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ENTER THE PARTISAN FIRM: HOW AFFECTIVE POLARIZATION SHAPES CORPORATION AND CAREER

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CHAPTER 3

Office Politics: How Affective Polarization and Partisan Homophily Alter Hiring Decisions

In the current political climate, echoes of rising partisanship permeate popular culture, whether it's congressional gridlock, spirited debate on social media, the invitation of partisan speakers on college campuses, or even once mundane topics such as the Thanksgiving dinner or modern dating. Politics, especially partisan politics, is pervasive. Yet, we might wonder, given the fierce competition in landing a job, especially in a top company, how partisan politics affects hiring decisions and the job applications more generally. In an effort to have harmonious workplaces and perhaps avoid working with a colleague of the opposite political party, might employers simply take a pass on otherwise well-qualified applicants if they do not adhere to a firm's political culture? In this study, I investigate how the party identification of job market applicants affect the likelihood of receiving an interview callback for jobs in selective labor markets, and how might this effect vary by applicant prestige, which I gauge by the selectivity of prior universities and employers. These specific research questions inform broader theoretical questions, namely, how does affective polarization and relatedly partisan homophily affect organizational decision making, and how might it contribute to changing partisan polarization within and between firms. Although myriad experimental studies have been conducted in labor markets, few explore the processes of affective polarization specific to selective labor market entry, experimentally adjudicate selection effects on applicant party identification, or evaluate the additive benefits or congruence of applicant party identification versus ostensible qualifications. To evaluate these questions, I designed and implemented a large-scale computational resume correspondence test, utilizing experimental manipulation of applicant partisanship in resumes and cover letters. I combine this experimental data with data on firm partisanship, which affords the unique opportunity to evaluate affective polarization and partisan homophily at the firm level. These theories critically require knowledge of how the partisanship of both the applicant and the firm align or diverge. In this way, my research illuminates the role of affective polarization and partisan homophily in corporate hiring and sheds light on potential mechanisms behind rising partisan polarization in American firms.

3.1 Affective Polarization and Partisan Homophily in Selective Labor Markets

To evaluate affective polarization and partisan homophily in labor markets requires some definitional constraints. First, by selective labor markets, I refer to those not only in traditionally elite labor markets such as (1) elite professional service firms (investment banking, management consulting, and corporate law), but also other generally high profile entry-level jobs at (2) top firms in technology, quantitative finance, asset management, healthcare, and energy, among other industries. More generally, I include several job types for advanced degree applicants at a variety of companies, including those in the Fortune 1000, NASDAQ technology sector, and Russell 3000. Examining such top, as well as more generally selective firms, remains important, particularly since placement in these firms, particularly the elite ones, is seen as a gateway to top incomes and future corporate leadership (Rivera 2011, 2012a, 2012b; Useem and Karabel 1986).

Second, I seek to understand how an applicant's partisan affiliation affects hiring in selective labor markets as a process of *affective polarization*. Scholars define "affective polarization" as "the tendency of people identifying as Republicans or Democrats to view opposing partisans negatively and copartisans positively" (Iyengar and Westwood 2015:691; Iyengar et al. 2019). The work by Iyengar and Westwood (2015) extends research documenting escalating affective polarization, notably acute increases in "negative views of the out party and its supporters. . . since the 1980s" (Campbell et al. 1960; Green et al. 2002; Iyengar and Westwood 2015:691; Iyengar et al. 2019, 2012). Critical to this analysis, affective polarization delimits individual attitudes and behavior such that individuals not only hold animosity toward opposing party members but also view them as less intelligent (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Pew Research Center 2016). In fact, the bias based on affective polarization toward political out-groups "exceeds discrimination based on race" (Iyengar and Westwood 2015:690). Given the well-known examples of racial discrimination in labor markets (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016; Pager 2003), the findings on affective polarization suggest that a parallel process of partisan discrimination in labor markets may also occur.

Specifically, we might expect effects on two dimensions. Recall that Iyengar and Westwood (2015) include both (a) negative evaluations about opposing partisans and (b) positive evaluations of copartisans under the rubric of "affective polarization," however, the strength of these two (a) negative and (b) positive effects might vary (Iyengar and Krupenkin 2018; Iyengar et al. 2019). Indeed, the majority of studies focus on (a) negative evaluations of opposed partisans (Green et al. 2002; Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2012; Pew Research Center 2016), going so far as to say that "this phenomenon of animosity between the parties is known as affective polarization" (Iyengar et al. 2019: 130). Thus, for convenience, I will continue to refer to (a) the negative evaluations about opposing partisans as affective polarization or partisan animus while using the term partisan homophily or partisan matching to refer to (b) positive evaluations of copartisans or those members of the same political party. In this way, we can speak more succinctly about two discrete phenomena.

Ostensibly to evaluate affective polarization (and partisan homophily) relies on an intrinsically dyadic phenomenon. We must know the party of two individuals, groups, or combinations thereof. In this case, we must know the identification of the job applicant and that of the one receiving the materials or more generally the partisanship of the company and its subunits. Without capturing both the partisanship of both the applicant and firm, we can still comment on whether generalized discrimination against one party or the other exists in the job market, an approach taken in the majority of discrimination studies in other domains.[1] Yet, understanding the degree to which the partisan backgrounds of applicant and firm match or mismatch is needed to inform the affective polarization and partisan homophily hypotheses. To this end, my work here builds on (Mausolf 2020a), which employs a method of determining the political partisanship as well as the strength of that partisanship for individuals in firms using Federal Campaign Finance (FEC) data.

3.1.1 Hypothesized Results of Affective Polarization and Partisan Homophily in the Context of Diversity

Given partisanship measures for a subset of firms, we can extend the above discussion to some provisional hypotheses. Since the bias against political out-groups "exceeds discrimination based on race" (Iyengar and Westwood 2015:690), and studies evaluating racial discrimination on job market callbacks have found significant racial effects (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016; Pager 2003), I hypothesize that fictitious applicants whose partisan identity opposes the firm to which they apply will be less likely to receive callbacks than the politically neutral, matched control, and similarly will be less likely to receive callbacks than those individuals matching the partisanship of the firm. Although I anticipate the effects of partisan homophily to be similar although from a likely weaker mechanism, I hypothesize that in general, applicants whose partisan identity matches the firm will have a slightly better chance of a callback than a matched politically neutral applicant. Across all applicants, I posit that copartisans (those with matching partisanship) will on balance receive a greater number of callbacks than opposing partisans (applicants with opposed partisanship), a hypothesis consistent with past studies of affective polarization, including

[1] For example, the typical correspondence test evaluating applicant race, ethnicity, or resume whitening does not consider or evaluate how the race or ethnicity of the individual receiving the applicant profile (or similarly firm diversity) might affect the likelihood of providing a callback for that applicant (*c.f.* Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016).

evaluations of resumes (Iyengar and Westwood 2015), or the effects of an applicant matching or mismatching the partisanship of the geographic area wherein the job resides (Gift and Gift 2015). I posit that these effects will vary by the partisan polarization of the firms, such that firms exhibiting strong partisanship will be more likely to exhibit both the (a) affective polarization hypothesis and (b) partisan homophily hypothesis while firms that are either more moderate, or even bipartisan in their affiliation, may exhibit weaker, or even statistically insignificant effects for both hypotheses. In fact, for truly bipartisan firms or firms with a high degree of political diversity, these firms might even have a preference for the politically neutral applicant rather than someone with an overt signal of partisan allegiance.

This latter supposition raises an important intuition for the hypothesized effects of affective polarization and partisan homophily, in that while they may be powerful mechanisms, that very mechanism in all likelihood will work against applicant success under conditions of uncertainty or in firms manifesting partisan diversity. Where partisanship of the firm is unknown, politically neutral applicants might be more successful than the randomly assigned partisan profile. However, given other pieces of information such as (1) the partisan profile for the general population where a firm's office is located, (2) the average partisanship and partisan polarization exhibited by similar firms with known partisanship (such as energy companies versus technology firms), and (3) the average partisanship and polarization for similar jobs (such as software engineer versus financial analyst), we could likely approximate or classify the partisanship of unknown firms, using, in part, the measures along these and other features for known firms as training data. If such a classification process were reliable (using different evaluation metrics such as precision and recall), then I would anticipate that the affective polarization and partisan homophily hypotheses might also hold for firms with classified approximations of partisanship. Although I do not perform this latter method here, it remains a possibility for future studies.

3.1.2 Considering the Positive and Negative Motivations of Diversity

Relative to the overall thrust of research on affective polarization and partisan homophily, while both trends suggest that copartisans would be more likely than opposing partisans to receive a callback, we can also glean additional insight from the diversity literature. Although there is some evidence to suggest that bipartisan teams may produce higher quality work (Shi et al. 2019),[2] and that teams with functional diversity may yield greater innovation and creativity (Burt 2000, 2004; DiTomaso et al. 2007; Dobbin and Jung 2011; Hambrick et al. 1996), the vast majority of research reveals negative effects for diverse teams, particularly those with diversity on salient social dimensions, which would include partisanship (DiTomaso et al. 2007; Williams and O'Reilly 1998). Beyond averting the downsides of diversity, firms might try to capitalize on the benefits of homogeneity such as improved social connectivity, trust, and emotional attachment (Brewer 1981; Ibarra 1992, 1995; McPherson et al. 2001; Meyerson et al. 1996; Reagans and McEvily 2003). Firms might also frame these benefits of homogeneity in terms of emphasizing the importance of organizational or cultural fit, which consistently proves to be an integral feature (Goldberg et al. 2016; King et al. 2010; Rivera 2012b; Stinchcombe 1965). Although firms might arguably try to promote diversity to avoid or assuage legal sanctions, regulation, or negative press (Dobbin and Sutton 1998; Kalev and Dobbin 2006; Kalev et al. 2006; Skaggs 2008), political partisanship is not a protected class under Equal Employment Opportunity Commission guidelines (U.S. Equal Employment Opportunity Commission 2020), and even protected classes such as race, gender, or sexual orientation have not preempted ostensible discrimination (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016; Tilcsik 2011). Relative to the hypotheses on affective polarization and partisan homophily, therefore, most evidence in the diversity versus homogeneity and organizational fit literature substantiate the overall hypothesis that

[2] In Shi et al. (2019), for example, we see higher quality work produced by bipartisan teams in an open-source environment, namely Wikipedia editor contributions. The same dynamics may not transpire with teams in a typical corporate environment.

applicants aligning with the partisanship of the firm will receive more callbacks than applicants whose partisanship opposes that of the firm.

3.1.3 Additional Intervening Criteria for Partisan Effects: Applicant Prestige and Job Type

Beyond differences that may occur from whether the partisan direction and strength for a firm can be determined, I also anticipate that the general hypothesized effects may vary by the selectivity of firms. For example, we might wonder whether the effect of partisan homophily varies by the *selectivity of the corporation*, or more generally the job industry. Since my analysis extends beyond traditionally elite labor markets and includes other selective firms in the Fortune 1000, NASDAQ tech sector, and Russell 3000, my results, while illuminating effects for elite labor markets, will also be informative for a broader population of job applicants (*c.f.* Rivera and Tilcsik 2016).[3]

Relatedly, the study also examines how partisan homophily *varies by applicant prestige,* which I measure by the selectivity of past educational institutions and employers. Do the effects of *partisan homophily and affective polarization* outweigh the effects of applicant prestige (for example in university, degree, or skills)? In other words, it is not simply a question of whether party identification shapes selective labor market outcomes, but whether political partisanship might be an understudied effect that interacts with or outweighs human capital approaches to labor market success and failure. While the experiment does not test prestige effects within pairs, we can look across pairs to evaluate whether the effects of partisanship (affective polarization and partisan homophily) have stronger or more pronounced effects for high prestige or low prestige applicants. Before positing these effects, I need to first elaborate on why applicant prestige might matter.

[3] Broadening the scope in this way can allow for experimental manipulation of both elite labor markets and selective labor markets. As Rivera and Tilcsik (2016) note, experimental approaches to elite labor markets are challenged by the frequent method of campus recruitment by elite firms (Rivera 2011, 2012b, 2012a). This rationale was used by Rivera and Tilcsik (2016) to focus on selective but not elite law firms. Still, while recruitment for elite firms may often occur or be advertised through on-campus events, applicants, including those from elite universities can still submit resumes and applications online through employers, particularly when done at the correct time in the recruitment cycle.

Although a number of studies have examined the effects of elite credentials along with intersecting facets of college major, family socioeconomic status, human capital investment, and elite college preparatory academies (Altonji, Blom, and Meghir 2012; Barrow and Malamud 2015; Dale and Krueger 2002; Hoekstra 2009; Levine 1980; Useem and Karabel 1986), those in particular that have used correspondence tests or in-person audits have found employers prefer applicants with elite educational backgrounds, higher prestige, or markers of high social class (Gaddis 2015; Rivera 2012b; Rivera and Tilcsik 2016). In combination, these studies suggest that on balance, high prestige applicants will receive significantly more callbacks than equally skilled applicants from less selective educational and employment backgrounds. I hypothesize my experiment will similarly demonstrate that high prestige applicants with highly selective educational and employment backgrounds will receive more callbacks than equally qualified applicants from less selective backgrounds.

Using a bounded rationality approach (March and Simon 1958), employers may favor elite-credentialed applicants to minimize search costs, assuming elite universities have selected and rewarded those with the greatest ability (Rivera 2012b). Employers might also prefer elite applicants as a status symbol (Rivera 2011). Rivera (2012b) also points to a mechanism known as cultural matching, a term coined in DiMaggio (1992) and reminiscent of DiMaggio and Mohr's (1985) use of culture in matching marital partners. Given the excessively long hours (sometimes 80 or more) that employees at top firms dedicate, I suggest that once applicants are deemed to be well-qualified, employers seek to match politically (or conversely avoid working with someone of an opposed partisan identity) as well as match on other cultural attributes, looking not just for good employees but also friends (Iyengar and Westwood 2015; Rivera 2012b). This matching process depends not only on the employer but also the perspective of the potential employee such that the entire job search can be thought of as a process of matching applicants to jobs (Kalleberg and Sørensen 1979; Sørensen and Kalleberg 1981; Tilly and Tilly 1998), (*c.f.* DiMaggio 1992; Schneider 1987).

Given past findings that applicant prestige matters (Gaddis 2015; Hoekstra 2009; James et al. 1989; Rivera 2011, 2012b), we might also expect to see such effects in this analysis. That said, I hypothesize that applicant prestige may matter less for certain technology-oriented fields like data science and software engineering and matter more for business (MBA) and quantitative finance positions. This rationale generally follows from the premise that in high-intensity professions, especially elite professional service firms—such as law firms, investment banking, or consulting—only consider applicants from a select subset of super-elite, prestigious universities (Rivera 2011, 2012a, 2012b). This preference stems from viewing admission to these schools as not only a measure of merit but also as one creating a shared experience since many of the top firms' current employees also attended these schools (Rivera 2011, 2012b). As an added bonus, having a client-facing firm replete with elite-credentialed employees is also a selling point (Rivera 2011, 2012b). By contrast, highly technical jobs such as software engineering or data science often care less about where, or even whether, applicants received a degree and more about the caliber of demonstrable technical skills. At the same time, my creation of high prestige applicants is more in line with the approach taken by Gaddis (2015), which uses top universities but not necessarily only the "super-elite" top four schools evaluated in Rivera (2011).

Regardless of the job type or applicant prestige, however, we might also expect organizational variation in callback rates, especially as it relates to discrimination or bias. For example, if organizations have strong protocols discouraging discrimination, these policies may reverse or mitigate affective polarization and partisan homophily (Dobbin et al. 2011; Kalev et al. 2006; Pedulla 2016). Lastly, the degree to which partisan homophily and affective polarization matter may vary by how elite a firm is or how much time employees interact or travel in a typical week. Because more prestigious firms will have a greater number of applicants, they will be more likely to select an individual with a highly selective background on balance. With these caveats in mind, demonstrating a clear effect that affective polarization or partisan homophily matter more at one level of prestige than another will prove challenging. If enough data exists, the primary effect that may emerge across cases is that partisan matching might offer a larger benefit for applicants from less selective backgrounds, particularly if the firm exhibits strong partisan polarization. Since the hypothesized effect of applicant prestige may simply result in not enough positive responses to applicants from less selective backgrounds, however, the effects of partisan bias might only be measurable among high prestige applicants.

3.1.4 Expanding the Literature to Understand the Role of Partisanship in Hiring

Empirically, the primary questions regarding the effects of political partisanship in the hiring process as well as how applicant prestige matters have not been adequately explored in existing studies, which emphasize one of several dominant approaches. First, the majority of studies examining *elite* labor markets do not conduct experimental examinations (Rivera 2011, 2012a, 2012b). Rivera's primary work—while incredibly informative—employs qualitative rather than experimental methods to elite labor markets. Nonetheless, these studies illuminate the importance of applicant prestige, cultural matching, and intersections with diversity. In an effort to apply experimental methods, Rivera and Tilcsik (2016) study *selective* but not *elite* law firms, focusing on social class and not political partisanship.[4] Gaddis (2015) examines hiring relative to applicant prestige but does not examine elite firms specifically or evaluate political partisanship. Lastly, Iyengar and Westwood (2015) examine affective polarization based on party identity in a number of ways, including resume evaluation, but the evaluators were a random sample of adults from a survey institute and the study was unrelated to firms and actual job applications. Similarly, in studies evaluating the effect of political partisanship on job market callbacks, Gift and Gift (2015) showed that applicants

[4] As noted above, I believe there may be fruitful analyses for assessing callbacks from applications to selective firms, even if these companies also heavily participate in on-campus recruiting at elite universities. For example, top firms in management consulting (McKinsey and Company), investment banking (Goldman Sachs), hedge funds (Citadel), and technology (Google) each offers any interested prospect the opportunity to apply online. Company contacts may also be directly emailed with resumes and cover letters.

were less likely to receive a callback when their partisanship diverged from the majority party in a job locale, compared to a candidate with neutral partisanship or those aligned with the partisan majority.[5] Again, however, Gift and Gift (2015) does not evaluate these effects at the firm level or manipulate applicant prestige.

A second major approach is to examine applicant prestige. A number of scholars capture aspects of these ideas either qualitatively (Rivera 2011, 2012a, 2012b) or experimentally (Gaddis 2015; Rivera and Tilcsik 2016). Using survey or institutionally collected data, scholars have found conflicting evidence about the value and career mobility of an elite credential, especially considering the intersecting facets of college major, family socioeconomic status, human capital investment, and elite college preparatory academies (Altonji et al. 2012; Barrow and Malamud 2015; Dale and Krueger 2002; Hoekstra 2009; Levine 1980; Useem and Karabel 1986). Some of these studies evaluating applicant prestige are non-experimental and apply only to elite professional service firms Rivera (2012b). Others are experimental but only evaluate social class not educational credentials and are specific to selective law firms Rivera and Tilcsik (2016). On the basis of educational credentials alone, my study while holding skills constant, examines the effects of highly selective educational backgrounds versus less selective education (at both the graduate and undergraduate level) and captures those effects across a wide variety of jobs in the United States. The use of graduate degrees also offers a unique facet, as most studies, examine college graduates. As an additional layer of prestige, I also include highly selective versus less selective work experience.

A third and dominant dimension of experimental labor market analyses is to examine

[5]It is worth noting that some conflation of ideology and partisanship exists in Gift and Gift (2015). For example, the authors write, "three types of resume-county combinations: in-partisans (i.e., conservative resumes in Collin County and liberal resumes in Alameda County), out-partisans (i.e., liberal resumes in Collin County and conservative resumes in Alameda County), and non-partisans in both counties" (Gift and Gift 2015: 664). Despite the conflation of ideological and partisan labels, it appears what Gift and Gift (2015) tests most clearly is partisan alignment. For example, partisanship was manipulated on resumes by ascribing "Republican" or "Democratic" jobs and extracurriculars versus jobs and extracurriculars without partisan affiliation (Gift and Gift 2015: 654). Similarly, the designation of liberal/conservative counties relied on evaluating the proportion of votes given to the Obama versus McCain presidential tickets (Gift and Gift 2015: 659).

labor market discrimination by race, gender, or sexual orientation. Race is widely studied, including facets that examine discrimination on the basis of racially specific names or resume whitening (Bertrand and Mullainathan 2004; Gaddis 2015; Kang et al. 2016), racial intersections with criminal history (Pager 2003, 2007), and racial dimensions of joblessness (Pedulla 2016). Gender is likewise assessed by a number of studies, especially related to wages or motherhood penalties (Correll et al. 2007; Pedulla 2016). Sexual orientation has also been examined in audit studies (Tilcsik 2011). Given that these effects are already widely documented, my study focuses on the effects of partisanship versus applicant prestige on job market callbacks specific to white men. Future studies should compare the discovered effects for different intersections of race, gender, or social class.

Collectively, given the possible competing mechanisms, the empirical gap in the literature, and the unexplored interactions of partisanship and applicant prestige, these ideas deserve further elaboration with a thoughtful experimental design. Beyond augmenting gaps in the labor market literature, my study also contributes to a broader question that will help explain the emergence of party sorting in firms, extend the affective polarization literature to the firm level, and illuminate a debate in the organizational diversity literature.

3.2 Data and Methods

3.2.1 Experimental Method: Resume Correspondence Tests

In this analysis, I conduct a specific type of field experiment known as a *correspondence test* in order to assess callback rates for fictitious job applicants based on an experimental manipulation of applicants' political partisanship and prestige. These features are conveyed by their resumes and cover letters. Often used to examine ascriptive characteristics such as race and gender (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016), correspondence tests, which are alternatively referred to as "correspondence audit" studies are particularly well suited for applying to professional jobs.[6] To execute this experiment, I designed and wrote an end-to-end series of *Python* scripts which largely automate the experimental protocol, including searching for and identifying relevant jobs at a given set of companies, composing the cover letters to company representatives, making the resumes, and sending the emailed cover letters with attached resumes to respective company contacts. In the sections below, I outline additional details of the experimental design.

3.2.2 Experimental Design

In the experiment, I submit fictitious resumes and email cover letters to entry-level professional jobs for applicants completing an MBA, MS, or PhD. Specifically, I sent two email cover letters, each with a unique resume attached to a single representative at each company[7]. In this way, each firm receives a matched pair of fictitious applicants on subsequent days, where one is a treatment (partisan applicant) and the other is a control (neutral applicant).[8] This matched pair design is similar to past matched pair designs (Correll et al. 2007; Gaddis 2015;

[6] In labor market analyses, there are two principal types of field experiments: the audit study (sometimes called the "in-person audit study") and the correspondence study. Although there is some definitional looseness about these terms, the *audit study* typically refers to the use of trained actors, known as auditors, who apply or interview for jobs, whereas the *correspondence test* refers to sending fictitious resumes to job applications and measuring employer response (Bertrand and Mullainathan 2004; Pager 2003; Pager and Western 2012). For example, Pager and Western (2012) discuss Bertrand and Mullainathan (2004) among a section elaborating examples of audit studies. Here, Pager and Western (2012) mention "in-person audit studies" and "correspondence studies," without a clear delineation between the methods. Pager (2003) is clearly aware of the difference, spending considerable discussion on the matter. Adding to the confusion, Correll et al. (2007) closely mirror the exact correspondence-test method of Bertrand and Mullainathan (2004), but widely refers to their work as an audit study. Bertrand and Mullainathan (2004) explicitly differentiate their method from audit studies, spending several pages articulating the many weaknesses of the audit approach, particularly the use of trained auditors versus resumes. Pager (2003) conversely advocates the merits of audit studies over correspondence tests. More recent literature seems to adjudicate the confusion by using the terms "in-person audit" versus the terms "resume audit," "correspondence audit," and "computerized audit" to refer to traditional audit studies versus correspondence tests (Gaddis 2015; Kang et al. 2016; Pager and Western 2012). In-person audit studies have many limitations, including cost, small sample size, effective auditor matching, auditor effects, and single-blind design, among others (Bertrand and Mullainathan 2004; Heckman and Siegelman 1993; Pager 2003).

[7] To ensure no duplicates existed after the company matching process, the protocol was restricted to unique email addresses. In this way, each firm contact receives only one pair of applicants.

[8] The details of the research design are described below, and the study was preregistered prior to running the experiment (Mausolf 2020d).

Table 3.1: 2x2 Between-Subjects, Matched Pair Design

	Democrat	**Republican**
High Prestige	Democrat, Highly Selective Neutral, Highly Selective	Republican, Highly Selective Neutral, Highly Selective
Low Prestige	Democrat, Less Selective Neutral, Less Selective	Republican, Less Selective Neutral, Less Selective

Notes: Applicant prestige is primarily indicated by the *selectivity* of past educational and professional experience and to a lesser extent by the socioeconomic signal of their first name.

Pedulla 2016; Tilcsik 2011),[9] and its delivery of cover letters and resumes by email follows a standard approach adopted by many scholars (Correll et al. 2007; Gift and Gift 2015; Rivera and Tilcsik 2016; Tilcsik 2011).[10] Echoing the approach of Pedulla (2016), both the order in which a firm representative receives the treatment and control as well as the resume and cover letter version for each pair is randomized and counterbalanced.[11] Beyond the first level of experimental design of using a matched treatment-test pair of applicants, I employ a second layer of experimental design, often characterized as a 2x2 between-subjects factorial design, similar to work by Rivera and Tilcsik (2016) and Kang et al. (2016). Organizations are randomly sent one of four matched-pairs of resumes, which vary in two-dimensions. First, the partisan treatment may take one of two conditions: Democrat or Republican. Second, the matched pair may be one of two prestige backgrounds: highly selective or less selective. This results in 4 unique pairs of matched applicants as shown in Table 3.1.

[9]Gift and Gift (2015) takes the paired design one step further by sending firms a set of three resumes, one Republican, one non-partisan, and one Democratic.

[10]The method of delivering applicant pairs varies. While Tilcsik (2011) sends applications by email (599) and Correll et al. (2007) use "email, fax, or paper" (1328), Gaddis (2015) applies to jobs using a third party job search website and eliminates jobs that require application on the company's website (1459), a convention that Pedulla (2016) also follows (286). Kang et al. (2016) intended to use a matched pair design but were required to only use a single application per firm by their IRB.

[11]Both the order and design for an applicant pair are randomly and independently assigned with equal probability, resulting in counterbalanced groups. For example, the following four order/version design pairs result: $[T_A, C_B]$, $[T_B, C_A]$, $[C_A, T_B]$, $[C_B, T_A]$, for each permutation of applicant prestige level (High/Low), and treatment condition (Republican/Democrat).

Although the assignment of one of the four matched pairs is randomized, the probability of receiving a given pair is not equiprobabilistic. Instead, both the treatment conditions (Democrat or Republican) and the prestige conditions (High or Low) have the following unbalanced probabilities of selection: Democrat, Pr(0.4); Republican, Pr(0.6); Highly Prestige, Pr(0.7); and Low Prestige, Pr(0.3). The inclusion probabilities for pairs is as follows: Republican, High Prestige, Pr(0.42); Democrat, High Prestige Pr(0.28); Republican, Low Prestige, Pr(0.18); and Democrat, Low Prestige, Pr(0.12). In brief, both High Prestige, and Republican applicants are more likely. The decision to have differential assignment probabilities for the pairs follows both theoretical and empirical assumptions.

In terms of prestige, high prestige applicants are considerably more likely to receive callbacks or interviews than those with less selective academic and employment histories (Gaddis 2015; Rivera 2012b; Rivera and Tilcsik 2016). Since my primary objective is to evaluate the effects of political partisanship—and I primarily gain analytical power if the partisan or non-partisan applicant receives a callback, versus neither applicant receiving a callback—I elected to send a greater number of resumes with a higher probability of receiving a callback into the field.

Regarding unbalanced partisan conditions, my previous analysis of partisan polarization in firms (Mausolf 2020a) reveals that more firms exhibit partisan polarization in the Republican versus Democratic direction, and of those firms not exhibiting extreme partisan polarization, the majority also lean Republican. Recall that I expect there may be differential and slightly stronger effects for affective polarization (in the valence of negative bias against the opposite party) compared to partisan homophily. In other words, a political mismatch will be less likely to receive a callback than a politically neutral applicant, and this effect will be stronger than the partisan homophily effect. While dependent on the difference in effect sizes, generally, we might anticipate needing more incidences of political matches than mismatches. In this way, even though the assignment of pairs to firms is random, by providing a greater number of

Republican versus Democratic partisans in the field, I slightly increase the likelihood that there will be a partisan match between the treatment condition and the firm.

3.2.3 Experimental Delivery and Matching

Two important tensions exist in correspondence audit study designs, and these merit discussion. One tension is the use of a matched pair of applicants versus a single applicant per firm. The second tension is the method of application. Regarding the use of matched pairs versus single applicants, matched pairs afford a higher number of observations to be gathered, and thus a higher degree of statistical power than using one applicant per firm, holding the number of firms constant (Gaddis 2015). Typically, at most, a single pair of applicants will be sent to a firm, although some studies have submitted three (Gift and Gift 2015). Another important benefit from a matched pair design is the capacity to directly observe within-pair differences between the treatment and control (Gaddis 2015: 1474), which is not possible with single-applicant designs. Furthermore, matched pair designs afford the ability to draw unbiased between-pair estimates provided there are no systematic differences in the assignment of pairs to jobs or other observable characteristics conveyed through application materials (Gaddis 2015: 1459, 1474; Pager 2003: 957). Although between-pair effects can endow meaningful insights, such effects are statistically "less efficient than within-pair comparisons" (Gaddis 2015: 1459; Pager 2003: 957). Similarly, in the typical single applicant design, only between-subject effects can be evaluated, and these are less efficient than within-subject effects or the within-pair effects found in a matched pair design. As a result, most studies using a single applicant design concede some of these benefits of matched pairs and cite that a rationale for utilizing a single applicant design was the result of their institutional review board's concerns about firm time burdens or restrictions prohibiting a matched pair (Kang et al. 2016: 486; Rivera and Tilcsik 2016: 1104). Although matched-pair designs have an increased risk of detection (Gaddis 2015; Kang et al. 2016; Weichselbaumer 2015), a number of steps can be taken to help avoid discovery. One of the most basic steps includes submitting fictitious applicants at different times, often one day apart (Gaddis 2015; Pedulla 2016; Tilcsik 2011). Similarly, researchers typically vary the resume and cover letter content in a number of ways (Gaddis 2015; Pedulla 2016). I conduct similar efforts to avoid detection of the experimental pair of applicants.

The second important tension in correspondence audit studies is the delivery method, typically by email or by directly applying online. Applying online certainly has benefits, including a lower risk of detection since those applications, when applied directly to a job through a third-party, will fall in a highly populated applicant pool. The use of online applications is common (Gaddis 2015; Kang et al. 2016; Pedulla 2016).[12] Typically, however, these application-based audits have limits, chiefly that they are only permissible to the extent a third-party job board permits application directly through their website. This restriction emerges (1) ethically as an institutional review board concern (Pedulla 2016: 286); (2) methodologically as an external firm application is computationally impractical, or otherwise time-prohibitive (Gaddis 2015); or (3) methodologically as such external applications often have long and unique requirements such as transcript authentication or essay responses that preclude valid experimental manipulation (Pedulla 2016: 286; Rivera and Tilcsik 2016: 1107). Ostensibly, these three restrictions often occur in combination. Although applying directly to a third-party standardized application avoids these downsides, this strategy excludes any company requiring a direct application. Unfortunately, most major corporations' job postings only offer the option to apply directly on an external company website. Since my study specifically targets such companies, direct application is unfeasible, leaving the second approach of email submission of resumes and cover letters.

As previously mentioned, the direct submission of applicant resume and cover letters, typically by email, is commonly used in correspondence audit studies and has a number of

[12] Many scholars took the online approach. See (Gaddis 2015: 1459; Pedulla 2016: 286), who both send two applicants per firm, or (Kang et al. 2016: 488), who sent a single application.

benefits (Correll et al. 2007; Rivera and Tilcsik 2016; Tilcsik 2011; Weichselbaumer 2015). Apart from the benefits of reaching employers inaccessible through direct company-specific online applications, the method has the advantage of computational efficiency and standardization. Furthermore, greater insight can be drawn from responses gleaned via an email campaign. Quite simply, application submission to third-party job-boards results in an opaque process of uncertainty. For example, once submitted, it is unclear who eventually examines that resume. It could be a singular human resource agent, the hiring manager, or a multistage panel review. Under such uncertainty, it is impossible to match the partisan affiliation of the person or group receiving the application because their identities remain unknown. Given enough information, for example, an email method could better disentangle affective polarization and partisan homophily at the level of the application recipient versus the firm. At the same time, if only the partisanship of the firm can be determined, this latter point matters little. In either case, as mentioned above, an email campaign has multiple experimental benefits over direct application.

3.2.4 Experimental Treatment and Control of Partisanship

Experimentally, I will manipulate political affiliation with three categories (Republican, Democrat, and neutral). This can be signaled on resumes through leadership experience, such as whether an applicant was (a) president or vice president of the Young Democrats or Young Republicans or (b) president or vice president of the Student Government Association (*c.f.* Gift and Gift 2015; Iyengar and Westwood 2015). In each case, the applicant has a comparable, recognizable leadership quality justifying its existence in application materials (Tilcsik 2011), but the political identity differs from representing a Democratic, Republican, or neutral affiliation. Similar signaling of self-identity has been used by denoting extracurriculars on resumes to signal race, sexual orientation, and political party (Gift and Gift 2015; Iyengar and Westwood 2015; Kang et al. 2016; Pedulla 2016; Tilcsik 2011). In this way, the proposed experimental intervention has ecological validity grounded in past research.[13] Whereas Iyengar and Westwood (2015) signal partisanship using the aforementioned Young Republicans or Young Democrats leadership experience, Gift and Gift (2015) signals partisanship by replacing the most recent employee experience with a partisan political campaign (in addition to partisan extracurriculars). Although Gift and Gift's (2015) method provides a strong partisan signal, the specific selective labor markets I target necessitate particular, often technical, employee experiences, and thus, their employment prospects might be denigrated by simply replacing them with entry-level campaign responsibilities. In this way, partisan signaling through extracurriculars preserves partisan allegiance without altering employable skills and experience. Like both Iyengar and Westwood (2015) and Gift and Gift (2015), partisan extracurriculars are signaled on resumes, but unlike Gift and Gift (2015), I also include the partisan signal within the cover letter to enhance its effect.

Importantly, for realism, the timing and form of the partisan signal slightly vary depending on the type of applicant. For the majority of applicants (all doctoral and masters candidates except MBAs), the experimental treatment and control is applied as an undergraduate extracurricular. Conversely, MBA candidates received the treatment and control as an extracurricular in graduate school. The decision to split the timing of the partisan and control signal emerged as the appropriate course of action during pretesting and interviews with career counselors, former human resource managers, and deans of corporate relations.[14] As a result, the treatment and control for MBA applicants are reflected accordingly as either a neutral student leadership position such as the president of the "Graduate Business Association"

[13]To further substantiate the ecological validity, consider a simple search of LinkedIn. Under the search/filter by people settings, a simple people search for variations of "College Democrats," "College Republicans," "Young Democrats," and "Young Republicans," in the title or company fields reveals that hundreds of students (or former students) list the organizations on their public LinkedIn profiles as current or past positions, often associated with leadership positions therein. Even more include positions in student government.

[14]My pre-testing interviews with career counselors, former human resource managers, and deans of corporate relations agreed that for MBA applicants, it would be more plausible and realistic to include such a graduate extracurricular but not an undergraduate extracurricular given the time expanse of 4-5 years of full-time employment that occurs between undergraduate and graduate education. Conversely, for masters and doctoral applicants on a continuous educational path, the inclusion of undergraduate leadership positions makes sense in lieu of professional full-time experience.

versus a partisan leadership position in the local Young Democrats or Young Republican group (as opposed to the college-specific group for undergraduates).[15] Furthermore, as an additional method of disguising the experiment, the leadership position (either "president" or "vice president") between treatment and control is both randomized and counterbalanced and at the same time similar enough not to sway the recipient toward one applicant versus the other. Lastly, to simplify the experiment and focus on the effect of party identification, all applicants were white males matched on educational prestige, credentials, and skills.[16]

3.2.5 Determining Applicant Prestige (Selectivity) Conditions

Applicant prestige will be manipulated across two levels: high prestige applicants with experience from highly selective universities and firms and low prestige applicants from less selective universities and firms. In both cases, applicants will have majors and skills optimized for the perspective industry. Following the model of (Rivera and Tilcsik 2016), who suggested that "firms might automatically dismiss applications from students who attend. . . school far outside their geographic area and have no history of living in the region" (1103), I also manipulated the region of the applicants' undergraduate and graduate education to best match the region where the available job was located. At a minimum, an applicant's undergraduate degree came from an institution located in the same region as the employer.

[15] In terms of timing, MBA applicants had the most recent partisan signal, followed by software engineering masters applicants, who while having an undergraduate partisan signal, had a much more recent experience than doctoral students, whose partisan alliance in undergraduate occurred approximately six-seven years ago (given a 5-6 year PhD). Yet, although pretests suggested differential timing of the partisan signal for enhanced applicant realism, given the consensus view of entrenched partisan stability (Bartels and Jackman 2014; Campbell et al. 1960), a leadership position in a post-adulthood partisan organization, whether it occurs in college or graduate school, should serve as a reliable signal of partisan allegiance.

[16] To avoid rousing suspicion on matched pairs, the political contrast will be between the test condition (Democrat or Republican) and the control, a neutral, non-partisan category. Republicans or Democrats will be signaled as "President of College Democrats/Republicans" and the neutral category will be varied as an equivalent leadership position in student government such as "Vice President of the Student Government Association" where the selection of leadership position as president versus vice president is independently and randomly assigned and counterbalanced between treatment and control.

Where possible, applicants also attended a graduate school in that region or the next best proximal region.

3.2.5.1 Undergraduate Degrees

In terms of undergraduate education, a certain tension exists that limits implementing an extremely rigid definition of high selectivity, such as the one articulated by Rivera (2012b). If students could only attend a highly exclusive school, such as Harvard, Princeton, or Yale, high-selectivity applicants could not have a regional match to many employers, a challenge, that Rivera and Tilcsik (2016) solved by choosing selective but not elite institutions. Because I am utilizing a matched-pair design and need to present similar but not identical applicants to employers, applicants cannot have attended the same undergraduate institution. For added realism, they must each attend a graduate school at a different institution than their undergraduate degree. Yet, if there should be discrete applicants, some generous degree of regional matching, and a measure of high selectivity that allows top institutions but does not create an insurmountable status distance between highly prestigious applicants—what might that threshold be?

As I will argue, a compromise is to define a highly selective undergraduate institution as one falling within the Top-25 National Universities (both public and private) as defined by the U.S. News and World Report. With this measure, I can have the requisite minimum of three highly selective undergraduate institutions in each of the following regions: the West, the Midwest, the Northeast, the Mid-Atlantic, and the South.[17] By contrast, less selective undergraduate institutions were determined as follows. They must be public institutions,

[17]A minimum of three undergraduate institutions is required per region and selectivity level. The rationale is simple. Since the matched pair must have different undergraduate institutions and match the region, at least two institutions per region and selectivity level are warranted. However, because (A) the graduate institution must also differ from a given applicant's undergraduate alma mater and (B) top graduate programs in a field are frequently at top-25 schools (e.g. Harvard, Stanford, Chicago), a third undergraduate institution is required in order to satisfy each requirement in randomly selecting the undergraduate institution from the possibilities.

with a national ranking lower than 150 (for example, 150-200+ ranking), an acceptance rate greater than 55%, and additionally have clubs for the treatment (Democrat and Republican) and control groups (Student Government or Student Council).

3.2.5.2 Graduate Degrees

Highly selective graduate degree programs were defined as those coming from the top graduate schools for a given degree field in the country, according to the U.S. News and World Report. In all cases, preference was given to selecting programs from the Top 10 schools, although schools in the Top 15 were given consideration if it would otherwise fulfill a regional match. Schools not ranked in the Top 15 were excluded from the top highly selective graduate schools for a job applicant.[18] In cases where a regional match was unavailable, a graduate program from a proximal region was randomly selected. Conversely, less selective graduate programs were those, which had the degree in question as well as a healthy-sized department, but which were unranked, that is, had a rank of "RNP" or rank not published or were simply listed as "Unranked" from U.S. News and World Report.[19] In computer science, for example, these were schools that fell below the Top 111 departments. This also afforded the ability to provide a regional match for all less selective graduate schools.[20]

[18] The top 15 rule generally applies for statistics graduate programs as well, but the U.S. News and World Report lumps rankings for generalist statistics departments and dedicated biostatistics departments. I exclude biostatistics departments and thus use the remaining statistics departments and ordering in classifying the top 15 rule.

[19] The only exception to the "RNP" or "Unranked" rule for the U.S. News and World Report was for finding less selective statistics departments. In particular, very few statistics departments exist compared to computer science or MBAs, for example. Only a few valid RNPs existed, that is, only a few of the RNPs in statistics had healthy-sized departments with a PhD in statistics versus mathematics. In a few instances, less selective departments were selected from schools ranked approximately 70-100 by the U.S. News and World Report. To confirm their low ranking, I ensured these schools were either unranked or ranked 300-400 for statistics programs by Q.S., another educational ranking system.

[20] For MBA programs, I included two primary types of MBAs, those with an MBA focused on general management and those with an MBA concentration in finance. Regarding the MBAs with finance backgrounds, the U.S. News and World Report did not have at least two less selective (RNP/unranked) universities with a finance MBA concentration listed in the primary regions (West, Midwest, South, and Northeast). Specifically, they lacked two for the South. In this case, the U.S. News and World Report's inclusion of finance MBA programs did not seem to be complete. I found a business program that was unranked in the best business schools, namely the University of North Texas. However, although the U.S. News and World Report does not

3.2.5.3 Internships and Work Experience

Highly selective and less selective work experience was tailored to the types of jobs being targeted. Highly selective professional experience included summer internships at top companies in the field, as defined by the appropriate ranking lists of the most prestigious companies. Typically, these were companies with top name recognition. Less selective internship experiences included positions at smaller and unranked companies in a field. Such companies generally did not have name-brand recognition or fall on a top-ranking list. Depending on the type of position and degree, applicants would either have two summer internships or a relevant full-time position prior to graduate school and an internship during graduate school.[21] In all cases, the two prior positions were for different companies and the matched pair could have no prior companies in common. Furthermore, since top-companies were those often being applied to, applicants could not claim past work experience at the company to which they were applying.

3.2.6 Creating Applicant Identities

In addition to signaling applicant prestige using both the selectivity of education credentials and past internships, I further signal socioeconomic status and race through fictitious applicants' names. The use of names to signal race and other attributes, perhaps, has the most recognized origin in Bertrand and Mullainathan (2004), wherein the authors utilize names to signal race and evaluate socioeconomic status. A number of subsequent studies have also utilized names to signal race, and as argued by Gaddis (2017), the most common approach has been to reuse names previously employed by scholars, especially Bertrand and Mullainathan (2004) or Levitt and Dubner (2005). Gaddis (2017) specifically investigates

have the University of North Texas listed in finance programs, a search of the university's website reveals a dedicated MBA finance concentration.

[21]For example, all MBA positions had a relevant full-time position prior to graduate school and an internship during graduate school. MS candidates in computer science had an internship in both graduate school and the summer before their senior year in college.

three dimensions of names, chiefly the racial signal of first names, the socioeconomic status of first names, and the racial signal of last names. The systematic survey analysis conducted therein highlights both a wide array of first and last names strongly perceived to be white in isolation. Furthermore, the racial signal of first and last names clarifies when issued in combination (Gaddis 2017). In other words, a white first and last name combination produced a more reliable signal of whiteness than either in isolation (Gaddis 2017: 479-480). By extension, the addition of a white middle name further increases the confidence of racial signaling. Accordingly, in constructing a name for each applicant, I utilized a white first, middle, and last name from Gaddis (2017).[22] Collectively, even without further strengthening perceived whiteness through using white middle names, each of my applicants first and last name combinations will be perceived as white by over 92.4 percent of potential recipients (Gaddis 2017). I display the selected name combinations in Table 3.2.

Table 3.2: Profiles of Experimental Applicants

Profile	Prestige Level	Party	Name
P01DH	High	DEM	Graham Spencer Andersen
P02DL	Low	DEM	Brian Daniel Larsen
P03NH	High	NEU	Ryan Connor McGrath
P04NL	Low	NEU	Dustin Robert Stein
P05RH	High	REP	Matthew Zachary Hartman
P06RL	Low	REP	Cody Hunter Walsh

After creating names for each applicant, I created a unique email address for each identity. Unique emails were created using Google's Gmail service. Email addresses (alternatively Gmail login identities) created a challenge of their own, given the ubiquity of the names for each of my six identities and the prevalence of Gmail. Desired attributes of the email were as follows: the inclusion of both the first name and last name, preferably in that order. Second, I desired to preserve some semblance of professionalism by not interjecting nicknames or

[22]White first and middle names were taken from the list of first names found in Gaddis (2017), Table A1. In isolation, each first or middle name is perceived to be white: an average of 87.5% (min 74.4%, max 95.2%). Furthermore, respondents had congruent perceptions of each white first name chosen in the experiment of over "92.4 percent when given a white last name" (Gaddis 2017: 480). In isolation, each last name was perceived to be white by over 95% of respondents (Gaddis 2017: 476). Collectively, these results provide high confidence that each of my applicants' names will be perceived as white.

random number combinations into the email address. Third, since I included middle names (or middle initials) on all resumes and correspondence, I wanted to include some permutation of the middle name in each email address.[23] This increased the perceived professionalism and also lowered the likelihood that the email would already be claimed. To illustrate names, let F represent a person's first name, M represent a person's middle name, MI represent a person's middle initial, and L represent a person's last name. In almost every case, email addresses of the form $FML@gmail.com$ would be taken, and in about half of the cases, $FMIL@gmail.com$ would also be claimed.

To ensure consistency of email format, I arrived at the following combination, which worked in every case. Instead of simply including the middle initial (MI), I included a two-letter abbreviation of the middle name where the first initial comprised the consonant first letter of the middle name and the second letter comprised another consonant in the middle name, ideally the last letter, except in cases where the last letter was (a) not a consonant sound, (b) the same letter as the first letter of the last name, or (c) formed a suspicious concatenation of letters, such as 'hr.' I will represent this two-letter middle name combination as $M2$. Thus, each email address took the following form, $FM2L@gmail.com$, which are reflected as follows:

Table 3.3: Created Emails for Each Applicant Identity

Name	Email
Graham Spencer Andersen	grahamsrandersen@gmail.com
Brian Daniel Larsen	briandnlarsen@gmail.com
Ryan Connor McGrath	ryancrmcgrath@gmail.com
Dustin Robert Stein	dustinrtstein@gmail.com
Matthew Zachary Hartman	matthewzchartman@gmail.com
Cody Hunter Walsh	codyhtwalsh@gmail.com

[23] To clarify, each applicant identity has a given middle name that appears as their email identity. While every email cover letter's *FROM* field has the full name of the applicant, the name format in the email signature and resume vary between using the full middle name or only the middle initial. As mentioned elsewhere, the assignment of A/B resume cover letter versions is randomized and counterbalanced. Similarly, if a contact were to call any given applicant, the voicemail scripts for every applicant identity state their full first, middle, and last name.

Lastly, I procured a dedicated phone number for each fictitious applicant identity. Phone numbers were generated using an online service that allows unique lines in a requested U.S. area code. Like a traditional mobile number, the phones may be called and potential callers can leave a voicemail message. To add realism, each number was provided with a customized and professional voicemail greeting. Since only a matched pair would ever be sent to any given firm contact, only two unique greetings were produced (Table 3.4).

Table 3.4: Voicemail Scripts

Treatment or Control	Profile	Script
Treatment	P01DH P02DL P05RH P06RL	*Good day, you've reached the voicemail box of [FULL NAME]. Please leave your name, number, and a brief message, and I'll return your call.*
Control	P03NH P04NL	*Thank you for calling [FULL NAME]. If you leave your name and a good number to reach you, I will be happy to give you a callback shortly.*

Version A was provided as the script for the partisan identities, whereas version B was provided for the neutral control identities. The scripts were performed by two age-appropriate, midwestern, cisgender, and heteronormative males of similar build, disposition, and vocal tonality. Following the midwestern accents, treatment and control phone identities were given midwestern area codes.[24] Both selected area codes stem from areas encompassing either suburb and rural areas of major cities or large cities and the suburbs and rural areas surrounding them. In both cases, the areas codes do not signal any particular political partisanship and originate from areas with strong political diversity (containing battleground counties as well as counties going to Democrats and Republicans). Moreover, the area codes in question are not affiliated with any major research institution.[25]

[24]This approach differs slightly from Rivera and Tilcsik (2016) or Tilcsik (2011), which match applicant phone numbers to the region of the job. Although this method has its merits, because geographic regions and area codes are conflated with political partisanship, that is the experimental treatment (Gift and Gift 2015), I elected to instead control this possibility by selecting two analogous and politically ambiguous area

Table 3.5: Selected Area Codes for Applicant Identities

Treatment or Control	Profile	Area Code	Largest Cities and Counties
Treatment	P01DH P02DL P05RH P06RL	616	Michigan Grand Rapids, Holland, and Wyoming Kent and Ottawa Counties
Control	P03NH P04NL	763	Minnesota (North) Minneapolis, Anoka, and Andover Anoka, Hennepin, and Sherburne Counties

Notes: More details on the primary cities, counties, and election results can be found from the following sources: Michigan 616 Area Code Counties and Cities: (WorldAtlas 2018a); Michigan Election Results: (Politico 2016a, 2018a). Minnesota 763 Area Code Counties and Cities: (WorldAtlas 2018b); Minnesota Election Results: (Politico 2016b, 2018b).

3.2.7 Matched Pair Applicant Resumes and Cover Letter Designs

When the experimental protocol is created, the treatment (partisan applicant) versus control (neutral applicant) is randomly assigned to one of two conditions or profiles, which I will designate as a *profile* or *pair version* A or B, a fact with important properties. First, profiles A and B are delivered on different days, with one calendar day between the two delivery days. For example, the first applicants are delivered Tuesday, while the second applicants are delivered Thursday. Second, profile A and profile B differ in style and substantive content. Because a critical component of the matched pair design is that the firm recipient remains unaware of the experiment, the two resumes and cover letters must differ in a number of ways to avoid rousing suspicion, namely, style and substantive content. Third, because the assignment of treatment and control to pair version A or B is independent and random, my design avoids conflating treatment and control conditions with (1) the order in which a company receives the application or (2) the idiosyncratic differences between the resumes and cover letters, such as its style or substantive content.

codes for treatment and control. In this way, partisanship (or lack thereof) is conveyed by the experimental treatment and control on applicant materials, and not randomly conflated with the region of the job.

[25] University of Minnesota, Twin Cities is a 612 area code.

Here, I want to briefly differentiate style and substantive content from educational credentials and internship experience. Whereas undergraduate and graduate educational credentials and internship experience reflect either highly selective or less selective conditions, both the style and substantive content for each applicant resume and cover letter is designed to convey a high degree of both hard skills and soft skills. I define hard skills as demonstrable knowledge, such as programming languages, foreign languages, or quantitative method expertise among other possibilities. Soft skills include writing ability and the capacity to create a high-quality resume. Because both high and low prestige applicants use the same resume and cover letter templates, there is no measurable hard or soft skill differences between high and low prestige applicant pairs, only differences in the selectivity of institutions.

Beyond hard and soft skills, both resumes and cover letters offer similar hard attributes and softer background descriptions. I define hard attributes as elements that do not necessarily signal relevant skills but instead offer other unique individual attributes, such as an applicant's hobbies, interests, or achievements. Substantive background differences on resumes, which are also referenced in cover letters, include specific thesis titles and the descriptions of past work experience. Note that these descriptions, while linked to job types (such as data science), are independent of the exact internships and academic institutions.

Importantly, although both the cover letters and resumes have unique albeit equally high quality expressions of suitability and interest in the position, the structural formatting of the cover letters, resumes, and names in both materials differ to avoid suspicion. Cover letters have a number of differences, particularly in the length and number of paragraphs.[26] Resumes

[26]Structurally, profile A and profile B cover letters vary. One of the most noticeable structural differences is the overall length and paragraph structure. Whereas profile A is approximately 290 words distributed over four paragraphs, profile B is approximately 225 words spread over three paragraphs. The exact length difference varies depending on the particular job type applied for as well as the randomly selected educational and employment institutions for that applicant. Another structural difference in the cover letters is the contact information. Whereas profile A includes both a phone number and email in the signature, profile B only includes the phone number. Either candidate can still be contacted by email since the contact need only hit reply in both cases.

differ in the titles of sections and order and format they appear,[27] the spacing and format of resume headers,[28] the description of theses,[29] and the layout of content in sections.[30]

Lastly, the name format,[31] and phone number format,[32] differ in both materials. Furthermore, stylistic differences refer to changes in the measurable cover letter and resume

[27]Regarding resume structure, there are a number of differences. Profile A has the following sections, ordered as follows: "Education," "Skills," "Professional Experience," "Leadership, Awards, and Honors," and "Additional Information." Profile B presents different wording for these sections and alternates the order of appearance: "Education," "Work Experience," "Honors, Awards, and Accomplishments," "Technical Skills," and "Supplemental Qualifications." Some variation around the titles of sections exists depending on resume type and the content therein. For instance, in MBA resumes, we have (A) "Leadership, Honors, and Distinctions" versus (B) "Awards, Accomplishments, and Affiliations." While profile A has left-justified section headers, profile B uses center-justified header sections. To subtly differentiate the final section, profile B does not include hobbies or interests, whereas profile A has these attributes. In MBA resume types, profile B includes a summary statement, which is omitted in profile A. The exact formatting of A and B versions for each job type is available online (Mausolf 2020f), and an example of A and B versions is listed in Appendix C.

[28]Whereas profile A uses a single line header for contact information, profile B uses a multi-line header. Profile A simply lists the address, phone number, and email separated by a pipe: |. Profile B includes the "Address:" across two lines, "Phone:" (single line), and "Email:" (single line).

[29]Profile A includes the thesis title (set off using a bullet point) and then a list of "Keywords" with another bullet point. Profile B sets off the thesis description with a bullet point, followed by the title, and keywords in form, "a thesis which develops and applies keyword1, keyword2, and keyword3." For MBA resumes, which do not have a thesis, a similar convention exists in differentially describing the MBA focus and concentrations.

[30]The layout of profile A and profile B differ. For sections noting years or time-periods (education, experience, honors), profile A lists dates in a left-justified column and content in a subsequent left-justified column. Profile B conversely lists content in a left-justified column and uses a subsequent right-justified column for dates. In other words, dates are on the left side of the page for profile A and on the right side of the page for profile B. In profile A, non-date sections (skills and additional information) have a descriptive (such as programming or languages) in the same left-justified date column. Substantive content falls into a subsequent left-justified column. By contrast, profile B rejects this formatting and instead uses two equal-width columns in each of the non-date sections, each containing bullet points. As with other differences, slight variations exist in the MBA resumes.

[31]As a method of further differentiation, I alter the name structure presented in the resume and emails. While all emails' *FROM* field (what appears in the inbox) list the full name of the applicant, the name format in the email signature, resume, and resume filename differ for profile A and profile B. While profile A utilizes the full first, middle, and last name in all materials, profile B utilizes the first name, middle initial, and last name for the email signature, resume, and resume filename.

[32]Profile A uses the common XXX.XXX.XXXX format for phone numbers in the email cover letter and resume. Profile B uses the format (XXX) XXX-XXXX. All cases leave out the international country code (+1). Pretesting interviews suggested the inclusion of a country code might suggest to employers that the applicant had an international background. Since all applicants are applying from U.S. universities to U.S. offices, not including the country code should not lead to confusion for employer contacts and also not confuse employers by possibly signaling the applicant has an international background.

design, such as the fonts employed for the resumes,[33] cover letters,[34] and email signatures;[35] bullet choice icons used for the resumes,[36] cover letter salutations and closings,[37] and email subject lines[38]. In order to provide further context, I have included a hypothetical example of profile A and profile B resume and cover letter for the treatment and control pair P03NH and P05RH applying to a fictitious *data science* job (Appendix C).[39] To reiterate a point above, although one pair version of a resume could randomly be more successful than the other, by independently randomizing and counterbalancing the experimental treatment to pair versions, this should not compromise the experimental validity in aggregate. Lastly, a number of other differences not enumerated or noted here also exist. The exact templates for each A/B version of resumes and cover letters for every job type exist on Github for reference (Mausolf 2020f).

[33] For example, the resume for profile A uses the default LaTex font, computer modern roman (a serif font), whereas profile B uses the sans-serif Helvetica. This change has several additional stylistic ramifications. For example, LaTex supports a typography convention known as $\backslash textsc$ or small caps, which can be used to emphasize certain attributes. This format is supported for computer modern roman but not Helvetica.

[34] In the HTML versions of the email cover letters, profile A uses the serif font Garamond whereas profile B uses a sans-serif Helvetica. In the email signatures, profile A uses Garamond in addition to Copperplate, where the latter font achieves the boldface effect for the school. Conversely, profile B uses Helvetica exclusively. Whereas profile A uses a smaller font for the applicant title and contact information, profile B uses the same font size throughout. Lastly, whereas profile A uses a justified spacing, profile B uses a standard non-justified spacing and a left page alignment.

[35] An additional stylistic difference between the matched pairs is in the color used for the graduate school name in each email signature. Profile A has some stylistic flourishes in the colors, namely the school has the *rgb* color of the graduate school the applicant attends and the hyperlinks for the phone and email are a shade of blue $rgb(17, 131, 204)$. Conversely, profile B lacks these color flourishes, and is instead, a consistent shade of black $rgb(0, 0, 0)$ throughout.

[36] Different bullet points are utilized between resume styles. Whereas profile A uses $\backslash diamond$ bullet points, profile B uses $\backslash circ$ bullet points.

[37] Whereas profile A uses an informal salutation of "Hi Firstname," profile B uses the more formal "Dear Firstname Lastname:" as a salutation. Whereas profile A uses "All the best," followed by the applicant's first name (and then the full email signature) as an email closing, profile B uses "Sincerely," and only the full signature to close the email.

[38] For most cases, the format of profile A subject line takes the form "{JOB TITLE} Opening - {COMPANY}" whereas profile B uses the subject line "Position | {JOB TITLE}." Thus, the primary differences occur in the word to convey a job (Position versus Opening), the placement of that word, and the use of a hyphen "-" versus a pipe "|" if it exists. Lastly, most profile A versions include the company name. Exceptions occur when the name of the company is included in the job title. For example, a job title might be "Economist/Statistician - Amazon Search" and in such a case, the subject line becomes "Economist/Statistician - Amazon Search Opening" not "Economist/Statistician - Amazon Search Opening - Amazon."

[39] The included resumes and cover letters in Appendix C are fictitious in that the job being applied to as well as the contact name were generated for the purpose of pretesting, and the account emailed was one of the master email accounts created for this study.

3.2.8 Identifying Firms and Contacts

As with any job search, an initial step is often to identify companies with potential jobs and then search those companies for relevant job openings based on job titles and associated keywords. To maximize prospects, a job applicant would likely target jobs with the best-perceived match to their background. The experimental job search I executed involved a similar albeit computational approach.

First, I identified high profile companies that were likely to have numerous jobs, particularly for the primary job fields of interest: data science, statistics, quantitative finance, software engineering, project management (MBA), financial analysis and planning (MBA), or business analytics (MBA). These job fields are of particular interest as being high-demand job fields with excellent compensation and can be found at a large number of firms. Unlike other top-paying jobs, such as management consulting, there are many more firms hiring for these positions and such positions have openings year-round rather than a highly specific recruitment season. To search for these jobs, I examined top companies, sourced from several ranking lists (Table 3.6).

Table 3.6: Company Lists to Search for Jobs

List	Companies
Fortune 1000	1,000
Institutional Investor Hedge Fund 100	100
Vault Consulting Top 50	50
Vault Best Boutique Consulting Firms	25
Vault Banking 50	50
Vault Accounting 50	50
Vault Law 100	100
Forbes The Cloud 100	100
CNBC Disruptor 50	50
Business Insider Top Valued Private Tech	25
NASDAQ Tech Companies	629
Glassdoor Top 100 (Large)	100
Glassdoor Top 50 (Medium and Small)	50
Russell 3000 Index	3,000
Total Deduplicated Companies	4,209

In most cases, these sources did not have a downloadable list, and so I wrote elementary Pythonic web-scrapers to collect this information as a CSV datafile. The CSVs from each source were appended, cleaned, deduplicated, and pre-processed for use in a more advanced series of web-scraping scripts, which searched for a number of full-time jobs for each company on a job aggregator,[40] and identified the best matching and most recent job of the possible choices.[41] Ideal jobs were then matched to an external database of relevant firm contacts.[42] These curated job opportunities with firm contact points were passed to the experimental protocol file, which was used in the computational deployment of the experiment, described in the following section.

[40] I wrote a web-scraper to search a popular job aggregator. Job types were rank-ordered such that if multiple ideal job matches were found at a firm and were posted within the same period, the job type with the highest rank was selected. The web-scraping script searched for ideal matching jobs for each job type using a series of targeted queries, and the search was performed at different levels of posting recency, such as 14 days or 30 days. Where multiple ideal jobs were found at different levels of recency, the most recent ideal job was selected. Web-scraping of ideal jobs from the aggregator was supplemented with manual job search queries on another popular professional social networking site. This was necessary, as not all companies had listed jobs on the primary aggregator searched with the web-scraper.

[41] During the search process, each company was searched for every one of the seven possible job types, each with their associated keywords and backup keys. For example, at technology firms, data science and software engineering were the top job types, respectively. Similarly, different types of firms were searched for the two primary types of MBA positions at different ranks. For MBA programs, I included two primary types of MBAs, those with an MBA focused on general management and those with an MBA concentration in finance. An examination of the supplementary code reveals a third 'mba_analyst' type. These applicants have an identical background to MBAs in general management and exist simply to apply to more generalized business analyst positions, which are less specific in the appropriate background. That is, in some cases, an MBA is preferred while in others, an MBA might be a disadvantage over an undergraduate depending on the firm's salary expenditure. Thus, such job types were applied to only in cases where the foregoing more specific job types did not exist. In other words, mba_analyst positions represented the lowest rank job type, selected only if no other jobs were found for the other six job types.

[42] A firm contact is no single type of representative and varies by firm. To the extent the possibility of multiple firm contacts existed, I strived to select ones who had positions using permutations of "Recruiter" or "Talent Acquisition." Interviews with former human resource officers and career counselors suggested that those in recruiting or talent acquisition would make the most sense as the first option of firm contact. Not only is this their daily job but also these individuals would receive more emails regarding current job opportunities than the average human resource manager or generalist. It should be noted that only full-time corporate recruiters or talent acquisition specialists were selected, not temporary "contract" workers who only exist on a temporary basis. Typically, HR managers reflected a secondary option where no recruiters existed. In terms of seniority, I elected to optimize contacts at the manager and other (non-managerial) levels, using higher positions, such as directors, only where no relevant lower-ranked human resources (recruiter, talent acquisition, or general HR) personal existed and no obvious hiring manager could be found. In some cases, no HR contacts existed. In such a case, I would select a plausible hiring manager. For example, if the job being applied for were a software engineer, I would select an engineering manager as a firm contact if no human resource options existed.

3.2.9 Computational Deployment of the Experiment

The computational deployment of the experiment is one of the more complex elements of this study. Pragmatically, the experiment is deployed using a custom Python module that I developed for this project (Mausolf 2020f). This repository contains dozens of Python scripts and several thousand lines of code. The basic computational process falls into a number of stages described in Table 3.7.

Since many of the substantive details of these steps have already been described in prior sections, I will focus most of the effort on the actual deployment of the experiment. Once provided an experimental protocol, the experiment can be run with a single command line prompt: *python experiment.py*. The immediate action after this running this command is the random assignment of the full experimental selection that matches job applicant backgrounds to undergraduate and graduate schools as well as internships based on their prestige level, job type, and region of the job's location (step 3). Once created, the code divides match version A and B applicants into two files to be executed with a one day gap in between calendar days (Tuesday and Thursday). For each of those applicants, two versions of an email are drafted and embedded in a single email, both an HTML version (which are how most emails appear) and a plain text version that will be readable to employer contacts who might have HTML disabled. Also attached to that email is a PDF version of the resume. Both the resume and cover letter are customized to the company, contact point, job type, education, and work experience using the details assigned in step 3. That email and attachment are then sent, concluding step 4. The actual time to deploy this process is relatively swift. For example, in testing, a batch of 1500 version (A) resumes/cover letters were created and sent in 89.57 minutes. The remaining 1500 version (B) resumes and cover letters took an additional 86.71 minutes to deploy following the specified time delay. In this manner, the delivery time would vary roughly an hour and a half between delivery days. It is important to note that online SMTP email services, as used in this experiment, supposedly have a rate

Table 3.7: Computational Process

Stage	Overview	Tasks
1	Pre-Experimental Processing	A: Web-scraping currently available jobs for specified companies, job types, and keywords B: Filter and identify ideal jobs using detailed criteria C: Collect business contacts for companies with jobs D: Fuzzy match company jobs and company contacts
2	Create Experimental Protocol	A: Load external jobs data, contacts data, and region data B: Randomly assign matched pair prestige states C: Randomly assign match pair versions (order/style/substance) D: Randomly assign treatments (Democrat / Republican) and control (neutral) to pair E: Match assignments to applicant profiles (names, emails, phone, login credentials) F: Log full experimental protocol details G: Save consolidated protocol (only needed columns) to run
3	Assign Applicant Backgrounds Using Protocol	[All steps, random selection without replacement] A: Select graduate school for each matched pair using region, job type, and prestige B: Select undergraduate school for each matched pair using experimental treatment/control condition, prestige, region, and graduate school C: Select internship for each matched pair using job type, prestige, and company being applied to
4	Deploy Experiment	[For each applicant] A: Write a cover letter using match pair version (A/B) template for given job type using all applicant information (e.g. name, email, phone, education, internships, treatment/control, among others factors) B: Compile both HTML and plain text versions of the above cover letter C: Create HTML/plain text email signatures using the above D: Modify the LaTex A/B resume template using the above information and compile a PDF version E: Write an email to each contact using the cover letter and signature (HTML/plain text) F: Attach the compiled resume for the applicant and send the email (Group A occurs Tuesday; Group B occurs Thursday)

limit of 500 emails per account over a rolling 24-hour period. Testing revealed this limit to be approximately 1100 per email account (1099, 1101, and 1099 in three tests). Depending on the number of jobs per account, the overall experimental protocol could hypothetically need to be divided into several batches in order to avoid surpassing the practical email limit. This is particularly true for the most common email account associated with the high prestige, politically neutral control. However, multiple batches were not necessary.

Although creating the code necessary to run this experiment is time-consuming, a greater degree of precision and reproducibility is garnered using the computational approach. After the experiment is run, a log exists capturing all the details, including those generated in steps 3 and 4. Because the code is scalable, the only elements necessary to, for instance, apply to 2000 jobs instead of 1000 jobs, is simply an expanded array of companies with jobs for one of the job types that this experiment targets. Of course, increasing the size also varies with the temporal fluctuations of firms' day-to-day available job openings as well as having an available contact point for a given firm.

3.2.10 Post-Experiment Data Preparation

In this study, I specifically evaluate how the alignment of a job applicant's political partisanship with that of the firm affects the likelihood of receiving a callback for a given job. To perform this analysis first requires defining a callback, among other types of response options, categorizing and cleaning responses, and determining the partisanship of firms.

3.2.10.1 Defining Callbacks, Other Responses, and Bounces

Following the precedent of other scholars, I define a callback as either an email or phone response (or combination thereof) to a given applicant indicating the desire to coordinate a subsequent preliminary interview or phone screen. Thus, simple responses, such as requests for additional information or requirements that the applicant first applies online, were coded as a reply but not a callback and thus excluded from the callback analyses. Besides the two main types of response (callback or reply), applicants might also receive additional reply types, such as an automated email or out of office reply. When evaluating the response, it is important to note that applicants might receive multiple rapid-fire replies before it was possible to notify them that the applicant was no longer interested, following IRB guidelines. For instance, a recruiter might initially reply asking if the applicant had already applied online, and shortly thereafter send another email and perhaps a call saying regardless, they would like to keep the ball rolling and set up an interview. Relatedly, automatic replies were sometimes, but not always, followed by another response (sometimes weeks later) asking to set up an interview. In this way, the ultimate outcomes (callback, other reply, non-response) were determined by manual review for each response. In determining the overall response, I set the result for that applicant as equal to the highest-level response. For example, if they received an automatic reply, a reply asking if they already applied online, followed by a callback to set up an interview, the overall outcome was designated as a callback.

Of course, since the experimental protocol described above relies upon sending emails to a firm contact, the success of the application depends first on the email reaching a valid, firm contact. Necessarily, the automated process resulted in a number of delivery issues, among them, bounces and invalid contacts. Since firm contact email addresses were sourced from a subscription dataset, even though such emails claimed to be recently validated, some were no longer valid in practice. Furthermore, emails could bounce or fail to be delivered due to corporate spam filters, which preempted delivery attempts. At times, rather than directly bounce, an automated response would indicate that the employee no longer worked at the company, which would be coded as a bounce. After the first wave of applications was deployed, I determined which set of firms had one or more bounce or other related errors for the applicant pair. In these cases, I generated a new experimental protocol given a new contact at each firm in question and deployed a second wave of the experiment.

3.2.10.2 Categorizing Experimental Outcomes

After deploying both waves of the experiment, I waited at least one month before coding the final experimental outcomes for each applicant,[43] which relied on a combination of manual coding and categorization of the email responses with computational adjudication of determining the applicant associated with a given reply, bounce, or error. To illustrate a challenge of this method not often discussed, we have the determination of which result belonged to a given applicant profile (and related randomized factors) in the experimental protocol. While it might seem that we could simply determine this information from the sender profile (and email), employer contact email, and experimental wave, this was not always true. In the case of a callback or reply, a frequent occurrence was some behind-the-scenes communication on the firm side, such that often the person replying had received the applicant's resume and cover letter from the person initially emailed or some series of preceding individuals. Often, the initial firm contact was not copied and the email history not included, making alignment with the result challenging, at least using an automated computational approach. This was particularly true in the case of voicemail replies. Similarly, the initial contact would frequently respond where the received email was some alternate variation of the original sent email. For example, an email might be sent to $first.last@corp.com$ whereas the response might come from $last.f@division.corp.com$. Bounces followed similar challenges, such as automated Gmail explananda denoting reasons for the bounce, which often included a version of the firm's domain in the details of the explanation. Computational coding of these thousands of outcomes highly facilitated the process, which I supplemented with a manual review and completion of cases not resolvable through automated processes. Similarly, automatically transcribed phone replies necessitated manual review to determine the company replying to the given applicant.

[43]The first wave of the experiment began on Tuesday 4/2/2019 and Thursday 4/4/2019, while the second wave of the experiment began on Tuesday 4/23/2019 and Thursday 4/25/2019. The final results of the email and phone replies were not conducted until after a month had elapsed since the last resumes were sent on 4/25/2019, which concluded on 5/28/2019.

3.2.10.3 Determining Firm Partisanship for Applicants

Of course, as previously stated, to properly analyze affective polarization and partisan homophily requires some knowledge of not only the partisanship of the fictitious applicant but also that of the firm. To calculate firm-side partisanship, I utilize the corporate politics data from Mausolf (2020a), which originated from the Federal Election Commission (Federal Election Commission 2018a).[44] For brevity, I refer to this as the FEC-CP data. In particular, I utilize company-level data on the mean party identity in a firm for a given election cycle (2008-2018), which I averaged to generate an overall partisan identity for the firm. Yet, this data contains only a subset of Fortune 500 firms, specifically, 334 firms for the period in question (Mausolf 2020a). Furthermore, a number of these firms either did not have a relevant job opening or valid email contact. For example, no firm contact could be identified or the firm had errors during the experiment. In total, I determined the political partisanship of 134 applicant-pairs using the FEC-CP data (Mausolf 2020a). I supplemented the FEC-CP data by determining the political partisanship of additional firms using data from OpenSecrets.org (Center for Responsive Politics 2020), specifically the search feature which enables a curious user to search for a firm and determine its partisan leaning by examining the overall contribution amounts given by individuals in a firm to each political party. Although an API exists for OpenSecrets, there did not appear to be an API feature to extract this type of information, and given the idiosyncratic locations and interactiveness of the data, writing a viable web-scraper would have proven more cumbersome than performing a manual search for a subset of 195 additional applicant-pairs, wherein I prioritized determining the partisanship for firms providing callbacks, bringing the total number of cases for which I had FEC and experimental data to 329 applicant-pairs or 658 applicants.

[44] In particular, I utilize data grouped by firm (thus ignoring occupational hierarchy) for election cycles 2008-2018, which captures a firm's most recent partisanship using the mean party identity [DEM, REP] (Mausolf 2020a). Because the mean is calculated across years and substantially more individuals contributed in 2016 and 2018, the mean is even more weighted toward recent partisanship.

3.2.11 Methods of Analysis

After deploying both waves of the experiment, categorizing the results, and determining the partisanship of firms, we have the following descriptive statistics of the data (Table 3.8). As shown in Table 3.8, I attempted to send 3,856 total applications, and of these, 2,670 matched pairs were received by firm contacts. Of the received applicants, I was able to determine the firm's political partisanship for 658 matched applicants. In my analysis, I primarily focus on the results for these applicants, which uniquely afford the opportunity to evaluate affective polarization and partisan homophily hypotheses. Before reviewing these results, briefly consider the overall results for each of these three groups (Table 3.8).

Following the experiment, I conduct several types of analyses. At the most basic level, I provide a series of descriptive statistics and bivariate statistics, such as bar-plots with confidence intervals and t-tests. I provide this basic descriptive analysis first for all overall applicants in the scenario of unknown partisanship about the firms being applied to. This follows the standard approach in most of the correspondence-audit literature when evaluating biases based on applications. For example, studies on racial bias in job applications using resumes typically focus on variations in the callback response by applicant features (Bertrand and Mullainathan 2004; Gaddis 2015), without considering, for example, how the level of extant firm diversity might influence the decision to give minority applicants a callback.

Yet, beyond the comparison for the overall state of partisan biases in job market callbacks, I provide analysis for the subset of applicants where we can determine the partisanship of the firm and thus evaluate the degree to which affective polarization and partisan homophily affect callback outcomes. Here, I offer similar bivariate statistics, such as bar-plots with confidence intervals and t-tests to compare differences between the outcomes of partisan mismatching or matching compared to neutral applicants, how this varies by the partisanship of the firm. Following the work in similar analyses, I also provide a number of formal models to substantiate the bivariate results.

Table 3.8: Descriptive Statistics of Experimental Job Applicants

	Sent Applicants	Received Applicants	Matched Applicants
Total Job Applicants			
Sent Applicants	3856	2670	658
Received Applicants	2,710 (70.28%)	2,670 (100.00%)	658 (100.00%)
Failed Applicants	1,146 (29.72%)	0 (0.00%)	0 (0.00%)
Application Results			
Received Callback	139 (3.60%)	139 (5.21%)	69 (10.49%)
Received Other Reply	442 (11.46%)	441 (16.52%)	108 (16.41%)
Received Any Response	581 (15.07%)	580 (21.72%)	177 (26.90%)
Applicant Profiles			
P01DH	540 (14.00%)	372 (13.93%)	73 (11.09%)
P02DL	236 (6.12%)	166 (6.22%)	43 (6.53%)
P03NH	1,369 (35.50%)	934 (34.98%)	222 (33.74%)
P04NL	559 (14.50%)	401 (15.02%)	107 (16.26%)
P05RH	829 (21.50%)	562 (21.05%)	149 (22.64%)
P06RL	323 (8.38%)	235 (8.80%)	64 (9.73%)
Applicant Partisanship			
Republican	1,152 (29.88%)	797 (29.85%)	213 (32.37%)
Neutral	1,928 (50.00%)	1,335 (50.00%)	329 (50.00%)
Democrat	776 (20.12%)	538 (20.15%)	116 (17.63%)
Applicant Prestige			
High Prestige	2,738 (71.01%)	1,868 (69.96%)	444 (67.48%)
Lower Prestige	1,118 (28.99%)	802 (30.04%)	214 (32.52%)
Job Type			
Data Science	1,048 (27.18%)	732 (27.42%)	310 (47.11%)
Quantitative Finance	30 (0.78%)	26 (0.97%)	14 (2.13%)
Statistics	28 (0.73%)	26 (0.97%)	2 (0.30%)
Computer Science	1,014 (26.30%)	686 (25.69%)	160 (24.32%)
MBA - Analyst	206 (5.34%)	162 (6.07%)	16 (2.43%)
MBA - Finance	680 (17.63%)	470 (17.60%)	66 (10.03%)
MBA - Project Management	850 (22.04%)	568 (21.27%)	90 (13.68%)
Job Region			
Northeast	854 (22.15%)	606 (22.70%)	162 (24.62%)
Mid-Atlantic	176 (4.56%)	126 (4.72%)	38 (5.78%)
Midwest	774 (20.07%)	510 (19.10%)	140 (21.28%)
South	980 (25.41%)	654 (24.49%)	168 (25.53%)
West	1,072 (27.80%)	774 (28.99%)	150 (22.80%)
Experiment Stats			
Firm Contacts	1928	1335	329
Unique Firms	1626	1318	323
First Wave	2,812 (72.93%)	2,042 (76.48%)	544 (82.67%)
Second Wave	1,044 (27.07%)	628 (23.52%)	114 (17.33%)

Notes: (1) Sent applicants include all emails that successfully sent (on the sender side). For example, sent applicants include emails that bounced due to a number of reasons such as invalid emails or corporate spam filters. *(2) Received applicants* include all emails believed to have been received by the intended recipient. This group excludes emails where one or more of the emails from the applicant pair bounced or reached an unintended company or recipient. Thus, the number of received applicants in column two is slightly lower than received applicants in column one, which includes applications where only one of the two applications sent. *(3) Matched applicants* is a subset of received applicants for which we also have data on the company's partisan leanings based on FEC contributions by individuals therein. The number of firm contacts is one half the total number of applicants, which in the case of (2) and (3) is slightly higher than the number of unique firms secondary to firm-deduplication errors across multiple employer lists (Table 3.6).

3.2.12 Formal Models

In this analysis, I specifically evaluate how the alignment of a job applicant's political partisanship with that of the firm being applied to affects the likelihood of receiving a callback for a given job. To evaluate the likelihood that an applicant receives a callback, I use logistic regression models, a type of maximum likelihood estimation often used for estimating the probability of a binary event happening or not. In this case, I model the probability that a given fictitious applicant will receive a callback. This type of logistic regression modeling for binary outcomes has been conducted in similar experimental correspondence-audit studies (Gaddis 2015; Pedulla 2016; Tilcsik 2011). A number of other studies use related models, such as the probit model or exact logistic regression, as well as other models, such as linear or Heckman models (Gift and Gift 2015; Kang et al. 2016; Rivera and Tilcsik 2016: 1110).

Logistic Regression Model:

$$\eta_i = logit(\pi_i) = log\Big[\frac{\pi_i}{(1-\pi_i)}\Big] = \beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i \tag{3.1}$$

Logistic Regression Model in Terms of Odds-Ratios:

$$\begin{aligned} \frac{\pi_i}{(1-\pi_i)} &= \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i) \\ \pi_i &= \frac{\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i}{1 + \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j x_i)} \end{aligned} \tag{3.2}$$

for $i = 1, \ldots, n$ job applicants;

$j = 1, \ldots, j$ coefficients;

where $\pi_i = Prob\Big\{\text{Callback}_i\Big\}$ for a given applicant i in the set of observations $Y_i \sim B(n_i, \pi_i)$; as predicted by regression covariates x and regression coefficients β. Using these models, in combination with supporting descriptive statistics, I evaluate the evidence relative to my hypotheses on affective polarization and partisan homophily. More generally, I establish the effects of partisan bias and applicant prestige in the general case where firm partisanship is unknown. Collectively, this research underscores the role of political partisanship, especially affective polarization and partisan homophily, in structuring entry into firms. More generally, this work illustrates how political partisanship might shape careers.

3.3 Analysis

Before diving into the modeling analysis of the experiment, first consider the results for all received applicants. Recall that all received applicants are those applicants for whom an application was successfully sent and we may know the partisanship of the firm, but in most cases, firm partisanship is unknown (*c.f.* column two in Table 3.8).

3.3.1 Overall Findings Without Partisan Matching

If we assess the results for all received applicant pairs, there was not a significant difference by applicant partisanship (Republican, neutral, or Democrat) or applicant prestige. Despite the lack of significance, higher prestige applicants received slightly more callbacks, as did Republican applicants. I display discrete bar plots for results by party and prestige in Appendix C, Table C.5. Below, we can discern this same pattern, but also appreciate that some differences might exist at the intersection of partisanship and prestige (Table 3.1).

Namely, we see a statistically significant difference in the callback rates of low prestige Democratic applicants compared to low prestige Republican applicants. In some ways, this may seem curious. On one hand, there is more variation in callback rates for low prestige applicants, and overall they have lower callback rates than high prestige applicants on balance, with the caveat that such results are not statistically significant. Taken another way, for low

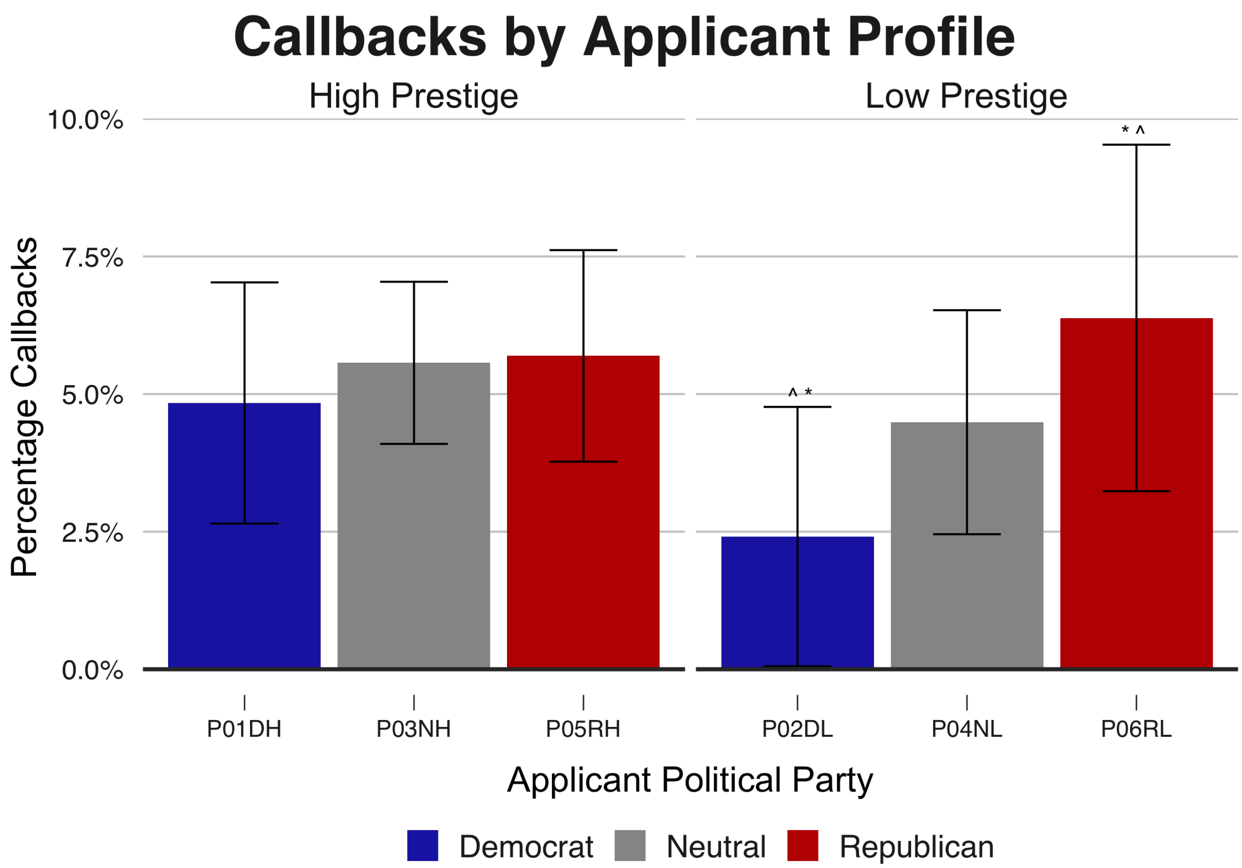


Figure 3.1: Results of the Experiment by Applicant Prestige and Party

Notes: N = 2670, all received applicant-pairs. Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The only significant difference is between low prestige Democratic and low prestige Republican applicants.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

prestige applicants to receive a callback, matching on other dimensions, such as partisanship might matter more, but it should be noted that this same pattern does not necessarily hold true for the smaller sample of matched applicants, which I evaluate in the section below.[45]

[45]As indicated, the statistically significant difference between low prestige Democratic applicants compared to low prestige Republican applicants only appears in the larger received applicants dataset. In the smaller matched applicants dataset, the statistical significance dissolves, although the general pattern of more callbacks for low prestige Republican applicants over low prestige Democratic applicants holds (Appendix C, Table C.6).

3.3.2 Evaluating Affective Polarization and Partisan Homophily in Matched Applicants

Turning to the primary analysis surrounding the evaluation of affective polarization and partisan homophily, we should keep several points in mind. First, we must recall that we would like to evaluate two discrete mechanisms of political partisanship, namely affective polarization (specifically its negative valence of animus towards out-party members) and partisan homophily, or the preference for copartisans. This given framework collectively presumes that copartisans will receive more callbacks than opposing-partisans—and this difference will be significant. To better understand the power of the mechanisms, as well as a better differentiate which lever is more powerful, we can make comparisons with respect to an employer's preference for politically neutral applicants. In other words, we must attune to how neutral applicants compare to either copartisans or opposing partisans. Understanding this difference can help to reveal which driver is more important for individual applicants in labor market entry.

To appreciate this difference, consider the experimental results in Figure 3.2. Here, we can see that politically neutral applicants have a callback rate of 10.63%. Note that this is about the same callback rate as all applicants in the FEC-matched subsample, 10.49% (Table 3.8).[46] Yet, whether applicants match with the partisanship of the firm or oppose it matters. Copartisans receive more callbacks (16.87%) and opposing-partisans receive fewer callbacks (4.14%) on balance. When comparing the callback rate of mismatched partisans to matched partisans, we see that the difference is statistically significant ($p < 0.001$), indicating a significant firm-level difference between a preference for copartisans and an aversion toward out-partisans. Thus, when trying to differentiate which mechanism has more leverage, we can see that while opposing partisans have a significant disadvantage compared to neutral

[46]The astute observer may note that this rate is slightly higher than the callback rate for all received applicants. In part, this reflects a process of data collection, particularly the manual search process, which prioritized determining the partisanship for applicant pairs where at least one of the applicants had a callback. Such observations were most relevant since at least in these cases, the response indicated the email had definitively been received and did not simply silently pass to a spam folder or a persistent but outdated email without a valid automated reply.

applicants ($p < 0.01$), copartisans do not necessarily have a parallel advantage. Although copartisans have a higher callback rate than neutral applicants, the difference is not significant at the $p < 0.05$ level, only the $p < 0.1$ level. Consistent with past studies, affective polarization is a more powerful driver of behavior than partisan homophily, and collectively, there exists a significant difference between these response patterns.

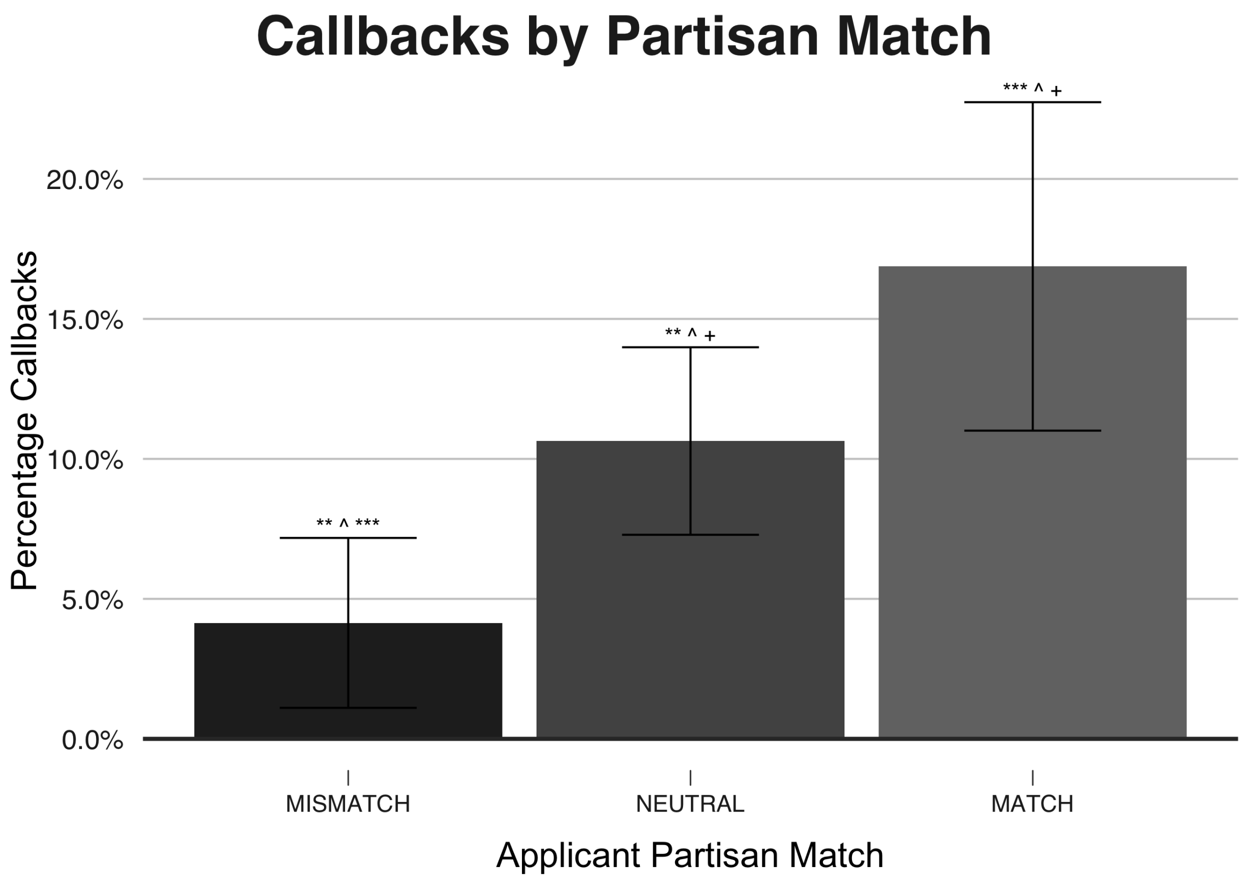


Figure 3.2: Experimental Results by Partisan Matching Status with the Company

Notes: All firms: N = 658 applicants. Results are only for applicants applying to companies with an identified partisan profile. Identifying that partisan profile is a considerable effort, incorporating analyzed data from the Federal Election Commission (Mausolf 2020a), as well as supplemental data on additional companies using the Center for Responsive Politics (2020). Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The p-value for each t-test is displayed in the figure above the CI upper bound with notation following the form $p1\hat{}p2$, where p reflects the significance seen below. The p-values, $p1\hat{}p2$, are the results for the group in question relative to the alternative two groups $group1\hat{}group2$, maintaining the consistent order (mismatch, neutral, match). *p < .05; **p < .01; ***p < .001

Indeed, these results show that affective polarization, in the sense of both partisan animosity and partisan homophily, operate at the firm level. Because this behavior is by definition partisan, and past studies have shown that Democratic and Republican firms have differences in firm-level behavior (Mausolf 2020a), we might wonder what differences in applicant callback patterns, if any, exist on the basis of firm partisanship. Examining the results in Democratic and Republican firms (Figure 3.3) reveals several important findings. First, the callback rate is higher in Democratic firms. Second, in both Democratic and Republican firms, there is a significant difference in the callback rate for opposing partisans versus copartisans, $p < 0.05$ and $p < 0.001$, respectively. Similarly, in both Democratic and Republican firms, opposing partisans face a callback disadvantage compared to neutral applicants, $p < 0.05$ in both cases. Only in Republican firms, however, do copartisans receive a significant callback advantage over neutral applicants, $p < 0.05$. Thus, echoing the overall results, we can see the results of affective polarization, especially the partisan animus experienced by opposing partisans for both Democratic and Republican firms.

Yet, from the applicant perspective, another façade emerges (Figure 3.4). Republican applicants, for instance, experience a smaller difference in callback rates on the basis of whether they match or mismatch with the partisanship of the firm. By contrast, Democrats see a large and highly significant difference in their callback rates, depending on whether they align with the partisanship of the firm. In this respect, the comparative risk of including a partisan signal is higher for Democratic applicants than Republican applicants if they inadvertently misjudge the partisanship of the firm. These results shed additional light on the overall higher callback rates for Republican applicants (Figure 3.1). If there are more Republican than Democratic firms, and out-party Republicans are less penalized than out-party Democrats, this could on balance offer some explanation for the slightly higher rates of callbacks for Republicans over Democrats in the experiment.

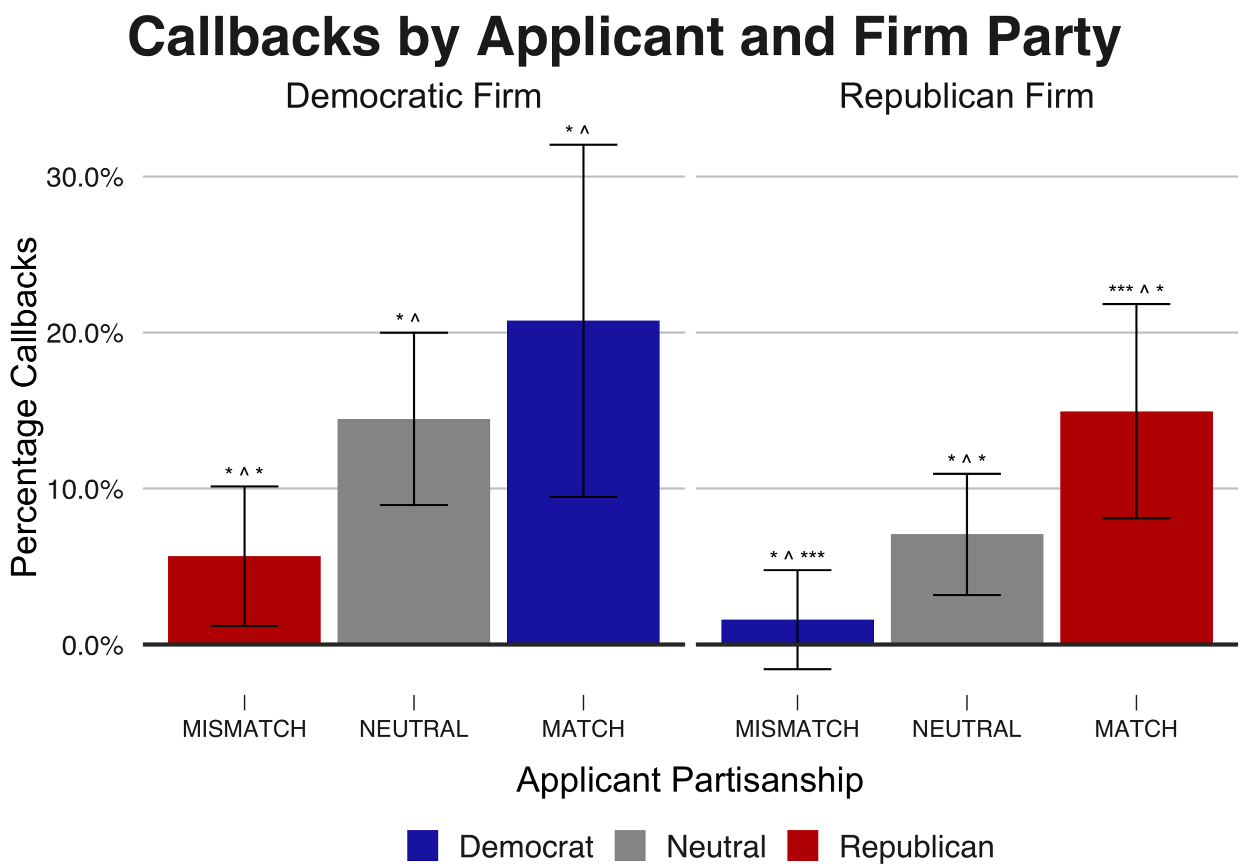


Figure 3.3: Callbacks by Applicant and Firm Partisanship

Notes: All firms: N = 658 applicants, Democratic Firms: N = 318 applicants, Republican firms: N = 340 applicants. Callback results displayed by the partisanship of the firm applied to and the partisanship of the application. As described, each firm received a matched pair of applicants (one partisan, one neutral). Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. The p-value for each t-test is displayed in the figure above the CI upper bound with notation following the form $p1\hat{}p2$, where p reflects the significance seen below. No stars are displayed for insignificant results. The p-values, $p1\hat{}p2$, are the results for the group in question relative to the alternative two groups $group1\hat{}group2$, maintaining the consistent order (mismatch, neutral, match).

*p < .05; **p < .01; ***p < .001

3.3.3 Matched Partisans Models

Although bivariate evaluations certainly elucidate the perils of partisanship in job applications, we would be remiss not to consider the results of multivariate modeling. As previously stated, I conducted a number of multivariate logistic regression models of the likelihood that a fictitious applicant receives a callback. In the main analysis, these models, like the figures above, reflect the results for the 658 applicants for whom I also had data on the partisanship

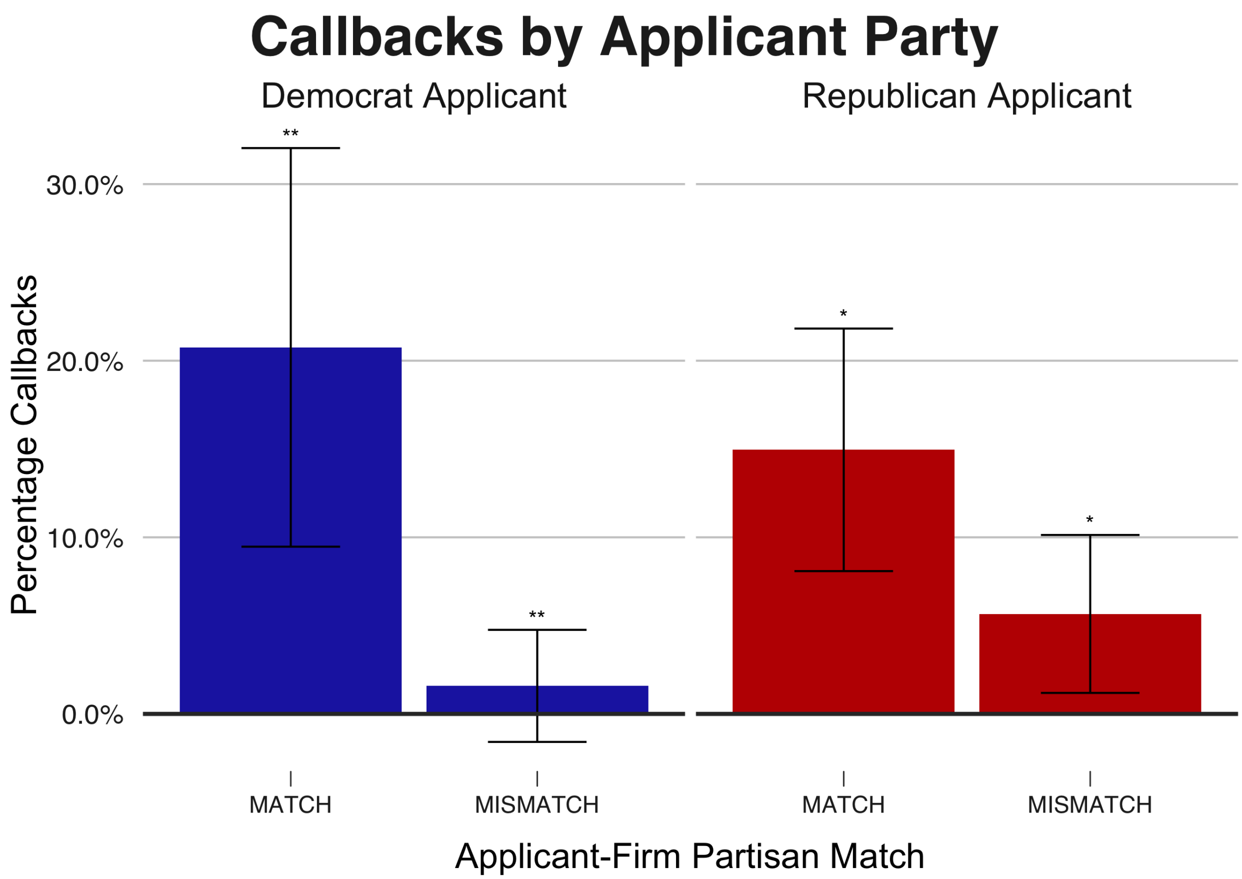


Figure 3.4: Callbacks by Applicant Party and Matching Status
Notes: N = 658. Mean callback rate with 95% confidence interval displayed. Two-sample t-tests for unequal variance calculated between partisan mismatches and matches within each applicant party. The p-value for each t-test is displayed in the figure above the CI upper bound.
*p < .05; **p < .01; ***p < .001

of the firm to which they had applied. In these models, we examine effects both within and between applicant pairs.[47] Examining the results, a lucid pattern shines through the shadows. Reflecting the discretized findings shown in the previous figures, mismatched partisan applicants—that is, fictitious applicants whose party opposes that of the firm receiving the application—are significantly less likely to receive a callback ($p < 0.001$), compared to the reference group of matched partisans, also known as copartisans. As seen in Table 3.9, these main effects remain robust under multiple parameterizations.[48]

[47] In Appendix C, I include discrete models for only matched pairs of Republican/neutral applicants and Democratic/neutral applicants as well as discrete models for only applicants applying to either Republican or Democratic firms.

[48] Likewise, the patterns remain if we examine the outcome (1) only for applicants applying to Republican firms (Table C.1), (2) only for applicants applying to Democratic firms (Table C.2), or (3) for only applicants

Table 3.9: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, Odds Ratios Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.171***	0.173***	0.163***	0.163***
Neutral Applicant	0.522*	0.526*	0.507*	0.509*
(Ref: Matched Partisan)				
Firm Partisanship				
Democratic Firm	2.052**	2.054**	1.901*	2.341**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.480	1.489	1.415	1.477
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.818	0.819	0.786
MBA: Analyst or Manager		0.830	0.891	0.827
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.279
South				1.028
West Coast				0.521+
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.116	1.124
Resume Version: B			1.109	1.117
Experiment Wave: Second Wave			0.420+	0.434+
Constant	0.117***	0.126***	0.139***	0.131***
N	658	658	658	658
Log Likelihood	-209.025	-208.748	-206.332	-203.976
AIC	428.049	431.496	432.663	433.952

Notes: N = 658. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

The patterns also remain if we alternate the reference group to neutral applicants (Appendix C, Table C.4). As before, opposing partisans are less likely to receive a callback, and copartisans are more likely to receive a callback when compared to neutral applicants. Across both sets of models, we can see that the relative statistical strength of the effects is greater for opposing partisans than either neutral applicants (Table 3.9) or copartisans (Table C.4). In other words, we have higher confidence in the findings suggesting affective polarization in the sense of partisan animus ($p < 0.001, p < 0.01$) versus the findings supporting a lesser disadvantage

applying to unique firms (Table C.3), all of which are found in Appendix C. In each case, opposing partisans are less likely to receive a callback than copartisans.

of partisan neutrality ($p < 0.05$) or the advantage of partisan homophily ($p < 0.05$). In sum, although these models support both affective polarization and partisan homophily, we comparatively find higher statistical confidence in affective polarization.

Apart from the primary results on affective polarization and partisan homophily, we can also assess the effects (or lack thereof) for alternative model explanations. As previously suggested, the results differ depending on the type of firm to which an applicant applies. For instance, consistent with the above bivariate analysis, applicants to Democratic firms were more likely to receive a callback in each model, ceteris paribus (Table 3.9). Thus, those applying to Democratic firms were more likely to receive a callback, controlling for an applicant's partisan matching status, suggesting that Republican applicants to Democratic firms had better callback prospects than Democratic applicants to Republican firms. The exact explanation for this phenomenon is not entirely clear. Perhaps, some typically Democratic firms, such as technology firms, have a greater demand for highly skilled, technologically proficient applicants than the Republican firms in the study, or conversely, because these positions require difficult to acquire skills and credentials, they may be less sensitive to dimensions such as partisanship, provided you otherwise have a highly qualified resume. Thus, the demand for highly specialized, highly skilled applicants might dampen the effects of political partisanship.

This latter supposition dovetails with a subsequent finding. For the jobs applied to in this study, I did not find clear evidence that firms prefer higher versus lower prestige applicants. In part, this may reflect the fact that skills remain more salient than prestige for technical jobs. Nonetheless, fitting in politically proved more important than applicant prestige, and these partisan effects vary by the partisanship of the firm. Generally, this analysis did not reveal any effects by job type, resume and cover material version, or the order in which applicants were received. Only a weak association ($p < 0.1$) exists suggesting that West Coast applicants were less likely to receive a callback, as were applicants applying in the second experimental wave. Both findings, while not meeting the standard $\alpha < 0.05$ threshold, illuminate potential improvements or experimental considerations, which I expand upon in the discussion.

3.4 Discussion

Political partisanship permeates and serves as a potential barrier or benefit in the job-application process in corporate America. In this analysis, I demonstrate in particular, that an individual job applicant's partisanship—while a salient signal—critically relies upon dyadic partisan mechanisms, chiefly affective polarization (Iyengar and Westwood 2015; Iyengar et al. 2019), and secondarily, partisan homophily (Huber and Malhotra 2017; Iyengar et al. 2018). As we have seen, applicants are at a statistically significant advantage when their partisanship aligns with that of the firm, proving more likely to receive a callback than either politically neutral or opposing partisan applicants. Indeed, these findings augment a litany of studies showing partisan or political homophily in various contexts (Huber and Malhotra 2017; Iyengar et al. 2018), or more generalized studies revealing homophily or affinity for like others in the workplace (Ibarra 1992, 1995; McPherson et al. 2001), particularly in job applications (Rivera 2012b).

Yet, more pivotal than the findings for partisan homophily, we witness the greater salience of affective polarization. In the analysis, I demonstrate that job applicants, whose partisanship opposes the partisan majority of the firm, remain significantly less likely to receive a callback compared to politically neutral applicants, or those who align with the partisanship of the firm. The findings underscore past analyses that reveal the power of affective polarization (Gift and Gift 2015; Iyengar and Westwood 2015; Iyengar et al. 2019; Mason 2015), particularly studies which reaffirm the import of partisan animus as the primary lever in affective polarization (Iyengar and Krupenkin 2018), especially as it relates to resume evaluation (Gift and Gift 2015; Iyengar and Westwood 2015). Regarding resume evaluation, my findings substantiate those of Iyengar and Westwood (2015), which showed a preference for copartisans over opposing partisans in resume evaluation. My results importantly differ from Iyengar and Westwood (2015). Iyengar and Westwood (2015) used a survey panel of respondents versus an experiment on employers; the applicants were high school seniors versus graduate-degree holders; and the outcome was scholarships, not a jobs.

Turning to studies that experimentally evaluate affective polarization in job callbacks, Gift and Gift (2015) show that affective polarization, especially aversion to opposing partisans, negatively affects job market callbacks (Gift and Gift 2015). Like Gift and Gift (2015), I similarly demonstrate that opposing partisan applicants prove less likely to receive a callback than politically neutral applicants. Although my work likewise exemplifies the greater salience of affective polarization (partisan animus) than partisan homophily, unlike Gift and Gift (2015), I also demonstrate that copartisans are more likely to receive a callback than neutral applicants. To underscore a key differentiation, my research here is the first study to illustrate that affective polarization and partisan homophily can operate at the firm level, illustrating the importance of matching or mismatching with the partisanship of the firm. Such dyadic partisan bias at the firm level deserves additional consideration, particularly for future studies of labor market political discrimination.

In part, a likely explanation for finding statistically stronger effects (both for partisan homophily and affective polarization) resides in a methodological distinction in the evaluation of dyadic partisan effects. In short, I show that the job market prospects of applicants are not simply a function of applicant partisanship and the partisanship of a given geographic region (Gift and Gift 2015), but rather, that the alignment or divergence of the applicant and firm partisanship also matters. In other words, since partisan animus is a stronger effect than partisan homophily (Iyengar and Krupenkin 2018), the null findings of partisan homophily in Gift and Gift (2015) follow, particularly given the partisan heterogeneity that exists across firms (Bonica 2016; Gupta and Wowak 2017; Mausolf 2020a).

Although my research clearly augments the literature on affective polarization (Iyengar and Krupenkin 2018; Iyengar and Westwood 2015; Iyengar et al. 2019), especially correspondence-audit studies of affective polarization (Gift and Gift 2015), I also demonstrate the importance of considering the partisanship of the firm in this dyadic process, and in so doing, I underscore the relevance of firm partisanship in understanding labor market and workplace dynamics. That partisanship can affect workplace dynamics is not inherently unique. For instance, we have seen how partisanship differentially affects copartisan versus cross-partisan workplace conversations (Cowan and Baldassarri 2018), how partisanship, especially affective polarization transcends a multitude of social interactions (Iyengar et al. 2019), and how fitting into organizational culture has pivotal effects on persisting or faltering in the workplace (DiMaggio 1992; Goldberg et al. 2016; King et al. 2010; Rivera 2012b; Rivera and Tilcsik 2016; Stinchcombe 1965). Yet, more often than not, evaluations of affective polarization exclude firms or organizational culture. My work seeks to emphasize the importance of this dimension, as well as highlight the need to consider partisanship in future analyses of organizational diversity.

Drawing further parallels to the analysis of organizations and prior audit studies of diversity, my work elucidates some clarity vis-à-vis the theoretical puzzle of whether organizations would embrace partisan diversity or instead preference partisan homogeneity. Given the findings that both indicate a preference for copartisans and bias against partisan minorities, my research suggests that organizations did not efficiently preempt partisan discrimination, if any efforts were implemented at all, such as best-faith efforts or other diversity initiatives designed to forestall future regulation, compliance reviews, or litigation (Dobbin and Sutton 1998; Kalev and Dobbin 2006; Kalev et al. 2006; Skaggs 2008). Although the data cannot illustrate whether these firms had or actually implemented any training or efforts to mitigate partisan bias, if those efforts were in place, the results suggest they were not effective. In part, this might reflect the lack of protection for political partisanship under current EEOC law (U.S. Equal Employment Opportunity Commission 2020), despite the fact that employees have previously pursued litigation at least partially on these grounds (Copeland 2019; McCabe 2019).[49] Even without such protections, efforts to combat partisan bias might prove difficult since, as previously mentioned, this bias can operate implicitly. Nevertheless, it is worth reiterating, that partisan animus appears to be a slightly weaker, although still significant effect in Democratic firms. This may reflect a positive halo effect of differences in diversity training or compliance in Democratic versus Republican firms and that this state softens but does not eliminate partisan discrimination in these firms (Dobbin et al. 2011; Kalev and Dobbin 2006).

Beyond regulatory incentives, my results similarly do not support the idea that companies might view partisan diversity as a valued form of diversity with potential upsides in innovation, unlike the case for functional diversity (Ancona and Caldwell 1992; Burt 2000, 2004), or the potential benefits seen on teams with disciplinary diversity (Wu et al. 2019), even though in some contexts, political diversity might offer higher quality work (Shi et al. 2019). Consistent with most other studies, my work instead suggests that the majority of studied firms instead perceive partisan diversity, like diversity on other salient social dimensions, as a disadvantage. This supposition aligns with studies revealing a number of negative externalities stemming from diversity on key social dimensions, including increased discord, ineffective communication, and lower productivity (DiTomaso et al. 2007; Reagans and McEvily 2003; Williams and O'Reilly 1998), as well as lower retention and less satisfaction (Boone et al. 2004; Elvira and Town 2001; Milliken and Martins 1996; Tsui et al. 1991; Walton et al. 2015). Likewise, my work substantiates studies suggesting analogous upsides to homogeneity (Meyerson et al. 1996; Reagans and McEvily 2003; Rivera 2012b).

Although my study does not speak specifically to whether partisan diversity would incur benefits or deficits, firms in their action, collectively embrace a position which might be explained by either a rational expectation to (1) minimize the costs of diversity *a la* affective

[49] See also the National Labor Relations Board settlement agreement in the matter of Google, Case 32-CA-164766.

polarization or (2) garner the benefits of organizational or cultural fit secondary to partisan homophily. To the extent these perspectives exist, neither would seem to be dissuaded by the potential although legally nebulous grounds on which partisan discrimination might be pursued. My findings, while suggestive in clarifying this puzzle, deserve further research to more directly outline how partisan biases, such as affective polarization and partisan homophily, translate to perceptions of organizational fit and the benefits or deficits of diversity versus homogeneity in the workplace.

Methodologically, this work augments a bevy of studies utilizing correspondence-audits in the evaluation of workplace discrimination, which often emphasize race, ethnicity, gender, social class, culture, and sexual orientation (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015; Kang et al. 2016; Pedulla 2016; Rivera 2012b; Rivera and Tilcsik 2016; Tilcsik 2011). Alongside Gift and Gift (2015), my work extends correspondence-audit studies to include partisan discrimination. Although the primary focus of my research was evaluating partisan bias, I also included variation on applicant prestige, controlling for skill. Although Gaddis (2015) finds a callback advantage for those with elite credentials, race generally mattered more than prestige. Although I also did not find any significant advantage for high prestige applicants, like Gaddis (2015), I found that my main effect, in this case, partisanship, outweighed prestige. Following the notion that the effects of partisanship outweigh those of race (Iyengar and Westwood 2015), the null finding for prestige makes sense, particularly since my research design isolates prestige while controlling for skill and exemplifying a high level of both hard and soft skills that prestige so often approximates. That all my fictitious applicants also had hard to obtain technical skills, applied technical experience, and graduate degrees likely also assuaged employer concerns for low prestige applicants, compared to the bias that low prestige applicants with only a college degree might otherwise incur. Although such findings might appear to complicate findings of social or cultural capital, we must recall that while attending elite, or otherwise selective schools, is often entangled in social and cultural capital (Coleman 1988; DiMaggio and Mohr 1985;

Lareau 2003; Stevens 2007), any skills, whether soft skills or hard technical skills that are shaped by social and cultural capital are fixed across levels of prestige in this experiment. In this way, my study simply suggests that when educational and occupational prestige is isolated from the skills, it may not be as deterministic as some studies suggest (Rivera 2011, 2012b). At the same time, the results are consistent with several past studies. For example, Dale and Krueger (2002) do not find any systematic benefit of attending a selective versus unselective school, and James et al. (1989) finds that more important than college prestige is mathematics ability, GPA, and obtainment of a technical degree, qualities all applicants in my study had. Another important facet is how we define high prestige. For instance, in both this study and Gaddis (2015), many of the high prestige universities would likely have received ridicule from the participants in (Rivera 2011: 78), where attending a lesser Ivy League school suggested failure and only a "super-elite" Ivy such as Harvard, Princeton, or Yale would suffice. Resolving this question would require further experimental analysis that manipulates applicant prestige at super-elite universities versus other prestige tiers controlling for applicant skills, social, and cultural capital. Experimentally, however, as noted here and Rivera and Tilcsik (2016), conducting experiments with only super-elite applicants has certain challenges.

Of course, I must also recognize a number of potential caveats. First, although the computational design and deployment of the correspondence by emailed resumes and cover letters afforded many benefits, because response hinged on email delivery to an appropriate contact, the process of finding such a contact (and then having a valid email), proved challenging, and potentially hurt the response rate. Although traditional online application methods may have yielded a better response rate compared to emails, they would have proved challenging to execute at scale without human error and likely many months to send thousands of tailored, randomized applications and cover letters. Second, and related to the callback, finding recently posted jobs likely affected callback rates. Although I ran multiple web scrapers for various job fields and prioritized more recent job postings for companies, in hindsight, I would prioritize more restrictions on the recency of job postings. For example, to maximize potential response, it may have been better to iteratively work in batches such that, I only applied to jobs posted in the past week, rather than proceed in larger bulk batches where some jobs applied to had been posted for a number of weeks and perhaps had many qualified applicants already in the pipeline.

Additionally, dyadic analyses prove doubly difficult since information is also needed on the firm. In the case of firm partisanship, determining the partisan leaning of the modal employee proves challenging in its own right (*c.f.* Bonica 2016; Mausolf 2020a), and even these analyses might not have as recent a partisan profile as optimal and may need supplementation to garner partisan profiles for additional companies. As such, beyond the standard caveats around the experimental design, we must also consider any errors in the partisan inference for the firm, as well as any selection biases or other random errors in the inclusion or missingness of firms for which partisanship could be determined. Furthermore, we might also expect complex randomness in firm response dynamics. For instance, the partisanship of the firm recipient might oppose that of the typical employee, thus affecting results. Similarly, responsiveness might vary depending on the number of firm employees the email passes through before a decision is made to respond. Of course, if the participants suspected the evaluation of partisan discrimination (or conversely were oblivious to the partisan signal), they might also simply respond favorably to both applicants. Lastly, the type of analyses chosen could also affect the results. Although many of these errors are difficult, or even impossible to detect, I nonetheless suggest that given the overall experimental robustness, demonstration of effects using various analytic approaches, the general consistency with the existing theory on affective polarization, and the preregistration of the study design, that the results prove veritable.

In sum, I have demonstrated in this analysis that job market candidates face the ramifications of political partisanship in job applications, particularly those of affective polarization and partisan homophily. Although applicants are more likely to receive a callback when their partisanship aligns with a firm, compared to an applicant who remains neutral, or otherwise conceals their partisanship, such actions also pose substantial risks. In particular, the misapprehension of the firm's dominant partisanship can quickly denigrate an applicant's prospect of receiving a callback. That is, firms, more often than not, passed over otherwise qualified applicants whose partisanship opposed that of the firm. Office politics have always existed, although now, in an era of rising partisan and affective polarization, it is not simply a quotidian turn of phrase, but rather a salient social fact, dictating which applicants are suitable and welcome to join a given firm.

APPENDIX C

Appendix Chapter 3: Experimental Methods Supplement

C.1 Example Experimental Materials

Subject: Data Scientist Opening - Facebook
From: Ryan Connor McGrath <ryancrmcgrath@gmail.com>
To: officepoliticsaudit
Date Sent: Sun, 31 Mar 2019 16:11:02 -0700 (PDT)
Date Received: Sun, 31 Mar 2019 16:11:04 -0700 (PDT)
Attachments: Resume_Ryan_Connor_McGrath.pdf

Hi Jonathan,

I am writing in response to your notice for the Data Scientist opening at your Menlo Park office. I am a doctoral candidate in computer science at Stanford University, where I specialize in studying recurrent neural networks for cloud computing. Facebook has excellent careers in data science and artificial intelligence, and I am confident, together, we would be a great match.

As a computer scientist, I have both the theoretical knowledge and applied experience to make a difference at Facebook. If you peruse my resume, you'll notice that I have not only developed enhanced RNN algorithms in Java, but I have also used Python, Spark, and SQL to apply deep neural nets and streamline ETL pipelines as a data science intern for both Airbnb and Microsoft. Collectively, my background in computer science as well as statistical and mathematical modeling gives me first-hand experience into the crux of today's complex puzzles in data science and their applications at the frontier of artificial intelligence.

Although I have a number of methodological strengths and my doctoral degree underscores my ability to tackle multifaceted problems, independence has its limits. Therefore, I also strive to work as a team player, whether it's by working with colleagues at Airbnb and Microsoft to communicate data-driven solutions or spearheading fundraising initiatives and leading a diverse set of students during my tenure as president of the Cal Associated Students. I think you will agree that my programming and mathematical background—combined with my outgoing charisma and penchant for team leadership—makes me a valuable recruit for the position at Facebook.

Jonathan, I am excited about this opportunity at Facebook and eager to discuss next steps. Attached, please find a copy of my resume. I look forward to speaking with you soon so that we can discuss the position further.

All the best,

Ryan

Ryan Connor McGrath
Ph.D. Candidate, Department of Computer Science
Stanford University
763.354.1118 | ryancrmcgrath@gmail.com

Figure C.1: Version A Cover Letter for P03NH to Hypothetical Data Science Job

Subject: Position | Data Scientist
From: Graham Spencer Andersen <grahamsrandersen@gmail.com>
To: officepoliticsaudit
Date Sent: Sun, 31 Mar 2019 16:10:24 -0700 (PDT)
Date Received: Sun, 31 Mar 2019 16:10:26 -0700 (PDT)
Attachments: Resume_Graham_S_Andersen.pdf

Dear Jonathan Williams:

I hope this email finds you well. I recently came across the Data Scientist position at Facebook's Menlo Park office. As a Ph.D. candidate in electrical engineering and computer science at the University of California-Berkeley, I research the application of nonparametric bound estimation for deep reinforcement learning, a type of computer vision. Given, Facebook's opportunities in machine learning and data science, I would love to contribute my talents.

With my background in computer science, I exhibit both the academic theory and pragmatic qualifications to be impactful at Facebook. As evidenced in my resume, I have used my dissertation to develop a C++ library that optimizes deep learning. Moreover, I have applied my computational skills in Python, SQL, and Hadoop to improve ETL server efficiency and provide impactful analytics during my summer data science internships at Google and Uber. Both within and outside the workplace, I embrace collaboration, such as my efforts at Google and Uber to share actionable data intelligence or my past initiatives as vice president of the UCLA Bruin Democrats to direct fundraisers and organize student activities.

In combination, my collaborative skills and computational abilities in artificial intelligence, mathematics, and statistics illustrate the value I can bring to Facebook, and I would be delighted to continue the conversation. To that end, I have attached my resume for review. I hope to hear from you shortly.

Sincerely,

Graham S. Andersen
Ph.D. Candidate
Department of Electrical Engineering and Computer Sciences
The University of California, Berkeley
Phone: (616) 528-3153

Figure C.2: Version B Cover Letter for P01DH to Hypothetical Data Science Job

Ryan Connor McGrath

353 Serra Mall, Gates 438, Stanford, CA 94305 | 763.354.1118 | ryancrmcgrath@gmail.com

Education

2019 Ph.D. Stanford University, Computer Science
◇ Thesis: *Adaptive Computational Offloading in the RNN Algorithm*
◇ Keywords: Recurrent Neural Networks, Artificial Intelligence, Parallel Computing

2015 M.S. Stanford University, Computer Science, GPA: 3.95

2013 B.S. University of California, Berkeley, Mathematics, GPA 3.86

Skills

Programming
◇ Python, C++, Java, Scala, R, Spark, Hive, SQL, PHP
◇ HTML, CSS, JSON, Node.js, Flask, Shiny
◇ Vim, Atom, Sublime, LaTeX, Git, SSH, Mac, Linux, Windows

Analysis
◇ Machine Learning; Recurrent Neural Networks; Parallel Computing; Tera and Giga Data; Time Series, Longitudinal Models; Natural Language Processing; Web-Scraping

Professional Experience

2014-Present — Stanford University, Stanford, CA
Graduate Research Assistant, Department of Computer Science
◇ Developed an enhanced LSTM algorithm in **Java** for deep learning. Supervised 3 junior programmers.
◇ Applied machine learning and RNN models to parallelized GPU clusters using **Python**, **Spark**, and **C++**, improving performance on complex pattern recognition tasks.

Jun-Sep 2018 — Airbnb, San Francisco, CA
Data Science and Analytics Intern
◇ Reduced computational complexity while improving precision by 15% in modeling facial recognition on a distributed **Spark** cluster using **Python** and **SQL**.

Jun-Sep 2017 — Microsoft, Redmond, WA
Data Scientist/Machine Learning, Intern
◇ Improved backend development of an ETL pipeline with **PHP** and **SQL**.
◇ Developed a predictive machine learning dashboard with **Python** and **SQL** to provide consumer insights to project managers.

2012-2013 — University of California, Berkeley, Berkeley, CA
Research Assistant, Department of Mathematics
◇ Conducted original research, synthesized literature, and assisted with proofs on network topologies.

Leadership, Awards, and Honors

2014-2019 — Stanford University
◇ Marshall Dissertation Completion Fellowship, Kaggle Competition Finalist, CVPR Presenter.

2009-2013 — University of California, Berkeley
◇ Graduated *magna cum laude*, Phi Beta Kappa, Dean's List.
◇ Spearheaded fundraising campaigns and managed student events as president of the Cal Associated Students.

Additional Information

Languages: English (native), French (proficient), Portuguese (elementary)

Office: Microsoft: Word, PowerPoint, Access, Outlook, Excel; Adobe: Acrobat Pro, InDesign, Lightroom; Google: Slides, Sheets, Documents, Gmail, Drive; Project management: Salesforce CRM, Trello, Basecamp; Other: Tableau, Gephi, Atlas.ti

Interests: Squash, Cycling, Travel, Hiking, Winter Sports

Figure C.3: Version A Resume for P03NH to Hypothetical Data Science Job

Graham S. Andersen

Address: 253 Cory Hall
Berkeley, CA 94720
Phone: (616) 528-3153
Email: grahamsrandersen@gmail.com

Education

Ph.D.	University of California, Berkeley, Electrical Engineering and Computer Science ○ Thesis: *Nonparametric Bound Estimation in Deep Reinforcement Learning*, a thesis which develops and applies deep reinforcement learning, artificial intelligence, algorithmic efficiency.	2019
M.S.	University of California, Berkeley, Statistics, GPA: 3.94	2015
B.S.	University of California, Los Angeles, Applied Mathematics, *summa cum laude*, GPA 3.91	2012

Work Experience

University of California, Berkeley, Berkeley, CA — 2013-Present
Graduate Research Assistant, Department of Electrical Engineering and Computer Science
○ Authored a mathematical proof for nonparametric bound estimation and wrote a *C++* library to demonstrate the algorithm's utility for deep reinforcement learning.
○ Maintained server data integrity and engineering for fellow researchers' machine learning projects.

Google, Mountain View, CA — May-Aug 2018
Data Science Intern
○ Optimized an ETL pipeline using *SQL* and improved the efficiency of deep learning models by 21% using a combination of *Python* and *C++*, thereby reducing server costs in both memory and computation time.
○ Deployed appropriate machine learning and computational methodologies in *Python* to furnish project partners with impactful measurement strategies and analytic insights.

Uber, San Francisco, CA — May-Aug 2017
Data Science, Computer Vision Intern
○ Harnessed *SQL*, *Hadoop*, and *Python* to drive impactful predictive analytics.
○ Collaborated with data engineers and junior developers in the creation of *Python* and *Django* based machine learning dashboards, which I shared with project leads to improve product strategy.

University of California, Los Angeles, Los Angeles, CA — 2011-2013
Research Assistant, Department of Applied Mathematics
○ Distilled prior mathematical research and worked with graduate fellows to devise proofs necessary for a paper on N-dimensional hypergraphs.

Honors, Awards, and Accomplishments

University of California, Berkeley — 2013-2019
○ Dissertation Improvement Grant, Department Hackathon Facilitator, KDD Presenter.

University of California, Los Angeles — 2008-2012
○ Latin honors - *summa cum laude*, Phi Kappa Phi, President's List.
○ Organized campus activities and directed fundraisers as vice president of the UCLA Bruin Democrats.

Technical Skills

○ Python, Java, C++, Julia, R, SQL, Hadoop, PrestoSQL
○ HTML, JavaScript, CSS, Markdown, JSON, Django, Tableau
○ Sublime, Emacs, Secure Shell, Git, Linux
○ Deep Reinforcement Learning, Machine Learning, NLP
○ Distributed Computing, Large Data, Data-Mining
○ Time Series, Multilevel Modeling

Supplemental Qualifications

○ *Languages*: *German* (advanced), *Spanish* (beginner)
○ *Business*: SAP CRM, Asana, Slack
○ *Microsoft Office*: Excel, Word, PowerPoint, Outlook, Access
○ *Google*: Slides, Sheets, Documents, Gmail, Drive

Figure C.4: Version B Resume for P01DH to Hypothetical Data Science Job

C.2 Supplemental Figures and Models

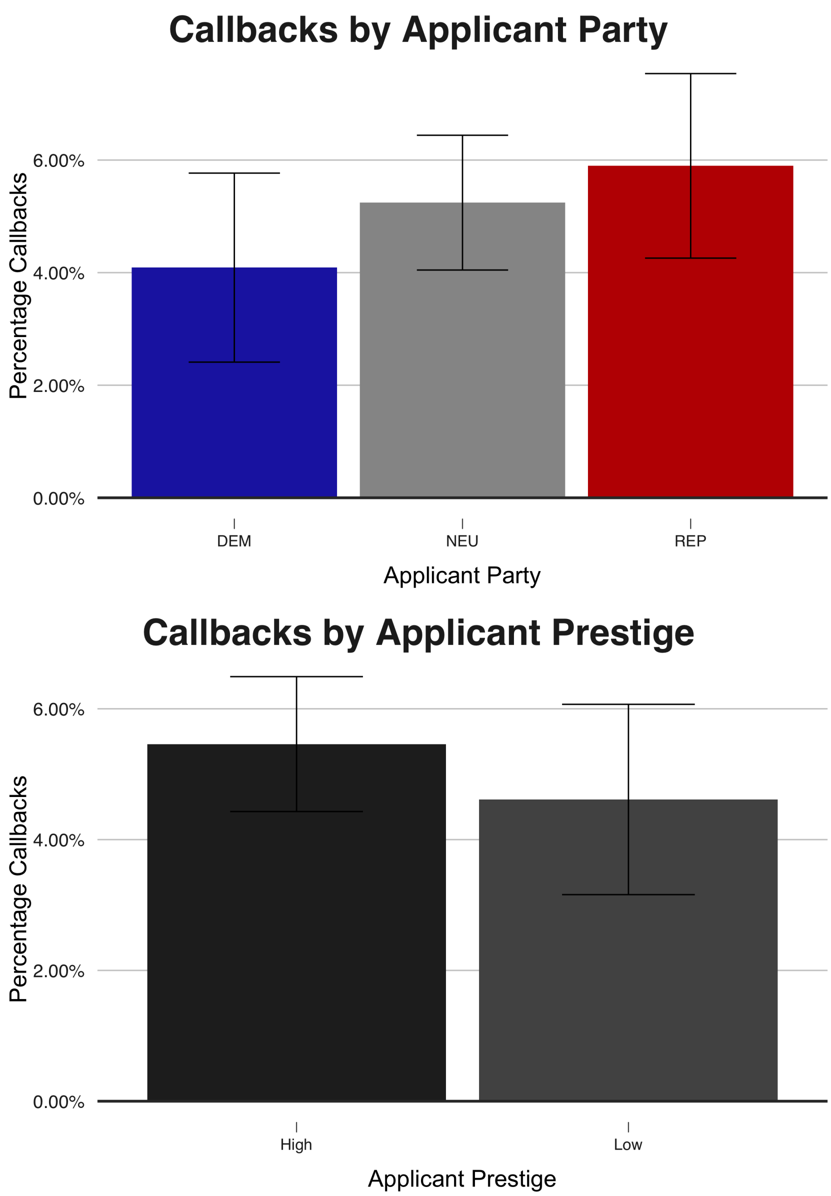
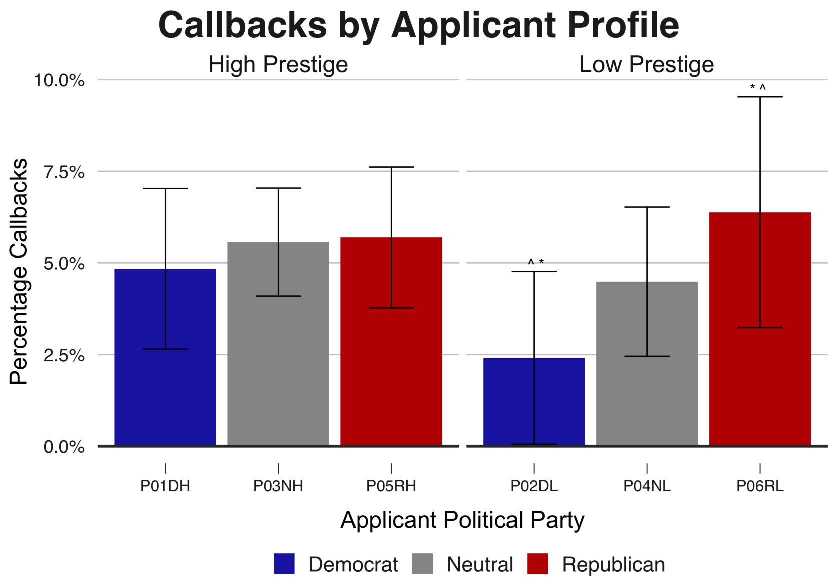


Figure C.5: Experimental Results by Applicant Partisanship and Prestige

Notes: N = 2670. Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party. No significant differences exist in either subplot.

(1) Received Applicants (N = 2670)



(2) Matched Applicants (N = 658)

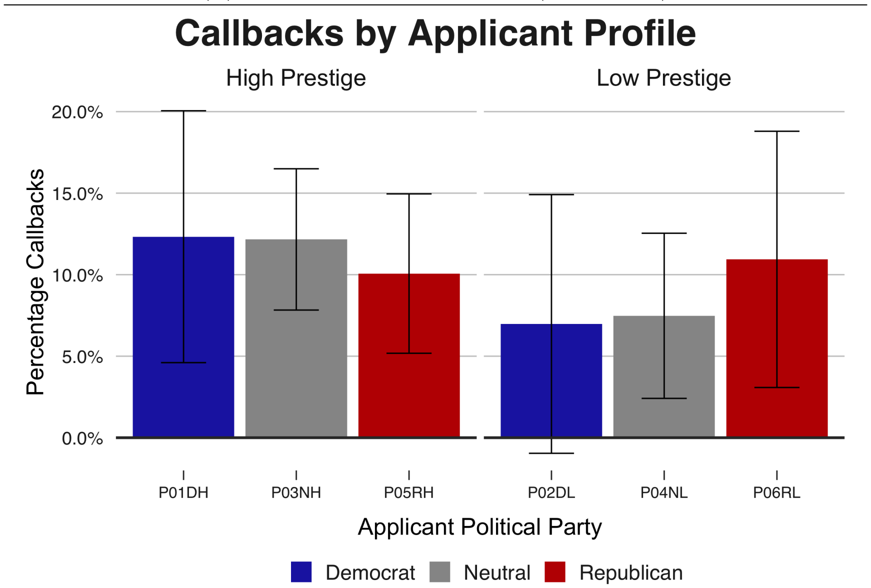


Figure C.6: Comparison of Callbacks using Party X Prestige for (1) Received Applicants versus (2) Matched Applicants

Notes: Mean callback rate with 95% confidence interval displayed. Confidence intervals generated for each group (bar) using a one-sample t-test with the default two-sided option in R. This yields a confidence interval equivalent to the 95% CIs generated from a two-sample t-test with unequal variance in Stata. Two-sample t-tests for unequal variance calculated between each applicant partisanship and the other two partisan types within each firm party.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table C.1: Logit Models of the Likelihood that a Job Applicant Receives a Callback at a Republican Firm, Matched Applicants, Odds Ratios (OR) Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.091*	0.107*	0.094*	0.093*
Neutral Applicant	0.431*	0.454+	0.424*	0.420*
(Ref: Matched Partisan)				
Applicant Prestige				
High Prestige	0.970	1.050	0.925	1.017
(Ref: Republican Firm)				
Job Type				
MS: Computer Scientist		0.805	0.817	0.785
(Ref: Lower Prestige)				
MBA: Analyst or Manager		0.173*	0.210*	0.209*
Region				
Midwest				1.557
(Ref: Ph.D. Data Scienctist-Quant)				
South				0.790
West Coast				0.312
Experiment Features				
Received Order: Second			1.499	1.611
(Ref: East Coast)				
Resume Version: B			1.401	1.366
Experiment Wave: Second Wave			0.376	0.381
Constant	0.180***	0.229**	0.200**	0.183**
N	340	340	340	340
Log Likelihood	-93.653	-89.604	-87.286	-85.363
AIC	195.305	191.208	192.572	194.727

Notes: N = 340. Republican firms only. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.2: Logit Models of the Likelihood that a Job Applicant Receives a Callback at a Democratic Firm, Matched Applicants, Odds Ratios (OR) Displayed

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.220**	0.222**	0.224**	0.227**
Neutral Applicant	0.630	0.639	0.643	0.651
(Ref: Matched Partisan)				
Applicant Prestige				
High Prestige	1.941+	2.032+	2.002+	1.917
(Ref: Republican Firm)				
Job Type				
MS: Computer Scientist		0.822	0.812	0.791
(Ref: Lower Prestige)				
MBA: Analyst or Manager		1.860	1.842	1.655
Region				
Midwest				0.770
(Ref: Ph.D. Data Scienctist-Quant)				
South				1.201
West Coast				0.590
Experiment Features				
Received Order: Second			0.909	0.909
(Ref: East Coast)				
Resume Version: B			0.924	0.929
Experiment Wave: Second Wave			0.606	0.571
Constant	0.170***	0.143***	0.166***	0.206**
N	318	318	318	318
Log Likelihood	-114.287	-112.573	-112.175	-110.960
AIC	236.573	237.147	242.350	245.919

Notes: N = 318. Democratic firms only. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.3: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, OR Displayed, Deduplicated Firms

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.173***	0.175***	0.166***	0.166***
Neutral Applicant	0.525*	0.530*	0.513*	0.515*
(Ref: Matched Partisan)				
Firm Partisanship				
Democratic Firm	2.058**	2.057**	1.905*	2.323**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.483	1.494	1.428	1.496
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.821	0.819	0.792
MBA: Analyst or Manager		0.831	0.883	0.820
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.271
South				1.019
West Coast				0.528
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.111	1.120
Resume Version: B			1.111	1.119
Experiment Wave: Second Wave			0.448+	0.460+
Constant	0.118***	0.128***	0.138***	0.131***
N	646	646	646	646
Log Likelihood	-207.748	-207.478	-205.421	-203.165
AIC	425.495	428.956	430.841	432.331

Notes: N = 646. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral). Only unique, deduplicated firms included. Although the original models include unique applicant pairs, because of errors in deduplicating list-ids, several firms received more than one pair of applications for different open positions to different firm contacts. These cases were removed from these models.
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table C.4: Logit Models of the Likelihood that a Job Applicant Receives a Callback, Matched Applicants, OR Displayed, Neutral Reference Group

	Pr{Applicant Receives Callback}			
	(1)	(2)	(3)	(4)
Applicant Partisan Matching				
Mismatched Partisan	0.328**	0.330**	0.322**	0.320**
Matched Partisan	1.915*	1.900*	1.974*	1.966*
(Ref: Neutral Applicant)				
Firm Partisanship				
Democratic Firm	2.052**	2.054**	1.901*	2.341**
(Ref: Republican Firm)				
Applicant Prestige				
High Prestige	1.480	1.489	1.415	1.477
(Ref: Lower Prestige)				
Job Type				
MS: Computer Scientist		0.818	0.819	0.786
MBA: Analyst or Manager		0.830	0.891	0.827
(Ref: Ph.D. Data Scienctist-Quant)				
Region				
Midwest				1.279
South				1.028
West Coast				0.521+
(Ref: East Coast)				
Experiment Features				
Received Order: Second			1.116	1.124
Resume Version: B			1.109	1.117
Experiment Wave: Second Wave			0.420+	0.434+
Constant	0.061***	0.067***	0.070***	0.067***
N	658	658	658	658
Log Likelihood	-209.025	-208.748	-206.332	-203.976
AIC	428.049	431.496	432.663	433.952

Notes: N = 658. Matched applicants are those applicants who applied to a firm where the partisanship of the firm could be determined, resulting in three match conditions (mismatch, neutral, and match) based on the partisanship of the firm (Democratic or Republican) and the partisanship of the test applicant (Democratic or Republican) and control applicant (Neutral).
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

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