Can “Democracy Vouchers” Diversify Political Donors?

A first look at political donors’ **occupational diversity** pre- and post-campaign finance reform in Seattle, Washington

Presentation Overview:

1. Introduction
2. Questions
3. Research plan & implementation
4. Preliminary results
5. Potential next steps
6. Audience questions

Introduction

- Donors' policy priorities appear to influence the political agenda (Enns, Kelly, Morgan, & Witko forthcoming, Hall & Wayman 1990)

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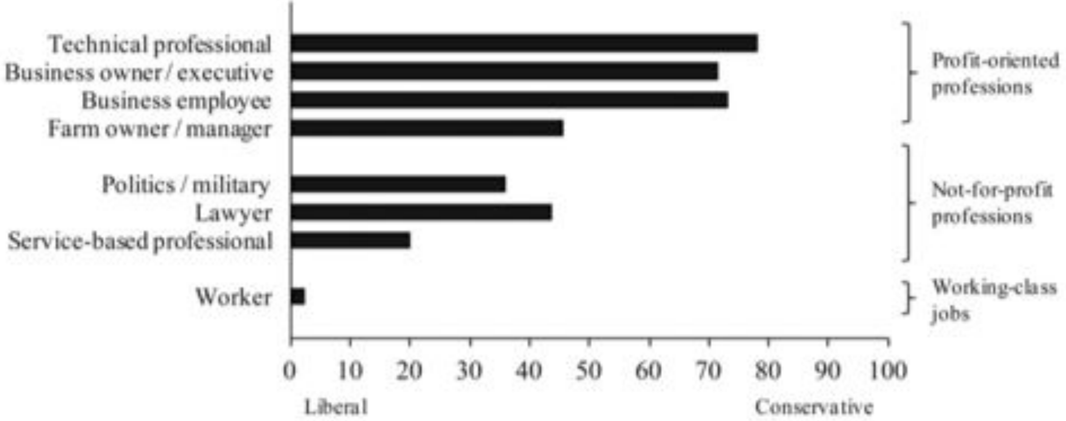
- **People from different occupational backgrounds have different policy preferences (Carnes 2013)**

Introduction

Example: White-Collar Legislators Prefer Conservative Policy



Rescaled AFL-CIO Scores, 1999-2008 (Nick Carnes)

Introduction

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- People from different occupational backgrounds have different policy preferences (Carnes 2013)
    - **And *economic* groups don't capture all these differences (e.g. Page, Bartels, Seawright 2013)**

Introduction

Table 8
Economic regulation and macroeconomic policy

	% wealthy	% general public
The government has an essential role to play in regulating the market	55%	71%[a]
Would like to live in a society where the government does nothing except provide national defense and police protection, so that people would be left alone to earn whatever they could	19%	27%[b]
The federal government has gone too far in regulating business and interfering with the free enterprise system	69%	65%[c]
The following need more [minus less] federal government regulation ["about the same as now" omitted]:		
Wall Street firms	+18	+45[d]
Food and food producers	+6	
Oil industry	+5	+50[d]
Health insurance industry	+4	+26[d]
Big corporations	−20	+33[d]
Small business	−70	−42[d]

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    - And *economic* groups don't capture all these differences (e.g. Page, Bartels, Seawright 2013)
- **Yet we've never measured how shifts in donor occupations affect the legislative agenda!**

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  - And *economic* groups don't capture all these differences (e.g. Page, Bartels, Seawright 2013)
- Yet we've never measured how shifts in donor occupations affect the legislative agenda!
- **This research is a preliminary step in that direction.**

Case Study: Seattle

- Looking at impact of Seattle’s new “democracy voucher” campaign finance program

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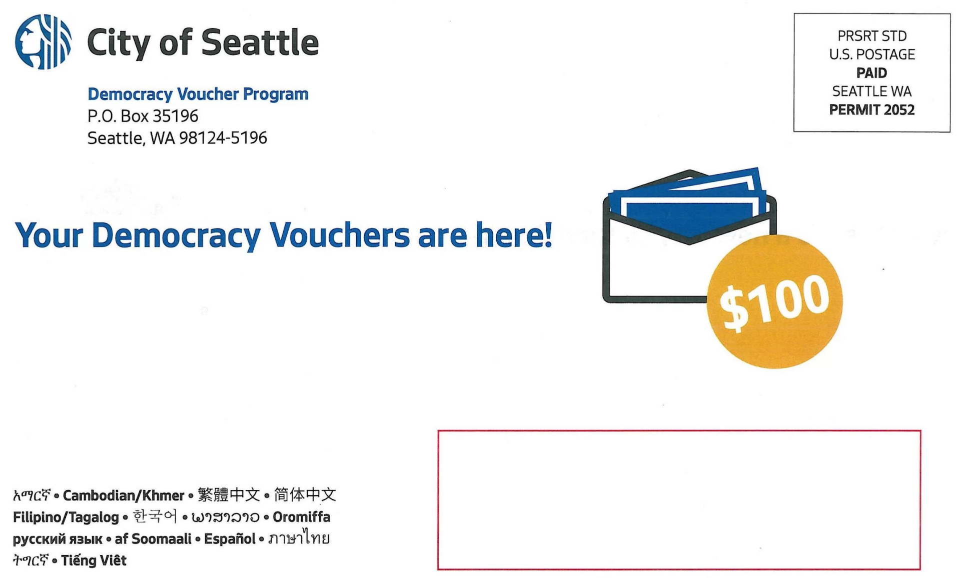
- **Every Seattle resident receives $100 worth of "democracy vouchers" (DVs) that they can contribute to eligible city council members**

Case Study: Seattle



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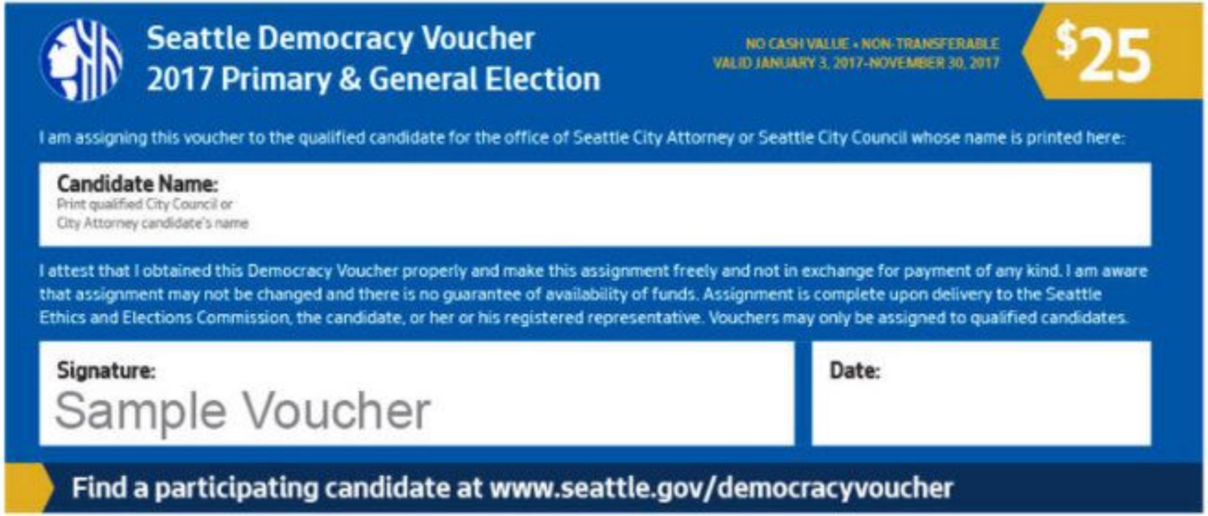

Case Study: Seattle

- Looking at impact of Seattle’s new “democracy voucher” campaign finance program
- Every Seattle resident receives $100 worth of "democracy vouchers" (DVs) that they can contribute to eligible city council members
- **In 2017, candidates funded primarily by DVs won all 3 races in which they were used:**
    - Position 8: Teresa Mosqueda (newcomer) raised 2/3 of campaign money from vouchers
    - Position 9: Lorena González (2015 incumbent) raised 70% of campaign money from vouchers
    - City Attorney: Pete Holmes (2009 incumbent) defended against privately-funded challenger by raising more than 50% of campaign money from vouchers

Research Questions

- How have the occupations of campaign donors shifted after implementation of Seattle's voucher-based campaign finance system?

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    - **Are certain occupational groups (e.g. certain business interests, labor, etc.) more or less represented among the donor pool now versus in previous comparable elections?**
    - **Looking at the 2017 election specifically, were the occupations of voucher donors systematically different from those who contributed using their own "real" money?**

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    - Looking at the 2017 election specifically, were the occupations of voucher donors systematically different from those who contributed using their own "real" money?
- **Future question: do shifts in donor occupations correspond to changes in Seattle’s legislative agenda?**

Research Plan

1. **Download, clean, and merge** relevant campaign contribution data.

2. **Identify clusters of similar occupations** for each dataset.

3. **Visually and statistically compare** the occupations of current vs. past donors and of voucher vs. non-voucher donors.

Dataset

- Campaign contributor data from 2015 and 2017 elections
  - 2013 redistricting issue
- Two electoral races: District 8 and District 9
  - At-large seats that were open in each election
  - Did not include City Attorney because no 2015 candidate
- n = 5,370 contributions from 3,767 unique donors with identifiable occupations

```
> length(unique(seattle$Occupation))
[1] 1200
```

```
 [1] NA                                 "Councilmember"                     "CONSULTANT"
 [4] "SENIOR MANAGER"                   "SENIOR RESEARCH SCIENTIST"         "SOCIAL WORKER"
 [7] "DOCTOR"                           "TROY LUND"                         "CREATIVE DIRECTOR"
[10] "PRODUCER"                         "DIRECTOR OF ARTS AND CULTURE"      "CULTURAL ANTROPOLOGIST"
[13] "YOGA INSTRUCTOR"                  "PHYSICIAN"                         "MARKETING"
[16] "LECTURER"                         "DEVELOPMENT DIRECTOR"              "PROJECT MANAGER"
[19] "REAL ESTATE BROKER"               "TEACHER"                           "ONCOLOGIST"
[22] "HOMEMAKER"                        "MUSICIAN AND EDUCATOR"             "PROGRAM MANAGER"
[25] "NURSE"                            "ACTOR"                             "PSYCHIATRIST"
[28] "EVENT PRODUCER"                   "ARNP STUDENT"                      "ARTIST"
[31] "PRIVATE BANKER"                   "ARTS AND ENTERTAINMENT"            "RESIDENT PHYSICIAN"
[34] "GRADUATE STUDENT"                 "MANAGER"                           "SOFTWARE ENGINEER"
[37] "RETIRED"                          "ENTERTAINMENT PROFESSIONAL"        "LEGAL ADMINISTRATION"
[40] "WRITER"                           "SOCIAL WORK"                       "OWNER"
[43] "ATTORNEY"                         "COMMUNICATIONS LEAD"               "BODY WORK"
[46] "STATION COFFEE OWNER"             "LOAN OFFICER"                      "SENIOR USER EXPERIENCE"
[49] "BUSINESS"                         "SALES MANAGER"                     "PLUMBING MANAGEMENT"
[52] "PLUMBER"                          "WEB DESIGN AND DEVELOPMENT"        "SCIECE WRITER"
[55] "EXECUTIVE COACH AND CONSULTANT"   "FILMMAKER"                         "RADIO ENGINEER"
[58] "TECHNOLOGY MARKETING"             "PARENT"                            "ARTS EDUCATION"
[61] "MUSICIAN"                         "REPORTING ANALYST"                 "BRIANNA CAMARDA"
[64] "DISEASE MODELER"                  "PROFESSOR"                         "REVENUE CYCLE IT CONSULTANT"
[67] "BOUTIQUE OWNER"                   "REAL ESTATE AGENT"                 "PROJECT ENGINEER"
[70] "ASSOCIATE PRODUCER"               "PHOTOGRAPHER"                      "LANDSCAPE ARCHITECT"
[73] "LAWYER"                           "TAXONOMIST/BROWSER DEVELOPER"      "RESEARCHER"
[76] "NANNY"                            "MANAGER/BARISTA/BAKER"             "ONLINE & EMAIL MARKETER"
[79] "ENGINEER"                         "WEB SITE OPTIMIZATION MGR"         "PROPERTY MANAGEMENT"
[82] "SALESPERSON"                      "ART GALLERY MANAGER"               "PHYSICAL THERAPIST"
[85] "ATTORNEY/DIRECTOR"                "WEB DESIGNER"                      "WAREHOUSEMAN"
[88] "COOK"                             "COMMUNITY ORGANIZER"               "SOFTWARE DEVELOPER"
[91] "GAME DESIGNER"                    "BOOKKEEPER"                        "CONSULTANT/FREE SOFTWARE"
[94] "ADMINSTRATIVE ASSISTANT"          "COMMUNICATIONS"                    "SPEECH WRITER"
[97] "REGIONAL SALES REP"               "EDUCATOR"                          "DATABASE ADMINISTRATOR"
```

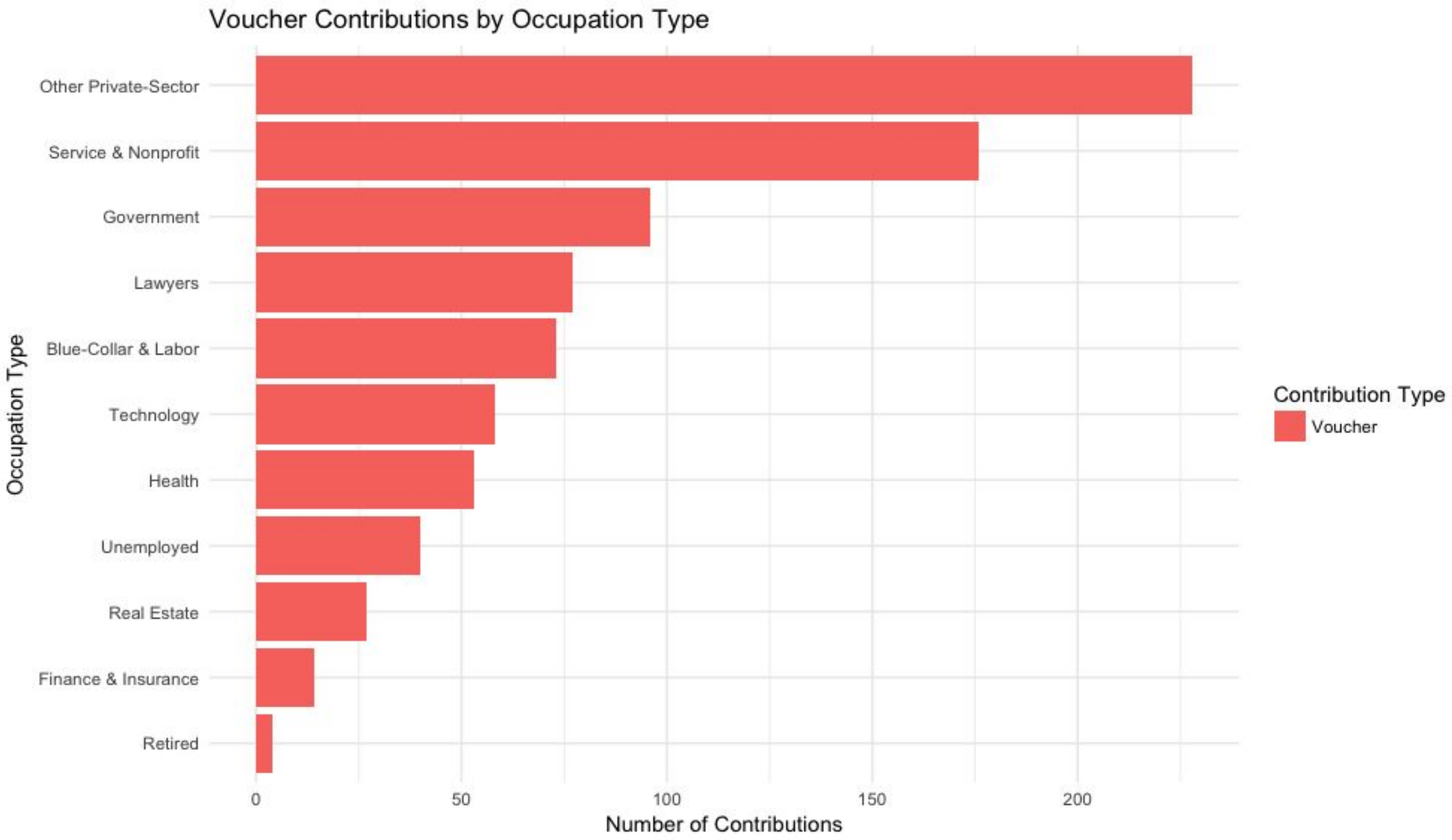
```
# Create lists of keywords for each occupation category
key_bus <- c("business", "chairman", "CEO", "chief", "COO", "board", "retailer", "client", "manager", "hr", "human resources",
             "sales", "vice president", "president", "director", "vp", "cfo", "executive", "management", "GM", "admin", "corporat",
             "advisor", "marketing", "brand", "public relation", "press", "media rel", "communic", "public aff", "content strat",
             "buyer", "strategic advisor", "owner", "entrepren", "founder", "supercargo", "mariner", "tester", "hospitality",
             "treasurer", "geograph", "farm", "agri",
             "artist", "theat", "music", "costume", "video", "producer", "danc", "actor", "actress", "art", "design", "film", "creativ",
             "painting cons", "journalis", "reporter", "news", "blogg", "editor", "writer", "author", "transport", "pilot", "driver",
             "taxi", "train", "transit", "costco", "retail", "warehouse", "shopkeeper", "merchandise", "chef", "meat", "restaur", "food",
             "brewer", "baker", "Sommelier", "chocolat", "gafco", "farmbox", "self", "coach", "comedian", "astrologer", "pianist",
             "analyst", "bookkeeper", "assistant", "customer", "photographer", "customer serv", "receptionist", "tour operator", "shopkeeper")
key_health <- c("lmp", "physician", "clinical", "dentist", "doctor", "trist", "surgeon", "veterin", "disease", "patient",
                "health", "medic", "primary care", "nurs", "trician", "psych", "doula", "massage", "caregiver", "logist", "therapist",
                "PHYISICIAN", "ortho", "acupunct", "Physicisn", "clinic", "behavior an", "dental", "therapy")
key_lawyers <- c("lawy", "legal", "attorn", "lobby", "partner", "arbit", "mediat", "counsel", "laywer", "atty", "attroney",
             "judicial")
key_techies <- c("engineer", "recruiter", "software", "hardware", "web", "online", "database", "techn", "software develop",
                 "web develop", "browser develop", "game develop", "data", "social media", "computer", "programmer", "system",
                 "ux", "graphic des", "user exp", "game des", "quality", "QA", "IT special", "tech supp", "Eng Supvsr",
                 "cyber sec", "customer succ", "help desk")
key_financers <- c("financ", "tax", "bank", "broker", "stock", "capital", "account", "fin'l", "invest", "wealth", "loan", "lender",
                   "insurance", "actuary", "cfa", "CPA", "shareholder", "securities", "manging member")
key_realtors <- c("realt", "land", "build", "real est", "archit", "contractor", "agent", "developer", "development",
                  "construct", "estimator", "leasing", "planning", "market leader")
key_gov <- c("politician", "represent", "council", "mayor", "commission", "legislat", "judge", "notary", "city", "senat",
                  "candidate", "colonel", "diplomat", "congressional", "parks", "librar", "transit planner", "urban planner",
                  "transportation planner", "city planner", "consult", "government relations", "leadership cens")
key_serviceprofs <- c("case manager", "case work", "social work", "outreach worker", "advocate", "youth work", "adoption", "community staff",
                      "health couns", "alcohol couns", "teach", "educat", "school", "colleg", "professor", "instructor", "faculty",
                      "lectur", "tutor", "principal", "dean", "superintendent", "executive dir", "profit", "policy", "organizing", "political",
                      "activist", "program", "chapter dir", "outreach", "volunteer", "exec dir", "fundrais", "grant", "organiz",
                      "youth development dir", "philan", "staffer", "community organizer", "development director", "fund raising", "pastor",
                      "rabbi", "cantor", "chaplain", "clergy", "homemaker", "mother", "mom", "caretaker", "nanny", "child care", "day care")
```

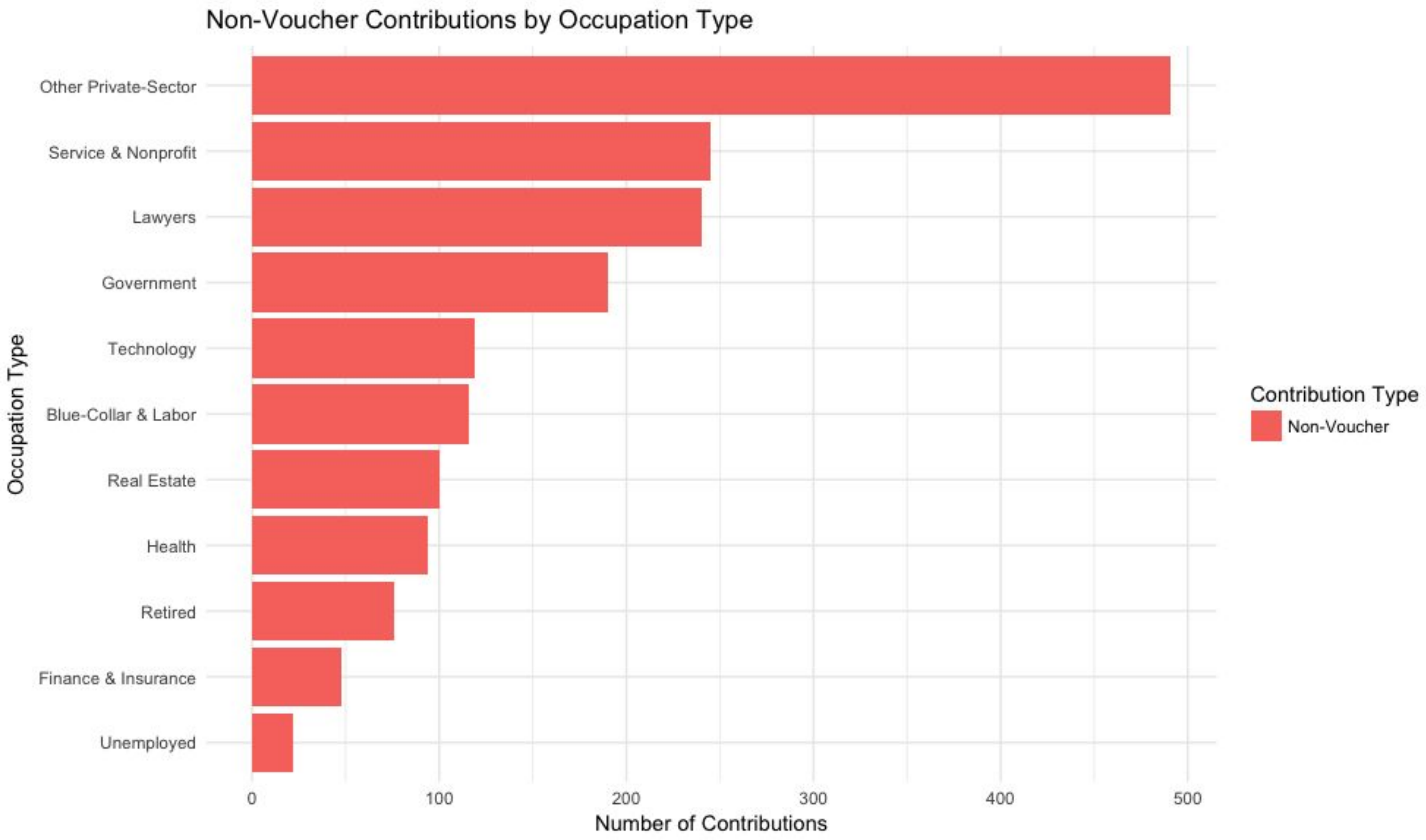
```r
# Create function to name the occupation type of a given donor
name_occtype <- function (Keywords, Occupation_Name) {
  for (i in 1:length(Keywords)) {
    seattle$OccupationType[(grepl(Keywords[i], seattle$Occupation, ignore.case = TRUE)==T) &
                           is.na(seattle$Occupation)==F] <- Occupation_Name
  }
  return(seattle$OccupationType)
}

# Name occupation types of donors using keywords
seattle$OccupationType <- name_occtype(key_bus, "Other Private-Sector")
seattle$OccupationType <- name_occtype(key_health, "Health")
seattle$OccupationType <- name_occtype(key_lawyers, "Lawyers")
seattle$OccupationType <- name_occtype(key_techies, "Technology")
seattle$OccupationType <- name_occtype(key_financers, "Finance & Insurance")
seattle$OccupationType <- name_occtype(key_realtors, "Real Estate")
seattle$OccupationType <- name_occtype(key_gov, "Government")
seattle$OccupationType <- name_occtype(key_serviceprofs, "Service & Nonprofit")
seattle$OccupationType <- name_occtype(key_workers, "Blue-Collar & Labor")
seattle$OccupationType <- name_occtype(key_retir, "Retired")
seattle$OccupationType <- name_occtype(key_unemp, "Unemployed")
```

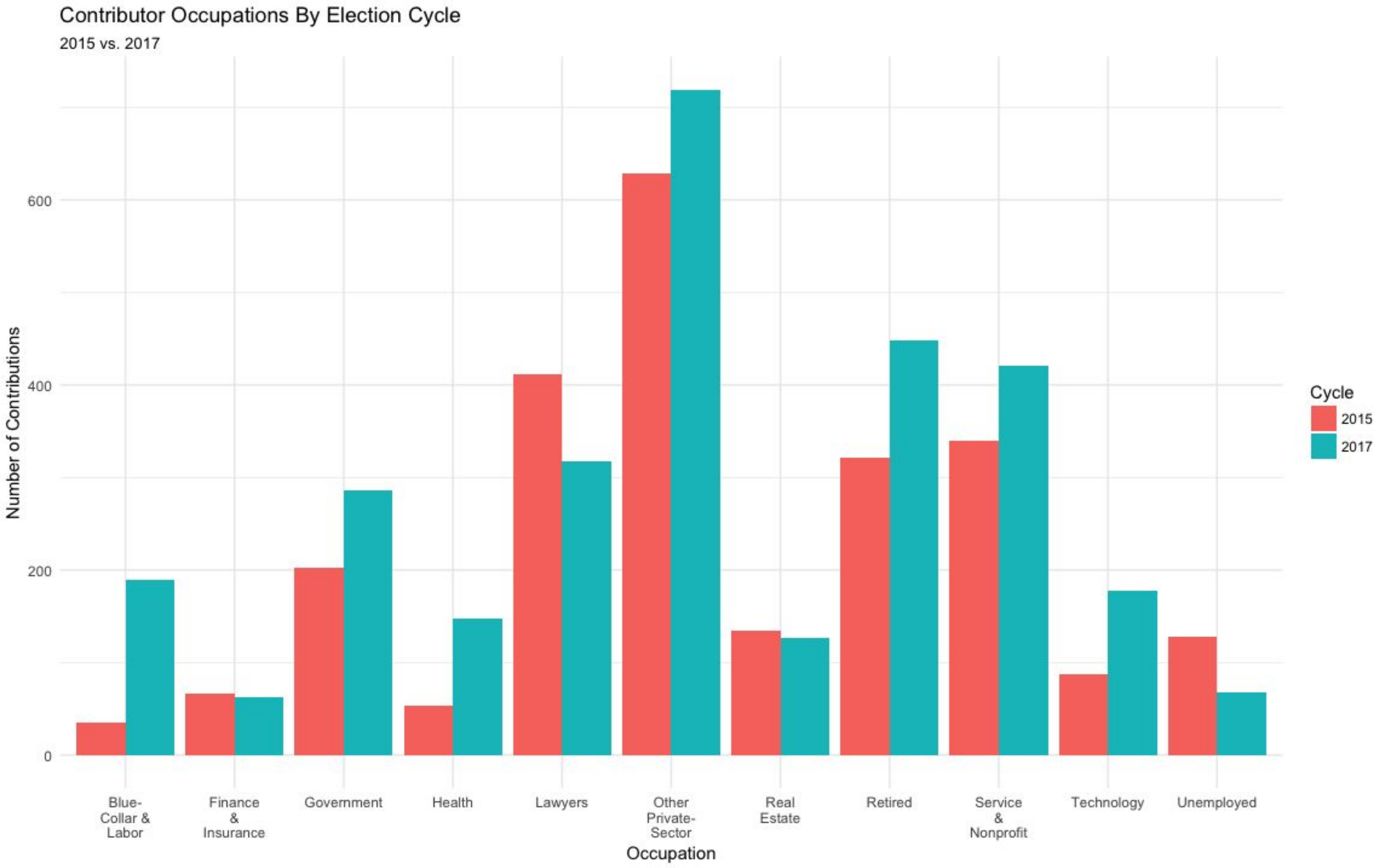
```
# Develop employer name keywords
empl_bus <- c("business association", "nicky", "united parcel", "sound testing",
              "public rel", "public affairs", "communication", "self", "biology", "hospital", "providence", "seattle children",
              "swedish", "group health", "medical center", "healing center", "hutch", "kaiser", "eye clinic", "pharmaceut",
              "UWMC", "polyclinic", "james squire", "nanostring", "sibcr", "boeing", "vulcan", "oecotext", "Nordstrom", "Costco",
              "have a heart", "DCMM", "starbucks", "pizza", "cheesemongers", "candies", "consult")
empl_health <- c("hospital", "providence", "seattle children", "swedish", "group health", "medical center", "healing center",
                 "hutch", "kaiser", "eye clinic", "pharmaceut", "UWMC", "polyclinic", "james squire", "nanostring", "sibcr")
empl_lawyers <- c("law", "pacifica", "perkins coie", "quinn", "schroeter", "foster pepper", "hillis clark", "K&L", "lane powell",
             "blue wave", "CBE", "ceis bayne", "davis wright", "PLLC", "wsaj", "wsba")
empl_techies <- c("amazon", "microsoft", "airbnb", "tamarac", "zillow", "parlay", "at&t", "technolog", "google", "tableau")
empl_financers <- c("coldwell", "banker", "Seattle CFO", "capital one", "wealth management", "insurance", "brighton jones", "capital")
empl_realtors <- c("pine street", "architects", "washington holdings", "jll", "AECOM", "seneca")
empl_gov <- c("city of", "gao", "government", "county", "housing authority", "state of", "house of rep", "wa gov", "washington gov",
              "port of seattle", "historic south", "center for infectious", "fisheries science", "USGS", "geological survey", "seattle department",
              "police")
empl_serviceprofs <- c("foundation", "nonprofit", "association", "organization", "community services", "alliance",
                       "transportation choices", "housing conso", "ymca", "ywca", "fuse washington", "fuse wa", "systems biology",
                       "action institute", "brookings inst", "university", "univ", "college", "public school", "school district", "school")
empl_workers <- c("boatman", "Boatmen", "Machinists union", "Sailors' union", "Service employees", "Riders union",
                  "SEIU", "UAW", "workers", "local", "labor council", "UA plumbers", "UFCW", "MLKCLC", "nurses association", "wsna",
                  "washington education association", "seattle education association", "teamster", "wfse",
                  "washington federation of state employees", "aerospace machinists", "aerospace workers", "speea", "smwia")
empl_retir <- c("retired")
empl_unemp <- c("not available", "unemployed", "none", "N/A")
```

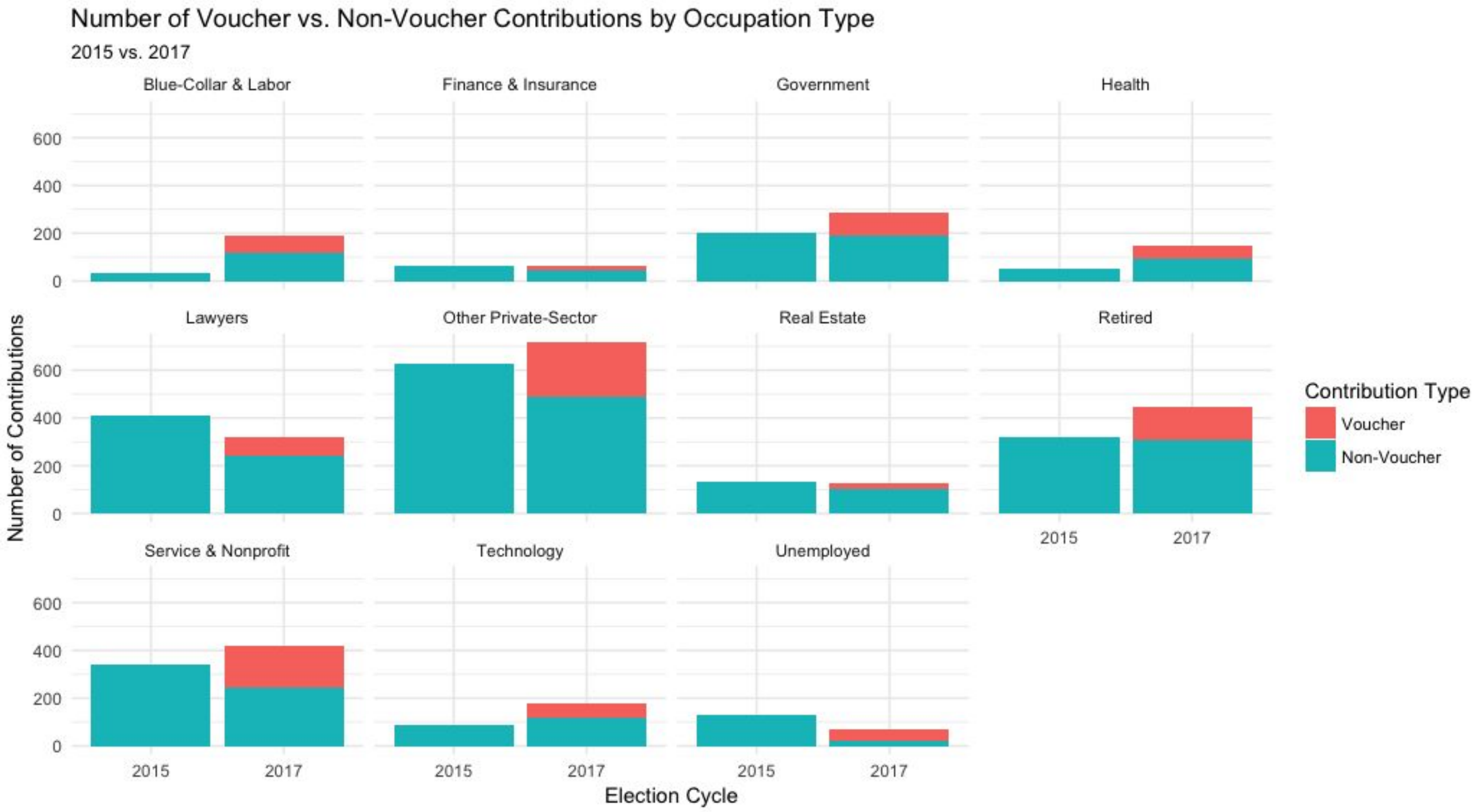
```r
# Create function to update occupation types using employer names
name_occup_emp <- function (Employer_Name, Occupation_Name) {
  for (i in 1:length(Employer_Name)) {
    seattle$OccupationType[(grepl(Employer_Name[i], seattle$EmployerName, ignore.case = TRUE)==T) &
                            is.na(seattle$EmployerName)==F] <- Occupation_Name
  }
  return(seattle$OccupationType)
}

# Name occupation types using employer name keywords
seattle$OccupationType <- name_occup_emp(empl_bus, "Other Private-Sector")
seattle$OccupationType <- name_occup_emp(empl_health, "Health")
seattle$OccupationType <- name_occup_emp(empl_lawyers, "Lawyers")
seattle$OccupationType <- name_occup_emp(empl_techies, "Technology")
seattle$OccupationType <- name_occup_emp(empl_financers, "Finance & Insurance")
seattle$OccupationType <- name_occup_emp(empl_realtors, "Real Estate")
seattle$OccupationType <- name_occup_emp(empl_gov, "Government")
seattle$OccupationType <- name_occup_emp(empl_serviceprofs, "Service & Nonprofit")
seattle$OccupationType <- name_occup_emp(empl_workers, "Blue-Collar & Labor")
seattle$OccupationType <- name_occup_emp(empl_retir, "Retired")
seattle$OccupationType <- name_occup_emp(empl_unemp, "Unemployed")
```

Preliminary Results

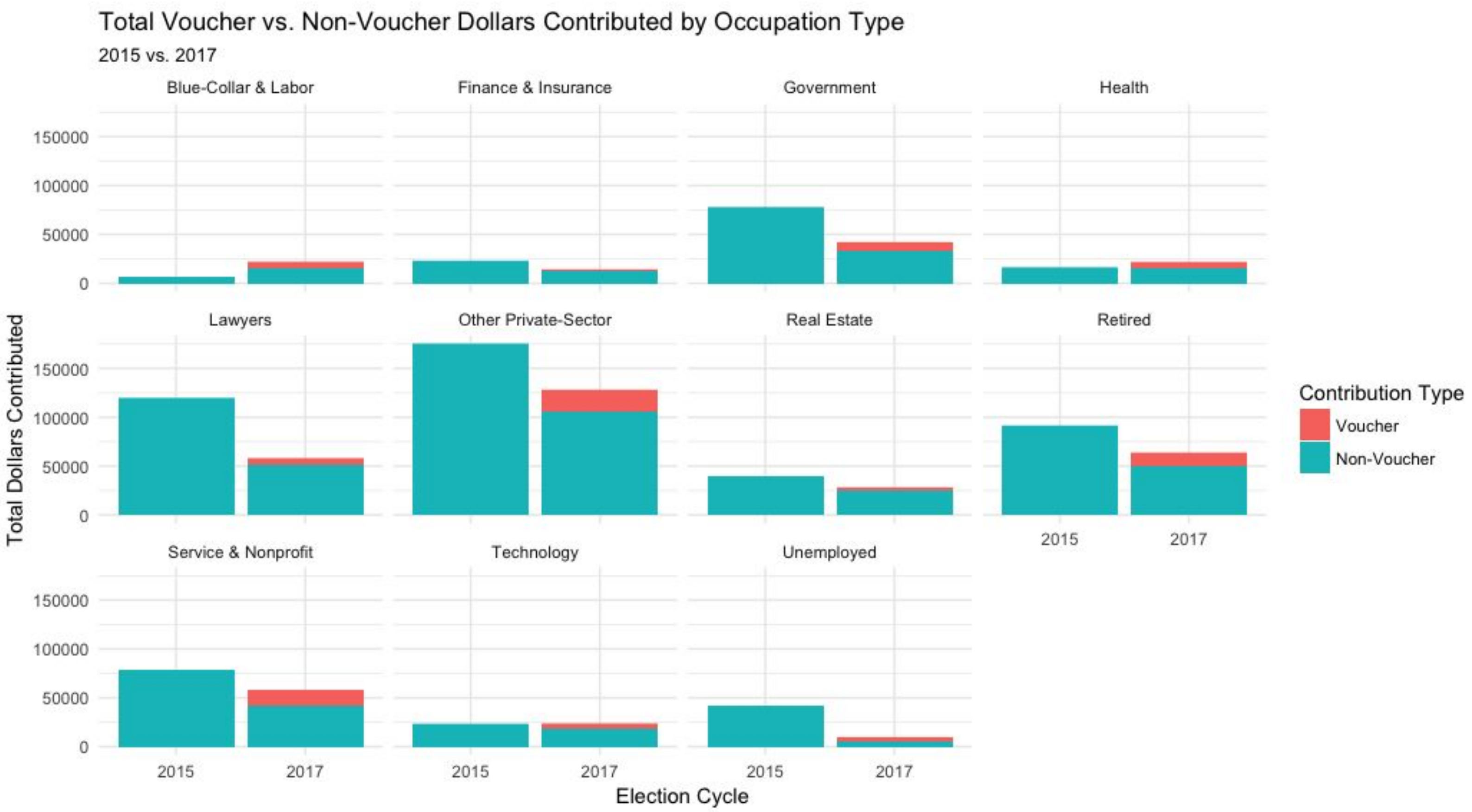

Voucher Contributions by Occupation Type
Occupation Type
Other Private-Sector
Service & Nonprofit
Government
Lawyers
Blue-Collar & Labor
Technology
Health
Unemployed
Real Estate
Finance & Insurance
Retired
0
50
100
150
200
Number of Contributions
Contribution Type
Voucher

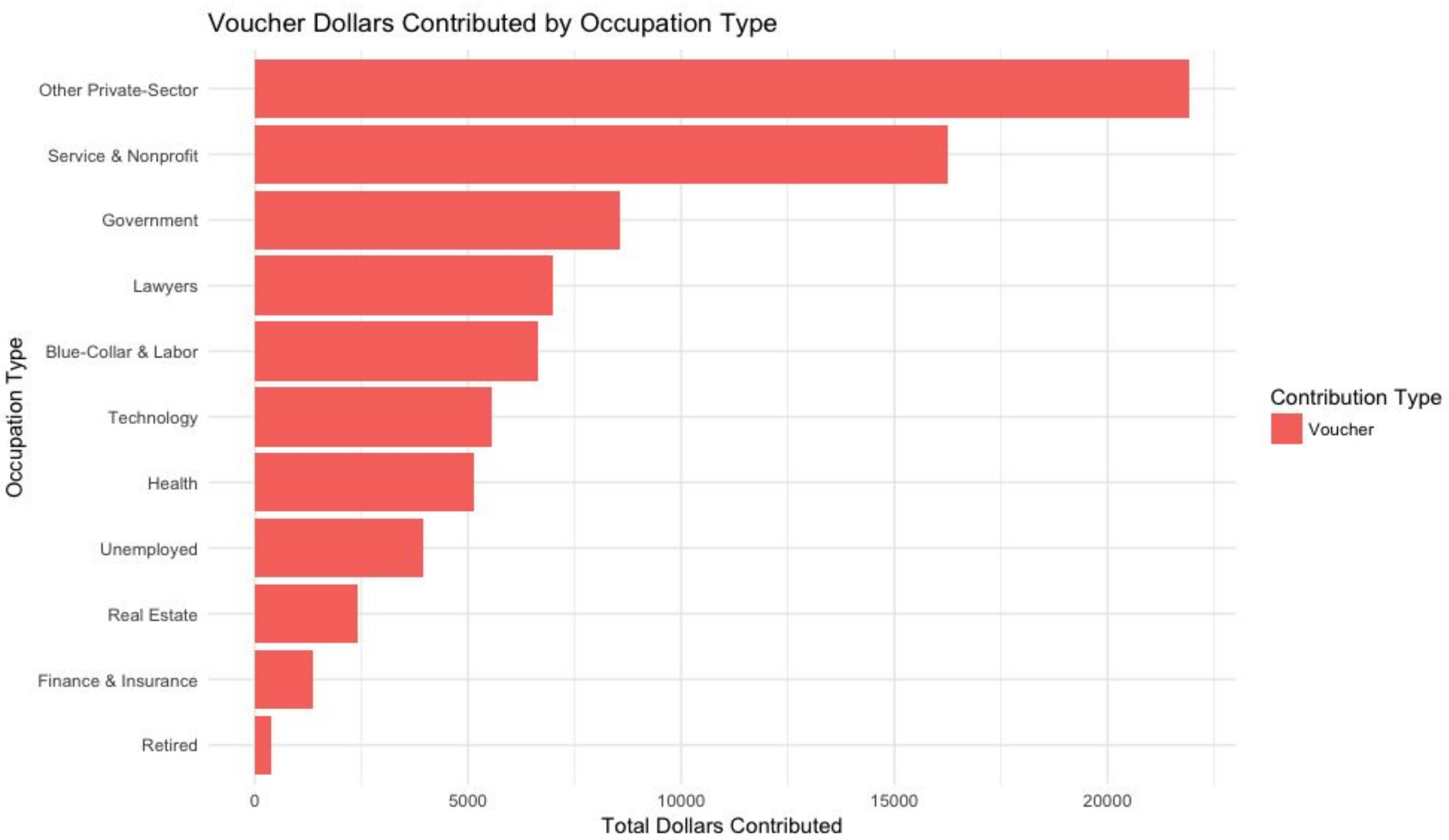

Non-Voucher Contributions by Occupation Type
Occupation Type
Other Private-Sector
Service & Nonprofit
Lawyers
Government
Technology
Blue-Collar & Labor
Real Estate
Health
Retired
Finance & Insurance
Unemployed
0
100
200
300
400
500
Number of Contributions
Contribution Type
Non-Voucher


Contributor Occupations By Election Cycle
2015 vs. 2017
Number of Contributions
0
200
400
600
Blue-Collar & Labor
Finance & Insurance
Government
Health
Lawyers
Other Private-Sector
Real Estate
Retired
Service & Nonprofit
Technology
Unemployed
Occupation
Cycle
2015
2017

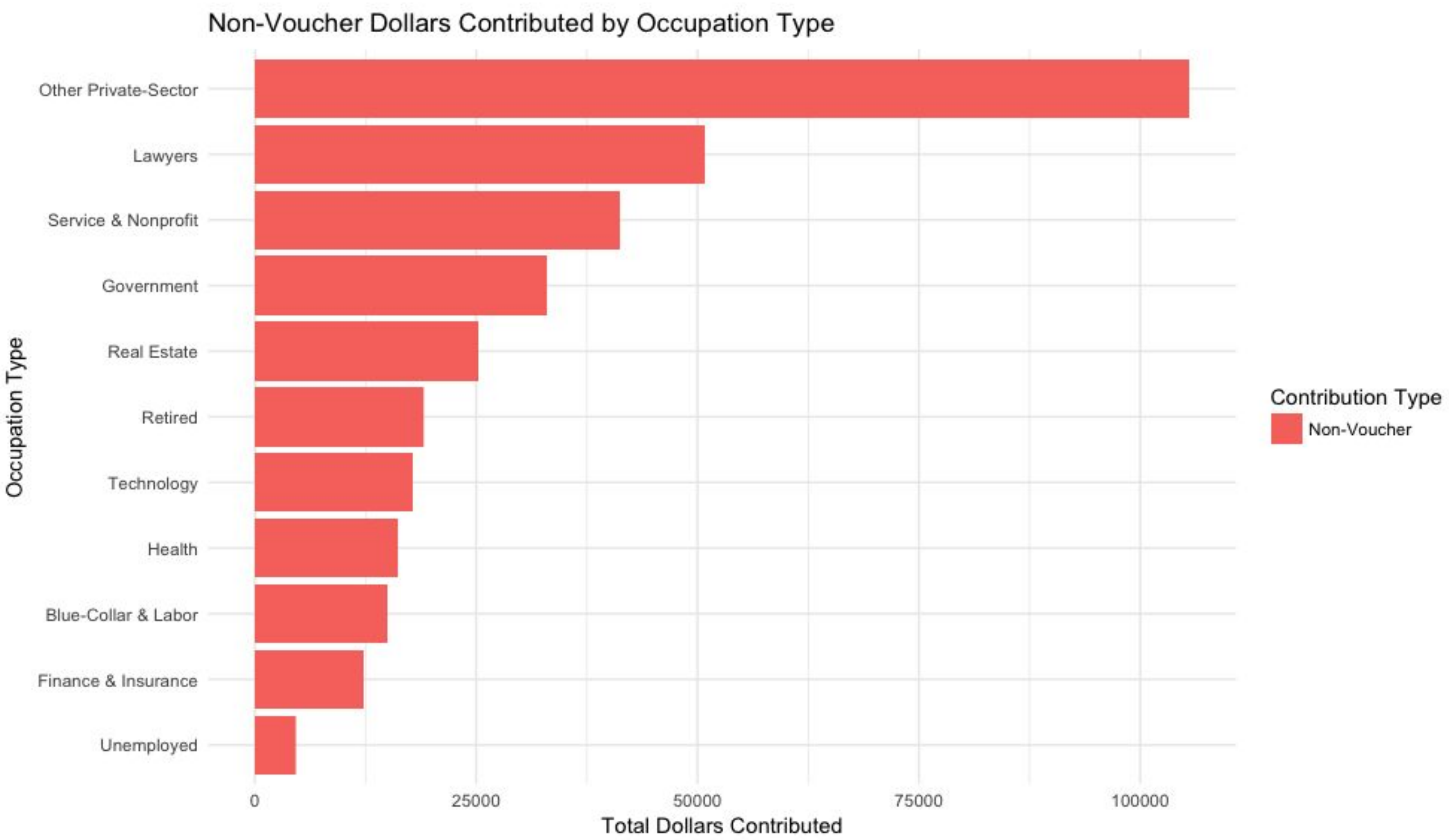

Number of Voucher vs. Non-Voucher Contributions by Occupation Type
2015 vs. 2017
Blue-Collar & Labor
Finance & Insurance
Government
Health
Lawyers
Other Private-Sector
Real Estate
Retired
Service & Nonprofit
Technology
Unemployed
Number of Contributions
0
200
400
600
2015
2017
Election Cycle
Contribution Type
Voucher
Non-Voucher

```
> seattle_occ_2017 <- within(seattle_occ_2017, OccupationType <- relevel(OccupationType, ref = "Blue-Collar & Labor"))
> reg <- lm(Voucher~OccupationType, data=seattle_occ_2017)
> summary(reg)

Call:
lm(formula = Voucher ~ OccupationType, data = seattle_occ_2017)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6471 -0.3277 -0.3147  0.6138  0.7874 

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)                          1.38624    0.03394  40.848  < 2e-16 ***
OccupationTypeUnemployed             0.26082    0.06598   3.953 7.89e-05 ***
OccupationTypeFinance & Insurance   -0.16044    0.06828  -2.350 0.018860 *  
OccupationTypeHealth                -0.02570    0.05131  -0.501 0.616491    
OccupationTypeTechnology            -0.05856    0.04880  -1.200 0.230243    
OccupationTypeReal Estate           -0.17364    0.05353  -3.244 0.001193 ** 
OccupationTypeGovernment            -0.05058    0.04374  -1.156 0.247581    
OccupationTypeService & Nonprofit    0.03181    0.04085   0.779 0.436237    
OccupationTypeLawyers               -0.14334    0.04288  -3.343 0.000839 ***
OccupationTypeRetired               -0.07151    0.04047  -1.767 0.077307 .  
OccupationTypeOther Private-Sector -0.06914    0.03814  -1.813 0.069960 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4666 on 2950 degrees of freedom
Multiple R-squared:  0.02411,	Adjusted R-squared:  0.0208 
F-statistic: 7.288 on 10 and 2950 DF,  p-value: 1.745e-11
```


Total Voucher vs. Non-Voucher Dollars Contributed by Occupation Type
2015 vs. 2017
Blue-Collar & Labor
Finance & Insurance
Government
Health
Lawyers
Other Private-Sector
Real Estate
Retired
Service & Nonprofit
Technology
Unemployed
Total Dollars Contributed
150000
100000
50000
0
2015
2017
Election Cycle
Contribution Type
Voucher
Non-Voucher



Voucher Dollars Contributed by Occupation Type
Other Private-Sector
Service & Nonprofit
Government
Lawyers
Blue-Collar & Labor
Technology
Health
Unemployed
Real Estate
Finance & Insurance
Retired
Occupation Type
0
5000
10000
15000
20000
Total Dollars Contributed
Contribution Type
Voucher


Non-Voucher Dollars Contributed by Occupation Type
Other Private-Sector
Lawyers
Service & Nonprofit
Government
Real Estate
Retired
Technology
Health
Blue-Collar & Labor
Finance & Insurance
Unemployed
Occupation Type
0
25000
50000
75000
100000
Total Dollars Contributed
Contribution Type
Non-Voucher

One concern

- Starting n = 27,999 contributions
  - But occupations are only required for donors whose total contributions amount to more than $100
  - 22,142 “no occupation” donations from individuals whose total contributions are <= $100
  - 487 “no occupation” donations from businesses/organizations
- After removing these, n = 5,370 contributions w/ listed occupations
  - Many still contributions <=$100 (credit card contributions, proactive data collection))

One concern (cont.)

What if some donors…

1. gave $100 or less in 2015 & didn’t report their occupations, but
2. supplemented with vouchers to give more than $100 in 2017 and *did* report their occupations?

   In this scenario, vouchers wouldn’t really be leading to a more occupationally diverse donor set; they’d just be helping *reveal* already-present occupations

One concern (cont.)

Total Observations in Table: 84

Blue-Collar & Labor	Finance & Insurance	Government	Health	Lawyers
4	1	7	8	6
0.048	0.012	0.083	0.095	0.071

Other Private-Sector	Real Estate	Retired	Service & Nonprofit	Technology
15	4	17	15	6
0.179	0.048	0.202	0.179	0.071

Unemployed
1
0.012

- Need to rerun tests without these 84 observations

Potential next steps

- Continue testing for significance of changes
- Look into interest group mobilization around these occupation groups
- Run text analysis of Seattle City Council meetings, proposed legislation

Questions? Ideas?