limited sample for such data—at most 6 000 people or so have moved to any given city since 2000; however, that seems unlikely. Median incomes hold standard values and can go up to $137 000; the top quintile can have a $648 000 mean income (Table S12). Concerning which variables were selected for demographic controls, the lasso results can give us more information.

Table 2: Lasso Regression Results by Dependent Variable

Variable	$ Indv Contrib	# Indv Contrib	Voter Turnout	Voter Registration	Turnout Rate
selected λ	43 998 652	47 076.755	302 870.28	33 484 911	17.717
λ convergence	X	X	X	✓	✓
# parameters	95	116	206	24	8

This data is particularly poorly suited to lasso estimation, with the variation in the data making lambda convergence (the shrinkage parameter) difficult. Nonetheless, lambda results may often have a minimal effect on the number of parameters selected and their relative coefficients. Voter turnout appears the most heterogenous of all the variables, with a wide variety of relevant demographic trends that contribute to its estimation. Voter registration and turnout rate exhibit more standard behaviour, with the amount of contributions showing slightly more homogeneity in predictors than its number. We must be cautious about ascribing too much credibility to these results, as they simply represent predictive power and not proper controls for causal inference procedures. However, contributions-based models from data 2 have remarkably low R^2 values for voter registration and turnout in comparison to contribution metrics of political participation. These results increase substantially in voter turnout and turnout rate, but voter registration lags substantially behind, even in controls.

Table 3: Regression Results for Variables of Interest

	# Indv Cont	**$ Indv Cont**	**Reg**	**Turnout**	**Turnout Rate**
# Corp	-2.297*** (0.189)	-2 839 (2 767)	-127.5 (408.3)	-416.4 (312.8)	-2.02×10^{-5}*** (5.10×10^{-6})
$ Corp	-5.02×10^{-6} (8.05×10^{-6})	-0.684*** (0.252)	-0.0374* (0.0205)	-0.0149 (0.0167)	-7.61×10^{-10}** (3.86×10^{-10})
# Big Tech	-0.0517 (0.0846)	-1 241 (1 628)	-236.2 (188.1)	-117.3 (153.1)	1.11×10^{-5}** (5.52×10^{-6})
$ Big Tech	-0.000737 (0.000448)	-13.31* (7.762)	3.385 (3.052)	2.169 (1.990)	1.37×10^{-8} (1.59×10^{-8})
# Big Tech Emp	0.0933* (0.0482)	1 583 (1 056)	-1.394 (135.5)	-38.34 (78.25)	-3.28×10^{-6} (3.28×10^{-6})
$ Big Tech Emp	0.000396*** (0.000131)	5.370** (2.451)	-0.0689 (0.129)	-0.0765 (0.0759)	-2.07×10^{-9} (3.26×10^{-9})
# Tech Indv	0.00657 (0.00831)	141.5 (151.8)	-46.45 (36.54)	-34.01*** (12.17)	-1.28×10^{-6}* (6.56×10^{-7})
$ Tech Indv	4.96×10^{-5}*** (1.87×10^{-5})	1.697*** (0.553)	-0.0267 (0.104)	-0.00867 (0.0640)	2.46×10^{-9}** (1.25×10^{-9})
# Corp	-5.208*** (0.661)	-4,630* (2,367)	-31.41 (42.60)	-285.0*** (63.10)	-2.66×10^{-6} (4.18×10^{-6})
$ Corp	2.97×10^{-7} (4.52×10^{-5})	-0.638*** (0.237)	0.00265 (0.00423)	0.000785 (0.00483)	-1.30×10^{-9}** (5.60×10^{-10})
# Big Tech	1.359 (0.827)	-28.62 (891.0)	29.14 (27.75)	54.54** (27.07)	1.01×10^{-5}*** (3.31×10^{-6})

$ Big Tech	-0.00603** (0.00275)	-8.505 (7.350)	-0.111 (0.192)	0.953** (0.466)	4.28×10^{-8} (2.78×10^{-8})
# Big Tech Emp	0.845** (0.347)	-510.3 (1,022)	25.23 (41.19)	-116.2* (58.97)	-4.73×10^{-6} (4.00×10^{-6})
$ Big Tech Emp	0.00154 (0.00150)	1.312 (2.872)	-0.00176 (0.105)	-0.0346 (0.252)	-2.72e-09 (2.16×10^{-8})
# Tech Indv	0.190** (0.0843)	44.39 (49.94)	-7.028 (5.558)	-4.747 (4.933)	-1.41×10^{-6}*** (4.44×10^{-7})
$ Tech Indv	0.000711 (0.000533)	3.336*** (1.029)	0.00119 (0.0232)	-0.0948** (0.0418)	-4.31×10^{-9} (5.73×10^{-9})

Robust standard errors in parentheses

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

Colour coded results: dark grey is data 1, light grey is data 2, and white is data 3

Looking at the first dataset, the economic significance of an additional dollar on the number of individual contributions is low, though prevalent. Every additional corporate contribution decreases the number of individual contributors by 2.3. There is a small negative effect resulting from every additional dollar, though this effect is too close to 0 and has more impact on other variables of interest. Big Tech corporate contributions have similarly negative, though smaller effects, unsurprising as the data starts in 1980 and before their rise as a major economic player. Individual contributions by tech employees both working for Big Tech and other firms provide positive results: every $10 000 from a Big Tech employee roughly increases the number of individual contributors by 4, with the number closer to 0 in response to technologist contributions. However, we cannot be sure if this arises from income effects rather than any mechanism impacting individual-corporate responsibility (Table 3). Concerning the controls, conservative candidates draw a larger number of donations, while conservative contributors are often associated with municipalities with overall lower levels of giving. More variable time FE appear here between 1996 and 2008 with presidential elections having fewer individual contributors, the exception being 2004 (Table S7).

The amount of individual contributions is understandably unaffected by the number of contributors, though familiarly negative effects from corporate contributions and benefits from individual amounts and numbers of contributions are both visible. A dollar from a tech employee, on the other hand, is worth about $1.70 for individual contributions while a Big Tech employee can have more impact, stimulating $5.37 in individual spending. Potentially, these could come from network effects: more technologist contributions mean increased contribution from their peers as well. Economic effects are also not controlled for, serving as a potential source of OVB (Table 3). More broadly, a longer-term decrease of individual contributions is noticeable in the year fixed effects in 2008 and later years. Conservative candidates receive less from individuals, but conservative contributors give more: altogether unsurprising given the political landscape in California (Table S6).

Looking at voting data since from this millennium, we see voter registration responding negatively to all metrics except big tech contributions, nonzero at the 5% level for technologist and Big Tech contributors, as well as corporate contributions. This could be confounded with uncompetitive races that see lower turnout, with technologists and their employers increasing out-of-district contributions in response. Nonetheless, such Big Tech effects give credibility to the contrarian theory of voting, whereby individuals are galvanised by visible corporate political influence in amounts. Being shaped by social discourse, such a theory explains the contradiction between the negative effects from the amount of donations and positive effects for the amounts donated, with the latter the more likely currency of community discussions about corporate political influence. Every additional corporate dollar leads to 0.04 fewer voters; every technologist contributor, on the other hand, is another 46 fewer voters—likely a result of homogenous districts and the growing currency of contributions as an outlet for political discourse (Table 3). In the absence of population controls, these results warrant further examination. 2016 and 2004 are the only years with more registered voters than 2018, signalling particular registration and turnout drives. More conservative contributors in a city lead to greater turnout, possibly as a result of the same galvanisation effect though targeted at liberal politicians; more liberal candidates and greater ideological differences between contributors and recipients act in the opposite direction. Independent recipient share is linked to highest turnout, followed by Republicans' in second place. These outcomes are intuitive given Californian political trends (Table S9).

Turnout, a more tangible metric for political participation, exemplifies all the same trends as mentioned before. An extra technologist's contribution is a loss of 34 voters: smaller effects prevail across the board except for Big Tech employees, who seemingly have a bigger election-day effect with their contributions. The number of corporate donations has a similar effect, speaking to the heterogeneity of the noticed chilling effect. Though statistical significance is fleeting in many cases, tighter standard errors more regularly exclude the possibility of zero or cross-sign values for coefficients, making us confident in the direction of the effect (Table 3). In the theme of suppressed turnout, more donations to PACs rather than candidates directly have a similar effect (Table S10).

Turnout rate, measuring voter follow-through, is by far the most interesting because it takes into consideration individuals with political awareness facing ideological or practical constraints in their journey to the ballot box. We see distinct and statistically significant suppression from overall corporate contributions, with more technologist contributors also leading to notably less turnout. Big tech metrics and the amount of technologist contributions broadly have positive turnout effects, providing evidence towards the rally-against-the-enemy hypothesis. Another explanation considers potential trickle-down political engagement from individual money in politics, though these effects may be correlated with an OVB of closer races or more community outreach. In either case, Big Tech employees' contributions are more exclusive and limited, making benefits difficult to access (Table 3). This regression is particularly interesting, concurrently analysing trends from the other two regressions. There is nothing distinctly new in the controls, though there are interesting trends like the 2012 FE flipping to positive, in this case correlating with follow-through behaviour (Table S11).

Including demographic controls gives broadly the same trends as the short regression, though signs flip for corporate donations and big tech corporate contributors. All effect magnitudes have increased, except for the effect of corporate donation amounts. As expected, more individual contributors result from more technologist contributions and contributors, as well as from Big Tech contributions, which likely signify a broader corporate consciousness about politics and may instead be responding to public backlash. However, corporate contributions, and those from big tech broadly, continue to discourage individual contributors (Table 3). Larger, denser cities with higher proportions of residents not working from home have less contributors, while super commuters (those who travel more than an hour to work) give more. More limited income effects are visible, with higher Q3 and 5th percentile incomes giving more but other income brackets giving less. Higher Latinx aggregate income lead to more contributors, as does that of more recent migrants, particularly from 2000 to 2004 (Table S14).

With the amount of contributions, negative effects arise from corporate contributions and positive effects stem from individual ones: altogether unsurprising and in line with noticeable trends. Cross-regression that looks at statistical significance confirms this trend while putting less weight on giving by Big Tech employees, with the latter having massive standard error in this regression (Table 3). Higher incomes actually lead to less contributions, more so for Latinx than for white subsets of the population. The same is true for higher home values, higher rates of home ownership, and increased upper quintile incomes. We see little interesting variation in time FE, and age effects paint a complicated picture about the age distribution of contributors, sometimes in 2 to 3-year increments, representing the role of generational effects. Bigger, denser cities with more foreign-born citizens all give less. Broadly speaking, per capita income and super commuters are associated with greater giving.

Voter registration is poorly predicted by the variables of interest, with values close to 0 and large standard errors. The only main conclusions that can be drawn are that more technologist contributors lead to less turnout, while more big tech corporate contributors have the opposite effect. This model generally performs poorly, showing little improvement from the inclusion of various controls, indicating complicated sociological trends that drive registration, particularly in this subsample of large cities (Table 3). Age effects are particularly relevant here, and bigger, denser cities with more workers have higher registration. Similar benefits stem from higher Latinx incomes, median incomes, and home values. Cities with more super commuters, unsurprisingly, also vote more, while cities with larger foreign-born and older population (over 70) shares vote less (Table S15).

Voter turnout shows more promising results: more contributions from technologists, regardless of employer, suppress turnout, as do more general corporate donations. Big Tech contributions have the opposite effect, speaking to the unique effects that they provide to community turnout despite controlling for various socioeconomic factors. This could be a factor of the galvanisation effect, coupled with greater municipal budgets for education and social services (Table 3). Super commuters vote the most, with diminishing effects for commutes under 40 minutes. Higher income inequality and foreign citizen share lead to less turnout, while higher incomes (especially for Latinx), larger populations, more poverty, and higher rent prices signal the converse. Q2 and Q5 income residents particularly show up to the polls, especially in 2008 and 2016 (Table S16).

Voter follow-through shows trends similar to the data 2 regression, giving confidence in the robustness of previous results: benefits in follow-through come from metrics of Big Tech contributions, and nothing else. Super commuters again exemplify more follow-through, as do a larger number of migrants, and Q4 and 5th percentile residents. We see less discernible effects across the board, though presidential elections years have higher follow-through that increases in open-seat elections. Most of these results are small and statistically insignificant, in part due to the limited range of the endogenous variable (Table S17).

Stemming the Tide: Limitations and Results

Though contributions and voting behaviour are both metrics of political participation, they give rise to divergent results. Corporate contributions limit individual contributions, while individual employee contributions have the opposite effect. These results are fairly intuitive but show that Big Tech plays second fiddle to bigger, more significant, and broader corporate contribution effects. The opposite is true for individual contributions that intuitively respond positively to technologist contributions. However, direct comparisons are difficult due to the more limited nature of Big Tech employee contributions. In number—breadth and generalisability of the effect—Big Tech uniquely stimulates contribution-based participation. In amounts, the relationship is more uncertain, though appears reversed: more work must be done to truly understand these effects.

In voter registration, turnout, and follow-through, we see inhibition across the board for corporate contributions and individual technologist contributions. This speaks to the chilling effect of political contributions and the rise of Big Tech, as individuals increasingly feel disenfranchised from their local races while more of their wealthy technologist peers are enabled to affect electoral outcomes outside of their uncompetitive home districts. Big Tech has the opposite result, as its contributions increase voter turnout: whether this is due to negative attitudes about tech or community externalities is unclear, though controls for the latter make us more confident in the former explanation.

Super-commuters are a particularly interesting group: more of them give (both in number and amount), register, and vote than any other group. Voters increasingly come from Q2 and Q5 income brackets (or at least are more responsive to changes in income there), while contributors tend to be in Q3 and the top 5th percentile. Both of these suggest interest sociological trends to further examine. Super commuters particularly are an everlasting symbol of the rise of Big Tech in the Bay Area, with past literature finding their prevalence to be linked to indicators of housing as well as small self-selection effects (Baldassari 2019, Mitra and Saphores 2019). This provides an interest population subset to look at when analysing voter participation trends going forward.

Looking at nonlinear specifications, log transformations were thoroughly explored. Their use was not deemed relevant for this paper, with unilateral logs for either just the endogenous or exogenous variables yielding dismal results; log-log specifications demonstrated a higher within-group R squared value, but saw those gains lapse in between-groups and overall metrics. However, they certainly warrant further exploration, as coefficients are more easily interpolable given the difference of scale between various regressors. In logarithmic transformations, all zero values are labelled as missing, drastically shrinking the size of the regression (due to a high prevalence of zero values and the rightward variable skews) and giving us results only for cities with contributions. This is certainly a useful direction in future work, though its consideration is excluded here.

Further work might also include logit and probit specifications for 0-1 values like contribution rate, voter registration rate, and voter turnout rate. As Stata does not support clustered standard errors for panel logit and probit regressions, these considerations were omitted for the one relevant target variable: a per-capita base for analysis might find such specifications particularly helpful. Looking at subsets of the data—most notably at cities with nonzero amounts of technological donations over the panel range of interest—would likely produce stronger and more relevant results, though it would exclude the comparative presence-absence tradeoff for communities that attracted technology companies. Simply, it would show a more accurate representation of the trends from the technology sector at the cost of broader discussions of corporate trends but is omitted from this analysis due to length constraints. Additionally, cities with technology workers and employers systematically differ from other Californian cities: they tend to be urban, wealthier, and generally more politically engaged. For controls, election characteristics such as race competitiveness, office type, and spending did not cleanly lend themselves to such inference. Future work could include quantitative or multinomial electoral controls, or otherwise subset at the data by outcomes to look at diverging trends using other DIME datasets.

Given the long nature of the panel data and particularly notable discontinuities, future work on trends in regression discontinuity would similarly help clarify causal factors in the trends identified in this paper. Using the Quandt Likelihood Ratio procedure, future work could see the effects on identified trends from the Citizens United ruling, the 2008 financial crisis, and IPOs for the technology companies (between 1980 for Apple and 2012 for Facebook). Dividing up trends in "Big Tech" to look at individual companies might also yield interesting work. This paper merely scratches the surface and provides a glance at deeper areas of research interest.

Preparing for the Fires: California's Future

The rise of Big Tech in California and the ensuing economic growth over the past decades is an undeniable characteristic in changing community demographics across the state. Though Big Tech often remains responsive to critiques about its direct political engagement, corporations tend to be more lackadaisical in their community affairs. Benefits noticeably arise in one way: by providing a common enemy, Big Tech presence stimulates voter turnout, even though it prices out individual contributors. However, this pricing out is in inevitability of corporate involvement in the political process across the state and is only slightly more exaggerated for Big Tech in relation to their peers.

Technology corporations do not only have direct impacts on their communities: the workers they attract, employ, and influence also make up an undeniable part of the demographic nature of communities. Housing prices continue to rise, locals are priced out, and the cost of living increases. Such workers are more likely to have a global and national mindset, with many coming from out of state. Though they participate politically through national and state-level campaign contributions, they simultaneously suppress voter participation in their backyard, due to growing ideological homogeneity, in defence of their economic interests.

The Big Tech wave is far from over, and much work remains to be done in determining the incentives behind individual and corporate donation behaviour to address such externalities at the source: these externalities not only exist but also are sizeable in nature. To counteract the growing monetisation of the Californian political landscape, further reforms beyond district and primaries may be necessary, looking at the direct role of corporations and their engagement with their communities. Communities are continuing to change: Apple and Google's construction developments are driving unaffordability for local residents while lukewarm affordable housing pledges serve as cover for minimising backlash, overturning voter referendums when they oppose such construction and appealing to governments directly (Wu, Rol, and Li 2018, Elias 2019). Given the spread of big tech across the state, the Bay Area's experience as ground 0 to the tech boom can guide proactive policy both state-wide and nationwide, as corporations look to expand nationally like Amazon's notorious HQ2 race that ended in northern Virginia (Capriel 2019). Community change is inevitable, and national interconnectedness will only increase with more collaborative digital infrastructure; however, governments should cautiously greet these changes while safeguarding recent accessibility gains. As voter turnout, particularly of various demographics, drives elections results, it helps to learn from the past and take these lessons to the future (Morgan and Lee 2017).

Bibliography

Abramoff, Jack. 2011. *Capitol Punishment : The Hard Truth about Washington Corruption from America's Most Notorious Lobbyist*. Washington, DC : WND Books. http://archive.org/details/isbn_9781936488445 (May 3, 2020).

'Amazon HQ2 Finally Takes Shape, the Arlington Way'. *Washington Business Journal*. https://www.bizjournals.com/washington/news/2019/12/19/amazons-hq2-finally-begins-to-take-shape-the.html (May 5, 2020).

Ansolabehere, Stephen, John M. de Figueiredo, and James M. Snyder. 2003. 'Why Is There so Little Money in U.S. Politics?' *The Journal of Economic Perspectives* 17(1): 105–30.

Baker, Anne E. 2016. 'Getting Short-Changed? The Impact of Outside Money on District Representation*'. *Social Science Quarterly* 97(5): 1096–1107.

Barber, Michael, and Mandi Eatough. 2019. 'Industry Politicization and Interest Group Campaign Contribution Strategies'. *The Journal of Politics*. https://www.journals.uchicago.edu/doi/abs/10.1086/707493 (May 3, 2020).

Barber, Michael J., Brandice Canes-Wrone, and Sharece Thrower. 2017. 'Ideologically Sophisticated Donors: Which Candidates Do Individual Contributors Finance?' *American Journal of Political Science* 61(2): 271–88.

'Bay Area Super-Commuting Growing: Here's Where It's the Worst'. 2019. *The Mercury News*. https://www.mercurynews.com/supercommuting-is-not-just-for-central-valley-dwellers-map-shows-growth-in-bay-area-commutes (May 5, 2020).

Bonica, Adam. 2016a. 'Avenues of Influence: On the Political Expenditures of Corporations and Their Directors and Executives'. *Business and Politics* 18(4): 367–94.

———. 2016b. 'Database on Ideology, Money in Politics, and Elections: Public Version 2.0 | SSDS Social Science Data Collection'. https://data.stanford.edu/dime (May 11, 2020).

Brabazon, Tara. 2014. 'When Bohemia Becomes a Business: City Lights, Columbus Avenue and a Future for San Francisco'. In *City Imaging: Regeneration, Renewal and Decay*, GeoJournal Library, ed. Tara Brabazon. Dordrecht: Springer Netherlands, 135–55. https://doi.org/10.1007/978-94-007-7235-9_11 (May 4, 2020).

'Census 2020 Hard to Count Map'. https://www.censushardtocountmaps2020.us/ (May 4, 2020).

Coppock, Alexander, Andrew Guess, and John Ternovski. 2016. 'When Treatments Are Tweets: A Network Mobilization Experiment over Twitter'. *Political Behavior* 38(1): 105–28.

Elias, Jennifer. 2019. 'Google's Plans for a Mega-Campus in San Jose Lurk behind Its Recent $1 Billion Housing Pledge'. *CNBC*. https://www.cnbc.com/2019/07/11/google-san-jose-expansion-helped-drive-1-billion-housing-pledge.html (May 5, 2020).

‘Exclusive: Amazon Turns to Chinese Firm on U.S. Blacklist to Meet Thermal Camera Needs’. 2020. *Reuters*. https://www.reuters.com/article/us-health-coronavirus-amazon-com-cameras-idUSKBN22B1AL (May 3, 2020).

de Figueiredo, John, and Elizabeth Garrett. 2005. ‘Paying for Politics’. *Southern California Law Review* 78: 591–668.

Fowler, Anthony, Haritz Garro, and Jörg L. Spenkuch. 2019. ‘Quid Pro Quo? Corporate Returns to Campaign Contributions’. *The Journal of Politics*: 000–000.

‘Google’s “Don’t Be Evil” No Longer Prefaces Code of Conduct’. 2018. *Search Engine Journal*. https://www.searchenginejournal.com/google-dont-be-evil/254019/ (May 3, 2020).
Gordon, Tracy M. 2003. ‘Crowd out or Crowd in?: The Effects of Common Interest Developments on Political Participation in California’. *The Annals of Regional Science* 37(2): 203–33.

Jayachandran, Seema. 2006. ‘The Jeffords Effect’. *The Journal of Law and Economics* 49(2): 397–425.

Kahneman, Daniel, and Amos Tversky. 1979. ‘Prospect Theory: An Analysis of Decision under Risk’. *Econometrica* 47(2): 263–91.

Li, Zhao. 2018. ‘How Internal Constraints Shape Interest Group Activities: Evidence from Access-Seeking PACs’. *American Political Science Review* 112(4): 792–808.

McCue, Kenneth. ‘Statewide Database | Home’. *Statewide Database*. https://statewidedatabase.org/ (May 11, 2020).

McNeill, Donald. 2016. ‘Governing a City of Unicorns: Technology Capital and the Urban Politics of San Francisco’. *Urban Geography* 37(4): 494–513.

Medeiros, Marcelo C., and Eduardo F. Mendes. 2016. ‘ℓ1-Regularization of High-Dimensional Time-Series Models with Non-Gaussian and Heteroskedastic Errors’. *Journal of Econometrics* 191(1): 255–71.

Mitra, Suman K., and Jean-Daniel M. Saphores. 2019. ‘Why Do They Live so Far from Work? Determinants of Long-Distance Commuting in California’. *Journal of Transport Geography* 80: 102489.

Morgan, Stephen L., and Jiwon Lee. 2017. ‘The White Working Class and Voter Turnout in U.S. Presidential Elections, 2004 to 2016’. *Sociological Science* 4: 656–85.

Payson, Julia A. 2019. ‘Cities in the Statehouse: How Local Governments Use Lobbyists to Secure State Funding’. *The Journal of Politics*: 000–000.

‘Pentagon Watchdog Clears Microsoft’s Cloud Win Over Amazon’. 2020. *Bloomberg.com*. https://www.bloomberg.com/news/articles/2020-04-15/pentagon-watchdog-clears-microsoft-s-10-billion-cloud-contract (May 3, 2020).

Petrova, Maria, Ricardo Perez-Truglia, Andrei Simonov, and Pinar Yildirim. 2020. *Are Political and Charitable Giving Substitutes? Evidence from the United States*. National Bureau of Economic Research. Working Paper. http://www.nber.org/papers/w26616 (May 3, 2020).

Robinson, Tony. 1995. 'Gentrification and Grassroots Resistance in San Francisco's Tenderloin'. *Urban Affairs Quarterly* 30(4): 483–513.

'Social Explorer'. *Social Explorer*. https://www.socialexplorer.com/explore-tables (April 19, 2020).

'Statewide Database | Precinct Conversion Diagrams'. https://statewidedatabase.org/diagrams.html (May 4, 2020).

Stockemer, Daniel. 2015. 'When Do Close Elections Matter for Higher Turnout? Gauging the Impact of the Interaction Between Electoral Competitiveness and District Magnitude'. *Journal of Elections, Public Opinion and Parties* 25(2): 178–94.

Tiku, Nitasha. 2019. 'Three Years of Misery Inside Google, the Happiest Company in Tech'. *Wired*. https://www.wired.com/story/inside-google-three-years-misery-happiest-company-tech/ (May 3, 2020).

Wu, Gwendolyn, Rol, and Li. 2018. 'Cupertino Approves Vallco Development South of Apple Park'. *SFGate*. https://www.sfgate.com/business/article/Cupertino-approves-Vallco-development-south-of-13243335.php (May 5, 2020).