Partisan Departures from the Administrative States

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Abstract

I utilize the most comprehensive census of US state bureaucrats ever conducted to examine whether executives remove political opponents from the bureaucracy following the rollback of civil service protections. Using the personnel and voter records of over 1.8 million unique employees (and nearly 41 million employee-period observations) across twenty-one states, I first show that the conditions exist for political targeting: the senior echelons of many Republican-controlled states' bureaucracies are predominantly staffed by Democrats. I then turn to a case of civil service retrenchment in Mississippi, where five agencies were temporarily exempted from the state's merit system between 2014 and 2020. I show that, although the exemptions led to large increases in involuntary terminations, Democratic civil servants were no more likely to depart than Republicans. Instead, the longest-serving bureaucrats were more likely to leave the state workforce, suggesting that commitment to the status quo rather than divergent policy preferences increased employees' departure risk.

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Newly-elected executives in the United States inherit expansive bureaucracies.[1] The curtailment of spoils in the 19th and 20th centuries by merit-based civil service systems insulated many bureaucrats from losing their jobs after an incumbent's electoral loss (Skowronek 1982; Ting et al. 2013; Anzia and Trounstine 2023). As a result, contemporary executives often pick their own staffs, agency heads, and other high-ranking department employees but lack direct control over who works in most government positions (Gailmard and Patty 2007). This can lead presidents and governors to become frustrated at bureaucrats' perceived incompetence or subversion, most recently exemplified by President Trump's frequent references to a "Deep State" of political opponents upsetting his policy goals (Clark, n.d.).

If executives are sometimes frustrated with career employees, what happens when they gain a free hand to manage employees previously covered by merit protections? Over the last three decades, a number of U.S. states have reclassified some or all bureaucrats from a protected civil service to an unclassified service. Reclassification makes it easier to terminate bureaucrats, which proponents argue increases managers' flexibility and employees' incentives to exert effort on the job (Sherk 2021; Ichino and Riphahn 2005; Martins 2009). Yet, removing employees' protections also introduces partisanship and ideology as possible criteria for professional advancement within public bureaucracies. Following reclassification, do governors and their political appointees take advantage of this opportunity to remove political opponents from the bureaucracy?

Testing for political targeting in the wake of reclassification requires detailed data on state bureaucrats' political views and employment histories. I introduce such data here. Using a new dataset of individual-level personnel and voter registration records of over 1.7 million unique bureaucrats (and over 40 million bureaucrat-period observations) across twenty-one U.S. states, I first show that

1. Unless otherwise noted, I use "executives" to refer to both presidents and governors.

the conditions for political targeting exist in state workforces. While a large body of work has measured and documented the consequences of political conflict between presidents and bureaucrats at the federal level (e.g., Richardson 2024; Potter 2017; Bolton, de Figueiredo, and Lewis 2021; Spenkuch, Teso, and Xu 2023; Doherty, Lewis, and Limbocker 2019a; Chen and Johnson 2014; Napolio 2023), data limitations have hindered similar studies in the states. I leverage this dataset to show that partisan control of government does not determine the partisan composition of senior echelons of the workforce. Many Republican-dominated states—the states most likely to reclassify bureaucrats into at-will positions (McGrath 2013)—have bureaucracies that are disproportionately staffed with influential Democrats.

Given the possible tensions in Republican-controlled states between senior Democratic bureaucrats and their principals, I test whether reclassification increases the likelihood of Democratic employees leaving the state workforce. I focus on the case of civil service retrenchment in Mississippi, a state seemingly likely to experience political targeting due to Republicans' control of state government (Grumbach 2023) and its history of public corruption (Glaeser and Saks 2006; Liu and Mikesell 2014). Since 1988, agencies in Mississippi have been periodically exempted from the civil service system. Between 2014 and 2020, five Mississippi state agencies received temporary exemptions from hiring, firing, and compensation rules (*PEER Report 670* 2022; *PEER Report 651* 2020). These exemptions, largely issued in the wake of significant scandals or policy failures, provided the governor and agency leaders considerable leeway to remove career bureaucrats.

Via a series of synthetic control models, I first demonstrate—using additional agency-level data on the number of terminations per month from 2005 to 2020—that involuntary dismissals dramatically increased after exemptions from the state's merit system. In the first six months following reclassification, terminations increased by 5 to 10 percentage points depending on the agency. These are large treatment effects: 171% to 634% increases relative to pre-exemption dismissal rates. Although reclassification led to large-scale dismissals, I find no evidence at the individual level that Democratic bureaucrats were more likely to depart than their Republican peers following the loss of job protections. I show that employees' time spent in the public workforce, not their personal political views, is a key factor in explaining which employees departed following the exemptions.

These findings suggest that executives take advantage of the retrenchment of merit-based civil service protections to remove employees seen as getting in the way of their policy goals, but not necessarily political opponents. In the case of Mississippi, although the pre-conditions for targeting political opponents exist, other, more salient dimensions of conflict took priority in the management of career employees following retrenchment. Namely, seniority and, perhaps by proxy, commitment to the status quo operation of an agency. Given that the removal of civil service protections followed serious cases of agency negligence or wrongdoing, political leaders ostensibly focused their attention on removing the employees most attached to old ways of doing business.

On the surface, these findings support the arguments of civil service reformers who contend that weakening public employees' protections will help root out poor performers and potentially improve the quality of government. Yet, while I show that retrenchment does not automatically lead to the targeting of partisan or ideological opponents in the workforce, I also demonstrate that weakening civil service systems opens the door for executives and their political appointees to more freely manage bureaucracies along salient lines of political conflict. This has implications for other cases of civil service retrenchment, including former President Trump's call to reclassify tens of thousands of senior employees into a new unclassified Schedule F designation if re-elected (Trump 2020; Swan 2022). Given the degree of animosity between the current Republican party and career federal bureaucrats, political targeting would be more likely to occur at the federal level than in

Mississippi. Furthermore, even if applied evenly without political targeting, removing protections for tens of thousands of employees could significantly disrupt the operations of the federal government by increasing turnover and reducing agency expertise.

Control and Reclassification in U.S. Bureaucracies

All executives rely on bureaucrats to implement their policy agendas. The administrative state is too large, multi-faceted, and complex to be effectively run by solely the executive and hand-picked staff. Turning campaign promises into a reputation for changing policy requires empowering bureaucrats with subject matter expertise to make decisions (Moe 1985). Discretion, however, comes with risks. While presidents and governors would prefer to delegate control to bureaucrats who share their preferences, modern bureaucracies are comprised of individuals who care about policy outcomes (Gailmard and Patty 2007). Executives thus have to contend with bureaucrats who have dissimilar preferences possibly exploiting their position to shift policy toward their own preferred outcomes.

Although principal-agent problems are ubiquitous, executives' tools for reducing agency costs vary with the institutional setting (Krause and Woods 2014). At the federal level, where most studies of intra-executive branch oversight focus (Brierley et al. 2023), the power to appoint high-level agency leaders is one of the most effective mechanisms (Lewis 2008; Wood and Waterman 1991). Presidents developed formal systems for controlling the distribution of government positions to loyal allies (Moe 1985; Kumar 2009). Once the task of one White House staff member in the Truman administration, over 100 staff now work to match appointees to positions in the federal workforce during presidential transitions (Lewis 2008).

Despite their control over the staffing of many senior positions in the federal bureaucracy, presidents—Republican and Democrat—have also been consistently frustrated by career staff outside the reach of political appointment (Pfiffner 1987; Heclo 1977; Flavelle and Bain 2017). In response, administrations developed informal, ad hoc mechanisms for marginalizing civil servants viewed as unable or unwilling to implement preferred policies. Employees can be relocated,[2] assigned a new unfavorable position,[3] or lose discretion as additional political appointees are "layered" above them in the organizational chart (Lewis 2008, p. 34). Recent research suggests that marginalization in conjunction with voluntary departures are responsible for increased, albeit limited, turnover among senior career employees in the federal bureaucracy after the election of a new administration (Spenkuch, Teso, and Xu 2023; Doherty, Lewis, and Limbocker 2019b, 2019a; Bolton, de Figueiredo, and Lewis 2021),[4] which is more prevalent among career employees who are ideologically opposed to the new administration (Bolton, de Figueiredo, and Lewis 2021; Doherty, Lewis, and Limbocker 2019a, cf. Doherty, Lewis, and Limbocker 2019b).

These findings suggest that, at the federal level, political conflict exists between administrations and bureaucrats, and that presidents are willing to informally marginalize career employees viewed as obstructing their policy goals. Little is known about whether these findings also apply in the states. For one, unlike in the federal bureaucracy, where a considerable amount of research has

2. President Nixon gave voice to this approach in a taped conversation with the Director of the Office of Management and Budget, telling him: "There are many unpleasant places where Civil Service people can be sent. . . Demote him or send him to the Guam regional office. There's a way. Get him the hell out" (Aberbach and Rockman 1976, p. 457). More recently, the Trump Administration relocated two research agencies in the Department of Agriculture from Washington to Kansas City after the agencies published a series of reports that did not fully support the administration's policy agenda (Morris 2021; *Evidence-Based Policy Making* 2022). Over half of the two agencies' staffs opted to not relocate, resulting in short-term decreases in productivity and reductions in both agency expertise and diversity (*Agency Relocations* 2022).

3. Senior career staff who worked closely with the Reagan and George H.W. Bush administrations, for instance, were concerned that they would be targeted by the incoming Clinton administration. As the president of the Senior Executives Association at the time put it, "There is a real danger that a career executive will be sent to the turkey farm – given a job with few responsibilities, few staff and no access to the boss" (Pear 1992). In a more recent example, careerists working on environmental and climate change policies voiced concerns about being assigned to new roles by the Trump Administration. One employee in the Department of the Interior, who conducted research on the effects of rising oceans, was directed to review oil and gas leases instead (Halper 2017).

4. The finding of increased turnover of protected civil servants following the election of a new administration from the opposing party has been replicated outside of the United States in South Korea (Kim and Hong 2019), Sweden (Dahlström and Holmgren 2019), and England (Boyne et al. 2010).

documented agencies' preferences (Chen and Johnson 2014; Bertelli and Grose 2011; Clinton et al. 2012; Richardson, Clinton, and Lewis 2018; Spenkuch, Teso, and Xu 2023), the extent of ideological or partisan conflict within state executive branches is not fully understood. If governors are going to target political opponents for removal, there must first be opponents working in positions of power for them to terminate.

Yet, even if political opponents are present in the workforce, governors might opt not to remove them when given the opportunity. For one, governors might be able to sufficiently control agencies' outputs regardless of personnel. Governors enjoy other oversight mechanisms not present at the federal level. Many governors have expanded powers of rule review relative to the president (Grady and Simon 2002; Schwartz 2020), more leeway to privatize and reorganize agencies, and the ability to line-item veto individual appropriations and statutory text (Holtz-Eakin 1988; Seifter 2017, 2018). Moreover, while nearly all governors have to work alongside other statewide elected officials, such as secretaries of state, attorneys general, and state treasurers, the frequency of one-party rule in the states and legal ambiguity concerning the independence of these actors often work in governors' favor (Seifter 2017, 2018).

Political opponents might not be targeted for other reasons too. Agency leaders may target poorly performing employees rather than political opponents. Moreover, even if a governor or agency head wants to dismiss political opponents, bureaucracies' multiple levels might hinder their plans, as the supervisors tasked with managing personnel might be less willing to use politics as a criterion for whom to fire (Huber 2007). It might also be difficult and costly to identify opposing bureaucrats due to their reluctance to make their political views public for fear of reprisal (Foy 2024).

However, if governors are interested in removing political opponents from the workforce, reclassification would provide them with an excellent opportunity. Unlike the well-documented ad hoc instances of marginalization at the federal level, reclassification affects agencies, swaths of senior bureaucrats, or an entire state workforce. Since 2012, at least Indiana, Arizona, Mississippi, Oklahoma, and Missouri have removed protections for some bureaucrats (Forman 2021; Stephenson 2012; Cournoyer 2012; Parson 2018). These states, which are predominantly under Republican control (McGrath 2013), followed in the footsteps of states like Georgia and Florida that initiated some of the earliest and most far-reaching reclassification reforms in, respectively, 1996 and 2001 (Gossett 2002; Bowman et al. 2003). While the specifics vary by case, all of these reclassification efforts turned classified bureaucrats, who were previously difficult to fire, into "at-will" employees who could be fired without cause or the ability to appeal their terminations. Survey evidence from employees affected by reclassification underscore that these policy changes empowered supervisors to more quickly and easily terminate employees (Coggburn 2006; Goodman and French 2011; Bowman et al. 2003).

Reclassification also makes it easier for personal political views to become a criterion for receiving and retaining a government job. With protections removed, supervisors are more easily able to fire employees seen as disloyal to the current administration. There is some survey evidence to support this point. Following the 2001 reforms in Florida, for instance, 31% of reclassified civil servants reported that the policy change "permits my office to hire more people who have friends or connections to government" (Bowman et al. 2003). In Texas, which has never had a merit-based civil service system, 2.6% of surveyed human resources administrators reported knowing "of a case where a competent employee was fired at-will so that another person with friends or connections to government could be hired" (Coggburn 2006). Likewise, 1.6% of Georgia state employees surveyed after the state's 1996 adoption of at-will employment "reported that they had been asked to resign a position or transfer to another position because of their political beliefs or political connections."

A larger share of respondents, 9.7%, said that their career progression was hindered by political interference (Nigro and Kellough 2000).

While these survey results are suggestive of political targeting, they are not definitive. Issues with recall, a lack of information about the reasonings behind managers' personnel decisions, and personal biases all might influence affected employees' survey responses. Moreover, the lack of a control group unaffected by reclassification makes it difficult to know employees' baseline views on the prevalence of political targeting. As such, the survey evidence points to the need for deeper investigations into personnel management following the loss of civil service protections.

State Bureaucrats' Personnel and Voter Records

I introduce a new dataset of personnel and voter registration files of 1,819,744 state employees across twenty-one states.[5] These records include nearly all public state employees in their respective states. The data cover street-level bureaucrats (e.g., correctional officers, state police troopers, and benefit eligibility specialists) tasked with implementing consequential policies, as well as higher-level bureaucrats (e.g., agency heads, governors' chiefs of staff, and budget analysts) who write regulations, formulate spending requests, and set departmental policies.[6]

Employees' personnel data was collected via public record requests to each state's human resources agency. The records include, at minimum, employees' first and last names, salaries, job titles, and employing agencies. In some states, the personnel files also note employees' middle ini-

5. The twenty-one states: Alaska, Arkansas, Colorado, Florida, Iowa, Idaho, Louisiana, Massachusetts, Maine, Minnesota, Mississippi, Montana, North Dakota, Nevada, South Carolina, Texas, Vermont, Washington, West Virginia, and Wyoming.

6. Most states exclude at least some employees from public disclosure. In most cases this is limited to hospital employees or undercover police officers, although some states exclude additional workers. Washington, for instance, excludes all state patrol officers and all employees who work in the ferry bureau of the Department of Transportation, since federal law prohibits releasing information about employees who have unsecured access to a vessel. Other states also differ in whether they include records for higher education and national guard employees.

tials, race, sex, civil service status, age, county of employment, and hire date. The data span at least from 2019 to 2021, although eight states' data spans at least a decade. The data is structured as repeated cross-sections of the states' workforces, with the frequency of the snapshots varying by state. Mississippi and Florida, for instance, provide monthly snapshots of who is employed in the state bureaucracy, while Minnesota and Nevada provide data at annual intervals. Overall, the dataset contains 40,888,087 period-employee observations.

Some states' personnel data proved inaccessible. South Dakota, for example, does not release lists of employees' payroll information to the public. Other states were unable to be contacted (e.g., New Mexico never responded to repeated contact attempts), charged exorbitantly high fees (e.g., Nebraska), or were unable to provide a sufficient amount of information (e.g., Oklahoma does not provide employees' first names). Nevertheless, the twenty-state sample includes states in the Northeast, Midwest, South, and West. Some of the included states, like South Carolina, Idaho, and North Dakota, have been under the control of Republican governors and legislatures for decades, while states like Washington and Maine lean more Democratic. Additional information about the data, such as the frequency, span, and available variables is located in Table A.1 in the Supplementary Information.

After pre-processing the personnel files—which vary significantly in format and content depending on the state's public disclosure laws and human resource software—I merged them with individual-level partisan affiliation data contained in voter registration records from late 2020 and early 2021.[7] The voter registration data were provided by the vendor L2. Of the twenty-one states in my sample, twelve register voters by party, which serves as the partisanship measure in the L2

7. Since the case study later in the paper uses longitudinal personnel data from Mississippi, I split the personnel data for that state into three groups and merge each group with voter registration data from (roughly) March 2014, March 2017, and March 2021. The specific dates of the snapshots vary across Mississippi and surrounding states. See Table A.6 for more information.

data. In the other eight states, L2 assigns partisanship based either on voters' most recent partisan primary participation (Mississippi, South Carolina, Texas, and Washington) or a proprietary algorithm that uses demographic, commercial, and campaign finance data (Minnesota, Montana, North Dakota, and Vermont).[8]

Matching state employees in the personnel dataset to their corresponding voter registration records is not a simple task. Administrative datasets often contain misspellings, middle initials present in one file might be missing in another, and the number of variables common to both datasets might be insufficient to uniquely identify record pairs. In order to minimize these difficulties, I merged each state's employees with the L2 data using an algorithm that first finds a set of potential voter matches for each bureaucrat using string-distance matching on first and last names before progressively dropping unlikely matches using available key variables.

The matching algorithm first finds, for each state employee, the set of voters in the state (and 50km border region surrounding the state) with extremely similar (but not necessarily identical) first and last names. A series of post-processing steps then culls unlikely matches from these sets of potentially matching voters. The specific variables used to post-process the matches varies by state depending on availability. The most common post-processing variable is employees' middle initial. When available, voters with different, non-missing middle initials are dropped from the set of potential matches. Additional information about the merge procedure and use of other post-processing variables (i.e., gender, race, age, original hire date, and county of employment) are listed in the Supplementary Information in Section A.1.

Matching administrative datasets that lack a large number of key variables or unique identifiers

8. For the states that record partisan primary participation but do not have voters register by party, L2 supplements the recent primary participation information with modeling that uses demographic and campaign finance data. More details can be found in the Supplementary Information in Table A.5.

requires making decisions about what to do with one-to-many matches. If one employee still matches to more than one voter after post-processing, partisanship is calculated as the mean partisanship of the matched voters.[9] If an employee is matched to only one voter (or more than one voter who share the same partisan registration), then the employee's partisanship is set to 1 for the given partisan affiliation. In the analyses that follow, I discretize this continuous measure of partisanship by defining someone as affiliated with a given political party if their probability of being registered with a given party exceeds 0.9.[10]

Overall, 72% of the 1,819,744 unique state employees and 78% of the 40,888,087 employee-period observations were matched to at least one voter.[11] These match rates fall well within other recent attempts to merge bureaucratic personnel files with L2 voter registration data. Spenkuch, Teso, and Xu (2023) matched 67.5% of federal bureaucrats to one (and only one) voter using a more conservative approach that matched names exactly and incorporated information on employment location and age. Likewise, in their study of U.S. police officers, Bocar et al. (2023) used a more liberal probabilistic matching algorithm to match 86% of the officers in their sample to a voter using first and last names and, in the case of some police agencies, middle initials.[12]

9. This approach is similar to that suggested by Enamorado, Fifield, and Imai (2019). The key difference is that, in my case, partisanship is calculated as the unweighted mean rather than the mean weighted by a probability estimate of the likelihood that the employee-voter pair is a true match. Using an unweighted mean is appropriate in this case because, after post-processing is complete, it is impossible (with the given information) to know whether one voter is a better match than another for a given employee.

10. Of the employees matched to at least one voter, 84% have a partisan probability of 0.9 or higher. Of those employees, only 6,135 employees have a partisan probability in $[.9, 1)$. The rest have a probability of 1. This indicates that most matches are either one-to-one matches or one-to-many matches of voters with the same partisan affiliation).

11. Table A.2 shows the share of state employees matched to at least one voter by state. It is difficult to know why the match rate for employee-period observations is higher than the match rate for unique employees. One possibility is that the employees who only work for the state for a short period of time are less likely to register to vote.

12. The 72% and 78% match rates treat one-to-one and one-to-many matches equivalently. Therefore, Table A.3 shows the share of state employees matched to one, two, five, and ten voters. In most states, over three-fourths of matches are one-to-one and less than 10% of state employees were matched to two voters. For comparison, 6.9% and 37.6% of the employees in Spenkuch, Teso, and Xu (2023) and Bocar et al. (2023), respectively, were matched to more than one voter. Spenkuch, Teso, and Xu (2023) were able to secure such a small share of one-to-many matches because the federal personnel file includes information on bureaucrats' age. South Carolina is the only state in my sample that provides information on state bureaucrats' age and, in that state, a similar share ($\sim$ 5%) were matched to more than

Table 1 – Socioeconomic Differences Between Matched and Unmatched State Bureaucrats Shows the mean share of female and white employees and mean salary of employees matched to, respectively, at least one or zero voters. The racial and gender comparisons exclude states where these data are unavailable. P-values calculated using two one-sided t-tests where the null hypothesis is that the difference between the two means is larger (less) than 10% (-10%) of the standard deviation of the pooled data. The larger of the p-values from these two tests is shown here.

	Unmatched Employees	*Matched Employees*	*P Value (Equivalence Test)*
Share Female	0.63	0.59	1
Share White	0.49	0.53	1
Mean Salary	$35,175	$45,906	1

Matched and non-matched bureaucrats can differ on observable characteristics due to real underlying differences across registered and non-registered voters or biases introduced by the merge process. Table 1 shows the differences in gender, race, and income across the matched and unmatched state bureaucrats. Following Spenkuch, Teso, and Xu (2023), the final column shows the results of a series of t-tests evaluating the null hypothesis that the difference in means is substantively large (defined as 10% of the standard deviation of the pooled data). All three socioeconomic measures display significant differences across the unmatched and matched datasets. Employees successfully matched to at least one voter are less likely to be female, more likely to be white, and have higher salaries. These differences likely result from real differences in voting registration across population groups. Nationally, higher-earners and white citizens are more likely to be registered to vote. Moreover, while females are more likely to be registered than males across the entire citizenry, male government workers were actually more likely to report being registered than their female coworkers in 2020 (U.S. Census Bureau, Reported Voting and Registration, 2020).

one voter. Table A.4 shows that an even smaller share of employees were matched to more than one voter who belong to different political parties.

The Partisanship of State Bureaucracies

Reclassifying civil servants as at-will employees provides an opportunity for the administration to remove political opponents from the state workforce. If this is to occur, however, political opponents must first occupy positions of power within state bureaucracies. Governors are likely not concerned with the political views of the mechanics tasked with maintaining the fleet of state police cars or the office clerks processing drivers' license applications. If governors attempt to remove formerly-protected employees for political reasons, they will likely focus their attention on the "spigots of policymaking" — bureaucrats who influence regulatory, budgetary, and policy outputs (Doherty, Lewis, and Limbocker 2019a).

I identify these influential bureaucrats, which I refer to as "spigots," using a two-stage approach that relies on employee information available across all twenty-one states: annual salaries and job titles. I first subset the personnel data to only those employees whose annual salary is in the top quartile for the given state and period. This drops many front-line bureaucrats who implement policy but do not have a role in higher-level agency decisionmaking. However, it does not remove highly-compensated street-level bureaucrats like doctors, nurses, and engineers. While often well-paid, these employees do not perform tasks where individual ideology or partisanship is likely to influence policy. I drop these employees from the data by removing employees whose job titles contain specific keywords.[13] Finally, I remove employees working in higher education, the national guard, or for a state board due to alternative organizational structures and drop part-time and

13. I drop all employees whose job title includes one of the following strings: engr, admin assistant, auto, biologist, case manager, case reviewer, clinical, clinician, conservation officer, corr officer, correctional officer, counselor, dentist, detective, doctor, dps officer, enforcement officer, eng , eng/assoc, eng/eng, engineer, epidemiologist, family prot spec, ferry captain, food, geologist, hwy patrol off, hydrologist, information technology, investigator, it professional, it tech, lieutenant, maint, mechanic, mine inspector, network systems analyst, nurse, nursing, nutrition, parole agent, patrol officer, pharmacist, physician, pilot, programmer, psychiatrist, psychologist, rn supervisor, school attendance, sec off, sergeant, social worker, special agent, statistician, teacher, therapist, trooper, and warehouse. See Table B.1 for the ten most common remaining job titles by state.

temporary employees.[14]

The geographical distribution of spigots is one way to validate my measure. While the workforce is distributed across a state, spigots should be concentrated in the area where key policy decisions are made: the state capital. For context, only about 20% of all full-time federal employees work in the Washington D.C. area, but 72.7% of the bureaucrats in the influential Senior Executive Service worked in or around Washington, D.C. in 2022 (Service, n.d.). Across the eleven states that make employees' work county available, 77% of spigots work in either the county of the state capital or an adjacent county. This is about 20 percentage points higher than the share of all state employees who work in the capital or surrounding counties.[15]

Figure 1 plots the shares of Democratic and Republican spigots, by state, as of early 2021.[16] The top panel shows the share of all spigots in each state that are registered Democrats and Republicans. The bottom two facets show the same information, except that they only include those spigots who are in, respectively, the unclassified and classified services (for the states that make classification status available). Breaking out these data by classification status is important because targeting should be focused on classified employees, as unclassified bureaucrats are already relatively easy to dismiss. State abbreviations colored red denote that both legislative chambers and the governorship have been controlled by Republicans since at least 2017 (i.e., a "trifecta"). Overall, looking at the top panel, a number of Republican controlled states (i.e., West Virginia, Florida, Texas, Arkansas, and Iowa) have more Democratic than Republican spigots. Moreover, while states like Washington and Vermont have the largest shares of Democratic spigots of any state in the sample, states like South

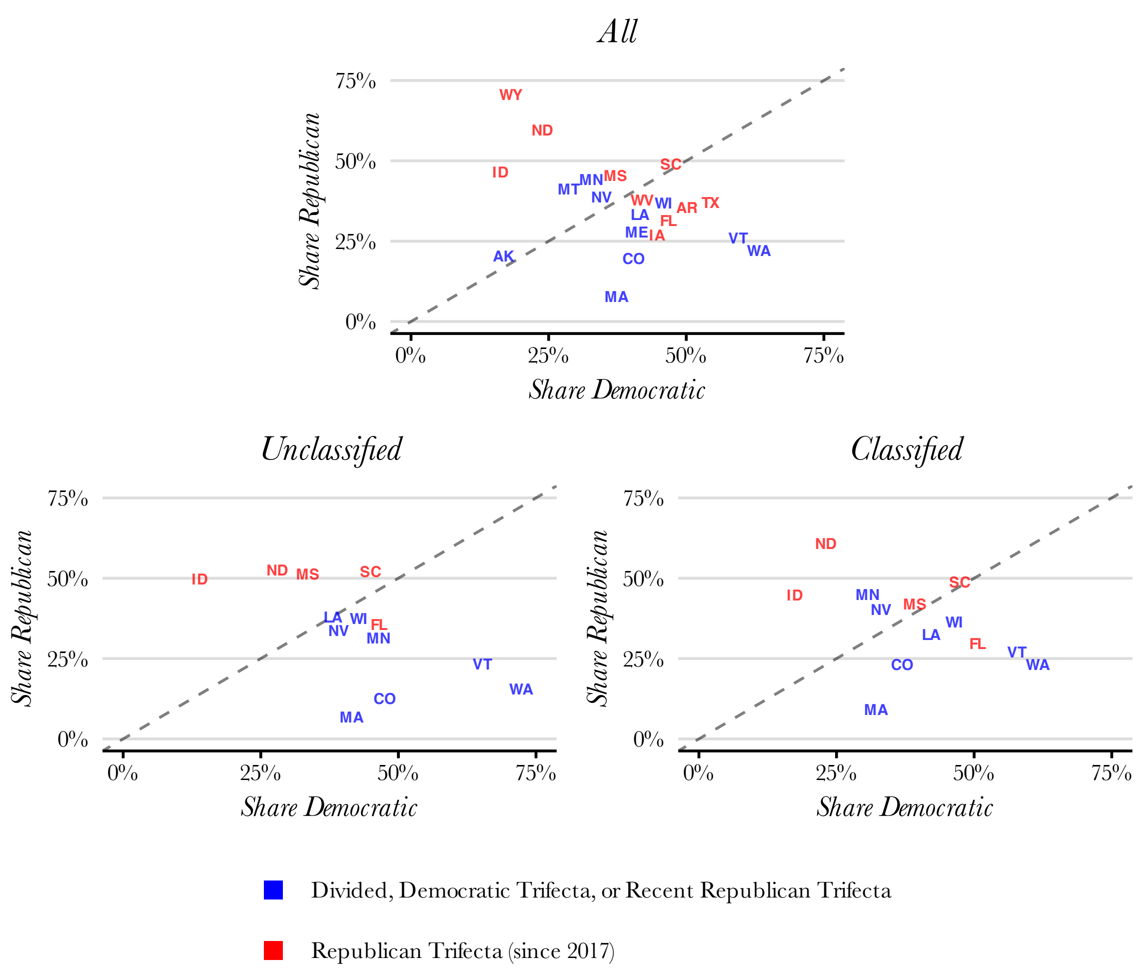
14. This is only possible in the twelve states that make full/part time and temporary status available. I also drop employees who are elected or in alternative classification systems that are not easily categorized as classified or unclassified.

15. See Figure B.1 for a state-by-state breakdown of the geographic distribution of bureaucrats.

16. Due to differences in the frequency of the data snapshots, the exact date of the data varies by state. Figure C.2 plots the shares of Republican and Democratic spigots over time.

Carolina, Texas, Arkansas, and Iowa employ more Democratic spigots than Democratic-controlled states like Massachusetts, Colorado, and Minnesota.

Figure 1 – Democrats Staff Senior Positions in State Bureaucracies Shows the share of senior state bureaucrats who are registered Democrats. The top facet includes all employees, while bottom left and bottom right include, respectively, all unclassified and classified employees (for the states that make this information available). Red state abbreviations indicate that the state's legislative chambers and governorship have been under Republican control since at least 2017. Data is a snapshot from early 2021 and only includes employees matched to at least one voter. An employee is deemed to be a registered a Democrat if their probability of being a Democrat exceeds 0.9. Data excludes national guard, state board, higher education, part-time (where available), and temporary employees (where available). Complete results by partisanship located in Tables C.1 and C.2. The labels are minimally jittered to eliminate overplotting.



The presence of Democrats in senior positions in state bureaucracies holds across classification status. Although Republican control of government is a better predictor of the relative partisanship of unclassified spigots, Republican-controlled South Carolina and Florida still employ a large share of Democrats relative to other states. Likewise, South Carolina, Mississippi, and Florida all employ a larger share of Democratic classified spigots than states like Minnesota and Massachusetts where Democrats have had more statewide success. As I show in the Supplementary Information, some of these Republican-controlled states not only have high shares of Democrats relative to other states' bureaucracies, but also compared to their own voting populations (Figure C.1). In short, Democrats hold positions of power within state workforces that have been controlled by Republicans at the gubernatorial and legislative levels for, in some cases, decades. If reclassification is a means for Republican governors to remove political opponents Democratic bureaucrats, there are plenty of Democratic bureaucrats for them to target.

Temporary At-Will Employment in Mississippi

Democrats staff influential positions in Republican-controlled states' bureaucracies, but are they targeted for removal following the loss of job protections? The existence of Democrats in senior echelons of state bureaucracies does not necessarily mean that they will be removed from their positions following the retrenchment of job protections. Agency leaders might be more interested in firing employees who are performing poorly, bureaucrats might be reluctant to share political views on the job or be difficult to replace, and mid-level managers might be hesitant to implement orders from political appointees to purge opponents.

I test whether political opponents are targeted for removal in the context of reclassification in Mississippi. Between 2014 and 2020, five Mississippi state agencies were granted temporary exemptions from the purview of the Mississippi State Personnel Board (MSPB), which exercises considerable authority over personnel management in Mississippi's public sector. Created in 1980 to oversee the state's merit-based civil service system, the MSPB assigns every position in the state's civil service into specific job classes. The MSPB is responsible for setting the range of allowable salaries within each job class, which provides the agency considerable influence over who is eligible for a raise and by how much (*PEER Report 651* 2020). The MSPB also adjudicates disputes between state employees and agencies. Since employees in the civil service enjoy a legal right to their jobs, they can appeal any "written notice of dismissal or action adversely affecting his compensation" to the Employee Appeals Board located within the MSPB (Mississippi Code 25-9-127 2020).

Since 1988, the Mississippi Legislature and Governor have authorized several agency exemptions from MSPB oversight, some of which were requested by the affected agency. The exemptions vary in scope, but usually provide an agency with wide discretion to fire, promote, and compensate employees without regard to salary bands or due process procedures. After the exemption period is over, the agency is once again under the purview of the MSPB and must adhere to all merit system policies. While exempted from the merit system, agencies operate with little oversight. Agencies do not have to justify why they want an exemption or describe their plan for reorganizing the workforce during the exemption.[17] Although exempted agencies are required via statue to submit annual reports detailing how many employees were hired, demoted, fired, or received a salary increase, none of the agencies exempted between 2014 and 2020 actually submitted the reports (Mississippi Code 25-9-127 2020; *PEER Report 651* 2020)

Table 2 lists the six temporary exemptions issued to five Mississippi state agencies between 2014 and 2020. Of the five agencies, all but the Department of Education are led by a political appointee who reports to the Governor.[18] All of the exemptions allowed agencies to disregard civil servants'

17. Beginning July 2021, exempted agencies have to submit annual reports to the legislature and MSPB describing how their exemptions are improving agency operations (*PEER Report 670* 2022).

18. The Department of Education is headed by the State Superintendent of Education, who is appointed by the nine-member Mississippi Board of Education. Five of the nine board members are appointed by the Governor. The

legal property rights to their jobs and treat them as at-will employees. Consequently, during the exemption periods, civil servants were considerably easier to demote or fire. Three of the exemptions also gave agencies wide latitude to increase or decrease employees' salaries without regard to MSPB rules.[19]

Lieutenant Governor and Speaker of the Mississippi House of Representatives each appoint two members.

19. Based on a report prepared for the Mississippi legislature, the exemptions from compensation rules led to a number of salary raises, which were in some cases significant. One employee's salary increased by 71% during the agency's exemption period, while the salary of an employee hired by the Department of Education between July 2014 and June 2016 had their salary readjusted after the completion of the exemption because it exceeded the maximum allowed for state employees (*PEER Report 651* 2020).

Table 2 – Agency Exemptions, 2014 - 2020 Shows each of the six temporary exemptions issued to Mississippi state agencies between 2010 and 2022. A checkmark under the *Compensation* header indicates that the agency did not have to comply with the MSPB's compensation plan. A checkmark under the *Property Rights* header indicates that the agency did not have to abide by the statute providing civil servants with property rights in their positions. For more information, see *PEER Report 670* (2022) and *PEER Report 651* (2020). Mississippi's School of the Arts was also excluded from the MSPB's purview beginning January 1, 2020. Since that exclusion was permanent, it is excluded from this table.

	Exemption Period		*Exempted Rules*	
Agency	*Begin Date*	*End Date*	*Compensation*	*Property Rights*
Marine Resources	4/16/2014	10/17/2014	✓	✓
Education	7/1/2014	6/30/2016	✓	✓
Corrections	7/1/2015	6/30/2016		✓
Corrections	7/1/2016	6/30/2017	✓	✓
Human Services	7/1/2016	6/30/2019		✓
Child Protection Services	7/1/2016[1]	6/30/2020		✓

[1]Before July 1, 2016, the Department of Child Protection Services was part of the Department of Human Services.

Contemporary accounts of the exemptions suggests that they were pitched as mechanisms for improving agency performance. At least five of the exemptions followed major scandals or cases of negligence on the part of the agency. In November 2013, the Executive Director of the Department of Marine Resources and six other agency employees were charged with, and pleaded guilty to, fraud (U.S. Attorney's Office 2013; Lee 2018). In the wake of the scandal, the legislature promptly passed a bill to reform the agency, giving the new Executive Director "flexibility in making an orderly, effective and timely reorganization of the Department of Marine Resources" (Wiggins 2014; Havens 2014). Likewise, eight months before the Department of Corrections was first exempted from merit rules, the Commissioner of the agency was indicted on federal corruption charges (Gates 2017). The July 2016 exemption of the Departments of Human Services and the newly-created Department of Child Protection Services stemmed from the settlement of a 2004 civil suit accusing the state of neglecting foster children in its care. As part of the revised settlement, the state and plaintiffs agreed that the "Governor will take all reasonable steps, within legal authority, to exempt [the Departments of Human Services and Child Protection Services] from State Personnel Board oversight for a period of at least 36 months, beginning July 1, 2016" (Lee 2015).

While described by supporters as a means of addressing governmental failures rather than a mechanism for removing opponents from the state workforce, these temporary exemptions still provided windows of opportunity for the Republican-controlled government to dismiss Democratic employees. Figure 2 shows the share of registered Democrats in every Mississippi state agency with more than ten classified civil servants, as of January 2016.[20] The Departments of Corrections, Human Services, and Education—all of which received at least one exemption between 2014 and 2020—are some of the largest, most Democratic agencies in Mississippi. The clear outlier is the Department of Marine Resources, which has among the smallest share of Democrats of any state agency. While it is difficult to assess whether the decision to reclassify these agencies in the first place was driven by its partisan makeup, it is clear that, upon reclassification, there were plenty of Democrats for managers to dismiss.

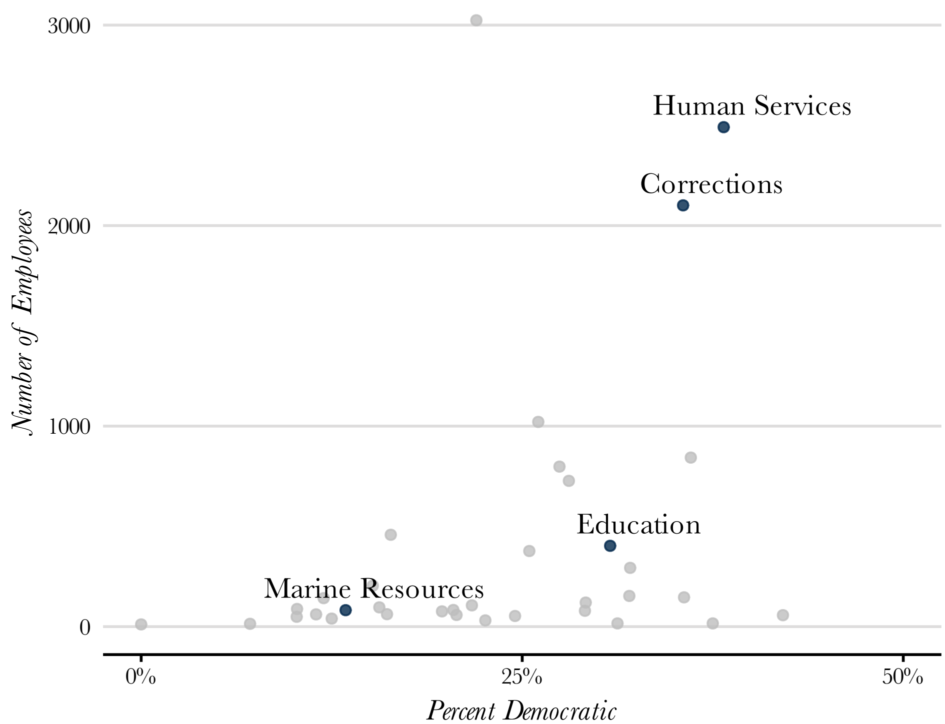
I test whether Democratic civil servants were more likely to depart Mississippi state government following reclassification using two datasets. The first is a subset of the individual-level personnel and voter dataset described above. These data span from January 2010 through June 2022 and include 40,267 unique employees classified in the state's merit system and 2,122,342 month-employee observations.[21] 71% of the month-employee observations and 72% of the unique employees between 2010 and 2022 were successfully matched to at least one voter.[22] In Mississippi, 80% of voting age citizens were registered to vote in 2020. Given national trends, this percentage is likely even

20. Employees in the Department of Child Protection Services are included in the Department of Human Services in this figure.

21. This sample excludes temporary and part-time employees. It also excludes employees in the national guard, higher education, state hospitals, Mississippi Bureau of Narcotics, and small state boards.

22. Of the employees successfully matched to at least one voter, 90% were matched to only one voter and 96% were matched to either one voter or more than one voter of the same partisan affiliation. See Tables A.2, A.4, and A.3 for more information.

Figure 2 – Exempted Agencies Mostly Large and Democratic Shows, for each Mississippi state agency with more than 10 classified civil servants successfully matched to a voter, the share of matched employees that are Democrats (As of January 2016). The four agencies that received an exemption from merit rules between 2014 and 2020 are highlighted in blue. Data excludes part-time and unclassified employees.



lower for the lower-earning individuals who comprise a relatively large share of the Mississippi state workforce ("U.S. Census Bureau" 2021b).

While these data provide an extremely granular look at the makeup of the Mississippi public workforce, they do not note why an employee leaves government employment. I observe the last month an employee works for the state. Therefore, in order to examine the effect of reclassification specifically on dismissals, I also collected, via public records requests to the MSPB, the number of resignations, retirements, and terminations in each agency for every month from January 2005 through January 2020. These agency-level data allow me to track not only the effect of reclassification on overall departures, but on the specific type of departure.[23] In particular, it allows me to pinpoint whether increased rates of departures are due to employees being terminated or leaving of their own accord.

Reclassification and Agency-Level Dismissals

I first examine whether employees in exempted agencies were more likely to be dismissed than their peers in other, non-exempt state agencies, regardless of partisanship. I empirically test for the effect of reclassification on dismissals using a series of synthetic control models (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010, 2015). Developed as a tool for estimating causal effects when the number of observations is small, a synthetic control model estimates an untreated version of the treated unit as the weighted average of a set of control units. This "synthetic control" unit resembles the treated unit in terms of observable characteristics. As such, it provides an estimate of how, in the wake of treatment, the treated unit's outcome would have evolved in a hypothetical world in which it remained untreated.

I estimate these models with the agency-level dataset that includes monthly counts of the number of terminations, retirements, and resignations in each agency from 2005 through 2020. The outcome of interest is the number of terminations in the agency in a given month as a share of the size of the agency's present workforce. I estimate separate models for the exemptions of the Departments of Human Services, Marine Resources, and Education. I do not fit a model for the 2015 exemption of the Department of Corrections because of a data quality issue with the dismissal

23. Figure D.1 shows that the number of departures per month in the personnel data closely resembles the sum total of resignations, retirements, and terminations from the dismissal data. Note that this figure excludes the Departments of Corrections and Mental Health. For unknown reasons, both agencies' monthly departure counts significantly differ across the two datasets.

data.[24] For the remaining three exempted agencies, I generate the respective synthetic version of the agency as the weighted mean of pre-treatment outcomes, agency size, and agency employee location (i.e., the number of employees in the county in which the state capital is located).[25] Inference involved running a series of placebo tests where each of the agencies in the control set was randomly assigned to receive treatment. A low p-value, therefore, suggests that the effect size for the treated unit is rare, relative to other untreated agencies for the same period.

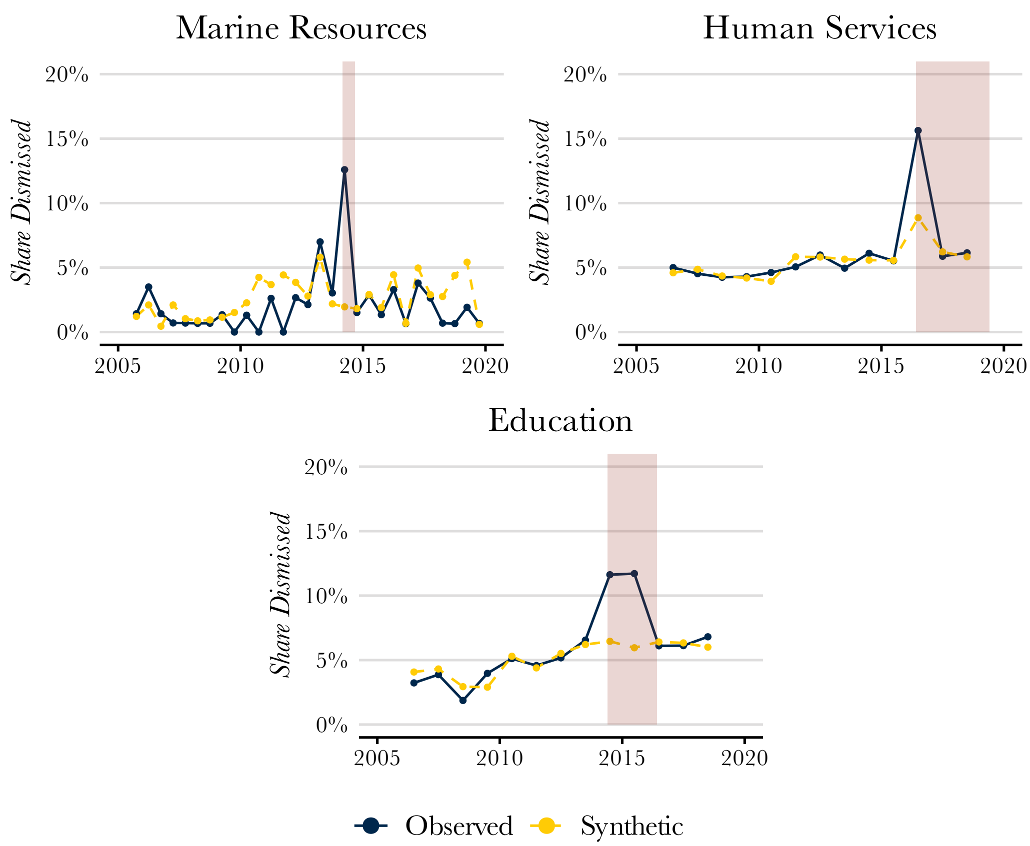
Figure 3 presents the results. The dark blue line shows the observed share of employees in the treated agency that were involuntarily dismissed in the given period. The outcome is calculated annually for the Departments of Education and Human Services, and semiannually for the Department of Marine Resources. The shaded regions represent the periods in which agency employees lacked civil service protections. In each of the three agencies, the first period following reclassification saw substantively and statistically significant increases in the number of terminations. Relative to the synthetic control, terminations increased by 11 percentage points in Marine Resources, 7 percentage points in Human Services, and 5 percentage points in Education. Relative to pre-treatment dismissal rates, these are extremely large treatment effects. In the first period of reclassification, terminations increased by 634% in Marine Resources, 211% in Human Services, and 171% in the Department of Education. Reclassification was a means for large-scale purges.[26]

24. As shown in Figure D.2, between roughly 2012 and 2017 the number of dismissals, resignations, and retirements is much higher than the number of departures calculated from the personnel data. Furthermore, the high turnover rate of the Department of Corrections is an outlier relative to other agencies in the state. Consequently, even without data quality issues, it would not be possible to generate a within-state synthetic control for the agency.

25. The specific variables used to fit the synthetic control varies across the models depending on fit. More information on the agencies and variables used to fit the synthetic control is available in the Supplementary Information.

26. In the Supplementary Information, I show that the effects of the exemptions on departures was limited to involuntary dismissals. Figure D.5 shows little significant effect of exemptions on retirements or resignations.

Figure 3 – Reclassification Increases Involuntary Dismissals from the Workforce Shows three separate synthetic control models comparing the share of employees in the given agency that were involuntarily dismissed from state employment in the given period (blue) against a statistically generated control (yellow). The unit of analysis for the Corrections and Education models is the agency-year. For the Marine Resources model, the unit of analysis is the agency-semiannual period. In each plot, a point represents the total number of employees involuntarily dismissed over the forthcoming 12 or 6 months divided by the number of employees in the agency at the start of the period. The shaded area in each of the plots represents periods where the given agency was not covered by the MSPB. All p values $< .001$. Additional information about the variables and other agencies used to create the synthetic controls is available in Figures D.4 and D.3.



Who Departs?

Reclassification increases the number of terminations from the state workforce. These agency-level findings do not, however, shed any light on which types of employees are most at risk of losing their jobs and whether, in particular, political opponents are targeted for dismissal. As such, in this section I use the individual-level personnel data to test whether, following reclassification, Democratic bureaucrats were more likely to leave the state workforce than their Republican colleagues. The structure of the data (monthly cross sections of individual employees) is well suited for a difference-in-differences analysis with heterogeneous treatment effects. As such, I use the `PanelMatch` R Package to estimate the treatment effect of exemptions on the probability of an affected employee departing the state workforce, moderated by individual partisan affiliation (Kim et al. 2022; Imai, Kim, and Wang 2023). This software provides a flexible suite of tools for estimating difference-in-differences estimators with staggered treatments, heterogeneous treatment effects, and more than two periods and/or groups — all of which are difficult to properly incorporate into more conventional two-way fixed effects methods (Imai and Kim 2021, 2019; Callaway and Sant'Anna 2021).

I subset the data to spigots in the Mississippi workforce (using the same two-stage process discussed above)[27] and trim the monthly snapshots into annual cross sections each July to reduce month-to-month fluctuations in departures. I also exclude any bureaucrat who was not a registered Republican or registered Democrat over the entire period in which they are observed in the dataset. This serves to increase the likelihood of uncovering an effect for political targeting (as Republicans would seemingly be even less willing to lose their jobs under a Republican administration

27. I include all employees who were defined as spigots at one point in time. I do this to avoid incorrectly defining someone as entering/leaving the workforce and collect information on talented employees rising through the organization. Unlike in the cross-state definition above, I drop employees who are not in the top salary quartile for the agency, rather than the state.

than non-partisan employees if political targeting is occurring).

Evaluating the treatment effect of exemptions requires estimating a counterfactual departure probability for exempted employees as if they never lost their job protections. Using `PanelMatch`, I construct sets of control employees from the agencies that were not exempted from the merit system who share the same work histories for the 3 years prior to the exemption. For instance, if a bureaucrat employed in the Department of Human Services upon that agency's exemption in July 2016 had worked for the state since December of 2015, their departure will be compared against employees in the rest of the non-exempt workforce who have also been employed by Mississippi since December of 2015. Of the 360 spigots who lost their job protections due to exemptions,[28] 50 (14%) could not be matched to any control employee in the rest of the state workforce. For the remaining employees, most were matched to a control set of employees that included at least 500 bureaucrats unaffected by reclassification (See Figure E.1).

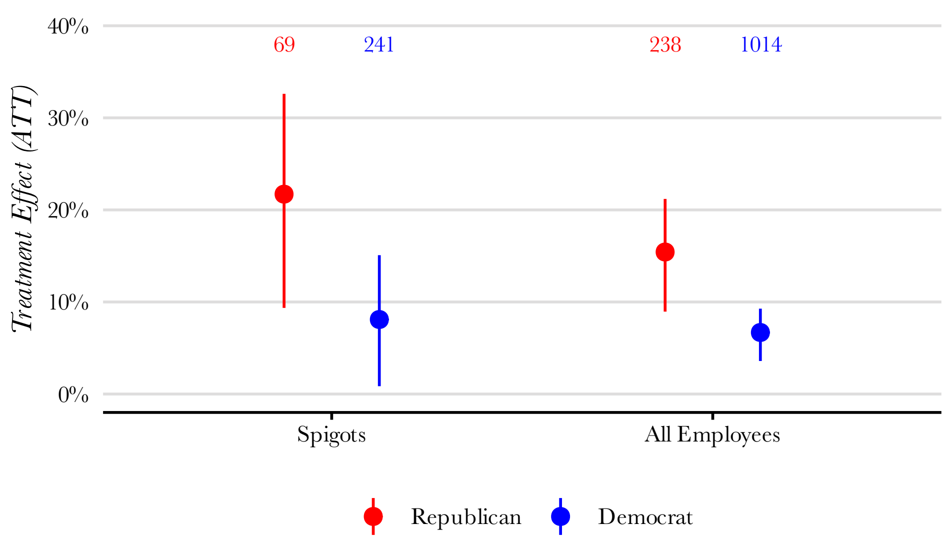
For each treated bureaucrat and corresponding control set, I utilize Covariate Balance Propensity Score matching to balance on employees' sex, race (white or non-white), years of experience working for the state, annual salary, and whether they work in the Jackson metropolitan area. Matching greatly reduces the observed differences between the treated and control groups. As I show in the Supplementary Information in Figure E.2, the magnitude of the standardized difference between the mean values of all covariates except county unemployment rate and annual salary are $< .2$ in the pooled model, indicating little difference in the means across groups (Normand et al. 2001; Austin 2011; Cohen 1977). This similarity suggests that, at least in terms of observable variables, the control sets serve as reasonable proxies for estimating the probability that a given treated employee

28. This number excludes employees in the Department of Marine Resources. I discuss below why I do not include this agency in the analyses.

would have left the workforce if they never actually lost their protections.

Point estimates of the average treatment effect on the treated are calculated by taking the mean of the difference between whether each treated employee departed the state workforce in the 12-month period following reclassification and the mean probability of departure for the corresponding matched set of control employees. Standard errors are calculated using a weighted bootstrap with 5,000 iterations (Imai, Kim, and Wang 2023). Figure 4 plots the treatment effect estimates and 95% confidence intervals for the model, pooled across the Departments of Corrections, Education, and Human Services.[29] The main results for spigots, moderated by partisanship, are included on the left-hand side of the plot, while the same results for all employees are shown on the right.

Figure 4 – Democrats No More Likely to Depart 12 Months After Exemption Shows point estimates and 95% confidence intervals from `PanelMatch` models estimating the treatment effect of spigots and all employees losing their job protections. The effects of the exemptions are moderated by partisanship. The number of employees in the treatment groups are shown above the point estimates.



As expected, given the results of the synthetic control models, the results show that removing

29. Marine Resources is excluded because its exemption began in April rather than July, making it difficult to sync up with the 12-month periodic snapshots of the analysis dataset. The Department of Child Protection Services is folded into the Department of Human Services in this analysis.

employees' job protections increased the likelihood of leaving the state workforce. However, the moderated treatment effects by partisanship show no consistent evidence of outpartisan targeting. Democratic spigots were no more likely to depart the workforce following the loss of job protections than their Republican colleagues. Removing job protections led to an 9 percentage point increase in the probability of Democratic spigots leaving the workforce. Influential Republican employees faced an even higher risk, becoming 22 percentage points more likely to depart following reclassification.

If employees' personal political views did not moderate departures in the wake of agency exemptions, what did influence personnel management in the wake of the loss of job protections? One potential factor is employee seniority.[30] While seniority provides expertise and skill, it also brings with it calcified views on how work ought to be conducted. For executives with relatively short time horizons interested in getting things done, long-time employees might therefore pose an obstacle to implementing policy agendas. The newest employees might also be at increased risk of leaving. These bureaucrats have less invested in remaining in their jobs and are also likely hired by some of the most senior employees. As a result, if an executive wants to remove the longest-serving employees, they might take some of their recent hires with them too.

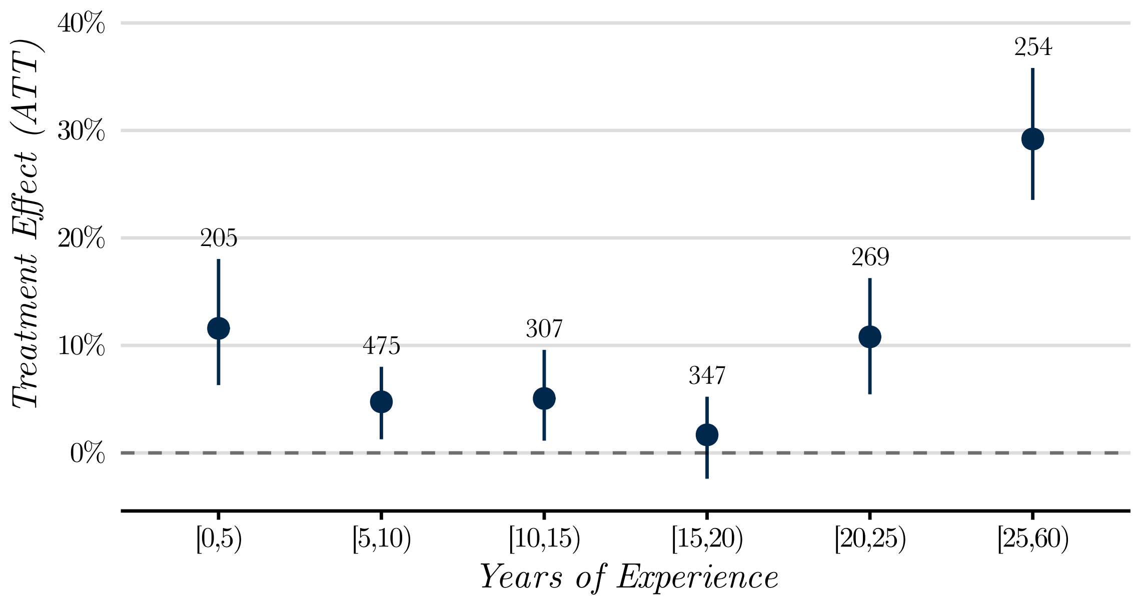
Following this logic, I run a similar `PanelMatch` model as above, except I test for heterogenous treatment effects by tenure length rather than partisanship. Also, unlike the models above, I include all employees regardless of their policy influence or partisan registration. I use all employees, even those unable to be matched to any voter, due to power concerns and the lack of a strong moderating relationship between partisanship and departing in Figure 4. Nevertheless, I do balance treatment

30. Another possible moderating factor is job performance. Poor performers quality might stand in the way of executives achieving their policy goals. Especially in the case of Mississippi's reclassification efforts, which followed issues of policy failure or scandal, reclassification might present an opportunity to replace poor performers. Unfortunately, it is very difficult to identify these employees, and I leave the moderating influence of performance on turnover following reclassification to future work.

and control groups on whether an employee was a spigot in the pre-treatment period, along with the other covariates used in the partisanship model above (Figure E.3).

Figure 5 shows the point estimates and 95% confidence intervals from this test of the moderating influence of tenure length. I also include above the estimates the number of employees in the last pre-treatment period pooled across the Departments of Education, Corrections, and Human Services for each of the tenure length values. The results show that while employees in exempted agencies were more likely to depart in the year following the loss of protections, the employees who had worked for the state the longest were at a heightened risk of leaving. Employees who had worked for the state for at least 25 years were 33 percentage points more likely to leave the state workforce after losing their job protections. Although sample size issues make it difficult to draw crisp conclusions within the group of employees who had served between 25 and 60 years, I show in Figure E.4 in the Supplementary Information that the risk of departing is even higher for the longest tenured employees in this subset. Finally, although not as large in magnitude as the effect for the longest-serving employees, the most recent hires also seem to be at slightly elevated risk of leaving, suggesting that they may have been targeted along with the most senior bureaucrats.

Figure 5 – Probability of Departing is Highest for Longest-Serving Bureaucrats Shows point estimates and 95% confidence intervals from one `PanelMatch` model moderated by employees' years of experience. The model includes all employees, regardless of whether they were matched to a voter, their seniority, or salary. Treatment effects are pooled across the Departments of Corrections, Education, and Human Services. Covariate balance information is shown in Figure E.3.



Discussion

Many governors enjoy a significant amount of control over the staffing of their bureaucracies. The reclassification of career bureaucrats into at-will positions opens the door for reorganizations, mass firings, and more flexibility in the management of personnel. The loss of job protections, however, also offers governors an opportunity to remove political opponents from the state workforce. Within the Republican-controlled states where reclassification has been most prevalent, there are numerous influential Democratic bureaucrats, setting up the possibility of political conflict. While this sets the stage for political targeting to occur, I show in a case study of reclassification in Mississippi that Democratic civil servants were not more likely to depart than their Republican peers following the loss of job protections.

My results suggest that individual employees were not targeted for removal based on their personal political views. Instead, other factors such as employees' length of service with the state ostensibly influenced departures following the loss of protections. However, this null finding for targeting does not mean that reclassification always lacks political motives or consequences. As I show, reclassification can lead to large-scale increases in dismissals from the workforce. Even if applied evenly at the individual level, strategic reclassifications can disrupt work on specific policies or programs. From the perspective of an executive, dismissing individual employees without regard to their personal views might even be preferable. Finding individual political opponents in the workforce is difficult, time-consuming work. It is considerably easier to target an agency or group of bureaucrats perceived as being in opposition to the administration and letting the personnel management process work itself out.

These results have implications for the potential future removal of protections for senior federal bureaucrats. If re-elected in 2024, President Trump has indicated that he will once again try to reclassify tens of thousands of federal bureaucrats in policy-related roles into a new unprotected Schedule F designation. My results suggest that, if this were to occur, the individual targeting of political opponents would not be automatic, although heightened political conflict and increased executive capacity at the federal level might make it more likely. Regardless of whether targeting happens or not, though, my results suggest that reclassification will likely have large effects on the federal workforce. Removing protections increases involuntary dismissals and departures and allows executives to remove specific types of employees (e.g., those who have worked in the agency for a long time). Increased turnover, especially if it is concentrated among long-time staff, can affect agencies' capacity, least in the short run, with possible downstream impacts on policy outputs.

My findings also inform the study of state politics. The states are more than just a testing ground for institutional variation or policies yet to appear at the federal level. State bureaucrats administer cap-and-trade programs, federal public welfare programs like Temporary Assistance for Needy Families and Medicaid, massive carceral systems, highway construction projects, state lands, public health projects, and other impactful policies. While scholars have examined the preferences of other state-level actors (Shor and McCarty 2011; Bonica and Woodruff 2012), this is the first attempt to systematically document the political views of entire state bureaucracies. Moreover, the null finding regarding political targeting in Mississippi is a small check to concerns over democratic "backsliding" within Republican-controlled states (Grumbach 2023). While Mississippi is only one case, its high rates of public corruption (Glaeser and Saks 2006; Liu and Mikesell 2014) and government scandals make it a seemingly likely place to uncover political cronyism.

Furthermore, the finding of much higher departure rates for longer serving employees points to the other dimensions of conflict that exist within state workforces. Especially within states under single-party control, principals might be focused on targeting other types of employees than political opponents. The longest serving employees, while possessing expert knowledge, might be perceived by the executive and agency leaders as an old guard that needs to be replaced with a more responsive group of new bureaucrats.

There are limitations to this study. While my twenty-state sample is large and contains regional and political variation, it might be missing important data points contained in the other states. Likewise, the analysis of political targeting is based on a single U.S. state. Therefore, the findings may not fully generalize to other states or the federal bureaucracy. For instance, in Mississippi, public sector unions lack the power to collectively bargain. In settings where unions are more powerful, the effects of reclassification might be more muted. Gubernatorial power might matter too. In other cases, an executive might be able to utilize staff or outside advocacy organizations to identify opposing employees and closely-aligned replacements.

Future work can use my findings to explore a variety of interesting, pressing questions. I use the variation in the partisan composition of senior echelons of state workforces as a jumping off point for my causal tests. Other work should try to explain why so many Democrats work in Republican-controlled states. Is it simply a product of the distribution of voters across and within states? Or do other factors, such as race, matter (e.g., Madowitz, Price, and Weller 2020)?

Other work should examine the impact of reclassification on other outcomes of interest. I focus solely on departures, but reclassification might also affect compensation and hiring patterns. Future analyses might also look to link up similar employee-level analyses with agency-level measures of service delivery to see if reclassification affects the operation of government. Scholars should continue to look beyond the federal workforce (and Mississippi) to answer these important questions. The other U.S. states that have reclassified their public employees into at-will employment in recent decades are a fertile ground for answering pressing questions about the staffing of American bureaucracies.

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Supplementary Information

Partisan Departures from the Administrative States

Benjamin Goehring

Contents

SI A Merge Procedure and Diagnostics

This section provides details on how I matched state bureaucrats to their corresponding voter registration information, as well as additional diagnostics about the merges. Important methodological advancements have occurred in recent years regarding data merging. Notably, Enamorado, Fifield, and Imai (2019) introduced the open-source `R` package `fastLink` for conducting probabilistic merges. I opted to not use `fastLink` for a few reasons. First, my project requires conducting many distinct merges with different sets of available key variables. As a result, since `fastLink` is probabilistic, it might return different types of matches across the states. For instance, in Arkansas, an employee might match to a voter with a non-matching middle initial, which would not occur in Alaska using the same probability threshold to define a true match. Second, although `fastLink` is considerably faster than other probabilistic approaches, it still takes significant computational resources. This problem is magnified in my case, as I need to run twenty different merges.

As a result, I opted to instead use my own algorithm to match state bureaucrats to voters. I walk through the algorithm below.

Subsection A.1 Merge Algorithm

1. Match the state personnel file to the voter file of the given state and neighboring states. (With the exception of the Mississippi employee merge, all merges use voter files that are point-in-time snapshots from late 2020 and early 2021. The Mississippi merge incorporates additional snapshots from earlier periods in time. See Table A.6 for more information about timing of the voter file snapshots for Mississippi and neighboring states.)

2. Filter the voter registration file to only include voters living in the given state or within 50km of the state border.

3. For each state employee, find all voters where the Jaro-Winkler string distance between both the first and last names is less than .025.[31]

4. Post-process the potential matches using the additional key variables available in the state (See Table A.1). If the key variable is available, remove any voters matched to a state employee who have:

    (a) A different, non-missing middle initial

    (b) A different race (unless the employee is only matched to one voter)

    (c) A different gender (unless the employee is only matched to one voter)

    (d) A birth date that is $+/-$ 1 year from the state employee's birth date

    (e) A date of birth that is more than 70 years from the last date I observe the state employee (unless the employee is only matched to one voter)

    (f) A date of birth that is more than 80 years from the last date I observe the state employee

    (g) A date of birth that is less than 18 years from the state employee's hire date

31. To speed up the merges, I blocked the employee and voter files on the concatenation of the first character of the first and last names.

(h) A residential address that is not in the same county or an adjacent county as the state employee's county of employment

5. Since more than one voter can still be matched to a given state employee, calculate the mean probability that each employee is a registered Republican, Democrat, non-partisan, and member of another party. For instance, if an employee is matched to a Republican voter and Democratic voter, they would be assigned to be a Republican with a probability of 0.5, a Democrat with a probability of 0.5, non-partisan with a probability of 0, and of another party with a probability of 0. If an employee is matched to one voter or more than one voter who all share the same partisan affiliation, their partisanship is set to 1 for the given partisanship category. See Tables A.3 and A.4 for more information about the number of one-to-one and one-to-one partisan affiliation matches by state.

Subsection A.2 Merge Diagnostics

Table A.1 – Personnel Data Details Shows the timespan, frequency, and available variables in each state's personnel data.

			Key Variables Used in Post-Processing:						
State	*Timespan*	*Frequency*	*Gender*	*Race*	*M. Initial*	*Age*	*Hire Date*	*County*	*Classification*
AK	2017-2021	Quarter			✓				
AR	2013-2022	Month	✓	✓	✓				
CO	2019-2022	Month			✓		✓	✓	✓
FL	2010-2022	Month	✓	✓			✓		✓
IA	2017-2021	Year	✓		✓			✓	
ID	2012-2022	Month			✓		✓		✓
LA	2019-2022	Month	✓	✓			✓	✓	✓
MA	2019-2022	Month			✓			✓	✓
ME	2010-2021	Year			✓				
MN	2011-2021	Year			✓		✓	✓	✓
MS	2010-2022	Month	✓	✓	✓		✓	✓	✓
MT	2019-2021	Year			✓			✓	
ND	2010-2022	Year					✓		✓
NV	2010-2021	Year			✓				✓
SC	2019-2022	Month	✓	✓	✓	✓		✓	✓
TX	2019-2022	Month	✓	✓	✓		✓		
VT	2009-2021	Year			✓				✓
WA	2019-2022	Quarter			✓		✓	✓	✓
WI	2009-2021	Year			✓		✓	✓	✓
WV	2018-2022	Month			✓		✓		✓
WY	2019-2021	Year						✓	

Table A.2 – Match Rates Shows the share of state employees and employee-period observations successfully matched to at least one voter by state. For the employee-level measures, A bureaucrat in Mississippi is counted as being matched if they are matched to a voter at least once.

	Employees			*Period-Employees*		
State	*N Matches*	*N*	*Share Matched*	*N Matches*	*N*	*Share Matched*
AK	22,739	27,589	0.82	232,699	263,839	0.88
AR	51,099	71,889	0.71	2,204,486	2,844,295	0.78
CO	51,292	65,794	0.78	1,313,597	1,600,375	0.82
FL	208,147	333,965	0.62	10,708,817	13,875,569	0.77
IA	77,228	103,448	0.75	245,801	304,381	0.81
ID	31,987	46,141	0.69	1,566,999	2,007,500	0.78
LA	102,633	143,660	0.71	1,127,131	1,532,538	0.74
MA	46,410	55,956	0.83	1,548,109	1,829,285	0.85
ME	22,963	30,440	0.75	125,334	152,514	0.82
MN	97,008	139,648	0.69	487,197	706,331	0.69
MS	43,436	60,029	0.72	2,314,153	3,245,938	0.71
MT	16,276	21,668	0.75	38,620	49,212	0.78
ND	15,143	21,382	0.71	88,901	111,529	0.80
NV	34,066	48,647	0.70	176,762	234,456	0.75
SC	72,530	94,902	0.76	1,830,162	2,309,601	0.79
TX	182,585	244,400	0.75	5,024,640	6,450,631	0.78
VT	19,920	27,788	0.72	116,330	148,650	0.78
WA	71,621	88,586	0.81	772,934	918,179	0.84
WI	82,099	114,171	0.72	407,580	507,570	0.80
WV	51,330	66,405	0.77	1,450,444	1,764,987	0.82
WY	8,977	13,236	0.68	22,005	30,707	0.72
Total	*1,309,489*	*1,819,744*	*0.72*	*31,802,701*	*40,888,087*	*0.78*

Table A.3 – Share of State Employees Matched to N Voters Among state employees matched to at least one voter, shows the share of state employees who were matched to 1, 2, 5, and 10 voters. Values rounded to the hundredth decimal place.

	Share of State Employees Matched to:			
State	*1 Voter*	*2 Voters*	*5 Voters*	*10 Voters*
AK	0.96	0.03	0	0
AR	0.8	0.08	0.01	0
CO	0.88	0.07	0.01	0
FL	0.52	0.1	0.03	0.01
IA	0.92	0.06	0	0
ID	0.87	0.07	0.01	0
LA	0.85	0.09	0.01	0
MA	0.75	0.13	0.01	0
ME	0.83	0.09	0.01	0
MN	0.86	0.08	0	0
MS	0.9	0.07	0	0
MT	0.97	0.03	0	0
ND	0.81	0.09	0.01	0
NV	0.85	0.07	0.01	0
SC	0.95	0.04	0	0
TX	0.62	0.11	0.02	0.01
VT	0.85	0.08	0.01	0
WA	0.88	0.08	0	0
WI	0.87	0.08	0	0
WV	0.74	0.11	0.02	0
WY	0.84	0.11	0.01	0

Table A.4 – Share of State Employees Matched to N Partisan Affiliations Among state employees matched to at least one voter, shows the share of state employees who were matched to 1, 2, and 3 different partisan affiliations. Values rounded to the hundredth decimal place.

	Share of State Employees Matched to:		
State	*1 Partisan Affiliation*	*2 Partisan Affiliations*	*3 Partisan Affiliations*
AK	0.97	0.02	0
AR	0.84	0.1	0.05
CO	0.93	0.05	0.02
FL	0.6	0.15	0.16
IA	0.96	0.03	0.01
ID	0.9	0.07	0.03
LA	0.91	0.07	0.02
MA	0.85	0.1	0.04
ME	0.86	0.09	0.04
MN	0.93	0.05	0.03
MS	0.96	0.04	0
MT	0.98	0.01	0
ND	0.85	0.1	0.05
NV	0.88	0.07	0.03
SC	0.99	0.01	0
TX	0.76	0.12	0.12
VT	0.88	0.08	0.03
WA	0.94	0.04	0.02
WI	0.93	0.05	0.02
WV	0.79	0.13	0.07
WY	0.92	0.06	0.02

Table A.5 – Voter Registration and Partisan Modeling Describes how voter-level partisanship is calculated for each state in the L2 data. Unless otherwise noted, partisanship is modeled using "a great many public and private data sources including demographics available through the voter file, exit polling from presidential elections, commercial lifestyle indicators, census data, self-reported party preferences from private polling and more."

State	*Description*
AK	Registered partisanship
AR	Registered partisanship
CO	Registered partisanship
FL	Registered partisanship
IA	Registered partisanship
ID	Registered partisanship
LA	Registered partisanship
MA	Registered partisanship
ME	Registered partisanship
MN	Modeled
MS	Most recent even-year partisan primary participation. If not available, most recent odd-year partisan primary participation. Additional imputation using self-reported race and campaign finance data.
MT	Modeled
ND	Modeled
NV	Registered partisanship
SC	Most recent even-year partisan primary participation. If not available, most recent odd-year partisan primary participation. Additional imputations using demographic and campaign finance data.
TX	Most recent even-year partisan primary participation. If not available, most recent odd-year partisan primary participation. Additional imputations using demographic and campaign finance data.
VT	Modeled
WA	Most recent presidential primary participation. If a voter did not participate in a presidential primary, their partisanship is modeled using demographic and campaign finance data
WI	Modeled
WV	Registered partisanship
WY	Registered partisanship

Table A.6 – Mississippi Personnel and Voter File Dates Shows the intervals used to bin the MS personnel file into three groups and the dates of the state voter files matched to the corresponding group.

	State Voter Files:				
Personnel File	*MS*	*AL*	*LA*	*TN*	*AR*
1-1-2010 to 12-31-2014	3-17-2014	3-18-2014	3-20-2014	3-18-2014	4-11-2014
1-1-2015 to 12-31-2019	3-7-2017	3-7-2017	2-14-2017	2-17-2017	3-29-2017
1-1-2020 to 6-30-2022	3-23-2021	2-4-2021	1-22-2021	3-29-2021	3-16-2021

SI B Validating "Spigot" Definition

This section provides additional information about how I filter the personnel dataset to influential, senior employees (i.e., "spigots"). Table B.1 shows, for each state, the ten job titles that are most common, after filtering out employees who are not in the top salary quartile for the state and period as well as common strings in titles of jobs that are not involved in regulatory, budgetary, or policy work. Table B.2 shows the most common job titles for exempted agencies and the rest of the workforce in the last pre-treatment period. Figure B.1 shows the share of states' full workforces and spigots that are employed in the capital and adjacent counties. The increased share of spigots in the capital metropolitan area suggests that my definition of who is influential in states' bureaucracies is picking up on real differences in employee influence.

Table B.1 – Most Common Job Titles Among Top-Quartile, by State Shows, for each state, the ten most frequent job titles among the employees with the top-quartile of salaries after removing high-paid non-regulatory positions like nurses, doctors, and engineers.

State	Ten Most Frequent Job Titles
AK	attorney iv; attorney v; division director - px; attorney iii; division operations manager; fish & game coordinator; attorney 4; program coordinator ii; accountant iv; protective services specialist iv
AR	tax auditor ii; attorney specialist; public school program advisor; asp corporal; ddssa claims adjudicator iii; dhs program administrator; family service worker supervisor; software support analyst; dhs program manager; adc/dcc captain
CO	program management ii; program management i; management; program management iii; administrator v; environ protect spec ii; administrator iv; asst attorney general ii; senior executive service; state patrol supervisor
FL	senior attorney; government operations consultant ii; operations & mgmt consultant mgr - ses; government analyst ii; senior management analyst ii - ses; operations review specialist; senior management analyst supv - ses; operations & mgmt consultant ii - ses; environmental specialist iii; correctional probation senior officer
IA	public service manager 1; exec off 2; info tech specialist 5; public service manager 2; info tech specialist 4; asst attorney general 3; program planner 3; exec off 3; public service executive; exec off 1

ID	deputy attorney general; program manager; administrative; isp specialist; analyst 4; project manager 1; trans operations team leader; coordinator-supt off; programs bur chf-h&w; it manager ii
LA	state police master troop; rn 3; med cert specialist 2; asst attorney gen; director; attorney 3; instructor; prog mgr 1-a-dhh; it management consult 1; ed program consultant 3
MA	program coordinator iii; counsel ii; administrator viii; administrator vi; program manager vii; administrator vii; correction officer iii; program manager v; program manager vi; administrator ix
ME	public service manager ii; asst attorney general; asst district attorney; senior technician; game warden; public service coordinator i; environmental specialist iv; public service manager i; human services caseworker supv; public service manager iii
MN	state prog admin coordinator; state prog admin prin; state prog admin manager sr; state prog admin director; planner principal state; educ specialist 2; systems analysis unit supv; management analyst 4; state prog admin manager; transp specialist
MS	division director ii; bureau director ii; staff officer ii; office director ii; attorney general-special assistant; staff officer iii; bureau director, deputy; business systems analyst ii; branch director ii; dhs-area social work supv
MT	lawyer; program manager; lawyer2; operations manager; computer systems analyst; bureau chief; project management specialist; section supervisor; resource conservation mgr; lawyer 2
ND	other-not cls-prof; health/human svc prgm admin iv; transportation srvcs supv ii; appointed–not classified; asst atty gen-not classfd; auditor iv; other-not cls-ofcl/admin; health/human svc prgm admin v; transportation proj mgr; systems administrator ii
NV	sr deputy atty general (ea); management analyst 3; dep atty general (ea); education programs professionl; admin services officer 3; correctional case work spec 2; environmental scientist 3; developmental specialist 4; social services program spec 3; admin services officer 2
SC	program manager i; program manager ii; education associate; program coordinator ii; program manager iii; attorney iii; accounting/fiscal manager i; it manager i; attorney iv; dpty/div director-exec comp
TX	mgr iv; mgr v; program specialist v; program specialist vi; director ii; child protective svcs spec iv; mgr ii; director iii; systems analyst v; mgr iii
VT	staff attorney iv; staff attorney iii; deputy state's attorney; deputy commissioner; correctnl facility shift super; commissioner; community corr program supvsr; systems developer iii; aot technician vi; social services supervisor
WA	wms band 2; wms band 3; asst atty gen; wms band 1; it system admin - journey; it app development - journey; management analyst 5; social service specialist 5; it business analyst - journey; it app development - sr/spec
WI	supervising officer 2; attorney; assistant district attorney; program and policy analyst-adv; supervising officer 1; conservation warden; education consultant; asst st pub defndr atty; is systms devmnt svcs spec; is systms devmnt services spec

WV	corporal; health human resources program manager 1; administrative services manager 1; asst attorney general; environmental resources specialist 3; administrative services manager 3; administrative services manager 2; coordinator ma+45; attorney 3; environmental inspector
WY	natural resources program principal; executive management 2; executive management 3; executive management 1; education program consultant; practicing attorney 4; natural resources program manager; practicing attorney 2; natural resources program supervisor; wy business council special classified

Figure B.1 – Share of Matched Employees in State Capital Area Shows the share of, respectively, all state employees and spigots who are employed in the capital containing the state capital city and adjacent counties.

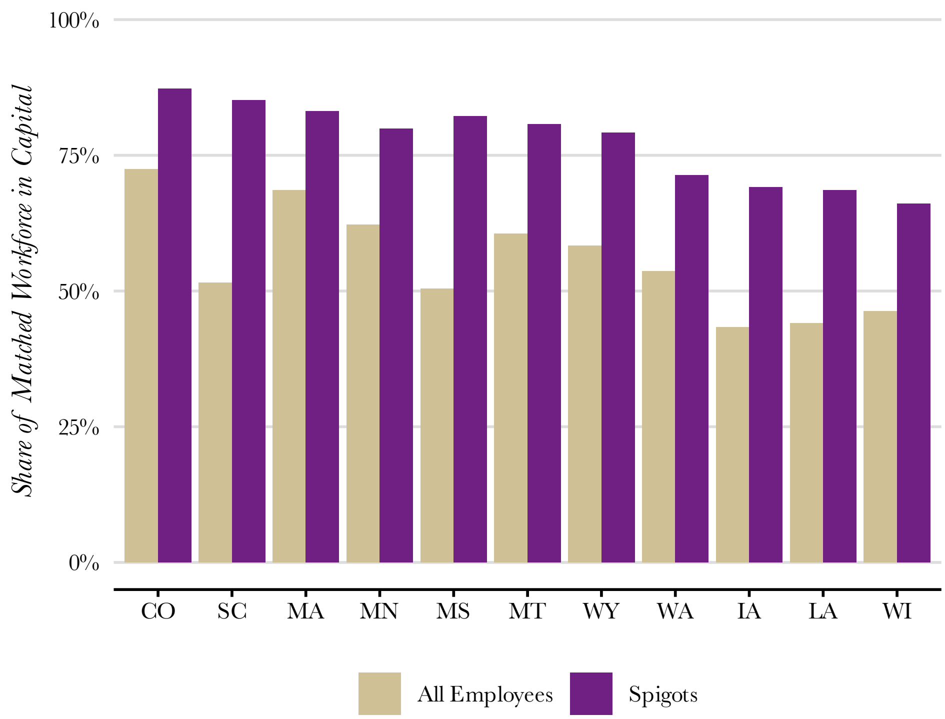


Table B.2 – Most Common Job Titles for Spigots in Exempted Agencies Shows, for the Departments of Corrections, Human Services, and Education, the ten most frequent job titles in the last pre-treatment period, as well as the ten most frequent positions in same period across the rest of the state workforce used as a control. In order to avoid post treatment bias or introducing addtional departures into the data, I classify someone as a spigot if they earned in the top quartile or did not have a spigot-related string in their job title at any time before the onset of treatment. For spigots in control agencies, I deem this to begin with the onset of the first exemption in 2014.

Exempted Agency	10 Most Frequent Job Titles
Corrections	
Control	branch director ii; bureau director, deputy; division director ii; dot-manager; bureau director i; bureau director ii; dor-tax auditor/accountant iii; staff officer ii; business systems analyst ii; dot-administrator i
Treatment	corr-correctional supervisor; corr-correctional commander; branch director i; corr-comm corrections, assoc dir; branch director ii; projects officer iii,special; corr-asst dir offender serv; correctional officer iv (sgt); op/mgmt analyst principal; personnel officer ii; personnel officer iii; personnel officer iv; projects officer iv,special
Education	
Control	branch director ii; bureau director, deputy; division director ii; bureau director i; dot-manager; bureau director ii; dor-tax auditor/accountant iii; staff officer ii; business systems analyst ii; staff officer i
Treatment	division director ii; v/h impt tchr ii(dual end)-pr; branch director ii; educ-spec education prog coord; educ-specialist, senior; op/mgmt analyst principal; regional service officer; v/h impt tchr iii(dual end)-pr; accountant/auditor iii; accountant/auditor iv, professional; accounting specialist sr; accounting/auditing bureau dir; business systems analyst i; business systems analyst ii; division director i; educ-budget officer senior; lead business systems analyst; personnel officer v; school facilities supervisor; school safety administator; school safety specialist; senior business systems analyst; senior communications analyst; systems manager i; v/h impt education spec sr; v/h impt voc tch i(dual end)pr; v/h impt voc tch i(sng end)
Human Services	
Control	bureau director ii; branch director ii; dot-manager; bureau director, deputy; dot-administrator i; division director ii; business systems analyst ii; dor-tax auditor/accountant iii; staff officer ii; bureau director i; staff officer i
Treatment	dhs-area social work supv; dhs-county director ii; projects officer iv,special; dhs-supervisor iii; dhs-county director i; dhs-county director iii; dhs-supervisor ii; dhs-program manager; accountant/auditor iii; dhs-child support reg dir; dhs-program admor sr

SI C Additional Descriptive Results

This section includes additional descriptive results about the partisanship of state employees. Figure C.1 compares the partisanship of states' bureaucracies to their voting populations. Figure C.2 shows the share of partisan spigots in each state over time. Finally, Tables C.1 and C.2 show raw counts and shares of partisan bureaucrats in states' bureaucracies. Data from these tables are used to create Figure 1.

Table C.1 – The Partisanship of State Bureaucracies, by State and Affiliation Shows the number and share of matched bureaucrats by partisan affiliation. Temporary and part-time employees (where available), as well as employees working for state boards, the national guard, and higher education institutions, are excluded. The first two columns show results for employees in the top salary quartile for the state, removing street-level bureaucrats; the next two columns show data for all employees who earn in the top salary quartile; and the final two columns show results for all state employees regardless of earnings.

		Top Quartile, Subsetted		All	
State	Partisanship	N	Share	N	Share
AK	Democratic	336	0.16	2159	0.15
	Non-Partisan	395	0.19	2246	0.16
	Other	864	0.42	6418	0.45
	Republican	406	0.20	3048	0.21
	Prob. < Threshold	70	0.03	402	0.03
AR	Democratic	1609	0.41	6548	0.36
	Non-Partisan	566	0.15	4881	0.27
	Other	1	0.00	6	0.00
	Republican	1158	0.30	4371	0.24
	Prob. < Threshold	549	0.14	2530	0.14
CO	Democratic	1729	0.38	6869	0.31
	Non-Partisan	1696	0.37	8409	0.38
	Other	26	0.01	261	0.01
	Republican	834	0.18	5396	0.24
	Prob. < Threshold	277	0.06	1367	0.06
FL	Democratic	3751	0.30	21509	0.33
	Non-Partisan	1437	0.11	7966	0.12
	Other	74	0.01	465	0.01
	Republican	2557	0.20	11787	0.18
	Prob. < Threshold	4806	0.38	24047	0.37
IA	Democratic	1522	0.42	6374	0.36
	Non-Partisan	983	0.27	5566	0.31
	Other	14	0.00	114	0.01
	Republican	935	0.26	5214	0.29
	Prob. < Threshold	134	0.04	610	0.03
ID	Democratic	307	0.15	1563	0.15
	Non-Partisan	701	0.34	3298	0.32
	Other	7	0.00	138	0.01
	Republican	878	0.42	4281	0.42
	Prob. < Threshold	175	0.08	944	0.09

LA	Democratic	1524	0.36	9877	0.42
	Non-Partisan	907	0.22	4956	0.21
	Other	17	0.00	128	0.01
	Republican	1214	0.29	5590	0.24
	Prob. < Threshold	533	0.13	2921	0.12
MA	Democratic	1575	0.32	10409	0.30
	Non-Partisan	2306	0.46	16137	0.47
	Other	14	0.00	302	0.01
	Republican	324	0.07	2733	0.08
	Prob. < Threshold	764	0.15	5054	0.15
ME	Democratic	795	0.37	3113	0.30
	Non-Partisan	520	0.24	2680	0.26
	Other	63	0.03	400	0.04
	Republican	520	0.24	2693	0.26
	Prob. < Threshold	262	0.12	1324	0.13
MN	Democratic	1214	0.30	7191	0.28
	Non-Partisan	910	0.22	8011	0.32
	Republican	1633	0.40	8049	0.32
	Prob. < Threshold	343	0.08	2105	0.08
MS	Democratic	759	0.36	4774	0.43
	Non-Partisan	358	0.17	2572	0.23
	Other	1	0.00	1	0.00
	Republican	924	0.44	3384	0.30
	Prob. < Threshold	78	0.04	441	0.04
MT	Democratic	728	0.28	3117	0.27
	Non-Partisan	744	0.29	4184	0.36
	Other	1	0.00	3	0.00
	Republican	1044	0.41	4275	0.36
	Prob. < Threshold	48	0.02	176	0.01
ND	Democratic	213	0.20	901	0.17
	Non-Partisan	149	0.14	1342	0.25
	Other	1	0.00	2	0.00
	Republican	531	0.51	2366	0.44
	Prob. < Threshold	156	0.15	809	0.15
NV	Democratic	535	0.31	4742	0.31
	Non-Partisan	309	0.18	3039	0.20
	Other	104	0.06	894	0.06
	Republican	596	0.35	4927	0.32
	Prob. < Threshold	176	0.10	1723	0.11

SC	Democratic	1346	0.47	15884	0.58
	Non-Partisan	112	0.04	1567	0.06
	Republican	1392	0.49	10065	0.36
	Prob. < Threshold	5	0.00	67	0.00
TX	Democratic	8284	0.42	45823	0.43
	Non-Partisan	1312	0.07	10490	0.10
	Republican	5608	0.29	26534	0.25
	Prob. < Threshold	4308	0.22	23519	0.22
VT	Democratic	899	0.54	3521	0.49
	Non-Partisan	213	0.13	1449	0.20
	Other	2	0.00	19	0.00
	Republican	378	0.23	1409	0.20
	Prob. < Threshold	170	0.10	816	0.11
WA	Democratic	5578	0.59	25073	0.52
	Non-Partisan	1364	0.14	8604	0.18
	Other	3	0.00	41	0.00
	Republican	2037	0.21	11802	0.24
	Prob. < Threshold	545	0.06	2855	0.06
WI	Democratic	2287	0.43	11942	0.42
	Non-Partisan	876	0.17	6098	0.21
	Other	1	0.00	1	0.00
	Republican	1800	0.34	8730	0.31
	Prob. < Threshold	338	0.06	1603	0.06
WV	Democratic	953	0.33	4645	0.30
	Non-Partisan	374	0.13	2395	0.15
	Other	74	0.03	459	0.03
	Republican	831	0.29	4607	0.29
	Prob. < Threshold	625	0.22	3545	0.23
WY	Democratic	207	0.17	956	0.15
	Non-Partisan	122	0.10	757	0.12
	Other	7	0.01	69	0.01
	Republican	802	0.64	4001	0.63
	Prob. < Threshold	111	0.09	544	0.09

Table C.2 – The Partisanship of State Bureaucracies, by State, Affiliation, and Classification Shows the number and share of matched bureaucrats by partisan affiliation and classification. Temporary and part-time employees (where available), as well as employees working for state boards, the national guard, and higher education institutions, are excluded. The columns show results for, respectively, classified and unclassified employees in the top salary quartile for the state, removing street-level bureaucrats.

		Classified		Unclassified	
State	Partisanship	N	Share	N	Share
CO	Democratic	1056	0.35	673	0.44
	Non-Partisan	1135	0.37	561	0.37
	Other	18	0.01	8	0.01
	Republican	657	0.22	177	0.12
	Prob. < Threshold	165	0.05	112	0.07
FL	Democratic	1701	0.32	1993	0.29
	Non-Partisan	638	0.12	771	0.11
	Other	32	0.01	38	0.01
	Republican	993	0.18	1494	0.21
	Prob. < Threshold	2017	0.37	2676	0.38
ID	Democratic	217	0.16	90	0.13
	Non-Partisan	469	0.34	232	0.33
	Other	3	0.00	4	0.01
	Republican	557	0.41	321	0.46
	Prob. < Threshold	128	0.09	47	0.07
LA	Democratic	1317	0.37	207	0.33
	Non-Partisan	778	0.22	129	0.21
	Other	15	0.00	2	0.00
	Republican	1011	0.28	203	0.32
	Prob. < Threshold	445	0.12	88	0.14
MA	Democratic	606	0.28	969	0.35
	Non-Partisan	1101	0.50	1205	0.43
	Other	7	0.00	7	0.00
	Republican	170	0.08	154	0.06
	Prob. < Threshold	318	0.14	446	0.16
MN	Democratic	1028	0.28	186	0.43
	Non-Partisan	824	0.22	86	0.20
	Republican	1504	0.41	129	0.30
	Prob. < Threshold	311	0.08	32	0.07

MS	Democratic	509	0.38	250	0.32
	Non-Partisan	244	0.18	114	0.15
	Other	1	0.00	n/a	n/a
	Republican	543	0.40	381	0.49
	Prob. < Threshold	48	0.04	30	0.04
ND	Democratic	173	0.20	40	0.22
	Non-Partisan	121	0.14	28	0.16
	Other	1	0.00	n/a	n/a
	Republican	456	0.52	75	0.42
	Prob. < Threshold	121	0.14	35	0.20
NV	Democratic	387	0.30	148	0.35
	Non-Partisan	231	0.18	78	0.19
	Other	82	0.06	22	0.05
	Republican	468	0.36	128	0.31
	Prob. < Threshold	135	0.10	41	0.10
SC	Democratic	1257	0.47	89	0.45
	Non-Partisan	106	0.04	6	0.03
	Republican	1289	0.49	103	0.52
	Prob. < Threshold	5	0.00	n/a	n/a
VT	Democratic	725	0.54	174	0.56
	Non-Partisan	182	0.13	31	0.10
	Other	2	0.00	n/a	n/a
	Republican	316	0.23	62	0.20
	Prob. < Threshold	127	0.09	43	0.14
WA	Democratic	4379	0.56	1199	0.68
	Non-Partisan	1161	0.15	203	0.12
	Other	3	0.00	n/a	n/a
	Republican	1781	0.23	256	0.15
	Prob. < Threshold	445	0.06	100	0.06
WI	Democratic	2072	0.44	215	0.40
	Non-Partisan	774	0.16	102	0.19
	Other	1	0.00	n/a	n/a
	Republican	1612	0.34	188	0.35
	Prob. < Threshold	304	0.06	34	0.06

Figure C.1 – Partisanship of Senior Democratic Employees vs Voters The top panel shows the share of senior state bureaucrats who are registered Democrats relative to the share of the state population that are registered Democrats. The bottom panel is the same except it subsets the voter data to only include those voters whose household income is estimated to be greater than $100,000 by L2. Data is a snapshot from early 2021 and only includes employees matched to at least one voter. An employee is deemed to be a registered Democrat if their probability of being a Democrat exceeds 0.9. Data excludes national guard, state board, higher education, part-time (where available), and temporary employees (where available). The labels are minimally jittered to eliminate overplotting.

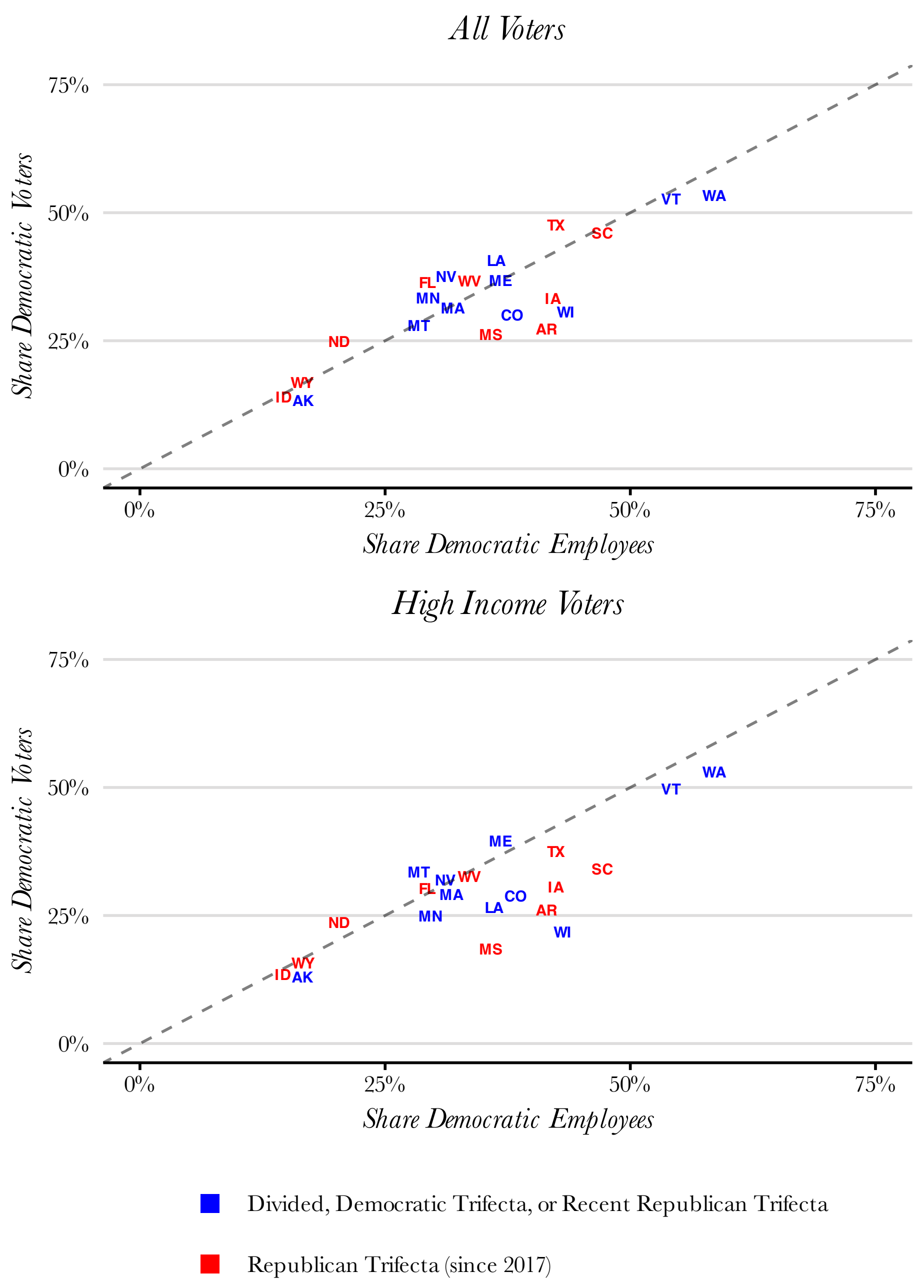
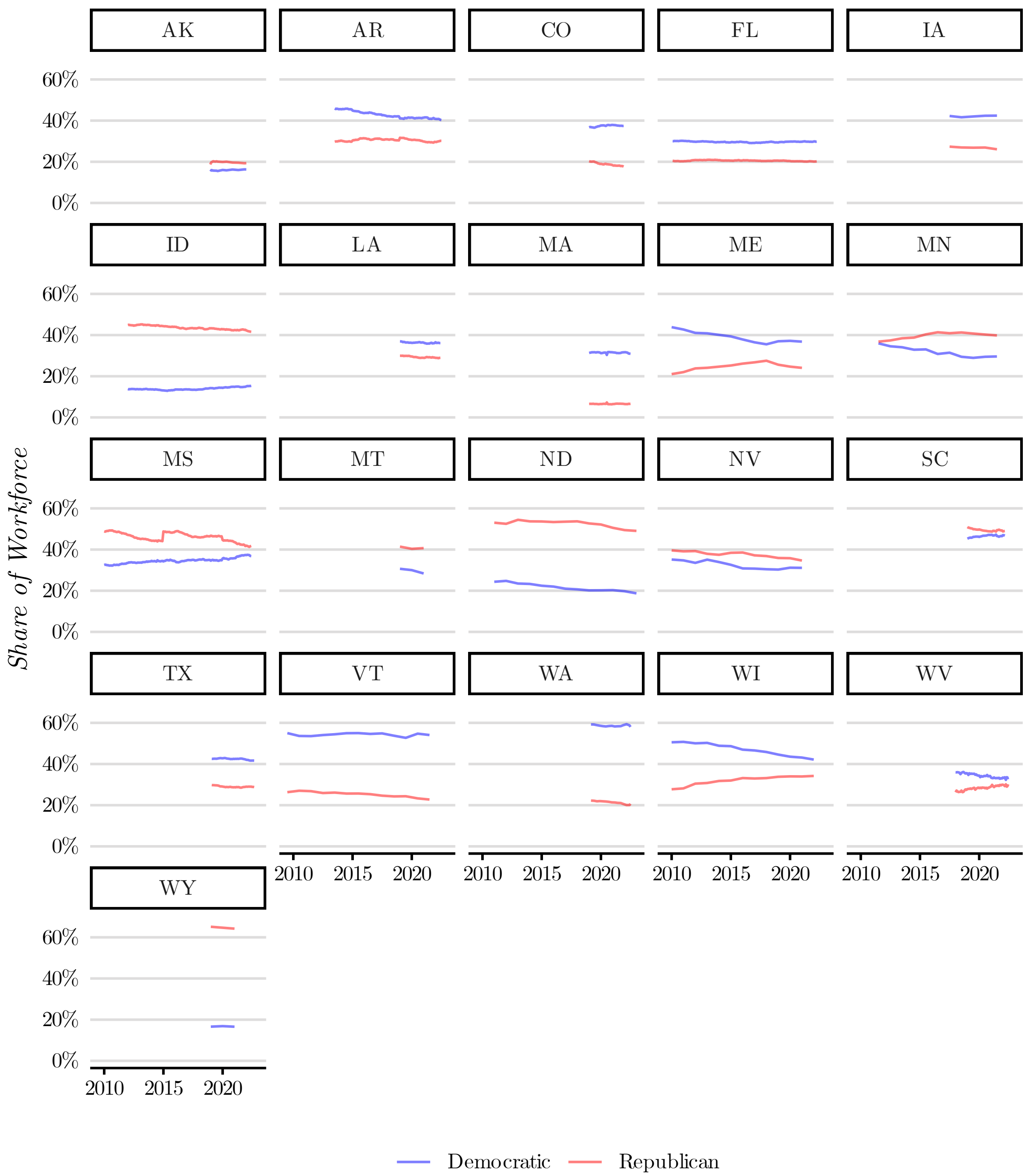


Figure C.2 – Partisanship of Senior Employees Over Time Shows the share of spigots in each state that are Democrats and Republicans. An employee is deemed to be a registered Democrat (Republican) if their probability of being a Democrat (Republican) exceeds 0.9. Data excludes national guard, state board, higher education, part-time (where available), and temporary employees (where available).



SI D Synthetic Control Diagnostics and Robustness Checks

This section includes diagnostic information on the synthetic control models shown in Figure 3 as well as alternative models examining the effect of reclassification on resignations and retirements. Figures D.1 and D.2 compare the number of resignations, retirements, and involuntary dismissals in an agency-month against the number of departures, as calculated from the individual-level personnel and voter registration data. They show that the two different datasets closely map one another, except in the cases of the Departments of Mental Health and Corrections. It is unknown why these two agencies have discrepancies. Next, Figures D.3 and D.4 show the variables and agencies (and associated weights) used to construct the synthetic controls of the agencies that experienced reclassification. Finally, Figure D.5 follows a similar design as Figure 3, except the outcome variable is the share of retirements and resignations, rather than the share of involuntary dismissals. This plot shows that the effect of reclassification is isolated to involuntary rather than voluntary departures.

Figure D.1 – Comparison of Dependent Variables – All Agencies Compares the number of departures from Mississippi state agencies using the aggregated number of dismissals, resignations, and retirements, and the aggregated individual-level measure of departures from the personnel data. The counts exclude the Departments of Corrections and Mental Health. Both agencies are large and their dismissal data is highly uncorrelated with the departure data for unknown reasons. The measures include unclassified and part-time state employees.

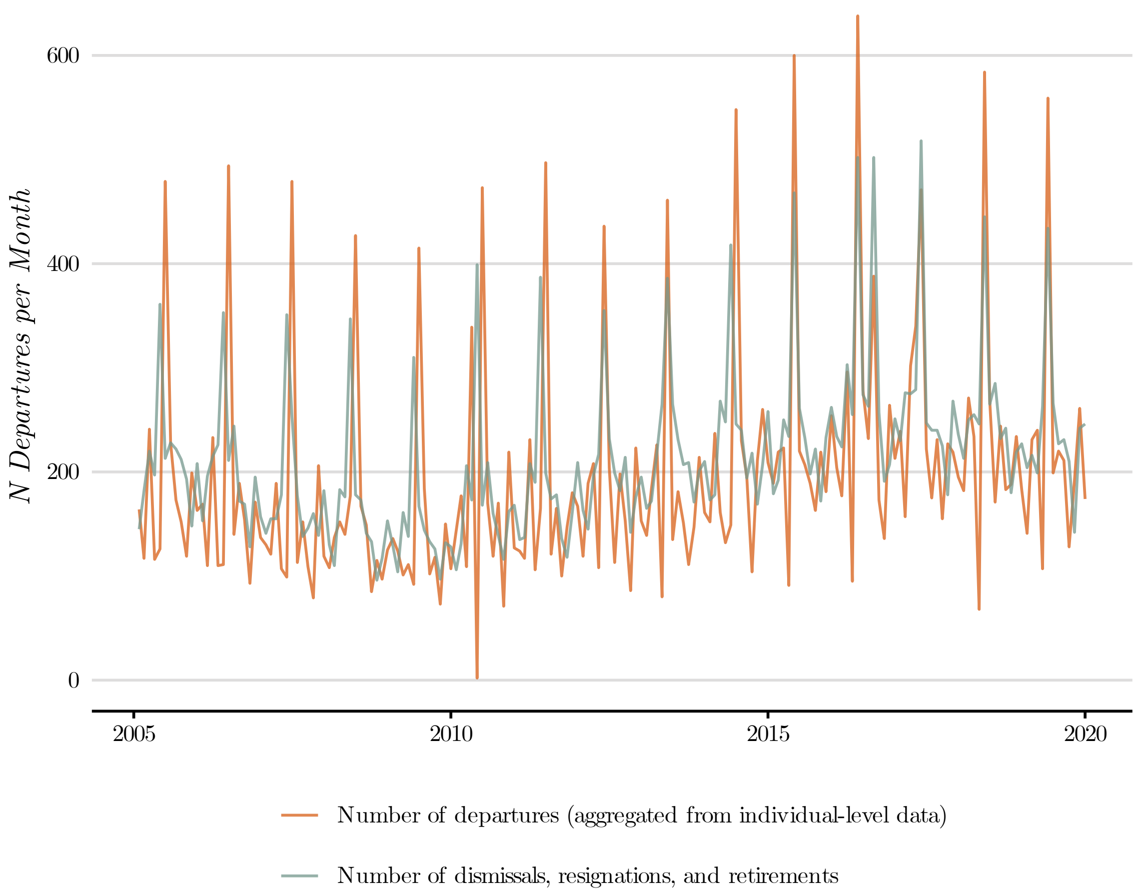


Figure D.2 – Comparison of Dependent Variables – Reclassified Agencies Compares the number of departures from the Departments of Corrections, Education, Human Services, and Marine Resources using the aggregated number of dismissals, resignations, and retirements, and the aggregated individual-level measure of departures from the personnel data. The measures include unclassified and part-time state employees.

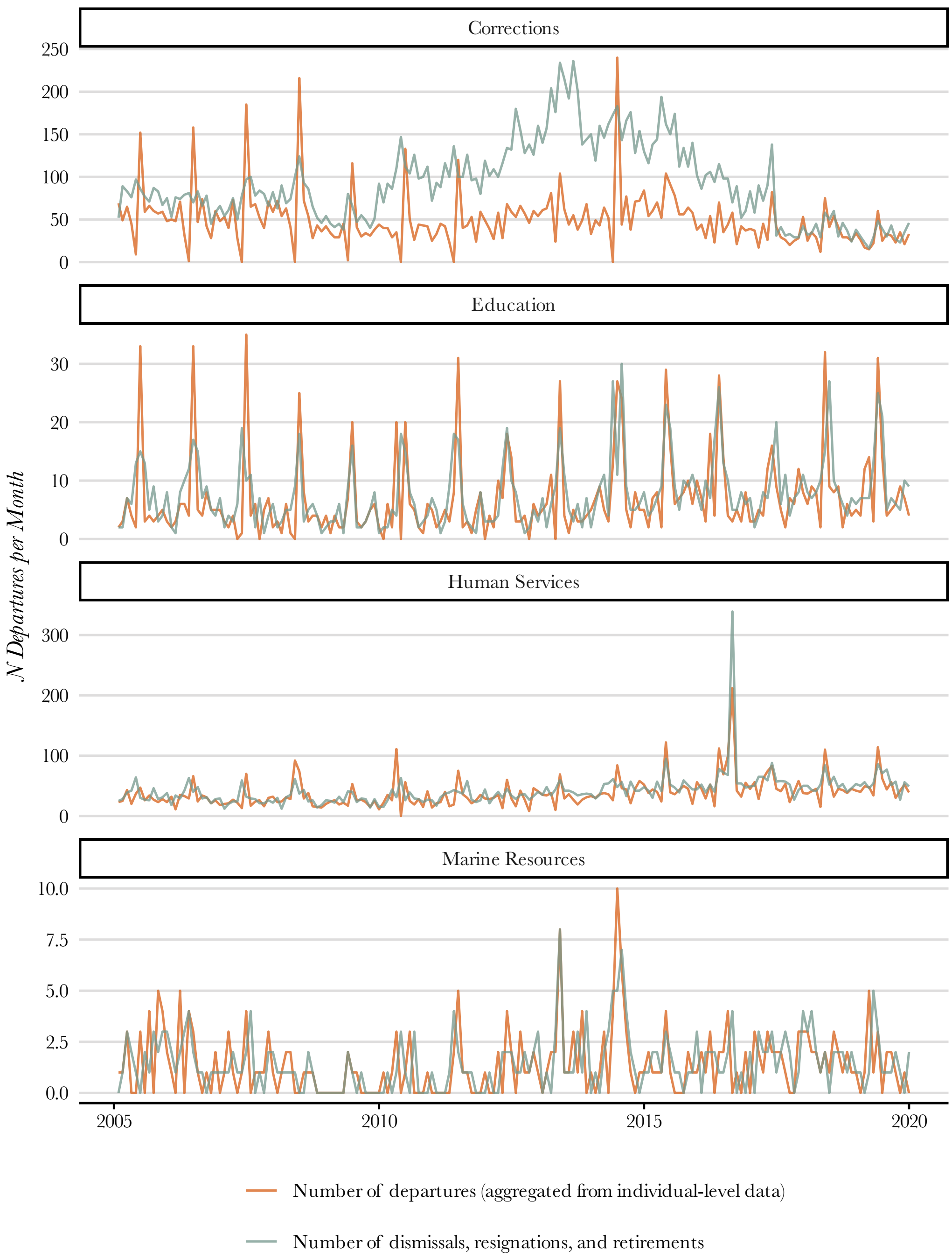


Figure D.3 – Agency Weights for Involuntary Dismissal Models in Figure 3 Shows the weights of the untreated units used to create the respective synthetic controls for the models testing the effect of reclassification on involuntary dismissals in the Departments of Education, Human Services, and Marine Resources. The agencies are ordered from right to left by number of employees. The variables used to generate the weights are shown in Figure D.4.

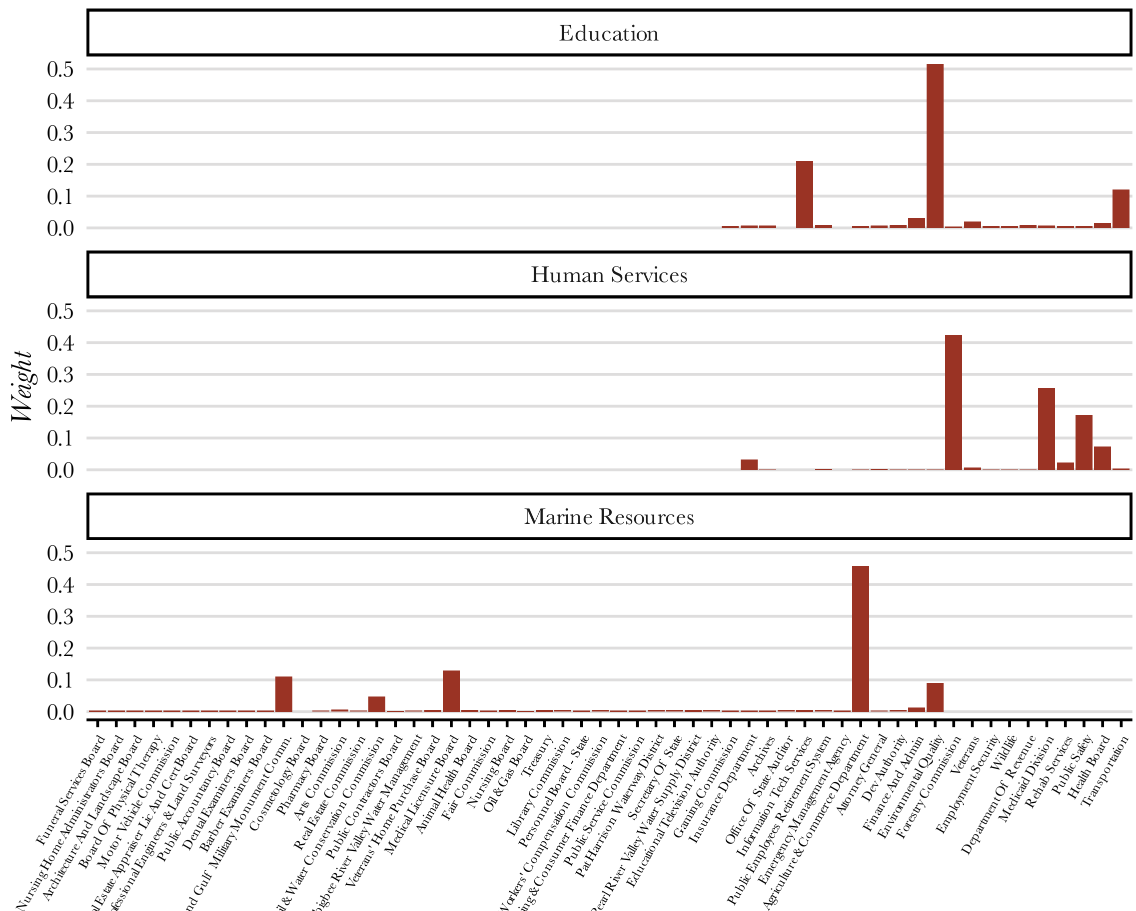


Figure D.4 – Variable Weights for Involuntary Dismissal Models in Figure 3 Shows the pre-treatment outcome variables and covariates used to generate the respective synthetic control models testing the effect of reclassification on involuntary dismissals in the Departments of Education, Human Services, and Marine Resources.

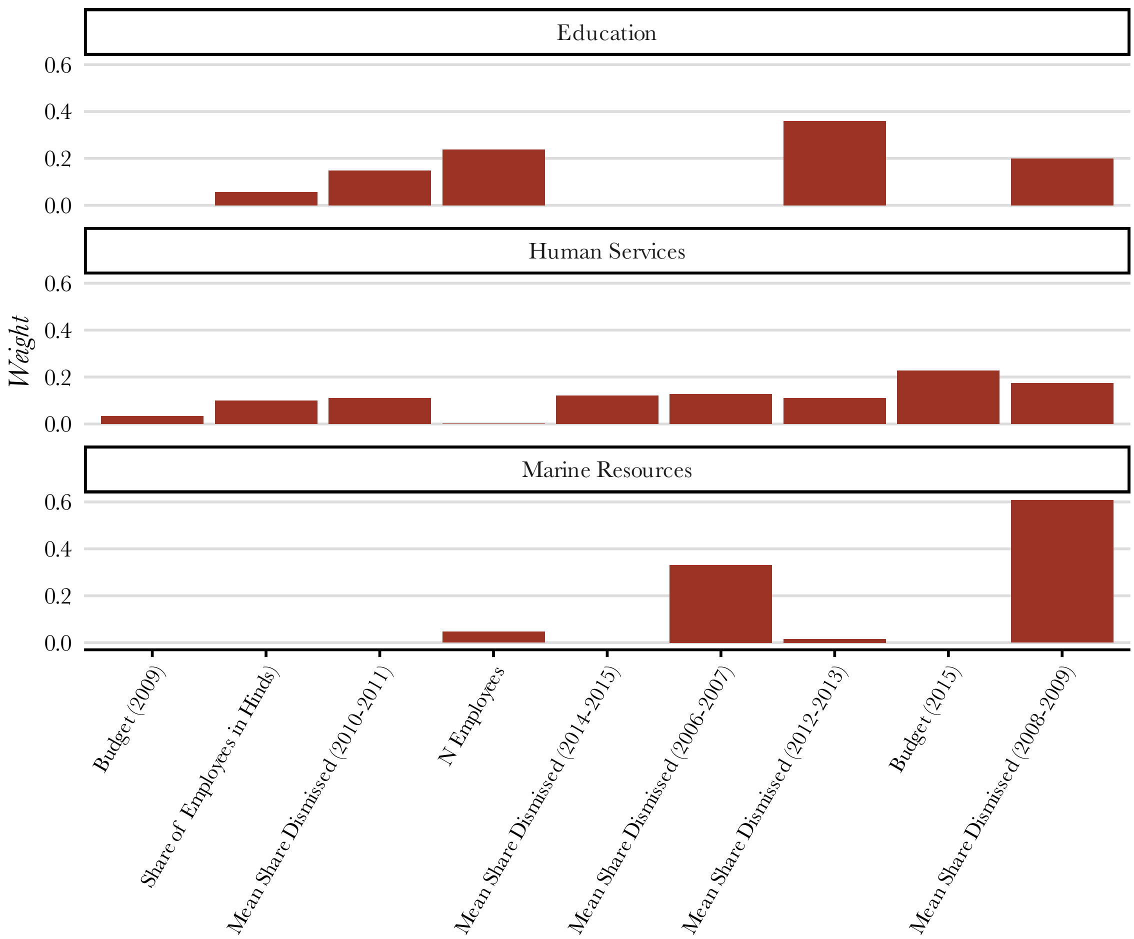
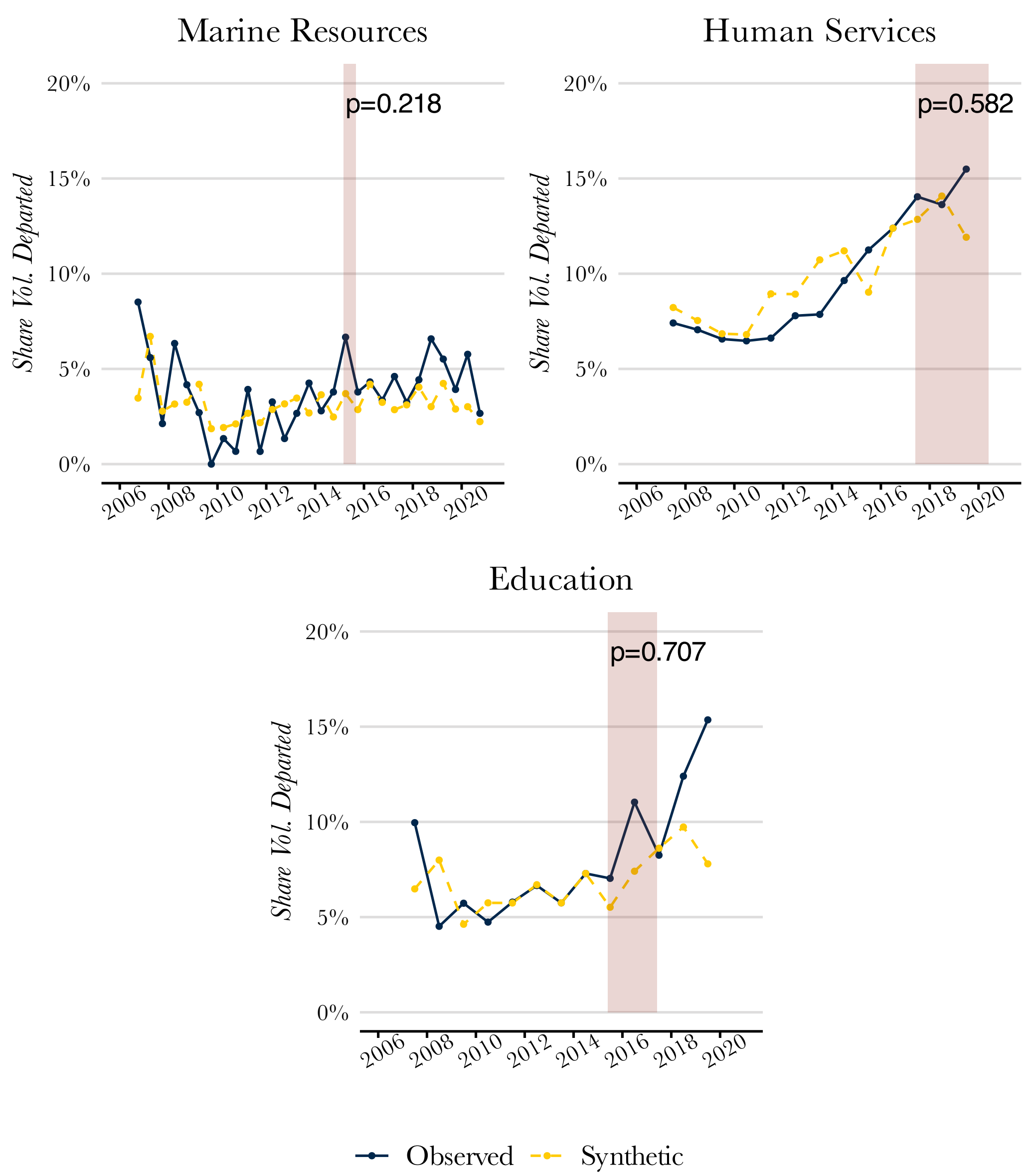


Figure D.5 – Effect of Reclassification on Resignations and Retirements Shows three separate synthetic control models comparing the share of employees in the given agency that resigned or retired from state employment in the given period (blue) against a statistically generated control (yellow). The unit of analysis for the Human Services and Education models is the agency-year. For the Marine Resources model, the unit of analysis is the agency-semiannual period. In each plot, a point represents the number of employees who retired or resigned over the forthcoming 12 or 6 months divided by the total number of employees in the agency at the start of the period. The shaded area in each of the plots represents periods where the given agency was not covered by the MSPB. The p value (rounded to the hundredth) represents the probability of observing a treatment effect as extreme via a series of placebo exercises where treatment is randomly assigned to an agency in the control set.



SI E `PanelMatch` Diagnostics and Robustness Checks

This section provides diagnostic information and robustness checks for the individual-level analysis examining whether Democrats were more likely to depart following reclassification than Republicans. Figures E.1 and E.2 show the size of the control sets and the covariate balance, respectively, for the four `PanelMatch` models in Figure 4. Figure E.3 shows differences between mean covariate values for treated and control groups in the `Panel Match` model moderated by tenure length. Figure E.4 shows an alternative version of the model moderated by tenure length with additional values for the years of experience moderator.

Figure E.1 – Histogram of Number of Matched Control Units Shows, for the `PanelMatch` model using only spigots in Figure 4, the frequency of sets of matched control employees of various sizes. Overall, the histograms show that most treated employees were able to be matched to control employees.

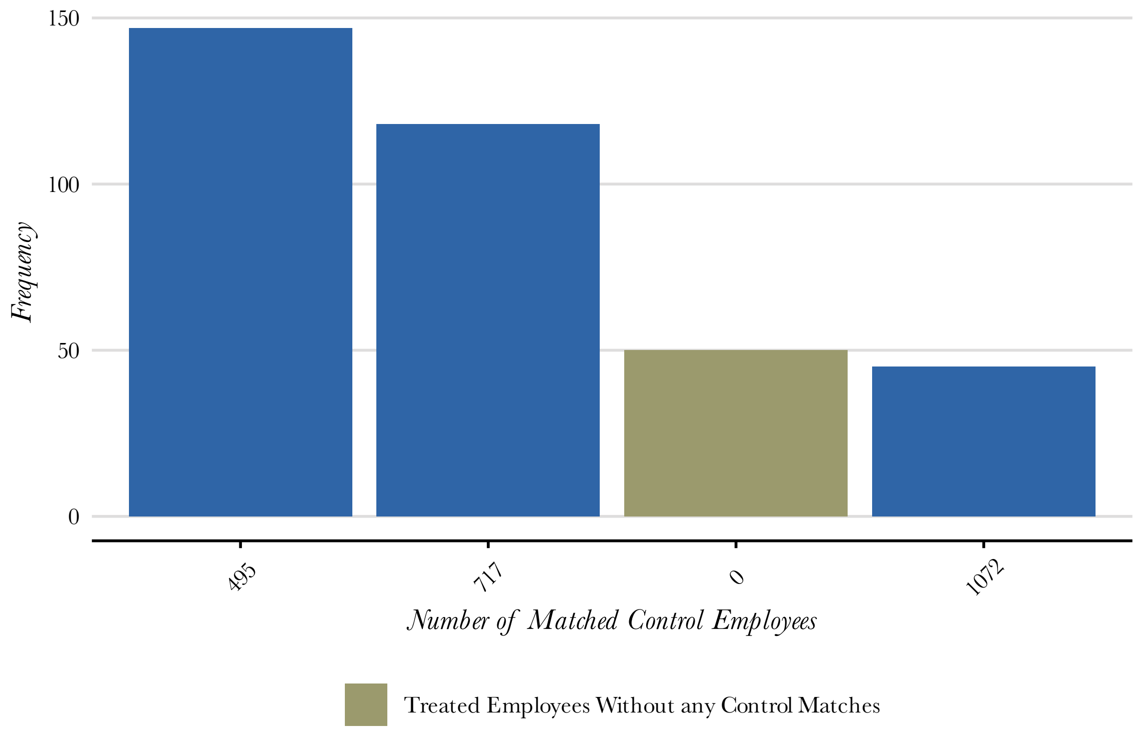


Figure E.2 – Covariate Balance across Treatment and Control Groups Shows, for the `PanelMatch` model using only spigots in Figure 4, the covariate balance in pre-treatment periods between treated and control employees. Covariate balancing is conducted using Covariate Balance Propensity Score matching.

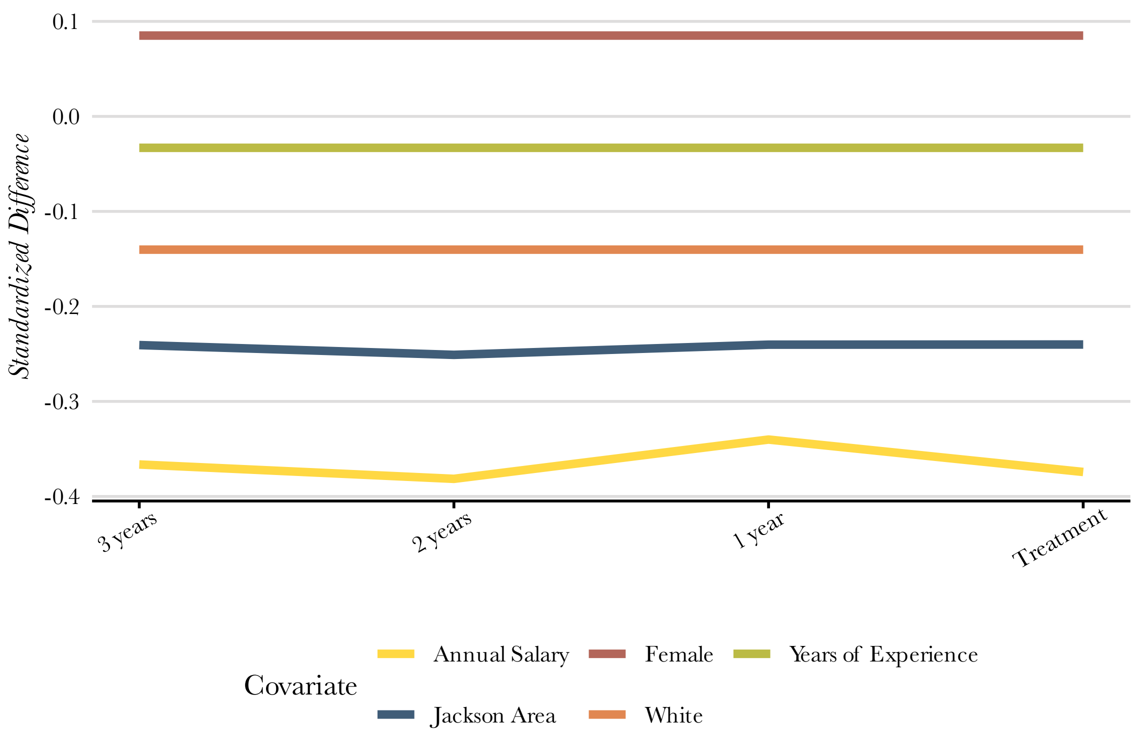


Figure E.3 – Covariate Balance Across Treatment and Control Groups for Tenure Length Model Shows, for the model in Figure 5, the covariate balance in pre-treatment periods between treated and control employees. Covariate balancing is conducted using Covariate Balance Propensity Score matching.

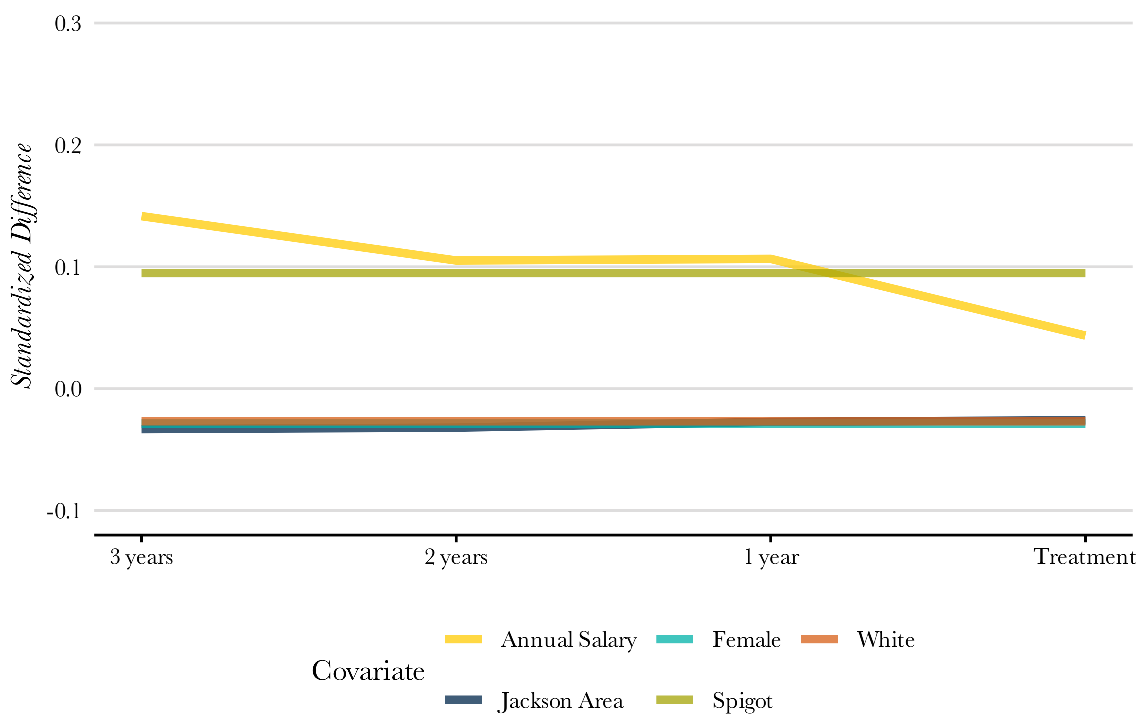


Figure E.4 – Treatment Effect Estimates for All Employees, Moderated by Years of Experience Shows point estimates and 95% confidence intervals from one `PanelMatch` model moderated by employees' years of experience. The model is the same as in Figure 5 except there are additional categorical values for the years of experience variable. The model includes all employees, regardless of whether they were matched to a voter, their seniority, or salary.