Do Street-level Bureaucrats Discriminate Based on Political Ideology?

An Empirical Investigation

by

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ABSTRACT

Street-level bureaucracy (SLB) theory argues that public servants take shortcuts when making decisions about the delivery of public services. These shortcuts can lead SLBs to treat citizens unfairly. Public administration and political science researchers have found some evidence that street-level bureaucrats act in biased ways towards ethnic and racial minorities, citizens of lower socioeconomic status, and religious minorities. I expand on the SLB literature on discrimination by examining whether SLBs discriminate based on the political ideology of citizens. According to the Ideological-Conflict Hypothesis, individuals act in biased ways towards others whose political values conflict with their own. Using the Ideological-Conflict Hypothesis, I test whether SLBs working in local governments discriminate against citizens based on political ideology and whether discrimination is related to type of service delivery (e.g. needs based versus universal). I carry out two audit experiments to test for discrimination. One audit experiment tests for political ideology discrimination in a need-based program among a sample of public housing authorities in the United States (US). The sample is limited to areas where over 60% of citizens voted for the Democratic candidate in the 2020 Presidential Election (n = 274)—and where over 60% voted for the Republican candidate (n = 274). The other audit experiment tests for political ideology discrimination in the delivery of a universal service using a sample municipal parks departments in US cities. The sample is cities with over 25,000 residents where at least 60% of citizens in the county voted for the Democratic candidate in the 2020 Presidential Election (n = 227) and counties where at least 60% of citizens voted for Republican candidate (n = 227). The treatment signals that an email is from a conservative citizen, a liberal citizen, or a citizen with no identifiable political ideology. The results of my dissertation provide some support for the Ideological-Conflict Hypothesis and evidence indicates SLBs discriminate based on political ideology. The results do not find differences in political discrimination for needs-based public service delivery compared to universal public service delivery.

DEDICATION

I dedicate this dissertation to my loving wife. She has been my rock for the last eight years. I love you, Avarie.

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CHAPTER 1

INTRODUCTION

Local, State, and Federal governments in the United States (US) deliver a variety of public services to citizens. Public servants such as teachers, police, and social workers, are responsible for providing public services to citizens. These 'street-level bureaucrats' (Lipsky, 1980) are required to treat citizens equally and use their discretion to provide public services according to the rules set out in public policy. While public servants are tasked with treating all citizens equally on an individual basis, public servants often face high workloads and are given significant discretion (Lipsky, 1980). Due to high workloads and discretion, street-level bureaucrats often take mental shortcuts while delivering public services—resulting in public service delivery that is not tailored to the individual circumstances of citizens (Lipsky, 1980).

Street-level bureaucracy (SLB) theory (Lipsky, 1980) thus argues that public servants are fallible human beings that take shortcuts when delivering public services—potentially leading to disparate public service outcomes. Researchers have theorized that street-level bureaucrats act in biased ways towards individuals based on race, ethnicity, socioeconomic class, sex, sexual orientation, and religious beliefs (Adam, Grohs, & Knill, 2020; Grohs, Adam, & Knill, 2016; Maynard-Moody & Musheno, 2003; Pfaff, Crabtree, Kern, & Holbein, 2021; Raaphorst & Groeneveld, 2019; Raaphorst, Groeneveld, & Van de Walle, 2018;). Public administration scholars have used five explanations to explain why street-level bureaucrats may discriminate against citizens.

The five explanations are 1) taste-based discrimination, 2) statistical discrimination, 3) implicit bias, 4) double standards, and 5) moral judgments.

Researchers have applied SLB theory to investigate whether bureaucrats discriminate based on race, ethnicity, socioeconomic status, and religious beliefs. The empirical results of these studies show mixed evidence of discrimination. I expand the SLB literature on discrimination by examining whether SLBs discriminate based on the political ideology of citizens. Psychology research has shown individuals can be intolerant, biased, and discriminatory towards others who do not share their political ideology (Brandt et al., 2014; Crawford & Pilanski, 2014; Ditto et al., 2019; Wetherell et al., 2013). According to the Ideological-Conflict Hypothesis (Brandt et al., 2014), both conservative and liberal individuals in the United States “express intolerance towards groups with whom they disagree” (Brandt et al., 2014 p. 27). Intolerance and bias have been shown to occur when individuals perceive conflict against their own world view and values in opposing political ideologies (Brandt et al., 2014). Furthermore, research has shown that individuals can hold double standards for and against those who share or do not share their political ideology (Crawford, 2012).

In this dissertation, I add to the literature on discrimination by street-level bureaucrats by exploring whether public service delivery outcomes vary based on recipient political ideology. Drawing from the Ideological-Conflict Hypothesis (Brandt et al., 2014), I expect to find SLBs in US local governments discriminate against public service recipients based on political ideology.

The literature on SLB discrimination provides evidence that discrimination may vary depending on the type of public service being administered—but this phenomenon has not explicitly been tested. In this dissertation, I also examine whether political discrimination varies for SLBs providing universal or needs-based public services. Foundational SLB theory suggests that SLBs view some clients as more or less deserving of help (Maynard-Moody & Musheno, 2003). These perceptions allow SLBs to use their considerable discretion to help those they perceive as more deserving—and neglect those they perceive as less deserving (Maynard-Moody & Musheno, 2003). I expect that SLBs providing a needs-based public service have stronger tendencies to judge client worthiness than SLBs providing universal public services, where all receive a service regardless of need or worth. Based on this hypothesis, I expect that SLBs providing needs-based public services will be more likely to assign moral judgments to clients based on client political ideology. I hypothesize this will lead to stronger evidence of discrimination in needs-based public service delivery compared universal public service delivery.

To test for political discrimination by SLBs—and whether discrimination varies based on the type of public service—I run two audit experiments, one for a needs-based service and one for a universal service. In the first audit experiment, I test for political discrimination in a needs-based public service context by sending emails from fictitious individuals with a clear political ideology to a sample of Public Housing Authorities in the U.S (N = 548). In the second audit experiment, I test for political discrimination in a universal public service context by sending emails from fictitious individuals with a clear political ideology to a random sample of parks departments in the U.S (N = 454). The results of the public housing experiment show that SLBs in the Democratic-majority sample are more likely to respond emails with the liberal treatment—and SLBs in the

Republican-majority sample are more likely to reply to emails with the conservative treatment. The parks department experiment found that SLBs in the Democratic-majority sample were less likely to respond to emails with the liberal treatment. The Republican-majority sample showed no evidence that SLBs were more or less likely to respond to the conservative or liberal email treatment. The results of my experiments did not show evidence that SLBs in needs-based public service delivery are more likely to discriminate based on political ideology than SLBs delivering universal services. I find evidence that females are more likely to receive a response from SLBs. Finally, I find that community factors—population, income, and racial diversity—do not predict political discrimination.

In this dissertation, I begin by describing the theoretical foundations for street-level bureaucrat discrimination. I then review the empirical evidence of whether SLBs discriminate based on a variety of characteristics. Following this, I describe a theory of political ideology discrimination—known as the “Ideological-Conflict Hypothesis” (Brandt et al., 2014)—and provide my rationale for how this theory predicts SLB discrimination based on political ideology. Next, I describe the research design, method, and data I employ to test for SLB ideological discrimination. Finally, I report the results and implications of my findings.

CHAPTER 2

STREET-LEVEL BUREAUCRATS, DISCRIMINATION, AND POLITICAL IDEOLOGY BIAS

There is a substantial body of literature on street-level bureaucrats (SLBs) and discrimination. Scholars draw on multiple theories of discrimination to explain why street-level bureaucrats may discriminate against certain public service recipients. Discrimination is “unfair or prejudicial treatment of people and groups based on characteristics such as race, gender, age or sexual orientation” (APA, 2019). Researchers test for discrimination based on race, ethnicity, socioeconomic status, sex, sexual orientation, and religious beliefs. Political discrimination is another form of bias that can influence the actions of people from all political persuasions. In this chapter, I review theories of street-level bureaucracy and explanations given for street-level bureaucrat discrimination. I then review the empirical evidence of street-level bureaucrat discrimination based on race, ethnicity, socioeconomic status, sex, sexual orientation, religious beliefs, and political beliefs. Next, I discuss the phenomenon of political discrimination and how it applies to street-level bureaucrats. Finally, I outline how political discrimination by street-level bureaucrats may vary based on type the public service: needs-based or universal.

Theories of Street-level Bureaucracy & Discrimination

In the preeminent work on street-level bureaucracy, Lipsky (1980) details how front-line public servants play a crucial role in implementing public policy. Lipsky

(1980) describes ‘street-level bureaucrats’ as public servants who “interact directly with citizens in the course of their jobs, and who have substantial discretion in the execution of their work” (p. 3). According to Lipsky, SLBs are expected to administer public services to citizens on an individual basis. Lipsky argues this expectation is unrealistic due to the tremendous number of citizens and clients that SLBs are tasked with serving. Instead of treating all citizens as individuals, street-level bureaucrats take shortcuts in how they administer public services to meet citizen needs and the demands of their jobs (Lipsky, 1980). Building on Lipsky’s theory, scholars have explored how street-level bureaucrats—who have high workloads and limited resources—find ways to cope with their demanding jobs. Street-level bureaucrats have been shown to cope with demanding jobs by behaving in ways that help them “master, tolerate, or reduce external and internal demands and conflicts they face on an everyday basis” (Tummers, Bekkers, Vink, & Musheno, 2015, p. 1100).

Building on Lipsky’s theory that SLBs adopt behaviors and shortcuts that are not always conducive to providing optimal, individualized public service, public administration scholars have explored whether SLBs act in discriminatory ways towards some of the citizens they serve. Drawing from in-depth interviews, Maynard-Moody and Musheno (2003) illustrate that SLBs make moral judgments based on their clients’ identities and character—and treat clients accordingly. SLBs use their significant discretion to help those they judge to be deserving of extra help—and do less for those they view as undeserving (Maynard-Moody & Musheno, 2003).

Researchers use theories of discrimination to explain why SLB discretion and judgment can lead to biased treatment of citizens of various backgrounds. Public administration scholars have used five explanations to explain why street-level bureaucrats may discriminate against citizens. The five explanations are 1) taste-based discrimination, 2) statistical discrimination, 3) implicit bias, 4) double standards, and 5) moral judgments.

Taste-based discrimination theory (Becker, 1971) is one possible explanation for public service outcome discrepancies. According to the economic theory of taste-based discrimination, explicit hostility towards minority groups from individuals belonging to majority groups could lead to discriminatory market outcomes. Thus, the explicit prejudice of individual street-level bureaucrats (who, it is assumed, generally belong to majority groups) towards minorities could lead to disparate public service outcomes. Assouline, Gilad, and Ben-Nun Bloom (2021) argue that taste-based discrimination *could* be a factor in street-level bureaucrats treating citizens from minority groups poorer than they do individual citizens from majority groups. However, they argue that taste-based discrimination is less probable to be at the root of the decisions of street-level bureaucrats in professional settings. Instead, the authors argue that less-explicit factors may influence street-level bureaucrats to treat minority citizens less favorably.

According to statistical discrimination theory (Phelps, 1972; Schwab, 1986), individuals discriminate against others based on rational or irrational assumptions about that person’s group identity. According to the theory, individuals who *do and do not* belong to a group with negative stereotypes apply these negative stereotypes to individuals from that group. Assouline, Gilad, & Ben-Nun Bloom, (2021) apply statistical discrimination theory to doctors in Israel who review disability claims from Israeli citizens of both Jewish and Muslim nationalities. The authors argue that statistical discrimination could be a factor in discrepancies in outcomes for Muslim applicants as medical evaluators apply negative stereotypes to applicants.

A third approach to explaining SLB discrimination is unconscious or implicit bias (see Pedersen, Stritch, & Thuesen, 2018; Assouline, Gilad, & Ben-Nun Bloom, 2021). Implicit or unconscious bias theories stem from psychological theories of unconscious cognition (Greenwald, 1992; Greenwald & Krieger, 2006). Unconscious cognition theories argue that unrecognized mental forces influence behavior—and that not all behavior is a result of conscious thought (Greenwald, 1992). Theories such as the Racial Classification Model (Soss, Fording, & Schram, 2008) draw on unconscious cognition theories to argue that individuals have unconscious racial biases that lead individuals to discriminate based on race. Implicit or unconscious bias theories are different than taste-based and statistical discrimination theories. Implicit bias theories assume discrimination is not a conscious decision by street-level bureaucrats. Instead, people harbor unseen prejudices towards clients of different backgrounds.

A fourth approach to studying discrimination is double standards theory. Public administration scholars argue that SLBs hold clients to double standards based on their race, ethnicity, gender, socioeconomic status, and so forth. (Raaphorst, Groeneveld, & Van de Walle, 2018). According to the double standards explanation, street-level bureaucrats may hold negative stereotypes about certain groups. When these stereotypes are challenged by interacting with a client, street-level bureaucrats hold these clients to a higher standard than should be expected (Raaphorst, Groeneveld, & Van de Walle, 2018). The double standards theory is another possible explanation for disparities in public service outcomes for different groups. If public servants are subconsciously holding minority citizens and working-class citizens to higher standards than should be expected, these groups will inevitably receive poorer treatment than other groups of citizens.

Moral judgment is the fifth theory used to explain SLB discrimination. The moral judgment explanation posits that SLBs stereotype certain groups of people as being morally inferior to others. The belief that some groups are morally inferior is argued to stem from deep-seeded cultural beliefs that dominate society (Raaphorst, & Groeneveld, 2019). Since SLBs hold these social and cultural beliefs, they view certain citizens or groups of citizens as morally inferior and treat them differently than citizens they view as morally superior.

The five explanations used to explain SLB discrimination—taste-based discrimination, statistical discrimination, implicit bias, double standards, and moral judgments—range from overt discrimination and explicit bias to subtle and unconscious bias. Theories such as taste-based discrimination and statistical discrimination describe discriminatory behavior as intentional—or at least conscious. Others such as implicit bias and double standards explanations suggest discrimination occurs due to subconscious and unintentional mechanisms. The moral judgment explanation relies on cultural and sociological explanations for discrimination. While providing definitive proof for which of these explanations drives discrimination is difficult, researchers have investigated whether discrimination occurs in the interaction between street-level bureaucrats and their clients. This research enlightens whether public services are being delivered in a fair and impartial manner. Fair and impartial delivery of public services is (or should be) the primary goal of street-level bureaucrats.

Empirical Evidence about Street-level Bureaucrat Discrimination

Social scientists apply theories of discrimination to test whether SLBs discriminate against public service recipients. Scholars test for SLB discrimination based on race, ethnicity, socioeconomic status, sex, sexual orientation, religious beliefs, and political beliefs. Studies done on this topic focus on SLBs who provide universal public services such as schoolteachers, police officers, and tax collectors. Other studies focus on SLBs who provide needs-based public services such as social workers and public housing authority employees. Research is done in a variety of settings including Denmark, Israel, Germany, and the United States. The literature on SLB discrimination draws on multiple methods including audit experiments, survey experiments, observational studies, interviews, and others. This section discusses previous research and results of empirical studies testing for discrimination based on race, ethnicity, socioeconomic status, sex, sexual orientation, religious beliefs, and political beliefs. The section also analyzes the differences between the findings of SLBs providing universal and needs-based public services.

Race and Ethnicity

Scholars have studied whether street-level bureaucrats act in biased ways towards public service recipients based on race and ethnicity. In this section, I provide an overview of empirical studies on SLB racial and ethnic discrimination. I first examine the research that examines SLBs providing a needs-based public service. I then examine research on SLBs providing universal public services. Finally, I compare and contrast the two streams of research.

Needs-based public services. Researchers look for racial and ethnic discrimination by SLBs providing needs-based public services. These studies include a variety of SLB contexts and cover multiple countries. The SLBs researchers examine include doctors (Assouline, Gilad & Ben-Nun Bloom, 2021), public housing authority workers (Einstein & Glick, 2017), employment case workers (Holzinger, 2020; Pedersen, Stritch & Thuesen, 2018), eldercare employees (Jilke, Van Dooren & Rys, 2018), and social workers (Schram, Soss, Fording & Houser, 2009; Strier, Abu-Rayya & Shwartz-Ziv, 2021). The studies have taken place in Austria (Holzinger, 2020), Belgium (Jilke, Van Dooren & Rys, 2018), Denmark (Pedersen, Stritch & Thuesen, 2018), Israel (Assouline, Gilad & Ben-Nun Bloom, 2021; Strier, Abu-Rayya & Shwartz-Ziv, 2021), and the United States (Einstein & Glick, 2017; Schram, Soss, Fording & Houser, 2009).

Studies of SLBs providing needs-based public services find evidence to support the hypothesis that SLBs discriminate based on race and ethnicity. Researchers point to disparate public service outcomes for certain racial or ethnic groups as evidence of discrimination. For example, Assouline, Gilad, and Ben-Nun Bloom (2021) examine disability claims in Israel to see if Jewish doctors approved Jewish applicants more than Muslim applicants. The study concludes that Jewish doctors are more likely to provide partial disability benefits to Jewish applicants than to Muslim applicants (Assouline, Gilad & Ben-Nun Bloom). Similar results are found in a study of social workers in the US. A survey experiment asks 104 social workers whether they would sanction a woman who violates rules for receiving benefits (Schram, Soss, Fording & Houser, 2009). The results reveal that social workers are more likely to sanction women with putative Black names than women with putative White names (Schram, Soss, Fording & Houser, 2009).

The results of studies such as these two suggest that SLBs do not treat individuals of certain racial or ethnic backgrounds as fairly as they treat others. These findings violate the important public values of equality and fairness in public service delivery.

Scholars also find empirical evidence that disputes the hypothesis that SLBs providing needs-based public services discriminate based on race and ethnicity. For example, the study of Jewish doctors mentioned in the previous paragraph did not find evidence of discrimination across all circumstances. Assouline and colleagues (2021) find that Jewish doctors were more likely to recommend partial disability benefits for Jewish applicants than for Muslim applicants. However, the scholars do not find disparate outcomes for applications receiving full benefits. Thus, Jewish doctors appear to only favor Jewish applicants in some instances, but not in others. If the hypothesis holds that Jewish doctors are biased against Muslim applicants, the disparities would likely appear for applications requesting both partial and full benefits.

Another study in Israel contradicts the hypothesis that SLBs discriminate based on race and ethnicity. Using in-depth qualitative interviews of 80 social workers in Israel, Strier, Abu-Rayya, and Shwartz-Ziv (2021) find evidence that social workers actively seek to ensure Jewish and Muslim welfare recipients are treated equally and fairly. For example, social workers would sometimes receive national directives that would unfairly benefit Jewish welfare recipients over Muslim welfare recipients. In these instances, social workers would make great efforts to change or adapt these policies to ensure they were fair for everyone. While these studies do not prove that SLBs never discriminate based on race or ethnicity, the results suggest that some SLBs make conscious efforts to treat people of various backgrounds equally.

Universal public services. Researchers look for racial and ethnic discrimination by SLBs providing universal public services. These studies examine schoolteachers (Andersen & Guul, 2019), public schools (Bergman & McFarlin Jr, 2018; Olsen, Kyhse-Andersen & Moynihan, 2020), school principals (Oberfield & Incantalupo, 2021), municipal government employees (Giulietti, Tonin & Vlassopoulos, 2019; Grohs, Adam & Knill, 2016), police officers (Holmberg, 2000; Hong, 2021), and election officials (White, Nathan & Faller, 2015). The studies take place in Denmark (Andersen & Guul, 2019; Holmberg, 2000; Olsen, Kyhse-Andersen & Moynihan, 2020), Germany (Grohs, Adam & Knill, 2016), United Kingdom (Hong, 2021), and the United States (Bergman & McFarlin Jr, 2018; Giulietti, Tonin & Vlassopoulos, 2019; Oberfield & Incantalupo, 2021; White, Nathan & Faller, 2015).

Researchers find proof for racial and ethnic discrimination amongst SLBs providing universal public services. Scholars detect overt discrimination in some instances and more subtle forms of discrimination in others. White, Nathan, and Faller (2015) performed an audit experiment of election officials in the US and find an overt example of disparate treatment for Latino citizens. In the audit experiment, emails asking about voting information demonstrated disparate treatment based on race/ethnicity. Emails from fictitious citizens with putative Latino names received fewer responses from election officials than emails from fictitious citizens with putative White names (White, Nathan & Faller, 2015). Thus, in this instance SLBs were shown to provide more information about voting to citizens due to race/ethnicity.

Other studies look for more subtle forms of discrimination. For example, Grohs, Adam, and Knill (2016) examined whether SLBs in German municipal governments were faster, friendlier, and more thorough in their responses to email inquiries from putative German emailers than putative Turkish emailers. The results showed that responses to Turkish emailers were less thorough than to German emailers (Grohs, Adam & Knill, 2016)—a much more subtle form of bias than simply not replying to an email based on the senders' ethnicity.

Other studies of SLBs providing universal services find mixed evidence of racial/ethnic discrimination (Andersen & Guul, 2019; Bergman & McFarlin Jr, 2018; Grohs, Adam & Knill, 2016; Oberfield & Incantalupo, 2021; Olsen, Kyhse-Andersen & Moynihan, 2020). The aforementioned study by Grohs, Adam, and Knill (2016), for example, find that emails from fictitious German and Turkish emailers received similar rates of responses from German municipal government employees and that there was no difference between the speed of response and friendliness of response for these emails. The authors find that responses to Turkish emailers were less thorough. In another study, Bergman and McFarlin Jr (2018) find evidence that emails sent to charter and public schools in the US from Latino emailers received less responses (two percentage points) than White emailers. The study did not find disparities between Black and White emailers (Bergman & McFarlin, Jr, 2018). Results such as these suggest that there may be additional factors that influence whether or not SLBs show racial and ethnic bias. More work can be done to identify what factors may predict SLB racial/ethnic discrimination. Research by Andersen and Guul (2019), for example, shows workload to be a contributing factor to the presence of discrimination.

Comparing needs-based and universal public service delivery. There are many similarities between the studies examining racial and ethnic discrimination among SLBs providing needs-based and universal public services. Table 1.1 summarizes the empirical scholarship on SLB racial and ethnic discrimination. Both bodies of literature use a variety of methods and examine SLBs in multiple countries. Two of the seven studies on needs-based public service delivery show no evidence of racial and ethnic discrimination. The other five studies show evidence or mixed evidence of discrimination. Each of the nine studies on universal public service delivery show evidence or mixed evidence of discrimination. This suggests that there may be less racial and ethnic discrimination in needs-based public service delivery than in universal public service delivery. There may be several reasons why there appears to be less discrimination among SLBs providing needs-based public services. For instance, it may be that SLBs in these contexts receive more training in on anti-discrimination. The differences could also be due to the limitations of these studies such as low sample size and low response rates. When disparities are found between public service outcomes for certain racial and ethnic groups, the differences are usually less than 5 percentage points. For example, there was a two-percentage point difference between responses for Black and White students in Giulietti, Tonin, & Vlassopoulos (2019) and a two-percentage point difference between Latino and White students in the study by Bergman and McFarlin (2018).

Table 1.1: Studies on SLB discrimination based on race and ethnicity

Author(s)	Service Context	Method	Population	N	Country	Races/Ethnicities Studied	Evidence for Discrimination	Limitation
Assouline, Gilad & Ben-Nun Bloom, 2021	Needs-based	Multinomial logistic regression	Israeli Doctors	19,279	Israel	Jewish and Muslim	Mixed	Omitted variable bias
Einstein & Glick, 2017	Needs-based	Audit experiment	Public Housing Authorities	1,017	USA	Black, Latino, and White	Mixed	Signaling confounders
Holzinger, 2020	Needs-based	Qualitative interviews	Austrian Employment Service	32	Austria	Hungarian	No	Small sample size; Subjective
Jilke, Van Dooren & Rys, 2018	Needs-based	Audit experiment	Eldercare facilities	664	Belgium	Flemish and Maghrebian	Mixed	Small sample size
Pedersen, Stritch & Thuesen, 2018.	Needs-based	Survey experiment	Danish employment case workers	1,335	Denmark	Danish and Middle-Eastern	Yes	Low survey response rate
Schram, Soss, Fording & Houser, 2009	Needs-based	Survey vignette experiment	Welfare social workers	104	USA	Black, Latino, and White	Yes	Small sample size
Strier, Abu-Rayya & Shwartz-Ziv, 2021	Needs-based	Semistructured interviews	Israeli social workers	80	Israel	Jewish and Muslim	No	Small sample size
Andersen & Guul, 2019	Universal	Vignette survey experiments	Danish public school teachers	890	Denmark	Danish and Middle-Eastern	Mixed	Based on hypothetical scenario
Bergman & McFarlin Jr, 2018	Universal	Audit experiment	Charter and Public Schools	6,452	USA	Black, Latino, and White	No	Not nationally representative
Giulietti, Tonin & Vlassopoulos, 2019	Universal	Audit experiment	Various local government SLBs	19,000	USA	Black and White	Yes	Sample errors

Grohs, Adam & Knill, 2016	Universal	Audit experiment	Municipal governments	501	Germany	German and Turkish	Mixed	Small sample size; Confounding variable
Holmberg, 2000	Universal	Qualitative interviews	Police encounters	476	Denmark	Danish and Middle-Eastern	Yes	Subjectivity
Hong, 2021	Universal	Multiple regression	Police officers	462	UK	Black and White	Yes	Omitted variable bias
Oberfield & Incantalupo, 2021	Universal	Audit experiment	Public high school principals	3,260	USA	Black and White	Mixed	Signaling confounders
Olsen, Kyhse-Andersen & Moynihan, 2020	Universal	Audit experiment	Danish primary schools	1,698	Denmark	Danish and Muslim	Mixed	Signaling confounders
White, Nathan & Faller, 2015	Universal	Audit experiment	Local election officials	6,825	USA	Latino and White	Yes	Randomization error

The empirical literature examining racial bias in both needs-based and universal public service delivery (see Table 1.1) has limitations. In both contexts, studies using non-experimental methods are limited by omitted variable bias and spurious correlations. While the authors of these studies go to great efforts to control for relevant factors, it is difficult to control for all variables that could lead to disparities (or the lack thereof) in public service outcomes. Experimental studies are also limited. The methods scholars use to signal race/ethnicity in their experiments could easily be confounded with other factors such as religion, age, socioeconomic status, etc. Qualitative studies are subject to limitations including small sample sizes and researcher subjectivity bias.

Despite the limitations of these studies, the empirical literature on racial and ethnic bias in public service delivery suggests that racial and ethnic discrimination does occur in both needs-based and universal contexts. Ten of the twelve studies (see Table 1.1) show either overt or subtle differences in how individuals from different racial and ethnic backgrounds are treated by SLBs. This shows that, sometimes, SLBs favor/disfavor individuals based on racial and ethnic characteristics when delivering needs-based and universal public services. Such unequal treatment of citizens violates the important public value of equality that public officials are tasked with upholding. More work needs to be done to unpack what other factors alleviate or exacerbate such discrimination to understand what can be done to improve equal treatment of citizens.

Socioeconomic status

Street-level bureaucrats (SLBs) interact with individuals of various levels of socioeconomic status (SES). Since SLBs may take shortcuts or rely on biases and stereotypes when delivering public services, researchers have explored whether SLBs discriminate based on SES. There is evidence that SLBs may discriminate based on SES, but many studies have shown that SES bias is not prevalent in SLB interactions with the public. This section details the evidence for and against the hypothesis that SLBs discriminate based on SES. The section also discusses how these findings differ from needs-based and universal public services.

Evidence for socioeconomic status bias. There is some evidence that SLBs have biases against individuals of lower SES. Maynard-Moody & Musheno (2003) gathered stories from street-level bureaucrats from multiple occupations in the US. The study revealed that street-level bureaucrats often were trying to decide who was worthy of receiving public services—and the help and attention of street-level bureaucrats. While many factors, such as personality, race, and sex altered their perceptions, class played a large role in how SLBs determined which clients were most deserving (Maynard-Moody & Musheno, 2003). Public service recipients of lower SES appear to receive poorer treatment (Maynard-Moody & Musheno, 2003). A study in France (Dubois 2010) drew similar conclusions as Maynard-Moody and Musheno. Researchers observing the French welfare system concluded that lower-SES citizens were treated unfairly by French welfare officers due to the gap in class between welfare officers and citizens (Dubois, 2010). These studies show that individuals of lower SES may receive poorer treatment from SLBs than others. If this is the case, SLBs are not providing fair and equal treatment to the people they are tasked with serving.

Socioeconomic bias by SLBs may not only affect citizens of lower SES. A study of social workers in Denmark finds evidence suggesting that SLBs may discriminate against others who are of low *and* high SES (Harrits & Møller, 2014). Harrits and Møller (2014) find that teachers and nurses evaluating the home life of fictitious children in a survey are more likely to suggest changes in home life situations when dealing with lower- and upper-class clients than when dealing with middle-class clients (Harrits & Møller, 2014). Harrits and Møller reason that the middle-class participants in the study may have been biased by their perceptions of what a 'normal' home situation should look like and thus made recommendations accordingly. Other work shows that an individual's SES could lead to more or less favorable treatment by SLBs. Drawing on 11 interviews with Danish tax collectors, Raaphorst & Groeneveld (2018) find that tax collectors made assumptions about clients based on their socioeconomic status (level of education, type of work, etc.). Raaphorst and Groeneveld (2018) point out that these assumptions worked both for and against citizens based on their SES. In some instances, tax collectors assumed individuals of low SES were more likely to misconstrue their taxes (either inadvertently or purposefully). At other times, the tax collectors gave citizens of lower SES the benefit of the doubt and held middle- and upper-class citizens to a higher standard (Raaphorst & Groeneveld, 2018). These studies provide nuance to the discussion of SES bias in public service delivery. Socioeconomic bias does not appear to be a one-way street where SLBs only look down on individuals of low SES. Instead, SLBs may treat the citizens and clients they serve unfairly if there is a SLB-client SES mismatch.

Evidence against socioeconomic status bias. There is also evidence that SLBs do not discriminate based on SES. Using three different survey experiments which varied ethnicity, class, and behavior of a fictitious potential student, Andersen and Guul (2019) find that Danish teachers did not respond more or less favorably to including students of low socioeconomic status in their school and classroom than other students. A study of Dutch tax evaluators finds similar results (Raaphorst, Groeneveld, & Van de Walle, 2018). Raaphorst, Groeneveld, and Van de Walle (2018) had 26 Dutch tax evaluators read descriptions of the tax situations of fictitious clients with varying socioeconomic statuses (Raaphorst, Groeneveld, & Van de Walle, 2018). Raaphorst et al (2018) evaluate whether clients from different classes were held to double standards by the tax collectors. However, the study finds no evidence that citizens of lower or higher class were held to different standards (Raaphorst, Groeneveld, & Van de Walle, 2018).

Two audit experiments also find no evidence of SES discrimination (Carnes & Holbein, 2018; Giulietti, Tonin & Vlassopoulos, 2019). Carnes and Holbein (2018) perform an audit study of 719 principals in two US states. They find no evidence that principals responded less to individuals of lower SES than individuals of high SES (Carnes & Holbein, 2018). Giulietti, Tonin and Vlassopoulos (2019) ran an audit experiment to look for evidence of racial and SES discrimination among a variety of local government SLBs in the US. Giuletti and colleagues sent emails from putative Black/White emailers of high/low SES. The results show no difference in the likelihood that individuals or high or low SES received a response. These two audit studies provide substantial evidence that SLBs can treat public service recipients equally regardless of economic standing. This is an encouraging finding and suggests that SLBs either do not hold biased beliefs about individuals of lower SES or are able to stave off any conscious or unconscious biases they do hold regarding SES.

Needs-based and universal public services. The literature on SLB discrimination based on SES focuses largely on universal public services. As can be seen in Table 1.2, only two of the eight studies take place within a needs-based public service context. The two studies that take place in needs-based public service contexts find evidence of SES discrimination. This suggests that the nature of needs-based public service delivery may lend itself to SES discrimination. Maynard-Moody and Musheno (2003) find that SLBs can use their considerable discretion to provide more or less service to clients in needs-based programs. SLBs were observed to view some clients of lower socioeconomic status as less-deserving of help—or more to blame for their situation (Maynard-Moody & Musheno, 2003). These conclusions would help explain the disparity in the empirical evidence of SES discrimination between studies done in needs-based and universal public service contexts. Further research on SES discrimination in needs-based public services would help to investigate whether a difference exists.

Table 1.2: Studies on SLB discrimination based on socioeconomic status

Author(s)	Service Context	Method	Population	N	Country	Evidence for Discrimination	Limitation
Maynard-Moody & Musheno, 2003	Both	Story analysis	Counselors, police, teachers	48	USA	Yes	Small sample
Dubois, 2010	Needs	Field Observations	Welfare officers	N/A	France	Yes	Limited scope
Andersen & Guul, 2019	Universal	Vignette survey experiment	Danish public schoolteachers	890	Denmark	No	Hypothetical situation
Carnes & Holbein, 2019	Universal	Audit experiment	Public school principals in North Carolina and Kentucky	719	USA	No	Small sample size
Giulietti, Tonin & Vlassopoulos, 2019	Universal	Audit experiment	School district, library, sheriff, treasurer, veteran support, county clerks	19,000	USA	No	Disparate samples
Harrits, & Møller 2014	Universal	Vignette survey experiment	Teachers and Nurses	58	Denmark	Yes	Discrimination not sole focus of study
Raaphorst & Groeneveld, 2018	Universal	Semi-structured interviews	Dutch tax officials	11	Netherlands	Mixed	Very small sample size. Subjective interpretation of stories.
Raaphorst, Groeneveld & Van de Walle, 2018	Universal	Experiment	Dutch tax officials	26	Netherlands	Mixed	Small sample size

Conclusion. Overall, the hypothesis that SLBs discriminate based on SES is not strongly supported by empirical evidence. Three of the six studies done in universal public service delivery find no evidence of SES discrimination and two of the studies show mixed results. It appears that SES discrimination may occur more often in needs-based public service contexts. However, there are only two empirical studies done on this topic and both employ qualitative methods. While qualitative methods are valuable, scholars could use additional methods to see if the findings of these studies are found using other means. Based on the evidence that is available, however, it appears that SLBs providing needs-based public service delivery are more prone to discriminate based on SES. These findings correspond with the theory of street-level bureaucracy which argues that SLBs can use their discretion to favor or disfavor clients whom they view as 24 more/less deserving (Maynard-Moody & Musheno, 2003). In such instances, SLBs are violating their charge to treat their clients fairly and impartially.

Sex

SLBs may interact with public service recipients differently based on the individual's sex. SLBs may take shortcuts, rely on stereotypes, or hold double standards when dealing with women or men. Researchers have investigated whether SLBs discriminate based on sex. To the author's knowledge, five studies investigate whether SLBs discriminate based on client sex. In this section, I review the empirical evidence for the hypothesis that SLBs discriminate based on the sex of clients. I further examine the research for differences in studies done in needs-based and universal public service delivery contexts.

Table 1.3: Research articles on SLB sex discrimination

Author(s)	Method	Service Context	Population	N	Country	Evidence of Discrimination	Limitation
Kalla, Rosenbluth & Teele, 2018	Audit study	Both	Elected and appointed public officials	8,189	USA	No	Provide minimum information about sample.
Einstein & Glick, 2017	Audit study	Needs-based	Public housing authorities	1,017	USA	No	Sample limited to larger metropolitan areas
Pedersen, Stritch & Thuesen, 2018	Survey experiment	Needs-based	Employment case workers	1,335	Denmark	No	Hypothetical situation
Grohs, Adam & Knill, 2016	Audit study	Universal	Municipal governments	501	Germany	Mixed	Small sample size. Religion is a confounder
Pfaff, Crabtree, Kern & Holbein, 2021	Audit study	Universal	Public school principals	47,000	USA	No	Not all 50 states included

I located five studies measuring SLB discrimination based on sex. Table 1.3 summarizes the empirical literature on SLB bias based on sex. As shown in Table 1.3, four of the five studies do not find evidence of sex discrimination. One of the five studies found evidence of discrimination based on sex, but the results did not reveal a consistent pattern of discrimination against men or women. Grohs, Adam, and Knill (2016) perform an audit experiment on bureaucrats working in German local governments. The authors examine discrimination based on ethnicity (German and Turkish) and sex (men and women). Grohs and colleagues (2016) randomly send four separate types of emails which have a unique request. Depending on the request, women sometimes receive better and more thorough responses than men, and sometimes receive poorer and less thorough responses (Grohs, Adam, and Knill (2016). This study demonstrates that SLB discrimination based on sex may not be consistent towards men or women. However, more work can be done to verify whether, or why, anti-male and anti-female discrimination may occur.

The other four studies on SLB sex discrimination suggest that SLBs do not discriminate based on the sex of public service recipients. An audit experiment of elected and unelected public officials in the US finds no disparities between response rates for fictitious male and female students seeking career advice (Kala, Rosenbluth, & Teele, 2018). Similar results are found in two email audit experiments which vary the putative sex of the emailer (Einstein & Glick, 2017; Pfaff, Crabtree, Kern & Holbein, 2021). These audit experiments look for evidence among public housing authorities (Einstein & Glick, 2017) and public school principals (Pfaff, Crabtree, Kern & Holbein, 2021). Taken together, the null results of these four studies suggest that sex bias is not a prevalent factor in public service delivery.

The five studies on sex discrimination do not show differences among needs-based and universal public service delivery contexts. The studies take place in both universal (public schools and municipal governments) and needs-based (employment case workers and public housing authorities) service contexts. Neither context indicates more or less sex discrimination than the other. Future work could reveal one service context may be influenced by sex bias than the other, but the current evidence does not support that hypothesis. Overall, the literature for SLB discrimination based on sex suggests women and men generally receive equal treatment from government employees.

Sexual Orientation

I found only one published study in the mainstream English language public administration journals which looks at whether SLBs discriminate based on sexual orientation. In an audit study investigating whether foster care agencies show a bias towards homosexual couples, Mackenzie-Liu, Schwegman, and Lopoo (2021) sent emails to 1,147 public and nonprofit foster care agencies in the US. The respondents from public foster care agencies can be considered SLBs as they are responsible to responding to public enquiries. Mackenzie-Liu, Schwegman, and Lopoo (2021) sent emails from both a fictitious homosexual male or female couple and a fictitious heterosexual couple requesting help with becoming foster parents. The results of the audit study show that all couples, regardless of sexual orientation, received similar rates of responses. However, homosexual male couples received slower and less-helpful responses than homosexual female couples and heterosexual couples. This study provides initial evidence that SLBs may not treat homosexual male public service recipients fairly. Future work in different SLB contexts can provide more evidence for the question of whether SLBs discriminate based on sexual orientation.

Religious beliefs

Research indicates individuals hold more favorable views towards those who share their religious beliefs—and less favorable views towards those who do not (Johnson, Rowatt, & LaBouff, 2012). The actions of street-level bureaucrats could be influenced by religious biases. Only one study has examined religious discrimination by SLBs explicitly (Pfaff, Crabtree, Kern, & Holbein, 2021). Pfaff and colleagues sent emails to over 47,000 school principals in 33 US states and found that fictitious Muslim and Atheist parents received lower response rates from SLBs than fictitious Christian parents (Pfaff, Crabtree, Kern, & Holbein, 2021). The study also reveals that fictitious parents who indicated a high intensity of religious devotion—regardless of their religious beliefs—received fewer responses than parents indicating lower levels of religious devotion (Pfaff, Crabtree, Kern, & Holbein, 2021).

Studies of ethnic bias may provide indirect evidence of religious discrimination, especially in cases where ethnicity is closely related to religious beliefs. Researchers exploring ethnic bias have examined populations where religious beliefs and ethnicity are difficult to separate. Studies in Israel, for example, look at discrepancies between Israeli citizens of Jewish and Palestinian ancestry—and find mixed evidence for the hypothesis that discrimination occurs (Assouline, Gilad, & Ben-Nun Bloom, 2021; Strier, Abu-Rayya, & Shwartz-Ziv, 2021). Religious beliefs could influence the results of these studies as ethnicity (Jewish/Palestinian) and religious beliefs (Judaism/Islam) are closely entwined. In these cases, client ethnicity may be a clear signal to SLBs whether a client holds similar or different religious beliefs. More work could be done to disentangle ethnicity from religious beliefs to see if religious beliefs is an independent or compounding contributing factor in SLB discrimination.

The findings of Pfaff and colleagues (2021)—and the studies where ethnicity and religion are correlated—provide preliminary evidence that SLBs may not only discriminate based on the observable characteristics of clients such as their race or sex. SLBs may also discriminate based on client religious beliefs. If this is so, SLBs may be providing unequal treatment for clients with varying political or ideological beliefs. SLB ideological discrimination, then, would be an additional hindrance to the ideal public service ethos of fair and impartial treatment towards all.

Political Beliefs

My search of public administration literature journals retrieved only one study on whether SLBs discriminate based on political beliefs. An audit study on discrimination based on political beliefs sent emails to German local government email addresses requesting to host a pro same-sex marriage event or an event opposed to same-sex marriage (Adam, Grohs, & Knill, 2020). The results showed that there was no discrepancy in response rates to these events—but that responses to pro same-sex marriage emails were not as thorough (Adam, Grohs, & Knill). This study reveals that there may be subtle ways in which SLBs provide poorer service to clients due to client political beliefs. Since only one study deals with this topic, more work needs to be done to see if political discrimination occurs in other contexts. Studies done in other countries and other public service contexts may reveal different results. The results could also be different in a needs-based public service context where SLBs may be more inclined to view clients with differing political views as less deserving of help than those with similar views.

Summary

The empirical evidence whether SLBs discriminate based on race, ethnicity, gender, sexual orientation, religion, and political beliefs shows that SLBs can act in discriminatory ways. In some instances, experiments, qualitative studies, and other empirical studies have shown disparities in how citizens (fictitious or otherwise) of different backgrounds are treated by street-level bureaucrats (see Tables 1.1, 1.2, and 1.3). While some evidence suggests SLBs have biases towards clients of certain backgrounds, other studies show either no evidence or mixed evidence for SLB discrimination against clients. Most of these studies, however, examine physical characteristics such as race, ethnicity, sex, etc. Only two studies have been conducted on whether SLB discrimination occurs based on a person's beliefs. Pfaff, Crabtree, Kern, and Holbein (2021) found evidence of SLB religious bias and Adam, Grohs, and Knill

(2020) found mixed evidence of political discrimination. I add to this small body of literature by testing for SLB bias based on political ideology.

There is some evidence that discrimination may occur more often in needs-based public service delivery contexts such as welfare. This disparity is found when comparing studies done on socioeconomic discrimination. In this dissertation, I add to this body of work by investigating whether street-level bureaucrats discriminate based on the political beliefs of the citizens they serve. There is a growing body of literature showing that (and possibly why) individuals discriminate against others who have political beliefs that differ from their own. Since individuals are prone to discriminate based on political ideology, street-level bureaucrats could (unintentionally or otherwise) treat clients differently based on their political beliefs. I also add to this body of literature by examining whether there are differences in the amount of political ideology discrimination for needs-based and universal public services.

SLBs have a responsibility to be impartial when serving citizens. My dissertation examines whether SLBs treat their clients of different political persuasions equally and fairly. While people are inclined to view those with political views who conflict with their own with disapproval, SLBs must be able to fight this inclination when serving clients. This is likely not an easy task. If SLBs discriminate based on political ideology, public servants and researchers must try to find ways to counteract such bias.

Political Ideology Discrimination

Psychologists have investigated whether individuals discriminate against people and groups who hold opposing political views than their own. Much of the early research on political bias and discrimination argued that, in the US, individuals holding conservative political views were intolerant towards individuals holding liberal views—but not the other way around (Sibley & Duckitt, 2008). Psychologists theorized multiple reasons why conservatives were predisposed to bias and intolerance (Brandt et al., 2014; Hodson & Busseri, 2012; Jost, Glaser, Kruglanski, & Sulloway, 2003; Sibley & Duckitt, 2008) including personality differences and the nature of conservative values. Researchers then began to dispute the prevailing theory that conservatives discriminated—and liberals did not (Brandt et al., 2014). Psychologists instead hypothesized that both liberals and conservatives would show bias against individuals and groups whose values did not align with their own. New evidence emerged showing that political bias is not just a conservative problem, but a human problem (Brandt et al, 2014; Ditto et al., 2019; Morgan, Mullen, & Skitka, 2010).

Ideological-Conflict Hypothesis

The "Ideological-Conflict Hypothesis" (Brandt et al., 2014) argues that individuals show intolerance towards individuals and groups whose political values conflict with their own. Thus, specific values people hold do not inherently incline people towards intolerance—instead people are intolerant of individuals and groups generally who hold rival values. This theory is more universal in nature than previous theories that argued that political conservatives were intolerant and political liberals were not (Ditto et al., 2019). The Ideological-Conflict Hypothesis is supported by empirical evidence and stems from a phenomenon known as motivated information processing. The evidence for the Ideological-Conflict Hypothesis and a summary of motivated reasoning is laid out below.

Evidence for the Ideological-Conflict Hypothesis. Studies testing the Ideological-Conflict Hypothesis provide evidence that individuals who hold conservative or liberal values are equally likely to express intolerance towards groups who they identify as politically different (Chambers, Schlenker, & Collisson, 2013; Crawford & Pilanski, 2014; Lindner & Noseck, 2009; Wetherell et al., 2013). For example, Crawford and Pilanski (2014) ran a survey experiment on US adults in which respondents indicated their political views (conservative, moderate, or liberal) and then were asked questions about their feelings on a series of left- or right-leaning organizations. The survey participants were asked how warm or cold they felt towards the organizations, how much (if any) threat the organizations posed, and how strongly they agreed or disagreed with statements that gauged their tolerance for these organizations (e.g. members of the organization should not be able to speak in public). The results of the study conclude that both self-identified conservatives and liberals showed more intolerance towards organizations with different political viewpoints (Crawford & Pilanski). The participants were especially likely to show intolerance if they viewed the organizations as being a threat their own political values (Crawford & Pilanski, 2014). The results of two other, independent studies testing this theory showed similar results (Chambers, Schlenker, &

Collisson, 2013; Wetherell et al., 2013). These studies show that people of all political persuasions can be intolerant of others whose values they disagree with and/or feel threatened by. Political discrimination, then appears to stem from the fact that "all people are motivated to defend core beliefs and moral commitments" (Ditto et al, 2019, p.276).

Theoretical foundations of the Ideological-Conflict Hypothesis. The Ideological-Conflict Hypothesis draws on the concept of motivated information processing (Kunda, 1990). Motivated information processing argues that people filter information in biased ways to support their world view or self-image (Kunda, 1990; Brandt et al. 2014). The Ideological-Conflict Hypothesis draws on motivated information processing theory by arguing that the desire to maintain one's world view causes people to justify intolerant behavior towards individuals and groups with differing political views. This argument is supported by many studies that find that human cognitive processes are distorted by the desire to support one's political ideology.

Studies support the theory of motivated information processing by showing that people do in fact filter information in favor of their political ideology. For example, a meta-analysis of 51 studies found that both liberals and conservatives viewed information more favorably when it supported their political views but less favorably when similar information went against their political views (Ditto et al, 2019). People also have been shown to hold double standards of behavior for people 'on their side' politically and those 'not on their side' (Crawford, 2012). Research finds conservatives and liberals alike justify the failings of political actors they support by citing mitigating circumstances—

and blame the failings of political actors they do not support as evidence of their personal shortcomings (Morgan, Mullen, & Skitka, 2010).

Street-Level Bureaucrats and the Ideological-Conflict Hypothesis

Based on the Ideological-Conflict Hypothesis, I expect that SLBs will discriminate based on political ideology. Scholars find some evidence that SLBs provide unequal treatment for some clients based on the observable characteristics of their clients such as race, gender, or SES (see Tables 1.1, 1.2, and 1.3). Two studies find evidence that SLBs provide unequal treatment based on client political beliefs (Adam, Grohs, & Knill, 2020) and religious beliefs (Pfaff, Crabtree, Kern, & Holbein, 2021), respectively. SLBs interact with clients who hold political viewpoints that conflict from their own (Adam, Grohs, & Knill, 2020). In these circumstances SLBs may treat clients with different political values poorer than clients whose values align with their own. Many scientific articles support the Ideological-Conflict Hypothesis (Chambers, Schlenker, & Collisson, 2013; Crawford & Pilanski, 2014; Lindner & Noseck, 2009; Wetherell et al., 2013) and find that university students and samples of US adults show intolerance towards individuals and groups with differing political views. However, to my knowledge, the theory has not been applied to street-level bureaucrats. This dissertation tests the Ideological-Conflict Hypothesis on SLBs. Testing the hypothesis will provide further evidence of whether SLBs discriminate based on political ideology. Based on the Ideological-Conflict Hypothesis, I expect that SLBs will discriminate against clients whose political ideologies oppose their own. Therefore, I plan to test the following hypotheses:

H1: Street-level bureaucrats will discriminate based on political ideology.

H1a: Liberal SLBs will discriminate against conservative clients.

H1b: Conservative SLBs will discriminate against liberal clients.

Universal and Needs-Based Public Services

Local, state, and federal governments in the US provide public services that are either available for all citizens or tailored to meet the needs of a select group of citizens. Universal public services such as public education, trash collection, and policing are provided to all citizens regardless of their circumstances. Other public services such as welfare, housing assistance, and health care coverage are provided to citizens who meet certain criteria such as level of income or age. Studies on discrimination have been conducted in needs-based public service contexts including public housing (Einstein & Glick, 2017), welfare offices (Dubois, 2010), and eldercare facilities (Jilke, Van Dooren & Rys, 2018). Similar work has been done in universal public service contexts such as public schools (e.g. Andersen & Guul, 2019), tax collection (e.g. Raaphorst & Groeneveld, 2018), and municipal government departments (e.g. Kalla, Rosenbluth & Teele 2018).

Researchers have found evidence of SLB discrimination in both needs-based and universal public services. In studies on needs-based public service delivery, researchers find discrepancies in outcomes for clients of different ethnicities (Schram, Soss, Fording

& Houser, 2009), races (Assouline, Gilad & Ben-Nun Bloom, 2021), and socioeconomic statuses (Dubois, 2010). Researchers have found similar results in universal services. Evidence of discrimination is found for clients based on race (e.g. White, Nathan & Faller, 2015), religion (Pfaff, Crabtree, Kern & Holbein, 2021), and socioeconomic status (Harrits, & Møller 2014). This empirical evidence suggests that discrimination can occur in all kinds of public service contexts.

While researchers have found evidence of discrimination in both needs-based and universal public services, foundational SLB theory suggests that discrimination may be greater in needs-based public service contexts. Maynard-Moody and Musheno's influential book on street-level bureaucracy—*Cops, Teachers, Counselors: Stories from the Front Lines of Public Service* (2003)—reveals that SLBs use their considerable discretion to help clients who they perceive to be more deserving of their help. Maynard-Moody and Musheno write:

> *Cops, teachers, and counselors first make normative judgments about offenders, kids, and clients and then apply, bend, or ignore rules and procedures to support the moral reasoning. Identity-based normative judgments determine which and how rules, procedures and policies are applied. Morality trumps legality in terms of which rules, procedures, and policies are acted on; who gets what services and who is hassled or arrested; and how rules, procedures and policies are enacted*. [p. 155]

Maynard-Moody and Musheno argue that SLBs essentially discriminate based on the moral judgments they make about their clients. This conclusion coincides with theories of discrimination that posit that individuals can see people with certain characteristics as more or less moral than others (Raaphorst, & Groeneveld, 2019).

Based on the nature of needs-based public service delivery, I expect that SLBs providing needs-based public services will be more likely to assign moral judgments to clients based on client political ideology than SLBs providing universal public services. SLBs providing needs-based public services have a duty to assess who of their clients is eligible to receive services. Needs-based programs such as housing assistance are not available to all citizens. SLBs providing needs-based public services are expected to make judgments on who is eligible for public services. SLBs providing a universal public service do not have to make a judgment on who is or is not eligible to receive benefits. Public school teachers, for example, do not have to decide which children can or cannot receive an education. Maynard-Moody and Musheno (2003) demonstrate that welfare counselors sometimes made moral judgments about why certain citizens became eligible for needs-based services. Counselors would justify that an individual with characteristics different from their typical clientele must be in need due to unfortunate circumstances rather than their own shortcomings. In short, SLBs providing needs-based public services are put in the position of having to justifying who is more or less worthy of their help than SLBs providing universal public services.

Street-level bureaucrats may judge individuals who hold differing political viewpoints as less deserving of their help. The Ideological-Conflict Hypothesis (Brandt et al., 2014) posits that individuals have cognitive biases which favor individuals and groups who hold similar political beliefs. I expect that this phenomenon will be more likely to occur for SLBs providing needs-based public services—where moral judgments are more likely to influence how SLBs treat clients. Drawing on SLB theory, the Ideological-Conflict Hypothesis, and empirical evidence of SLB discrimination I expect to find evidence of discrimination in both needs-based and universal public services, but, that discrimination will be more evident in needs-based public service contexts. I test the following hypotheses:

H2: Street-level bureaucrat discrimination based on political ideology will vary by service type (universal vs. needs based).

> *H2a: SLBs delivering universal public services will discriminate based on political ideology.*
>
> *H2b: SLBs delivering needs-based public services will discriminate based on political ideology.*
>
> *H2c: Discrimination based on political ideology will be higher among SLBs delivering needs-based services, as compared to universal public services.*

Professional and Community Factors Influencing SLB Discrimination

Since street-level bureaucrats are tasked with distributing public services in a fair and impartial manner (Lipsky, 1980), scholars have gathered empirical evidence to gauge whether SLBs provide equal and fair treatment. The empirical evidence of whether SLBs discriminate is mixed (See Tables 1.1, 1.2, and 1.3). The mixed findings of SLB discrimination indicate there are several factors that influence whether or not SLB discrimination occurs. Researchers seek to discover what factors reduce SLB discrimination. For example, Andersen and Guul (2019) ran a field experiment to test whether teachers with lower workloads were less discriminatory than teachers with high workloads. Andersen and Guul (2019) find that teachers with high workloads were less likely to indicate they would accept a fictitious student with a non-traditional Danish name than teachers with low workloads. Studies such as these demonstrate that the question of whether SLBs discriminate or not is nuanced.

Street-level bureaucrats operate in various professional settings and live in a wide range of communities. These contexts may influence the likelihood of SLB discrimination based on political ideology. In this dissertation, I plan to test whether three factors are associated with more/less ideological discrimination. These three factors are community population, racial diversity, and income.

H3: Community characteristics will be significantly related to SLB discrimination by political ideology.

Population

I expect SLBs in larger cities have more resources available to them that could reduce political bias. Public servants who work in larger cities generally have greater resources and work in more-professionalized environments than those working in smaller cities (Coyle, Ponomariov & Estrada, 2018; Grimmelikhuijsen & Feeney, 2017; Moon, 2002; Watson & Hassett, 2004). Larger cities are more likely to have public servants working for an accredited organization (Coyle, Ponomariov & Estrada, 2018), greater capacity (Coyle, Ponomariov & Estrada, 2018), more resources (Grimmelikhuijsen & Feeney, 2017; Moon, 2002), and greater employee training (Watson & Hassett, 2004) than public organizations in smaller cities. Since SLBs working in larger cities, then, may have more capacity, resources, and training opportunities, I expect that SLBs working in these cities receive more antidiscrimination training and support. This training could reduce the forms of discrimination that scholars have theorized about: taste-based, statistical, and unconscious. Based on the expectation that public employees have access to greater anti-discrimination training—and the expectation that this training is effective—I hypothesize the following:

H3a: City population will be negatively related to SLB political ideology discrimination.

Racial Diversity

In the US, race is often associated with support or opposition of certain political issues. For example, a recent survey from Pew Research shows that conservatives are less racially diverse than liberals. Since race is correlated with political ideology, I expect city racial diversity to be correlated with political ideology discrimination.

H3b: Community racial diversity will be correlated with SLB political discrimination.

Income

Income may be another factor associated with political ideology discrimination. A Pew Research survey showed that higher income is associated with both being conservative and liberal. SLBs with higher income cities would be more likely to hold conservative or liberal political views and would be more likely to be intolerant of an opposing viewpoint. Since income is correlated with certain political viewpoints, I expect the following:

H3c: Income will be related to political ideology discrimination.

Citizen Sex and Political Discrimination

Researchers have theorized that SLBs could treat the people they serve unfairly based on sex. SLBs may hold biases based on sex. An SLB providing a public service could hold double standards for men and women. An SLB also may be prone to make moral judgements of a citizen's deservingness for public assistance based on sex. In instances such as these, SLBs could consciously or unconsciously provide better services to the men or women that they serve. If a pattern of disparate treatment for men and women is consistent across multiple situations, public service delivery could be unfair towards women or men.

While researchers have theorized that SLBs discriminate based on sex, the empirical research shows little evidence of SLB discrimination (Kalla, Rosenbluth & Teele, 2018; Einstein & Glick, 2017; Pedersen, Stritch & Thuesen, 2018; Grohs, Adam & Knill, 2016; Pfaff, Crabtree, Kern & Holbein, 2021). Thus, I expect to not see differences in the treatment of citizens based on sex.

H4: SLBs will not discriminate based on sex.

Contribution

As Andersen and Guul (2019) demonstrate, the prevalence of street-level bureaucrat bias is due to a myriad of factors. SLBs do their jobs in unique, varied situations. The population, political homogeneity, racial diversity, and level of income of the communities in which SLBs work may play a role in encouraging or discouraging political ideology bias. This dissertation provides further clarity on what factors contribute to SLB ideological bias. By making this contribution, my dissertation helps expand knowledge on SLB discrimination.

Street-level Bureaucrats as Information Gatekeepers

Street-level bureaucrats often interact with citizens and clients using information and communication technologies (Buffat, 2015). Using digital tools such as email and social media, street-level bureaucrats and other government employees are tasked with answering questions and providing information to the public (Epstein, Bode, & Connolly, 2021). In this way, SLBs act as gatekeepers for public access to assistance and information. The responsibility to act as information and assistance gatekeepers is an additional avenue in which SLB bias could lead to unequal public service outcomes.

Street-level bureaucrats have substantial discretion in how they perform their duties (Lipsky, 1980). If SLBs are actively engaged in providing thorough information and helpful assistance, SLBs can improve access to government services. Conversely, if SLBs neglect these duties, public service delivery will become suboptimal. SLB theory suggests that SLB biases causes SLBs to use their significant discretion to the benefit or detriment of clients of certain races, ethnicities, socioeconomic statuses, and more (Maynard-Moody & Musheno, 2003; Raaphorst & Groeneveld, 2019). As information gatekeepers, SLBs may be more responsive to certain clients and less responsive to others. Furthermore, SLBs may show bias by being more or less helpful, thorough, respectful, and friendly to individuals with certain characteristics (Adam, Grohs, & Knill, 2020; Bergman & McFarlin Jr, 2018; Einstein & Glick, 2017; Olsen, Kyhse-Andersen & Moynihan, 2020).

Street-level bureaucrats—acting in their capacity as information gatekeepers—may show bias towards those who hold opposing political viewpoints than their own. A study by Adam, Grohs, & Knill (2020), for example, demonstrated that fictitious emailers who supported same-sex-marriage in Germany received less-thorough email responses than fictitious emailers who opposed same-sex marriage. If this type of bias is prevalent in other countries and public services, citizens of various political beliefs may be receiving poorer access to information and assistance from SLBs than others. This would violate the SLB creed to treat all citizens fairly and impartially. Conversely, it is possible that SLBs may be more responsive to citizens who they perceive as being politically active. Epstein, Bode, and Connolly (2021) find that local government employees were more responsive to citizens who were frustrated—demonstrating that client attributes could influence responsiveness. Similarly, SLBs may be more motivated to respond to politically active citizens to avoid accusations of partisanship. This dissertation helps to clarify whether SLBs are more or less responsive, helpful, and friendly to public service recipients based on political ideology.

CHAPTER 3

RESEARCH DESIGN

I carry out two audit experiments to test whether SLBs discriminate based on client political ideology. The first experiment tests for discrimination among SLBs providing a universal public service. The second experiment does the same for SLBs in a needs-based public service. This section outlines the specifics of the two audit studies. I detail the study sample, the audit design and treatment, validation of the treatments, and my analytical approach. I discuss the strengths and weaknesses of the research design, ethical concerns, and internal and external validity of my experiments.

Universal Public Service Experiment Design

Research Question

My dissertation seeks to answer the research question: *"Do SLBs delivering a universal public service discriminate based on political ideology?"*. I answer this question using an audit experiment of municipal parks and recreation departments in the US. I also ask the following research question: *"Are parks and recreation department employees less responsive to inquiries from clients who hold conservative or liberal political ideologies?"*

Method

I use an audit experiment to test for political discrimination by public housing authority employees and parks department employees. Audit experiments are a "type of field experiment in which a researcher randomizes one or more characteristics about individuals (real or hypothetical) and sends these individuals out into the field to test the effect of those characteristics on some outcome" (Gaddis, 2018, p. 5). Researchers often use others means such as emails, letters, or resumés instead of fieldwork for audit studies (Gaddis, 2018). I send emails to public housing authorities from fictitious individuals who are signaled to hold either conservative political values, liberal political values, or no political values.

Researchers use audit experiments to test for discrimination (Bertrand & Duflo, 2017; Gaddis, 2018). According to the American Psychological Association, discrimination is defined as "unfair or prejudicial treatment of people and groups based on characteristics such as race, gender, age or sexual orientation" (APA, 2019). I measure discrimination by testing whether emails from fictitious conservative or liberal emailers receive a significantly different number of responses than emailers with no signaled political beliefs. I also measure differences in response times, tone, and helpfulness to determine whether emailers are treated differently by public housing authority employees based on their political identity. By measuring these variables, I test whether there is unequal treatment of political conservatives and political liberals by SLBs.

Sample

I expect that areas of the country that have a high percentage of Democratic or Republican votes in the 2020 election to demonstrate bias towards conservative or liberal emailers, respectively. It is reasonable to expect that SLBs generally hold more conservative values in more conservative communities and more liberal values in liberal communities. Thus, I expect that SLBs in communities with high levels of political homogeneity to show bias towards clients with different political beliefs.

I sent email inquiries to municipal parks departments in cities where at least 60% of citizens voted for the Democratic candidate in the 2020 Presidential Election—or where at least 60% voted for the Republican candidate. For contact information, I went to the parks department websites to gather the email addresses of the department directors. When department director email addresses were not present, I gathered the general contact email of the department.

I limit the sample to cities with populations of 25,000 or more, of which there are 1,521 in the US. I did not include cities with populations below 25,000 in the sample because many (if not most) of them do not have parks and recreation departments. I used data from the US Census Bureau and the MIT Election Lab to identify all cities with over 25,000 residents where 60% of citizens voted for the Democratic candidate— or 60% or more voted for the Republican candidate—in the 2020 Presidential Election. There were 227 cities with 60% or more voting Republican—and 524 cities with 60% or more voting Democratic. I use a random sample of 227 Democratic-majority cities and all the 227 Republican-majority cities. Thus, my final sample size is 454 parks departments.

Expected Number of Responses

For the parks and recreation department audit study, I expected to receive responses from around 55% to 71% of the SLBs in my sample. A recent audit study of multiple local government offices showed a response rate of 68% to 71% (Giulietti, Tonin, & Vlassopoulos, 2019). This study, however, is higher than most audit experiments of SLBs which generally have response rates around 55% to 60 percent% (e.g. Einstein & Glick, 2017). Currently, I am unable to find an audit study sent targeting city parks departments, but there is no theoretical reason to expect response rates for park districts to differ greatly from other studies of local governments.

Treatment

The study has two treatments and one control group. I assign an equal number of participants to the two treatment groups and the control group. Treatment 1 includes a request to hold an event that aligns with conservative political values. Treatment 2 includes a request to hold an event in line with liberal political values. Finally, a control group includes a request for an event with no discernable political ideology. Table 3.1 displays the number of individuals assigned to each treatment:

Table 3.1. Parks department audit study treatment allocation

Treatment	Conservative Event Request	Liberal Event Request	Politically-Neutral Request (Control)
Number of Emails	151	151	152

The emails ask for information about how to obtain a permit to hold an event in a local park. The emails also ask for information about requirements for trash removal. To signal political ideology, I indicate the emailer works as an events coordinator for a fictitious political organization. I also use the logo of a fictitious political organization in the email signature to signal whether the inquirer holds conservative or liberal views. The fictitious conservative organization is called “The Pro-Life Alliance”. The fictitious liberal organization is called “The Pro-Choice Alliance”. For the control group, I indicate the emailer works as the events coordinator for a politically-neutral organization. I also include a logo for the fictitious, politically-neutral organization in the email signature. The organization is called “The Alliance”. Research has shown that people in the US associate pro-life groups with conservative values and prochoice groups with liberal values—and that conservatives/liberals believe prolife/prochoice positions violate their values (Wetherell et al, 2013).

I use an ethnically ambiguous name in the email signature. This ensures that the treatment does not conflate ethnicity and political ideology. I use the names Michelle and Nathan, which have been shown to be ethnically ambiguous based on a study of names and ethnicity in New York from 2011 to 2016. I do not use a last name in the email signature to ensure that the ethnicity of the inquirer remains ambiguous. Exhibit A displays the email that I use, including the three email signatures:

Exhibit A: Email sent to parks departments.

Hi,

I would like to hold an event in a local park and heard I may need to get a permit. Could you let me know where I can find more information about receiving a permit? Also, I heard I may be responsible for trash removal. Is that true?

Thank you,

Michelle/Nathan
--
Events Coordinator
The **[Pro-Life/Pro-Choice/Heath & Wellness]** Alliance

The
Pro-Life
Alliance

The
Pro-Choice
Alliance

The

Alliance

Statistical Power

Using a one-way ANOVA, I find that the statistical power of this experiment exceeds the generally accepted threshold of 0.8 (80% chance that a treatment effect can be detected). In my analysis, I include the number of experimental groups, the number of observations I expect to receive, an estimated effect size (disparity between the control group and treatment group), and the significance threshold.

I specify three groups. I set the total number of expected observations to 248 which is the total number of emails I sent (454) multiplied by my expected response rate (55%). I set the estimated effect size to four percentage points. This compares to the treatment effect found in a previous audit study of local government SLBs (Giulietti, Tonin, & Vlassopoulos, 2019). Finally, I set the significance threshold to the standard 0.05 level. My analysis exceeds the 0.8 threshold (1.00) when I run the one-way ANOVA.

Needs-Based Public Service Experiment Design

Research Question

My dissertation explores the research question: *"Do SLBs delivering a needs-based public service discriminate based on political ideology?"*. I answer this question using an audit experiment of public housing authorities in the US. The audit experiment asks the following research question: *"Are housing authority employees less responsive to inquiries from clients who hold conservative or liberal political ideologies?"*

Sample

To answer whether SLBs delivering a needs-based public service discriminate based on client political ideology, I sent email inquiries to a sample of 548 housing authorities in the US. The sample includes PHAs in counties where at least 60% of citizens voted for the Democratic—or at least 60% voted for the Republican candidate—in the 2020 Presidential Election. Using the US Department of Housing and Urban Development (HUD) website and the MIT Election Lab I found that there are 2,531 housing authorities in the US that meet these criteria (not including US territories). There are 274 PHAs in counties where at least 60% of citizens voted for the Democratic candidate. There are 2,257 PHAs in counties where at least 60% voted for the Republican candidate. For my sample, I use all the 274 PHAs in Democratic-majority voting counties. And take a random sample of 274 PHAs in Republican-majority voting counties. My total sample is 548 PHAs.

I used the HUD website to gather contact email addresses of SLBs in these PHAs. The website provides a service where anyone can look up the contact information of the housing authorities in all 50 US states. According to the website, public housing authorities provide the email address and are responsible for updating the information. Public housing authorities are also responsible for updating their contact information when it changes. HUD updates the contact information provided by all public housing authorities weekly. Often, the public housing authority uses the executive director's email address as the publicly available address for contacting their agency or another employee of the agency. Other email addresses are a generic email address for the housing authority. The randomization of treatments distributes agencies across the two treatment groups and the control group randomly in the types of email addresses listed (executive director, employee, or generic agency email address). I send one email to each public housing authority in my sample, reducing the possibility that public housing employees and email recipients suspect they are participating in an audit experiment.

Expected Response Rate

Based on a recent audit study of US public housing authorities (Einstein & Glick, 2017), I expect to receive a response rate between 55% and 65%. My results may vary since the Einstein and Glick (2017) study only sent emails to public housing authorities (N= ~1,000) who were part of an identifiable metropolitan area. My study includes a sample of housing authorities. While the response rate of more rural areas may vary, the large sample ensures that my study is representative of a large portion of housing authorities in the US. This makes my results more externally valid.

Treatment

The experiment has two treatments and one control group. I assign an equal number of participants to each of the treatment groups and the control group. Treatment 1 is an identifiably conservative citizen. Treatment 2 is an identifiably liberal citizen. The control group is a citizen with no identifiable partisan political beliefs. Table 3.2 notes the sample by treatment:

Table 3.2. Housing authority audit study treatment allocation

Treatment	Conservative Client	Liberal Client	Politically-Neutral Client (Control)
Number of Emails	183	183	182

The email first states that the emailer wants to apply for housing assistance. Then, the email asks the question: *"Could you let me know where I can find more information about applying?"*. The email then refers to a wait list and ask: "*How long is the waitlist?"*. I do not specify that I am asking about Section 8 public housing assistance because not all housing authorities in the US use the Section 8 program. This ensures that the emails are relevant to all housing authority employees.

For the two treatment groups, I signal the emailer is an events coordinator for a fictitious political organization in the email signature to signal whether the inquirer holds conservative or liberal views. I also use a fictitious logo of the organization. The fictitious conservative organization is called "The Pro-Life Alliance". The fictitious liberal organization is called "The Pro-Choice Alliance". For the control group, I indicate the emailer is the events coordinator of a fictitious, politically-neutral organization. I include the logo for the organization in the email signature. The organization is called "The Alliance". Research has shown that people in the US associate prolife groups with conservative values and prochoice groups with liberal values—and that conservatives/liberals believe prolife/prochoice positions violate their values (Wetherell et al, 2013).

Similar to the first study, I use the ethnically ambiguous names Michelle and Nathan in the email signature. This ensures that the treatment does not conflate ethnicity and political ideology. I use the names Michelle and Nathan because they ethnically ambiguous names—based on a study of names and ethnicity in New York from 2011 to 2016. I do not plan to use a last name in the email signature to ensure that the ethnicity of the inquirer remains ambiguous. Exhibit B displays the email that I plan to use, including the three email signatures:

Exhibit B: Email sent to public housing authorities.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle

--
Events Coordinator
The **[Pro-Life/Pro-Choice/Heath & Wellness]** Alliance

The
Pro-Life
Alliance

The
Pro-Choice
Alliance

The

Alliance

This research design has strengths and weaknesses. Using an image as a treatment is not a commonly used practice. Many studies of SLBs use names to signal race or ethnicity. Other studies use names or misspellings to signal socioeconomic class. Since I am signaling political ideology, the use of names does not signal political beliefs. Furthermore, it is difficult to make a reasonable request to a housing authority that would signify political ideology. Therefore, using the fictitious organizations in the email signature seen in Exhibit B is a sufficient way to signal political ideology in a believable manner.

Using the topic of abortion in the treatment groups comes with tradeoffs as well. By including abortion, my study assumes that all conservatives oppose legalized abortion and all liberals favor legalized abortion. It could be argued that simply signaling the emailer as a 'conservative' or 'liberal' would make the results more applicable to conservative and liberal political ideologies. However, based on previous research, individuals have been shown to be intolerant towards individuals and groups who violate specific ideological values (Crawford & Pilanski, 2014; Wetherell et al., 2013; Chambers, Schlenker, & Collisson, 2013). By using the specific topic of abortion, the treatment signals a value violation for SLBs who disagree with the email sender. Research has shown that the pro-life / pro-choice distinction has been associated with violating liberal and conservative values, respectively, (Wetherell et al, 2013) and that both self-identified conservatives and liberals show bias towards pro-choice and pro-life people and groups (Crawford & Pilanski, 2014; Wetherell et al, 2013). Signaling an emailer as simply a conservative or liberal may not be specific enough to evoke a value violation, and thus I add the pro-life and pro-choice issue.

Using two questions in the treatment presents another tradeoff. By using two questions, I can measure variation between the treatment and control groups by coding whether housing authority employees generally respond to the same number of questions for all citizens. However, using two questions requires more effort from public housing employees. While the two questions increase the time it takes for SLBs to respond to the email, the questions do not take an unreasonable amount of time to answer.

I assign each housing authority to receive only one email (conservative, liberal, or control). I chose not to send multiple emails from the control group and the two treatment groups. This choice comes with some tradeoffs. If I had sent emails from all three groups (conservative, liberal, and control) to the housing authorities in my sample, I would get a clear picture of whether each agency treats these three groups fairly. I would also get the benefit of having a larger sample size, which makes the findings from the data analysis more reliable. However, doing so would increase the likelihood of SLBs realizing they are in an audit experiment. If the SLBs in my study realize they are part of an experiment, that might influence their behavior. Thus, I am sending one randomly assign email to each public housing authority to ensure the experiment is valid.

Statistical Power

Using a one-way ANOVA, I find that the statistical power of this experiment exceeds the generally accepted threshold of 0.8 (80% chance that a treatment effect can be detected). In my analysis, I include the number of experimental groups, the number of observations I expect to receive, an estimated effect size (disparity between the control group and treatment group), and the significance threshold. I specify three groups. I set the total number of expected observations to 301—which is the total number of emails I send (548) multiplied by my expected response rate (55%). I set the estimated effect size to five percentage points (which compares to the treatment effects found in a previous audit study of housing authorities (Einstein & Glick, 2017)). Finally, I set the significance threshold to the standard 0.05 level. My analysis exceeds the 0.8 threshold (1.00) when I run the one-way ANOVA.

Research Instrument, Ethical Considerations, Preregistration, and Treatment Validation

Research Instrument

To perform both audit studies, I use the *Yet Another Mail Merge* (YAMM) program. This online tool allows users to send up to 1,500 emails a day and tracks if emails are opened, if emails bounce back, and if the emails receive a response. YAMM also allows users to send email addresses using a customized email address. YAMM is an add-on that can be used with the Google email platform, GMAIL. Before using YAMM to send emails, I verified there is a valid connection between the GMAIL account I use and the email addresses I email. This process is known as 'pinging' email addresses. After pining the email addresses, I checked for spelling errors for the email addresses that are shown to be in error. After checking for errors, I removed all email addresses that were deemed to be invalid based on the ping.

To use YAMM, I created a Google spreadsheet of all the email addresses I contact. Then, I randomly assigned each of the email addresses to the conservative, liberal, or control group. I added a column in the spreadsheet indicating which treatment each housing authority or parks department is assigned.

I created a template email that included placeholders for whether the email is from a conservative, liberal, or politically neutral emailer. I then programmed the email template to pull in the appropriate text and picture assigned to the recipient. For example, if the Phoenix Park department is assigned to the control group, the YAMM program included the “Health & Wellness Alliance” email signature and logo in the email. Once I sent the emails. YAMM automatically filled in the spreadsheet I created with information on whether the email bounced back, was opened, and/or was replied to. Since I randomly assigned the housing authorities/parks departments to the control and treatment groups, invalid email addresses and emails caught in spam filters were randomly dispersed.

Some of the parks departments and public housing authorities in my sample provide a form for citizens to fill out to contact them instead of providing an email address. To contact these agencies, I added the appropriate email text into the form and sent the form. I then manually tracked responses to these emails in the same spreadsheet I used to track the emails. The randomization process randomly distributed these municipalities across the three treatment groups.

Before I ran the final experiment, I pre-tested sending out emails via the YAMM program. The pre-tests were successful, so I proceeded to perform the experiment.

Ethical Considerations

My dissertation research poses two ethical concerns that are common to audit studies of public servants (Butler & Brockman, 2011). First, my audit study relies on deception to test for political discrimination. If the public servants I email find out that they have been deceived, they may treat future emails from a legitimate inquirer with skepticism (Pfaff, Crabtree, Kern, & Holbein, 2021). While this is a possible risk, I minimized this risk by keeping the results of the study anonymous and secure. Since it is important to determine whether public servants discriminate based on political ideology, the benefits of the study outweigh the unlikely risk that the public servants in my sample find out they had been deceived. Additionally, audit studies provide experimental evidence for discrimination that is hard to gain using other methods, a less-deceptive alternative is not available.

The second ethical consideration is whether the possible harm done by the study outweighs the benefits. The audit experiments provide a positive social benefit by advancing research and knowledge on political ideology discrimination. If citizens are being denied equal access to public services based on political ideology, my research would provide an impetus for public administrators to take action to correct this wrong. The audit experiments require minimal effort and time from SLBs. SLBs were not overburdened by answering a brief email that asks questions they can answer easily[1]. Overall, the benefits of the study outweigh the costs.

Pre-Registration

I preregistered the two audit studies. Preregistering research is a process in which researchers make their plan for a research project publicly available before carrying out the project. Researchers state the research question, hypotheses, research design, and data analysis plan. By laying out a research plan for public reference, preregistering helps ensure that researchers do not alter their hypotheses after they have gathered data and run analysis. Preregistration also provides proof of the originality of a researcher's work. I preregistered my two experiments on the Open Science Framework website (https://osf.io/). The Open Science Framework is a commonly used preregistration platform run by the Center for Open Science.

Experiment Validation

Before carrying out my audit experiments, I took steps to 1) validate whether the intended treatments signal conservative and liberal political ideology; 2) test the effectiveness of my intended treatments; and 3) pre-test the effectiveness of the mail merge.

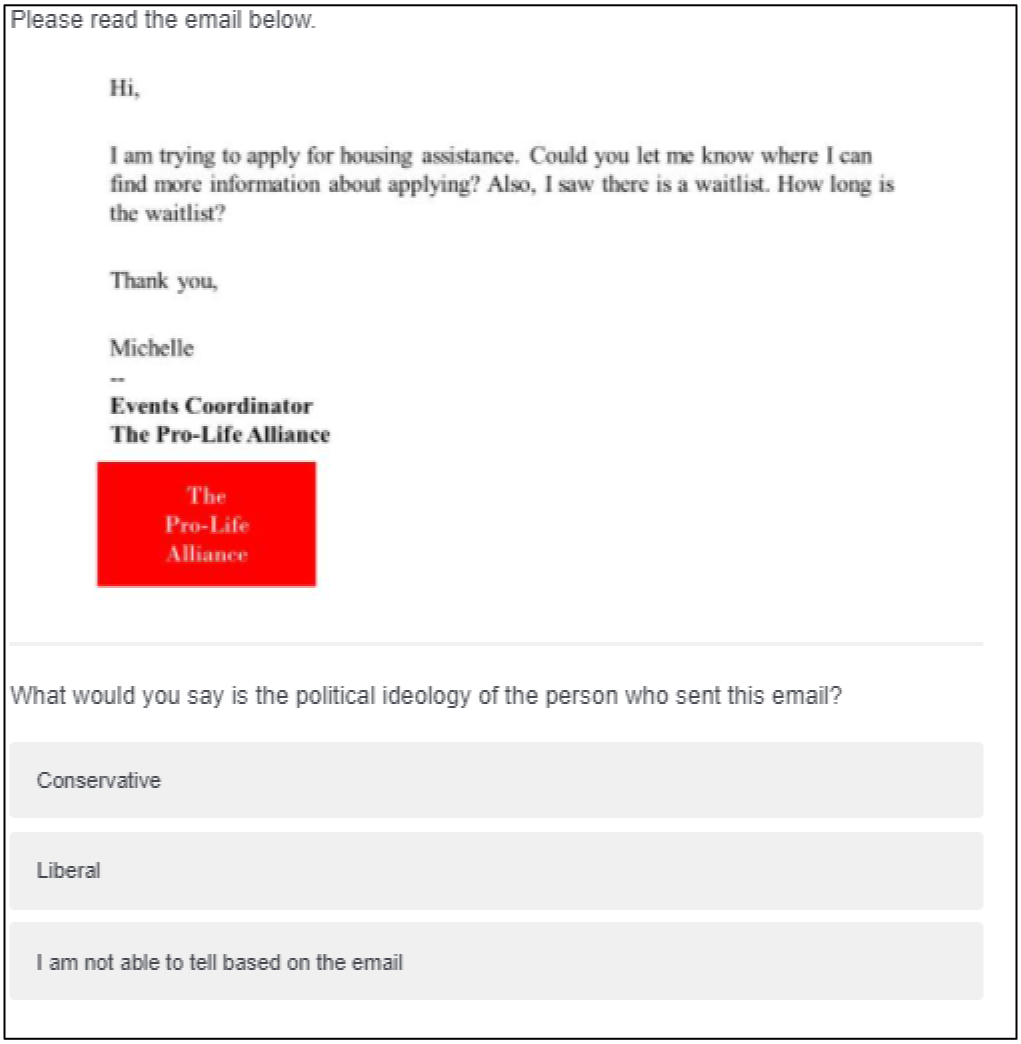
Political signaling. To test whether my treatments signal conservative and liberal political ideologies, I ran a survey on the Amazon Turk platform (MTurk). I recruited 150

[1] I am currently working on power analysis to test whether my studies are over-powered. If this is the case, I plan to adjust my sample size to ensure that I do not send emails to more SLBs than is necessary.

US adults (over the age of 18) to participate in the survey. Participants were paid at a rate of $15/hour. To ensure the participants live in the US. I used the advanced tools to confirm participant IP addresses are based in the US. I ask each MTurk participants to view one of the three following treatments:

1. The conservative treatment:
    - The conservative email credential (“Events Coordinator, The Pro-Life Alliance”)
    - The conservative logo (“The Pro-Life Alliance”)
2. The liberal treatment:
    - The liberal email credential (Events Coordinator, The Pro-Choice Alliance”)
    - The liberal logo (“The Pro-Choice Alliance”)
3. The politically-neutral treatment:
    - The politically-neutral email credential (Events Coordinator, The Health & Wellness Alliance)
    - The politically-neutral logo (The Heath & Wellness Alliance)

I randomly assigned 50 participants to each of the three groups (conservative, liberal, or neutral). After MTurkers reviewed the emails, I asked them to report whether they expect person sending the email to be 1) conservative, 2) liberal, 3) not politically motivated, or 4) don’t know. Figure 3.1 shows what the survey looked like for someone who was assigned to view the conservative treatment (including the question that is asked). Figure 3.2 shows the liberal treatment and Figure 3.3 shows the politically neutral treatment:


Please read the email below.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Pro-Life Alliance

The
Pro-Life
Alliance

What would you say is the political ideology of the person who sent this email?

Conservative

Liberal

I am not able to tell based on the email

Figure 3.1: Conservative treatment validation in MTurk survey with follow-up question

Please read the email below.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Pro-Choice Alliance

The
Pro-Choice
Alliance

Figure 3.2: Liberal treatment validation in MTurk survey

Please read the email below.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Health & Wellness Alliance

The
Health & Wellness
Alliance

Figure 3.3: Politically neutral treatment validation in MTurk survey

Once the participants completed the survey, I analyzed the data to see whether a high percentage of respondents associate “The Pro-Life Alliance” with conservative political ideology, associate “The Pro-Choice Alliance” with liberal political ideology, and associate “The Health & Wellness Alliance” with neither conservative nor liberal ideology. Table 3.3 shows how participants assigned to each treatment answered the question about the emailer’s political ideology.

Table 3.3: Treatment validation results, by assigned treatment

	The Pro-Life Alliance	**The Pro-Choice Alliance**	**The Appreciation Alliance**
Very conservative	17	4	0
Conservative	16	2	1
Moderate	4	2	11
Liberal	4	23	24
Very liberal	7	19	7
Not able to tell	6	6	17
Don't know	1	0	0
Total	**55**	**56**	**60**
Conservative/V conservative	60%		
Liberal/V Liberal		75%	
Not able to tell/Moderate			47%

Generally, MTurkers associated the conservative and liberal treatment with the expected ideology (60% correctly identified the “Pro-Life Alliance” email signature as conservative or very conservative ideology; 75% correctly identified the “Pro-Choice Alliance” signature as liberal or very liberal political ideology).

Around half (47%) of respondents assigned to the control group answered the emailer had moderate political views or that they could not tell the political ideology of the emailer. 40% of respondents guessed the emailer held liberal political beliefs. This may be the result of survey respondents assuming liberal political beliefs among those seeking government service. It is also possible that the email signature, "The Appreciation Alliance", may inadvertently indicate liberal political ideology to some respondents.

Because less than half respondents associated "The Appreciation Alliance" with being moderate or apolitical, I tested another control group using MTurk. I tested an email signature that showed a logo for an organization called "The Alliance". Table 3.4 shows the results of testing "The Alliance."

Table 3.4: Political perceptions of 'The Alliance' treatment

The Alliance	
Very conservative	1
Conservative	0
Moderate	4
Liberal	15
Very liberal	4
Not able to tell	25
Don't know	1
Total	**50**
Not able to tell / Moderate	**58%**

The results show this revised signature does a better job of signaling neutral political ideology as 58% of respondents were either not able to tell the political belief of the emailer—or thought the emailer was a moderate. This control method tests better than the “Appreciation Alliance”. Consequently, I used “The Alliance” as the control group for my experiment.

I ran a two-sample test of proportions to test whether the proportion of respondents assigned to the conservative/liberal/control group—who responded that the emailer was conservative/liberal/apolitical—was higher than in the other two groups. For example, I tested if the proportion of respondents who said the emailer was conservative (or very conservative) was higher in the conservative group than the liberal and control groups. The results for each of these six tests showed a statistically significant difference in proportions. This finding gives confidence that the email signatures I used are effective at signaling an emailer has conservative/liberal/neutral political beliefs.

Treatment effectiveness. To test whether my treatments are effective at catching the attention of an email recipient, I conducted a second MTurk survey after the first one was completed. I recruited 151 US adults to take the second survey. I used the advanced tools in MTurk so that the IP addresses of participants are based in the US. In the survey, I displayed an email from the conservative or liberal emailer and asked the participants to review the email carefully and then answer three questions about the email. The participants were required to stay on the page displaying the email for at least 15 seconds. After the 15 seconds, the MTurk participant could go to the next page. Once there, I asked participants (without them being able to look back) to answer three questions: 1) what was the political ideology of the emailer, 2) what was the name of the emailer, and 3) what the emailer was applying for? I randomized the order in which these questions are presented to MTurk participants. I recruited 151 MTurk participants to take this test – 49 participants viewed the conservative email, 53 viewed the liberal email, and 49 viewed the control email. Figures 3.4, 3.5, and 3.6 show an example of what someone assigned to the conservative, liberal, or politically neutral treatments, respectively, would see on the first and page of the survey. Figure 3.7 shows what all MTurk participants saw on the second page of the survey.

Please read the email below. You will be asked 3 questions about this email on the next page. When you are finished reading the email, please go to the next page.

Note: You will be allowed to advance to the next page after 20 seconds.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Pro-Life Alliance

The
Pro-Life
Alliance

Figure 3.4: First page of the treatment effectiveness survey with conservative treatment

Please read the email below. You will be asked 3 questions about this email on the next page. When you are finished reading the email, please go to the next page.

Note: You will be allowed to advance to the next page after 20 seconds.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Pro-Choice Alliance

The
Pro-Choice
Alliance

Figure 3.5: First page of the treatment effectiveness survey with liberal treatment

Please read the email below. You will be asked 3 questions about this email on the next page. When you are finished reading the email, please go to the next page.

Note: You will be allowed to advance to the next page after 20 seconds.

Hi,

I am trying to apply for housing assistance. Could you let me know where I can find more information about applying? Also, I saw there is a waitlist. How long is the waitlist?

Thank you,

Michelle
--
Events Coordinator
The Health & Wellness Alliance

The
Health & Wellness
Alliance

Figure 3.6: First page of the treatment effectiveness survey with politically neutral treatment

Based on the information in the email, what was the political ideology of the individual who sent the message?

- Conservative
- Liberal
- Do not recall

What was the name of the person who sent the email you just read?

- John
- Mary
- Michelle
- Daniel

What was the person applying for in the email you just read?

- Housing asssitance
- Food stamps
- Health insurance
- Tax credit

Figure 3.7: Second page of the treatment effectiveness survey

81.9% of respondents correctly recalled the name of the emailer and 98.7% of respondents correctly recalled the emailer was asking about housing assistance. The results in Table 3.5 show that participants generally correctly associated the email signatures with their intended political ideology.

Table 3.5: Treatment effectiveness results by assigned treatment

	The Pro-Life Alliance	The Pro-Choice Alliance	The Alliance
Very conservative	14	0	0
Conservative	14	2	1
Moderate	2	4	3
Liberal	10	25	22
Very liberal	0	14	4
Not able to tell	8	8	19
Don't know	1	0	0
Total	**49**	**53**	**49**
Conservative/V conservative	**57%**		
Liberal/V Liberal		**74%**	
Not able to tell/Moderate			**45%**

Table 3.5 shows that 57% of those assigned to the "Pro-Life Alliance" treatment presumed the emailer held conservative of very conservative political views. 74% of those assigned to the "Pro-Choice Alliance" guessed the emailer held liberal or very liberal views. 45% of respondents assigned to "The Alliance" indicated they could not determine political ideology from the email—or that the emailer held moderate political views. 55% of those assigned to the control group assumed the emailer held liberal or very liberal political views.

When I remove those who answered one, or both, of the attention check questions incorrectly (n=28), 49% of those assigned to the control group say they cannot tell or guess the emailer holds moderate views. 51% guess the emailer is liberal or very liberal.

These results demonstrate the MTurkers generally associated the pro-life and pro-choice treatments with conservative and liberal ideology, respectively. However, the control group is associated with neutral or moderate political views by half of the MTurkers. I previously ran a similar MTurk survey testing “The Alliance” as a control group. In that survey, 58% of respondents did not associate “The Alliance” with conservative or liberal ideology—or associated it with moderate political ideology.

These results show some limitations with the control group because it was not distinguishable from liberal ideology. Based on my previous findings that 58% of respondents associated the treatment with neutral or moderate political beliefs, the control email signature signals neutral political beliefs fairly well. However, the results of my treatment effectiveness survey indicates the salience of the neutral email signature is not significantly strong. With this limitation in mind, I decided to move forward with my experiment using these treatments.

Validity

Internal Validity

In this research design, I have tried to address many of the threats to internal validity that are common to experiments: power, instrumentation, selection bias, and attrition. The research design reduces the threat of selection bias by randomly assigning the SLBs to one of the two treatment groups or the control group. Random assignment helps ensure that any factors that could lead SLBs to be responsive to emailers are evenly distributed among the treatment and control groups. My research design also reduces the threat of low statistical power. If a study is underpowered, the internal validity of the study is threatened. My research design includes large samples. I based my power estimates on similar audit studies of SLBs and the pre-experiment power analyses showed that the experiments are sufficiently powered.

I took the following steps to improve the internal validity of my treatments. First, I tested whether the treatments I have included signal conservative and liberal political ideology to adults living in the United States. Second, I tested whether the experimental treatments are effective at catching the attention of my intended audience. Third, I verified email addresses were valid. I am confident that the experiments have sufficient internal validity. I validated that the treatments measure what I intend, the treatments are sufficiently noticeable, and emails addresses were valid.

External Validity

My research design provides valid conclusions for some external populations, but—like all experiments—not for others. I sent emails to a sample of local public housing authorities as well as a sample of city parks departments in cities with over 25,000 residents. By including a sample of these groups, my research design is applicable to SLBs in these fields. My research is also applicable to different types of public service delivery contexts. I performed two experiments in different settings: one for SLBs providing a universal public service and another for SLBS providing a needs-based service. However, I am not able to conclusively state that these findings would hold true for all SLBs. Street-level bureaucrats work in a variety of settings and have a variety of objectives. While there are certainly similarities in the basic functions SLBs provide, my findings may not be generally applicable to all SLBs. Finally, by using email for the audit experiments, the findings are limited to public service recipients who reach out via email as opposed to other ways such as phone calls, social media posts, or in-person visits.

CHAPTER 4

DATA AND ANALYSIS

In this chapter, I discuss the outcome variables I use to measure political discrimination. I detail the covariates that I expect to be correlated with the outcome variables and list the data sources of these covariates. After describing the outcome variables and covariates, I describe how I analyze my data to test whether SLBs discriminate based on political ideology.

Outcome Variables and Covariates

Outcome Variables

I have four measures to capture political discrimination: response to email, time to response, cordiality of response, and helpfulness of response. **Response** is a binary variable indicating if the SLB provided a non-automated response to the email (=1) or not (=0) within two-weeks. **Time to response** is a count variable indicating the number of hours it took for each SLB to respond. I coded Time to Response by recording when the email was sent and when an email was received. I adjusted the time for responses that were received after a weekend. In these cases, I subtracted the hours from Friday at 5:00 PM to Monday at 8:00 AM from their responses. I adjusted two weekends worth of hours for responses that came after two weekends had passed. Time to Response ranges from 0.02 to 214, with a mean of 16. To measure **cordiality of response**, I code for whether SLBs reply to the client's email includes the client's name in the email (=1) or not (=0). The email from a fictitious citizen is signed with a first name only (see the previous studies using this measure: Giulietti, Tonin, & Vlassopoulos, 2019; Einstein & Glick, 2017). Previous studies have used email greetings that do and do not use the recipients' name to measure cordiality (Giulietti, Tonin, & Vlassopoulos, 2019) or tone (Einstein & Glick, 2017). To measure **helpfulness of response**, I code how many questions from the email the SLBs answered (0= no response or no questions answered; 1 = one question answered; 2 = two questions answered). If the email receives a response, but the response does not answer any of the questions, the email is coded with a 0 for helpfulness, but is coded 1 in the response variable. In some instances, SLBs responded to the email and asked a coworker to answer the questions. If the coworker responded, I coded their response for how many of the questions they answered.

Covariates

I expect an SLB's environment could influence whether they exhibit political bias. I examine three covariates that could explain differences in response outcomes by political ideology: 1) city population, 2) city diversity, and 3) city income.

City population. Data for city population is taken from the 2019 census data per the US Census Bureau. I log the population data to make the data more normally distributed.

City diversity. To measure city diversity, I use the Diversity Index provided by the Census Bureau. The Diversity Index measures how likely two randomly selected people in an area will be of different races. The index is calculated by adding the proportion of residents in an area that are American Indian or Alaska Native, Asian, Black or African American, Hispanic or Latino, Native Hawaiian or Other Pacific Islander, and White. The index is measured on a scale of 0 to 100 with numbers closer to 100 being more diverse. The cities in my sample range from 7% to 77%.

Income. To measure **median household income,** I use data from the US Census Bureau. It is a continuous variable that ranges from $28,004 to 155,362, with a mean of 19,843.

Data Analysis

I use regression models to test for ideological discrimination. In this section, I outline three types of regression models to analyze the four dependent variables. First, I use Logistic regression to test the dependent variables response and cordiality. Second, I use Ordinary Least Squares (OLS) regression to predict the dependent variable for time to response. Finally, I use Poisson regression for the dependent variable for helpfulness.

Response and Cordiality

Because they are dichotomous variables, I use Logistic regression to test whether conservatives or liberals receive fewer and less cordial responses from SLBs. The logistic regression equation for measuring political discrimination based on responses is as follows:

$$Y = \beta_0 + \beta_1 CON_i + \beta_2 LIB_i + \beta_3 CPOP_i + \beta_4 CPB_i + \beta_4 CD_i + \varepsilon_i$$

Where Y is the dichotomous variable for response (1= response or cordial response, 0 = nonresponse or uncordial response), β_0 is the intercept, $\beta_1 CON_i$ is a dummy variable indicating an email from a conservative, β_2LIB_i is a dummy variable indicating an email from a liberal, β_3CPOP_i is the measure for city population, β_4CPB_i is the measure for community political beliefs, β_4CD_i is the measure of community diversity, and ε_i is the error term. The control group is used as the comparison group. In the analysis, I analyze the full experiment results and analyze the results for the Democratic- and Republican-majority subsets of the sample. I use this equation for both the Response variable and the Cordiality variable.

Time to Response

I use OLS regression to test whether conservatives and liberals receive slower responses from SLBs, a continuous variable indicating number of hours to receive a response. The OLS equation for predicting political discrimination based on time is as follows:

$$Y = \beta_0 + \beta_1CON_i + \beta_2LIB_i + \beta_3CPOP_i + \beta_4CPB_i + \beta_4CD_i + \varepsilon_i$$

Where Y is the continuous variable for time to response, β_0 is the intercept, β_1CON_i is a dummy variable indicating an email from a conservative, β_2LIB_i is a dummy variable indicating an email from a liberal, β_3CPOP_i is the measure for city population, β_4CPB_i is the measure for community political beliefs, β_4CD_i is the measure of community diversity, and ε_i is the error term. The control group is used as the comparison group. In the analysis, I analyze the full experiment results and analyze the results for the Democratic- and Republican-majority subsets.

Helpfulness

I use Poisson regression to test whether conservatives and liberals receive fewer and less helpful responses from SLBs, a count variable indicating how many of the questions asked in the emails received a response (0, 1, or 2). The Poisson regression equation is as follows:

$$Y = \beta_0 + \beta_1 CON_i + \beta_2 LIB_i + \beta_3 CPOP_i + \beta_4 CPB_i + \beta_4 CD_i + \varepsilon_i$$

Where Y is the count variable for helpfulness, β_0 is the intercept, $\beta_1 CON_i$ is a dummy variable indicating an email from a conservative, $\beta_2 LIB_i$ is a dummy variable indicating an email from a liberal, $\beta_3 CPOP_i$ is the measure for city population, $\beta_4 CPB_i$ is the measure for community political beliefs, $\beta_4 CD_i$ is the measure of community diversity, and ε_i is the error term. The control group is used as the comparison group. In the analysis, I analyze the full experiment results and analyze the results for the Democratic- and Republican-majority subsets of the sample.

Sampling Weights

I use sample weights in each of my regression models. I use the weights to account for the uneven number of parks departments and public housing authorities in Democratic/Republican majority areas. In the parks department experiment, I send emails to a sample departments in Democratic-majority parks areas—and to all the departments in Republican-majority areas. Conversely, I send emails to a sample of housing authorities in Republican-majority areas and to all housing authorities in Democratic-majority areas. I calculate sampling weights using the following formula:

$$\frac{1}{\text{probability of being sampled from the population}}$$

CHAPTER 5

EXPERIMENT RESULTS

I run two separate experiments to test my hypotheses. The Ideological-Conflict Hypothesis theorizes that individuals discriminate against those who hold political beliefs that conflict with their own political beliefs. My experiment results provide some evidence for this theory. I present the results of the parks department experiment. I then present the results of the public housing authority experiment.

Parks Department Experiment Results

I present the results of the parks department experiment in this section. First, I report descriptive statistics and the variation of the dependent variables. Second, I report descriptive statistics of all other variables in the model. Third, I describe how covariates are balanced across the three experimental groups. I also show how covariates are distributed among Democratic-majority and Republican-majority counties. Fourth, I present the results of the regression models. Table 4.1 shows the descriptive statistics of the variables I use in my statistical analysis.

Table 4.1 Parks Department Experiment Descriptive Statistics

	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables	Responded	450	.54	.50	0	1
	Response Time	244	10.48	23.67	0.02	160.07
	Cordiality	244	.63	.48	0	1
	Helpfulness	244	.59	.72	0	2
Covariates & Controls	Income	450	72315.69	19843.34	39681	155362
	Diversity	450	.52	.16	0.15	0.77
	Population	450	104323.53	446893.73	25158	8336817
	Republican Majority	450	.50	.5	0	1
	Democratic Majority	450	.50	.5	0	1
	Percent Republican	450	.49	.19	0.05	0.86
	Percent Democratic	450	.51	.20	0.10	0.92

Dependent Variable descriptive statistics and distribution

Responded. Of the 450 emails sent to Parks and Recreation departments[2], 244 (54%) received a response and 206 (46%) did not.

Response time. The average response time by SLBs was 10.5 hours. The standard deviation is around 24 hours, and the longest response time was 160 hours.

[2] Four of the 454 emails sent to parks department were not able to be delivered ("bounced").

Figure 4.1 shows the distribution of the response time variable. The majority (87%) of parks department respondents replied to the email within one day. I transformed the data using the log of response time to make the data parametric. The logged distribution is shown in Figure 4.2.

Figure 4.1: Response time distribution (parks department)

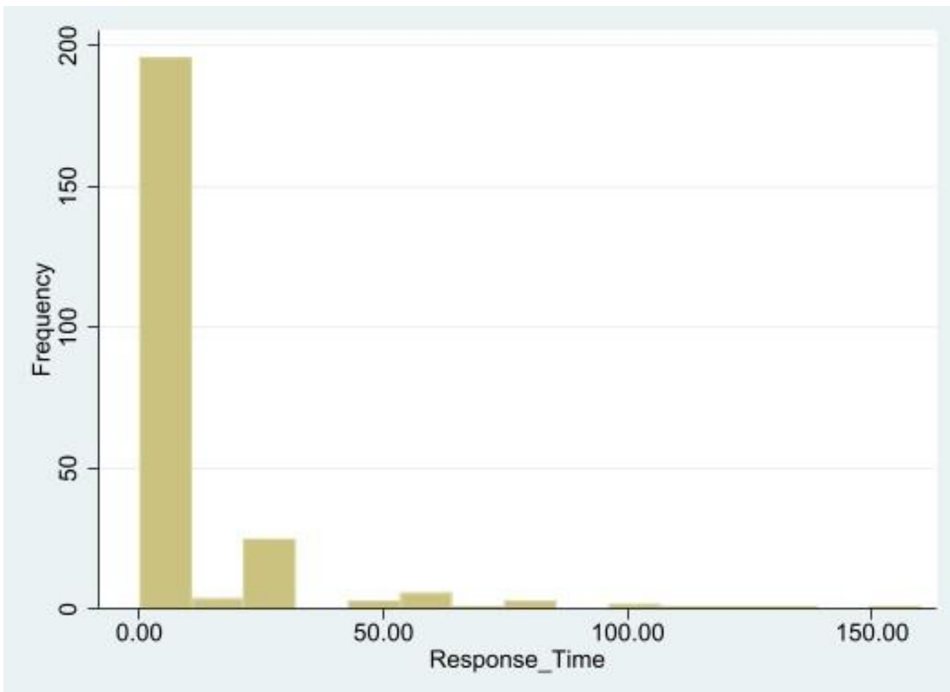
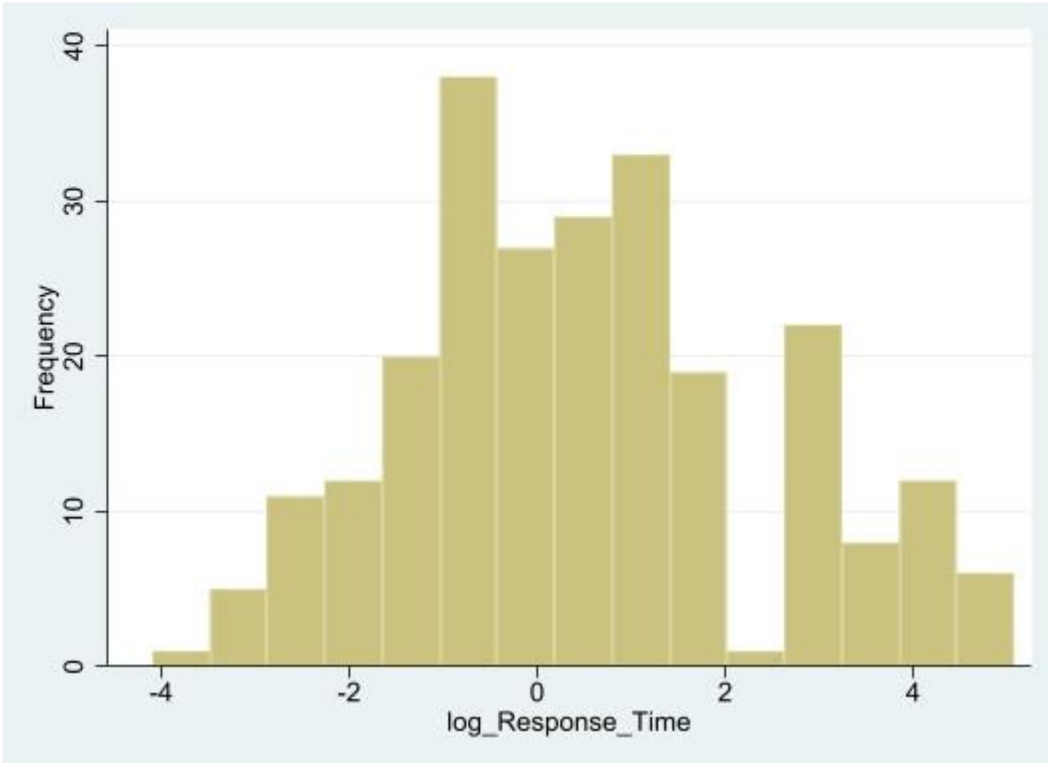


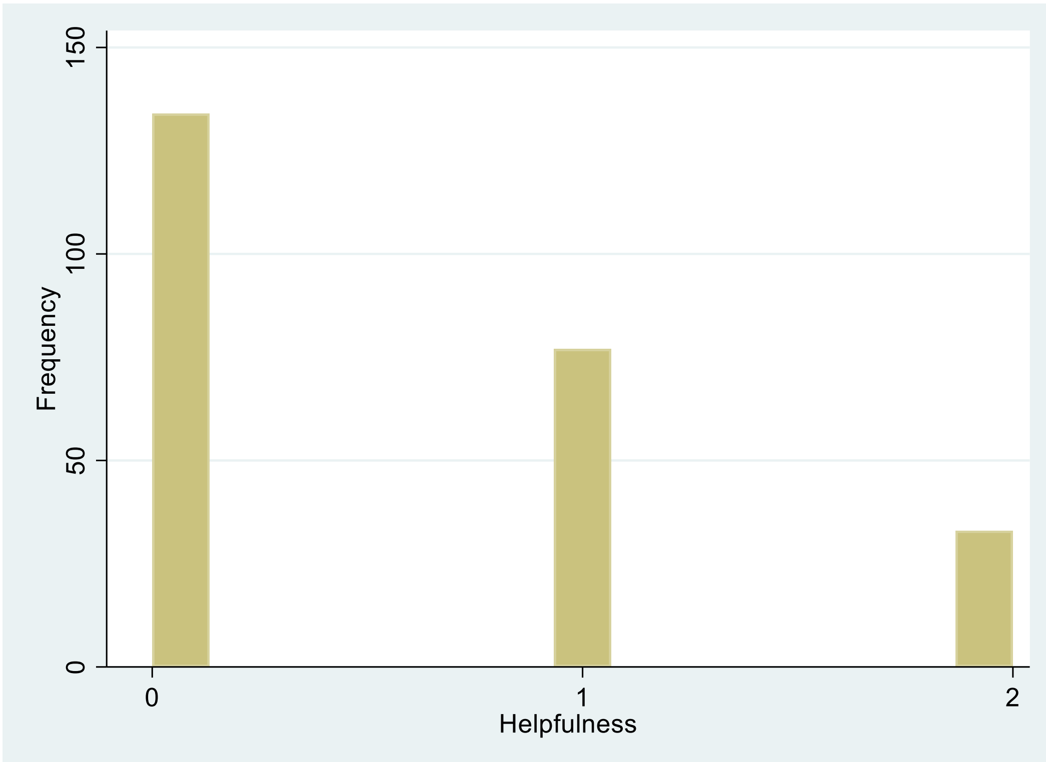
Figure 4.2: Logged distribution of response time (parks department)



Cordiality. Of the 244 responses from public housing authority (PHA) SLBs, 154 (63%) received a cordial response and 90 did not.

Helpfulness. Of the 244 responses from PHA SLBs, 134 (55%) did not answer any questions, 77 answered one question, and 33 answered two questions. Figure 4.3 shows the distribution of the helpfulness variable.

Figure 4.3: Helpfulness distribution (parks department)



Parks Department Experiment: Covariates and Independent Variables

The models include other variables that are important covariates to explain variation in the dependent variables. The mean county **income** of the sample is $72,315 with a standard deviation of $19,843. The mean **diversity** index of my sample is 0.52 with a standard deviation of 0.16. The lowest index score (least diverse) is 0.15 and the highest (most diverse) is 0.77. The mean **population** is 104,323 with a standard deviation of 446,893. The average percent of voters who voted for the Democratic candidate in the 2020 election (**percent Democratic)** is 51% and the average percent who voted for the Republican candidate is 49% (**percent Republican**).

Covariate Distribution by Experimental Group

Table 4.2 shows how the covariates are balanced across the three experimental groups.

Table 4.2 Parks Experiment Balance Statistics by Experimental Group

	Income	Diversity	Population	Republican Majority	Democratic Majority
Conservative Treatment	71880.15	.51	126390.80	.50	.50
Control Treatment	72465.57	.53	101857.68	.51	.49
Liberal Treatment	72609.15	.52	84395.00	.49	.51

The randomization process appears to have been successful at distributing income and diversity. The conservative, liberal, and control groups are all within $400 of each other. The groups are within 2% of each other as well. Population is less balanced than income and diversity. The liberal treatment group has an average population of around 84,000 as compared to over 100,000 in the conservative and control groups. This is due to the wider variation in population size among cities. Overall, I am confident that the randomization process has distributed the covariates well across the three experimental groups.

Covariate Distribution by County Type

Table 4.3 shows the descriptive statistics of the covariates for the Democratic- and Republican-majority counties in my sample.

Table 4.3: Parks Department Experiment Statistics by County Type

	Income	Diversity	Population
Democratic-Majority Counties	79837.43	.62	161625.31
Republican-Majority Counties	64793.94	.42	47021.76

The Democratic-majority counties in my sample have a higher average income of (about $15,000 higher) than the Republican-Majority counties. The Democratic-majority counties also have about a 20% higher average on the diversity index than the Republican-Majority counties. Democratic-majority counties also have a much higher average population (around 161,000) than the Republican-Majority counties (around 47,000). These figures demonstrate that Democratic-majority counties are richer, more diverse, and much larger than Republican-majority counties in my sample.

Parks Department Experiment Results

The results of the parks department experiment show little evidence of political bias by SLBs. Table 4.4 shows the regression results for the full sample of parks departments. Column 1 shows the results of the logistic regression testing for the likelihood of an email receiving a response. Column 2 shows the OLS regression results testing how long it took emails to receive a response[3]. Column 3 shows the logistic regression results testing the likelihood an email received a cordial response or not. Column 4 shows the Poisson regression results testing how many questions the emails

[3] Time to response has been measured in other studies with a dichotomous variable indicating whether a response was received within 24 hours (see Einstein and Glick, 2017). I tested my data using the same dichotomous variable. The regression results did not show any statistically significant relationships. I believe this is due to the limited variation in the data when measured dichotomously. The parks department sample had 86% of responses within 24 hours and the public housing authority sample had 80% of responses within 24 hours. Since measuring response time using hours has more variation, I decided to use this form of measurement.

received. The full sample results presented in column 1 indicate emails with the conservative or liberal treatment were not more likely to receive a response compared to the control group. The full sample results show that the liberal treatment received somewhat more helpful responses (see column 4) compared to the control group ($\beta = 0.55$, $p < .05$). The conservative treatment did not have a statistically significant difference in helpfulness than the control group. The results on the full Parks and Recreation sample results show evidence that the name Michelle received slower ($\beta = 0.55$, $p < .05$) but more helpful responses than the name Nathan ($\beta = 0.46$, $p < .01$). This does not support the Hypothesis 4 which states that SLBs will not discriminate based on sex.

Hypothesis H1a and H1b state that SLBs will discriminate against conservative and liberal clients. The results of the full experiment do not show bias. However, the full model does not delineate between SLBs who are more likely to be conservative/liberal. Tables 4.5 and 4.6 show the regression results for the SLBs in Democratic- and Republican-majority counties.

Table 4.4: Parks Department Experiment Results: Combined Model

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	1.33	-0.07	1.07	0.35
	(0.34)	(0.33)	(0.37)	(0.23)
Treatment: Liberal	0.73	-0.09	1.11	0.55**
	(0.19)	(0.35)	(0.41)	(0.23)
Name: Michelle	0.98	0.55**	1.58	0.46***
	(0.20)	(0.27)	(0.46)	(0.17)
Income	1.00	-0.00	1.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.64	-0.42	0.44	-0.52
	(0.47)	(1.00)	(0.43)	(0.57)
Population (log)	1.21	0.37**	1.02	0.07
	(0.19)	(0.19)	(0.22)	(0.13)
Constant	0.24	-3.18	0.85	-1.54
	(0.39)	(2.00)	(1.92)	(1.39)
Observations	**450**	**244**	**244**	**244**
R-squared		**0.04**		
Pseudo R-squared	**0.0135**		**0.0141**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5.A shows results of the experiment when the sample is limited to parks departments in Democratic-majority counties. H1a states that SLBs will discriminate against conservative clients. This hypothesis is not supported and instead shows that the liberal treatment was less likely to receive a response. Column 1 shows the liberal treatment was less likely to receive a response compared to the control group ($\beta = 0.56$, $p < 0.1$) It should be noted that the association is weak—it is only significant at the 90% threshold. Columns 2-4 do not show any evidence of biased responses based on political ideology. The name Michelle received more helpful responses ($\beta = 0.48$, $p < .05$) than Nathan. This does not support the hypothesis that there will be no sex discrimination

(H4). However, none of the other measures of bias (Columns 1-3) show differences between responses for Michell or Nathan—which supports H4.

The covariates of population, racial diversity, and income did not show consistent findings. H3a predicts population to be negatively related to SLB discrimination. Population was associated with faster responses ($\beta = 0.57$, $p < .01$), but was not associated with response, cordiality, or helpfulness. Similarly, income ($\beta = 1.00$, $p < .1$) and racial Diversity ($\beta = 0.04$, $p < .1$) were associated with receiving more cordial responses but were not associated with the other measures of discrimination. These findings do not show consistent evidence that there will be a relationship between income and political discrimination (H3c) —and a relationship between racial diversity and political discrimination (H3b).

Table 4.5.B shows the results of the Democratic-majority sample with the conservative treatment as the comparison group. The results in this table do not show a significant difference between the liberal treatment and the conservative treatment for any of the measures of discrimination—responded, time to respond, cordiality, and helpfulness.

Table 4.5.A: Parks Department Results: Democratic Majority–Control Treatment as Comparison Group

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	0.85	-0.19	1.45	0.01
	(0.29)	(0.40)	(0.65)	(0.24)
Treatment: Liberal	0.56*	0.22	1.34	-0.10
	(0.19)	(0.42)	(0.63)	(0.25)
Name: Michelle	0.84	0.00	0.89	0.48**
	(0.23)	(0.34)	(0.34)	(0.22)
Income	1.00	0.00	1.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.68	-2.44	0.04*	-1.15
	(0.86)	(1.65)	(0.06)	(0.96)
Population (log)	0.97	0.57***	0.81	0.12
	(0.15)	(0.16)	(0.16)	(0.13)
Constant	2.60	-4.83**	29.39	-1.50
	(4.88)	(1.95)	(73.31)	(1.56)
Observations	**225**	**128**	**128**	**128**
R-squared		**0.08**		
Pseudo R-squared	**0.0134**		**0.0521**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5.B: Parks Department Results: Democratic Majority – Conservative Treatment as Comparison Group

	(1)	(2)	(3)	(4)
VARIABLES	Responded	Response Time	Cordiality	Helpfulness
Treatment: Liberal	0.66	0.41	0.93	-0.10
	(0.22)	(0.43)	(0.45)	(0.25)
Treatment: Control	1.17	0.19	0.69	-0.01
	(0.40)	(0.40)	(0.31)	(0.24)
Name: Michelle	0.84	0.00	0.89	0.48**
	(0.23)	(0.34)	(0.34)	(0.22)
Income	1.00	0.00	1.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.68	-2.44	0.04*	-1.15
	(0.86)	(1.65)	(0.06)	(0.96)
Population (log)	0.97	0.57***	0.81	0.12
	(0.15)	(0.16)	(0.16)	(0.13)
Constant	2.22	-5.02**	42.63	-1.49
	(4.16)	(1.97)	(105.52)	(1.53)
Observations	**225**	**128**	**128**	**128**
R-squared		**0.08**		
Pseudo R-squared	**0.0134**		**0.0521**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6.A shows results of the experiment for Republican-majority counties. There is no difference in the likelihood that the conservative and liberal treatments receive a response compared to the control group. There is no relationship between the conservative or liberal treatment and responses, response time, and cordiality. The liberal treatment received more helpful responses ($\beta = 0.96$, $p < 0.01$) compared to the control group. There was no difference in helpfulness between the conservative treatment and the control group.

The name Michelle received slower ($\beta = 0.75$, $p < 0.05$), more cordial ($\beta = 2.01$, $p < 0.1$), and more helpful ($\beta = 0.51$, $p < 0.05$) responses than the name Nathan. This does not support the hypothesis that SLBs will not discriminate based on sex (H4). Income ($\beta = 1.00$, $p < 0.1$) and Racial diversity ($\beta = 0.14$, $p < 0.1$) were associated with higher and lower responses, respectively. These findings provide evidence for H3b and H3c. However, income and racial diversity were not statistically significant across the other dependent variables.

Table 4.6.A: Parks Department Results: Republican Majority–Control Treatment as Comparison Group

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	1.54	-0.01	0.90	0.53
	(0.51)	(0.44)	(0.43)	(0.35)
Treatment: Liberal	0.80	-0.12	1.02	0.96***
	(0.27)	(0.49)	(0.53)	(0.34)
Name: Michelle	1.08	0.75**	2.01*	0.51**
	(0.30)	(0.37)	(0.80)	(0.24)
Income	1.00*	-0.00	1.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.14*	0.15	0.20	-1.15
	(0.16)	(1.70)	(0.32)	(0.92)
Population (log)	1.65	0.00	1.70	-0.20
	(0.57)	(0.46)	(0.91)	(0.28)
Constant	0.03	0.88	0.01	2.10
	(0.12)	(4.90)	(0.06)	(3.06)
Observations	**225**	**116**	**116**	**116**
R-squared		**0.05**		
Pseudo R-squared	**0.0356**		**0.0296**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6.B: Parks Department Results: Republican Majority – Liberal Treatment as Comparison Group

VARIABLES	(1) Responded	(2) Response Time	(3) Cordiality	(4) Helpfulness
Treatment: Conservative	1.92*	0.11	0.88	-0.43*
	(0.65)	(0.43)	(0.42)	(0.23)
Treatment: Control	1.25	0.12	0.98	-0.96***
	(0.43)	(0.49)	(0.50)	(0.34)
Name: Michelle	1.08	0.75**	2.01*	0.51**
	(0.30)	(0.37)	(0.80)	(0.24)
Income	1.00*	-0.00	1.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.14*	0.15	0.20	-1.15
	(0.16)	(1.70)	(0.32)	(0.92)
Population (log)	1.65	0.00	1.70	-0.20
	(0.57)	(0.46)	(0.91)	(0.28)
Constant	0.03	0.76	0.01	3.06
	(0.10)	(4.94)	(0.07)	(3.00)
Observations	225	116	116	116
R-squared		0.05		
Pseudo R-squared	0.0356		0.0296	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6.B shows the results of the Republican-majority sample with the liberal treatment as the comparison group. The results show that the conservative treatment was more likely to receive a response than the liberal treatment—however the association is weak ($\beta = 1.92$, $p < 0.1$). The results also show that the conservative treatment received less helpful replies than the liberal treatment—but the association is weak ($\beta = -0.43$, $p < 0.1$)

Overall, the results of the parks department show little evidence of discrimination. The hypotheses that SLBs will discriminate based on political ideology are not consistently supported. Neither are measures of discrimination based on sex. The covariates of income, diversity, and population do not show consistent association with receiving a response, response time, cordiality, and helpfulness.

Public Housing Authority Experiment Results

I present the results of the public housing authority experiment in this section. First, I report the descriptive statistics and variation of the dependent variables. Second, I report and discuss the descriptive statistics of all the variables in the model. Third, I describe how covariates are balanced across the three experimental groups. I also show how covariates are distributed among Democratic- and Republican-majority counties. Fourth, I present the results of my regression models. Table 4.7 shows the descriptive statistics of the variables I use in my statistical analysis.

Table 4.7: Public Housing Authority Experiment Descriptive Statistics

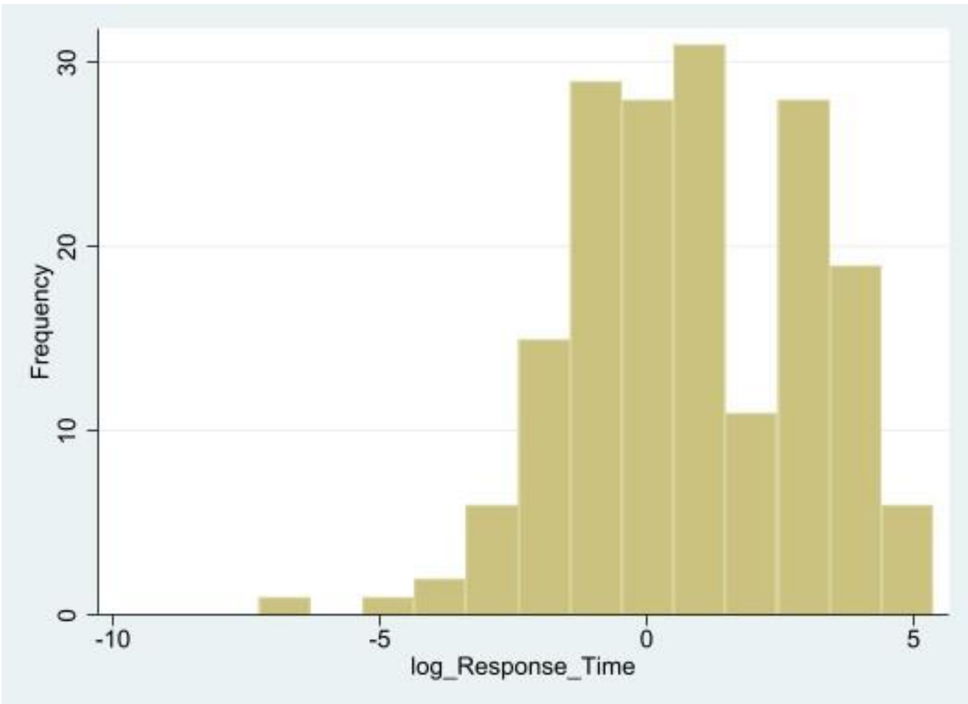
	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables	Responded	524	.34	.47	0	1
	Response Time	177	15.96	32.25	0.02	214.62
	Cordiality	177	.37	.48	0	1
	Helpfulness	177	1.52	.7	0	2
Covariates and Controls	Income	524	63653.86	19774.28	28004	155362
	Diversity	524	.47	.19	.07	.74
	Population	524	142318.62	679196.2	353	8336817
	Republican Majority	524	.5	.5	0	1
	Democratic Majority	524	.5	.5	0	1
	Percent Republican	524	.5	.22	.09	.9
	Percent Democratic	524	.48	.22	.09	.89

Dependent Variable descriptive statistics and distribution

Responded. In the PHA experiment, 177 out of 524[4] emails (34%) received a response to the email.

Response time. SLBs in the public housing authorities responded at an average of 15.9 hours, with a standard deviation of 32.3 hours and the maximum response time of 214 hours. Figure 4.4 shows the logged distribution of response time.

Figure 4.4: Logged response time distribution (public housing)

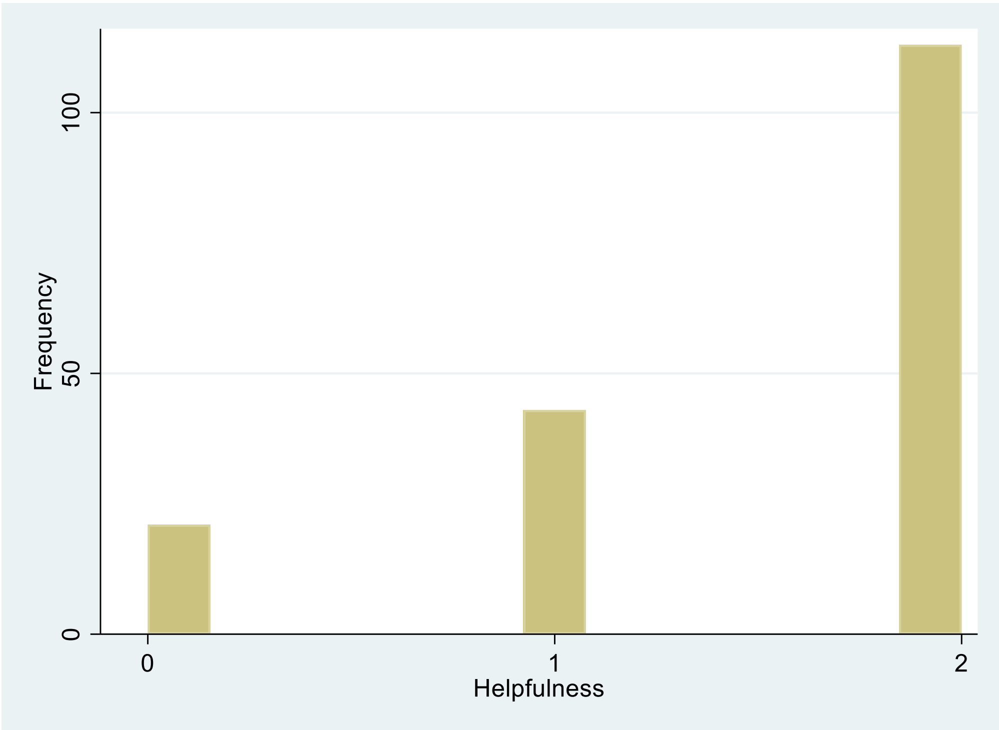


Cordiality. Of the 177 responses from PHA SLBs, 66 received a cordial response.

[4] 548 emails were sent out. 24 of the emails were not able to be delivered ("bounced").

Helpfulness. Of the 177 responses from PHA SLBs, 21 did not answer any questions, 43 answered one question, and 113 answered two questions. Figure 4.5 shows the distribution of the helpfulness variable.

Figure 4.5: Helpfulness distribution (public housing)



Public Housing Authority Experiment: Covariates and Independent Variables

I predicted other variables would be important covariates to explain variation in my dependent variables. The mean county **income** of my sample is $63, 653with a standard deviation of $19,774. The mean **diversity** index of my sample is 0.47 with a standard deviation of 0.19. The lowest index score (least diverse) is 0.07 and the highest (most diverse) is 0.74. The mean **population** is 142,318with a standard deviation of

679,196.2. The average percent of voters who selected the Democratic candidate in the 2020 election (**percent Democratic)** is 48% and the average percent who selected the Republican candidate is 50% (**percent Republican**).

Covariate Distribution by Experimental Group

Table 4.8 shows how the covariates are balanced across the three experimental groups.

Table 4.8: Public Housing Experiment Balance Statistics by Experiment Group

	Income	Diversity	Population	Republican Majority	Democratic Majority
Conservative Treatment	63983.49	.49	170134.52	.51	.49
Control Treatment	63328.67	.46	117993.47	.49	.51
Liberal Treatment	63643.96	.47	138455.01	.50	.50

The randomization process appears to have been successful at distributing income and diversity. Income for the conservative, liberal, and control group is all within $1,000. Each group is within 4% of each other for the diversity index as well. Population is less equal than income and diversity. This is due to the wider variation in population size among cities. Overall, I am confident that the randomization process has distributed the covariates well across the three experimental groups.

Covariate Distribution by County Type

Table 4.9 shows the descriptive statistics of the covariates for the Democratic- and Republican-majority counties in my sample.

Table 4.9: Public Housing Experiment Statistics by County Type

	Income	Diversity	Population
Democratic-Majority Counties	69630.27	.57	256997.63
Republican-Majority Counties	57722.91	.38	28511.70

The Democratic-majority counties in my sample have a higher average income (around $12,000 more) than the Republican-Majority counties. The Democratic-majority counties also have about a 20% higher average diversity index than the Republican-Majority counties. Democratic-majority counties have a higher average population (around 256,000) than the Republican-Majority counties (around 28,500). These data demonstrate that Democratic-majority counties are, on average, richer, more diverse, and much larger than Republican-majority counties in my sample.

Public Housing Authority Experiment Results

The results of the public housing authority experiment show evidence of political bias by SLBs. Table 4.10 shows the regression results of the experiment on all public housing authorities in the sample. Column 1 shows the results of the logistic regression testing for the likelihood of an email receiving a response. Column 2 shows the OLS regression results testing how long it took emails to receive a response. Column 3 shows the logistic regression results testing the likelihood an email received a cordial response or not. Column 4 shows the Poisson regression results testing how many questions the emails received.

Column 1 shows that both the conservative ($\beta = 1.82$, $p < 0.1$) and liberal ($\beta = 2.45$, $p < 0.01$) treatments were more likely to receive a response than the control group. These findings show some evidence in favor of H1 which states that SLBs will discriminate based on political ideology. SLBs may be more likely to respond to emails with those they agree with politically. However, the full model does not provide clear insight into this question. That is why I examine the results separately for Democratic- and Republican-majority counties (Table 4.11 and 4.12).

Column 1 shows that responses are less likely in areas with higher racial diversity ($\beta = 0.22$, $p < 0.1$). This does not support the hypothesis that community racial diversity will be correlated to SLB political discrimination. Racial diversity was associated with less-cordial responses ($\beta = 0.09$, $p < 0.1$) which does not support H3b. The name Michelle ($\beta = 0.19$, $p < 0.05$) received more helpful responses than Nathan—which provides evidence against the hypothesis that there will be no bias based on sex (H4).

Table 4.10: Public Housing Authority Experiment Results: Combined Model

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	1.82*	-0.11	1.27	-0.09
	(0.58)	(0.51)	(0.70)	(0.13)
Treatment: Liberal	2.45***	0.23	0.77	0.05
	(0.76)	(0.55)	(0.42)	(0.10)
Name: Michelle	1.01	-0.30	0.84	0.19**
	(0.25)	(0.47)	(0.35)	(0.09)
Income	1.00	0.00	1.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.22*	1.36	0.09*	-0.48
	(0.18)	(1.37)	(0.13)	(0.31)
Population (log)	1.02	0.07	1.06	0.04
	(0.08)	(0.12)	(0.14)	(0.03)
Constant	0.38	-0.72	1.13	-0.23
	(0.29)	(1.26)	(1.42)	(0.36)
Observations	**524**	**177**	**177**	**177**
R-squared		**0.04**		
Pseudo R-squared	**0.0287**		**0.0313**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the experiment for the Democratic-majority sample (and the Republican-majority sample shown later) shows evidence of political bias. Table 4.11.A shows the results of the experiment in the Democratic-majority sample. Column 1 shows that the liberal treatment was more likely to receive a response compared control group ($\beta = 2.75$, $p < 0.01$). The conservative treatment was not more or less likely to receive a response than the control group. This aligns with the hypothesis that SLBs will discriminate against conservative clients (H1a). The other measures of bias (response time, cordiality, and helpfulness) do not show differences in responses based on political ideology. The name Michelle was shown to receive more helpful responses than the name Nathan which does not support the hypothesis that SLBs will not discriminate based on sex (H4) ($\beta = 0.22$, $p < 0.05$).

The results of the Democratic-majority sample with the conservative treatment as the comparison group is shown in Table 4.11.B. The results show that the liberal treatment was just as likely to receive a response than the conservative treatment. There is no evidence that the liberal and control groups had statistically different results from the conservative treatment in response time, cordiality, and helpfulness.

Table 4.11.A: Public Housing Experiment Results: Democratic Majority – Control Treatment as Comparison Group

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	1.72	-0.06	1.31	-0.08
	(0.64)	(0.65)	(0.87)	(0.17)
Treatment: Liberal	2.75***	0.31	0.71	0.11
	(0.98)	(0.65)	(0.45)	(0.13)
Name: Michelle	0.99	-0.31	0.87	0.22**
	(0.29)	(0.56)	(0.44)	(0.11)
Income	1.00	0.00	1.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.26	1.74	0.07	-0.76**
	(0.27)	(1.98)	(0.13)	(0.37)
Population (log)	1.02	0.08	1.03	0.05
	(0.09)	(0.14)	(0.15)	(0.04)
Constant	0.29	-1.11	2.11	-0.35
	(0.29)	(1.63)	(3.49)	(0.49)
Observations	**261**	**72**	**72**	**72**
R-squared		**0.04**		
Pseudo R-squared	**0.0317**		**0.0376**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.B: Public Housing Experiment Results: Democratic Majority – Conservative Treatment as Comparison Group

VARIABLES	(1) Responded	(2) Response Time	(3) Cordiality	(4) Helpfulness
Treatment: Liberal	1.59	0.37	0.54	0.19
	(0.53)	(0.64)	(0.32)	(0.13)
Treatment: Control	0.58	0.06	0.76	0.08
	(0.22)	(0.65)	(0.51)	(0.17)
Name: Michelle	0.99	-0.31	0.87	0.22**
	(0.29)	(0.56)	(0.44)	(0.11)
Income	1.00	0.00	1.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.26	1.74	0.07	-0.76**
	(0.27)	(1.98)	(0.13)	(0.37)
Population (log)	1.02	0.08	1.03	0.05
	(0.09)	(0.14)	(0.15)	(0.04)
Constant	0.49	-1.17	2.76	-0.43
	(0.48)	(1.70)	(4.68)	(0.47)
Observations	261	72	72	72
R-squared		0.04		
Pseudo R-squared	0.0317		0.0376	

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results of the experiment for the Republican-majority sample shows some evidence that SLBs will discriminate against liberal clients (H1b). Table 4.12.A displays the results of the experiment for the Republican-majority sample. The conservative treatment was more likely to receive a response than the control treatment ($\beta = 2.5$, $p < 0.01$). This supports the hypothesis that SLBs will discriminate against liberal clients (H1b) because conservative emailers were statistically more likely to receive a response than the control group, but liberal emailers were not more likely to receive a response compared to the control group. The conservative ($\beta = -0.17$, $p < 0.1$) and liberal treatment

($\beta = -0.25$, $p < 0.5$) are both associated with less-helpful responses than the control group—which supports H1. Population is associated with a higher likelihood of response ($\beta = 1.20$, $p < 0.1$) and with the likelihood of receiving a cordial response ($\beta = 1.39$, $p < 0.1$). This provides some support for hypothesis H3a by showing that higher populated areas were more likely to respond and be more cordial. Racial diversity was associated with more-helpful responses ($\beta = 0.61$, $p < 0.05$) which provides some support for H3b.

In Table 4.12.B, the experiment results of the Republican-majority sample are displayed—with the liberal treatment as the comparison group. This table shows that the conservative treatment was more likely to receive a response than the liberal treatment ($\beta = 2.44$, $p < 0.01$). The table also shows that the control group treatment received more helpful responses than the liberal treatment ($\beta = 0.25$, $p < 0.05$).

Table 4.12.A: Public Housing Experiment Results: Republican Majority – Control Treatment as Comparison Group

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	2.50***	-0.60	1.20	-0.17*
	(0.79)	(0.53)	(0.61)	(0.10)
Treatment: Liberal	1.03	-0.15	1.44	-0.25**
	(0.34)	(0.60)	(0.80)	(0.12)
Name: Michelle	1.11	-0.01	0.74	0.04
	(0.29)	(0.44)	(0.32)	(0.09)
Income	1.00	0.00*	1.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.36	1.97	0.13	0.61**
	(0.30)	(1.38)	(0.17)	(0.27)
Population (log)	1.20*	0.04	1.39*	0.02
	(0.13)	(0.18)	(0.27)	(0.03)
Constant	0.22*	-1.28	0.05*	0.09
	(0.18)	(1.59)	(0.08)	(0.27)
Observations	**263**	**105**	**105**	**105**
R-squared		**0.08**		
Pseudo R-squared	**0.0397**		**0.0507**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12.B: Public Housing Experiment Results: Republican Majority – Liberal Treatment as Comparison Group

VARIABLES	(1) Responded	(2) Response Time	(3) Cordiality	(4) Helpfulness
Treatment: Conservative	2.44***	-0.45	0.83	0.08
	(0.77)	(0.55)	(0.43)	(0.12)
Treatment: Control	0.97	0.15	0.70	0.25**
	(0.32)	(0.60)	(0.39)	(0.12)
Name: Michelle	1.11	-0.01	0.74	0.04
	(0.29)	(0.44)	(0.32)	(0.09)
Income	1.00	0.00*	1.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.36	1.97	0.13	0.61**
	(0.30)	(1.38)	(0.17)	(0.27)
Population (log)	1.20*	0.04	1.39*	0.02
	(0.13)	(0.18)	(0.27)	(0.03)
Constant	0.22*	-1.43	0.07	-0.16
	(0.19)	(1.65)	(0.11)	(0.31)
Observations	**263**	**105**	**105**	**105**
R-squared		**0.08**		
Pseudo R-squared	**0.0397**		**0.0507**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Public Service Context and Sex-Ideology Interactions

I used pooled data to test the hypothesis that political discrimination will be higher among SLBs delivering a needs-based public service than a universal service (H2c). Table 4.13 shows the regression results using the pooled data for the combined Democratic-majority sample of my experiments. I interact the experimental group (conservative, liberal, or control) with a dummy variable for whether the SLB was delivering a needs-based public service (1 = needs-based). The results show that SLBs delivering a needs-based public service were less-likely to respond to those assigned to the conservative experimental group ($\beta = 0.26$, $p < 0.01$) than SLBs delivering a universal service. They were also less likely to respond to the control group ($\beta = 0.12$, $p < 0.01$). The results also show SLBs delivering a needs-based public service (in the Democratic-majority sample) were less cordial to those assigned to the conservative and control groups. However, the results show evidence that they are more helpful to the conservative, liberal, and control group than SLBs delivering a universal service.

Table 4.13: Pooled Results: Democratic Majority

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	0.83	-0.09	1.50	0.03
	(0.28)	(0.41)	(0.66)	(0.25)
Treatment: Liberal	0.54*	0.33	1.28	-0.02
	(0.18)	(0.44)	(0.60)	(0.25)
Conservative * Public Housing	0.26***	0.56	0.28**	0.83***
	(0.09)	(0.52)	(0.15)	(0.21)
Liberal * Public Housing	0.63	0.50	0.17***	1.07***
	(0.21)	(0.59)	(0.10)	(0.18)
Control * Public Housing	0.12***	0.45	0.31*	0.93***
	(0.05)	(0.53)	(0.19)	(0.22)
Name: Michelle	0.95	-0.18	0.90	0.26***
	(0.21)	(0.37)	(0.31)	(0.10)
Income	1.00	0.00	1.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.30	0.47	0.05*	-0.81**
	(0.27)	(1.45)	(0.08)	(0.34)
Population (log)	1.02	0.17	0.99	0.06
	(0.08)	(0.12)	(0.13)	(0.04)
Constant	2.31	-1.99	6.44	-1.30***
	(2.23)	(1.44)	(9.83)	(0.47)
Observations	**486**	**200**	**200**	**200**
R-squared		**0.04**		
Pseudo R-squared	**0.0736**		**0.0968**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The pooled results of the Republican-majority sample are shown in Table 4.14. The results show no evidence that SLBs (in Republican-majority counties) delivering a needs-based public service respond more or less than SLBs delivering a universal service. There is no evidence for differences in time to respond or cordiality. SLBs delivering a needs-based public service do appear to provide more helpful responses than SLBs delivering a universal service. Column four shows that liberal emailers generally received more-helpful responses ($\beta = 0.91$, $p < 0.01$). SLBs delivering a universal service gave more helpful responses for those assigned the conservative ($\beta = 0.98$, $p < 0.01$), liberal ($\beta = 0.55$, $p < 0.01$), and control sections ($\beta = 0.34$, $p < 0.05$).

Table 4.14: Pooled Results: Republican Majority

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Treatment: Conservative	1.53	0.02	0.90	0.58
	(0.51)	(0.44)	(0.42)	(0.35)
Treatment: Liberal	0.81	-0.16	1.02	0.91***
	(0.27)	(0.49)	(0.51)	(0.35)
Conservative * Public Housing	1.23	0.26	0.79	0.98***
	(0.49)	(0.57)	(0.44)	(0.21)
Liberal * Public Housing	0.89	0.95	0.99	0.55**
	(0.36)	(0.66)	(0.73)	(0.23)
Control * Public Housing	0.71	0.86	0.69	1.66***
	(0.28)	(0.68)	(0.46)	(0.37)
Name: Michelle	1.08	0.61*	1.79*	0.34**
	(0.26)	(0.33)	(0.62)	(0.17)
Income	1.00**	-0.00	1.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.18*	0.70	0.22	-0.38
	(0.16)	(1.34)	(0.28)	(0.57)
Population (log)	1.39**	0.17	1.61*	0.05
	(0.19)	(0.22)	(0.41)	(0.07)
Constant	0.17	-1.61	0.02	-1.24
	(0.22)	(2.27)	(0.05)	(0.81)
Observations	**488**	**221**	**221**	**221**
R-squared		**0.04**		
Pseudo R-squared	**0.0392**		**0.0426**	

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

I used pooled data from the two experiments to analyze the interaction effects of sex and political ideology. Table 4.15 shows the results of regression analyses using pooled data. I interact a dummy variable for sex (1 = email signed by Michelle, 0 = email signed by Nathan) with a dummy variables for experimental group (conservative, liberal, control). Table 4.15 shows the regression results for the two Democratic-majority samples in my two experiments. The name Michelle was not more or less likely to receive a response than the control group. The name interacted with conservative and liberal political ideology also was not more or less likely to receive a response. The same can be said for response time and helpfulness. Michelle interacted with liberal political ideology was less likely to receive a cordial response ($\beta = 0.19$, $p < 0.01$) than the control group. Michelle interacted with conservative ideology was not more or less likely to receive a cordial response.

Table 4.15: Pooled Results- Female Interacted with Political Ideology - Democratic Majority

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Name: Michelle	0.82	-0.40	2.29	0.20
	(0.25)	(0.49)	(1.25)	(0.14)
Liberal * Michelle	1.36	0.26	0.19***	0.14
	(0.50)	(0.71)	(0.12)	(0.14)
Conservative * Michelle	1.18	0.31	0.46	-0.08
	(0.44)	(0.62)	(0.29)	(0.18)
Income	1.00	0.00	1.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.50	0.16	0.21	-1.11***
	(0.44)	(1.43)	(0.32)	(0.37)
Population (log)	1.03	0.16	1.04	0.04
	(0.07)	(0.12)	(0.12)	(0.04)
Constant	0.32	-1.07	0.59	0.10
	(0.26)	(1.29)	(0.78)	(0.45)
Observations	486	200	200	200
R-squared		0.02		
Pseudo R-squared	0.00610		0.0524	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.16 shows the results of combined Republican-majority sample. The results show that Michelle interacted with conservative ideology was more likely—although weakly correlated—to receive a response compared to the control group (β = 2.26, $p < 0.1$). Michelle interacted with liberal ideology was more likely to receive a response than the control group (β = 0.73, $p < 0.05$).

Table 4.16: Pooled Results- Female Interacted with Political Ideology - Republican Majority

VARIABLES	(1) Responded (Odds ratio)	(2) Response Time (Coefficient)	(3) Cordiality (Odds ratio)	(4) Helpfulness (Coefficient)
Name: Michelle	0.86	0.44	1.95	-0.10
	(0.28)	(0.48)	(1.01)	(0.31)
Liberal * Michelle	0.90	0.64	1.14	0.73**
	(0.37)	(0.53)	(0.76)	(0.33)
Conservative * Michelle	2.26*	-0.01	0.75	0.41
	(0.94)	(0.49)	(0.44)	(0.32)
Income	1.00**	-0.00	1.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Diversity	0.18*	0.71	0.21	-0.26
	(0.16)	(1.29)	(0.26)	(0.60)
Population (log)	1.42***	-0.03	1.69***	-0.26***
	(0.14)	(0.14)	(0.28)	(0.07)
Constant	0.14**	0.60	0.01***	2.74***
	(0.11)	(1.39)	(0.02)	(0.55)
Observations	**488**	**221**	**221**	**221**
R-squared		**0.04**		
Pseudo R-squared	**0.0372**		**0.0438**	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

In this section, I showed the results of my experiments. The results of the public housing experiment show that SLBs in the Democratic-majority sample are more likely to respond emails with the liberal treatment—and SLBs in the Republican-majority sample are more likely to reply to emails with the conservative treatment. The parks department experiment found that SLBs in the Democratic-majority sample were less likely to respond to emails with the liberal treatment. The Republican-majority sample showed no evidence that SLBs were more or less likely to respond to the conservative or liberal email treatment. The results of my experiments did not show evidence that SLBs in needs-based public service delivery are more likely to discriminate based on political ideology than SLBs delivering universal services. I find evidence that females are more likely to receive a response from SLBs. Finally, I find that community factors—population, income, and racial diversity—do not predict political discrimination. I now turn to the implications of these results. My results have implications for street-level bureaucrats, SLB theory, and the Ideological-Conflict Hypothesis.

CHAPTER 6

IMPLICATIONS FOR STREET-LEVEL BUREAUCRATS AND THEORY

My findings have important implications for practice and theory. In this chapter, I discuss these implications. Before doing so, I discuss the limitations of my research.

Limitations of Research

This research has limitations which should be taken into account. The measurement of bias is one limitation of my research. In my statistical analysis, I measure whether an email receives a response or not. Since I randomly assign SLBs to receive one of the treatments or the control email, differences in response rates are assumed to be due to the political affiliation associated with the email. I also measure bias based on those that did respond. By measuring bias only in those that respond, these variables are not fully a representation of the sample. I cannot know how those who did not respond would have responded. I do not know how cordial, helpful, or quick their responses would be. Due to this, the measurements of bias—cordiality, helpfulness, time to response—have limited usefulness.

My dissertation is also limited by the stratification of my sample. I only used counties where at least 60% of citizens voted Democratic or Republican in the 2020 election. While this stratification is a useful proxy for the political orientation of the SLBs that received emails, it is still possible that an SLB living in a heavily Democratic/Republican leaning county does not necessarily hold liberal or conservative views respectively. Future research could be done to measure discrimination in association with SLBs stated political beliefs.

My dissertation is also limited by differences in samples. The Democratic-majority counties in my samples were richer, more racially diverse, and more populous than the Republican-majority counties in my sample. I used controls to account for these differences, but it should be noted that the samples were much different than one another based on the distribution of political beliefs in the country.

Finally, the control group I used in my experiments was more associated with liberal political beliefs than conservative political beliefs. A majority of the respondents who verified the email signatures I created associated the control group with being moderate or non-political, a portion of respondents associated the control group with liberalism. I expect one reason for this was the nature of the survey which asked respondents to guess political affiliation. The control group is a limitation of this study.

Implications for Street-level Bureaucrats

I find evidence that street-level bureaucrats discriminate against clients who make their political beliefs known. Specifically, I find evidence that SLBs in Democratic-majority and Republican-majority counties are less likely to respond to requests for information from liberal and conservative clients, respectively. Based on these findings, it appears that SLBs are not distributing public services fairly and equally. As a result, clients of certain political persuasions have less access to important information. While it is human nature for SLBs to have negative feelings towards people with opposing political viewpoints, these feelings cannot get in the way of treating all clients equally.

My findings suggest that public organizations may need to take action to quell political bias among SLBs. Public organizations could evaluate their processes for how client requests are processed. If public organizations find that clients may be treated unfairly, they could implement neutral standards for how all client requests are to be processed. For example, public organizations could set a standard that all client emails receive a response within a certain timeframe. Implementing such a policy would ensure that SLBs are held to the same standard for each citizen request they receive and leave less room for the natural impulse of political bias. Public organizations could also implement training programs to help SLBs treat all citizens equally, regardless of political persuasion. These training programs would need to be evaluated to ensure they are having a positive impact on SLBs.

This dissertation finds little evidence that SLBs delivering a needs-based public service are more likely to discriminate based on political ideology. While there is evidence of political biases among both experiments in needs-based and universal services, there was little evidence of a systematic difference between the two. My findings show that political discrimination likely comes from individuals working within a system and not from the type of service requested. Along those lines, my experiments showed little and inconsistent evidence that a community's population, racial diversity, and income were correlated with SLB political discrimination. Again, the evidence points towards individual SLBs as a conduit of bias as opposed to outside, community factors. This finding reiterates that SLBs need to try to find ways to treat all citizens equally.

More research can be done to explore ways to reduce political bias in public service delivery.

My findings also show some evidence of sex discrimination. I found evidence that the name Michelle received more helpful and cordial responses than the name Nathan. Michelle received slower responses than Nathan as well. I also found that the name Michelle when associated with conservativism was more likely to receive a response from SLBs in Republican-majority counties than the name Nathan. These findings demonstrate that citizens are treated differently by SLBs based on their sex and the intersection of sex and political ideology. Previous studies of SLBs and sex discrimination have found little evidence of discrimination. Perhaps the inclusion of politics adds a new dimension that influences outcomes between the sexes. As this was not the sole focus of my study, more work could be done in this area to explore these relationships.

Theoretical Implications

Street-level Bureaucrat Theory

The findings of my dissertation have implications for SLB theory. First, my findings could suggest that the theory that SLBs use their discretion in ways that lead to disparate outcomes for clients based on clients' characteristics applies to client political ideology. While SLBs at times discriminate based on race and ethnicity (Assouline, Gilad & Ben-Nun Bloom, 2021; Einstein & Glick, 2017) and socioeconomic status (Harrits & Møller, 2014; Raaphorst & Groeneveld, 2018), my dissertation finds evidence that they discriminate based on variable characteristics at times as well. This finding expands more opportunities to test the theory of SLB discrimination to other variable characteristics such as attitudes, affects, religious beliefs, social skills, and more.

My findings also suggest that SLBs delivering a universal public service are not more or less prone to discrimination than SLBs providing a needs-based public service. One theory of why SLBs discriminate argues that SLBs view certain clients as more or less deserving of help (Maynard-Moody and Musheno, 2003). I had hypothesized that SLBs delivering a needs-based service would be more prone to make judgments on who is more or less deserving of public services. These judgments would lead to clear evidence of more discrimination amongst needs-based SLBs. However, a disparity did not become apparent in the evidence. While I cannot know the thoughts and feelings of SLBs, my results provide evidence that SLBs in universal and needs-based public service are equally prone to determining who is more or less deserving of assistance.

Ideological-Conflict Hypothesis Implications

My findings have theoretical implications for the Ideological-Conflict Hypothesis. The Ideological-Conflict Hypothesis says that individuals will show intolerance to other people when those people have political beliefs that conflict with their own (Brandt et al., 2014). In the public housing experiment, I find evidence that SLBs in Democratic-majority areas show bias towards conservative clients—and that SLBs in Republican-majority areas show bias towards liberal clients. This evidence gives support for the hypothesis that individuals discriminate against those with conflicting political viewpoints. In the parks department experiment, I find little evidence that SLBs in

Democratic-majority and Republican-majority areas discriminate against conservative and liberal clients, respectively.

My findings find some evidence to support the Ideological-Conflict Hypothesis. Much of the original evidence to support the theory came from surveys (see Chambers, Schlenker, & Collisson, 2013 for example). I find similar evidence using a field study. Finding a similar result with a different methodology increases the likelihood of the theory being accurate. I also find evidence using a different population. Previous studies had been performed on a sample of university students and the general populous (e.g. Crawford & Pilanski, 2014). By finding evidence for the theory in a different population (street-level bureaucrats), my findings give some support the accuracy of the Ideological-Conflict Hypothesis.

Representative Bureaucracy and Polarization

My findings are also relevant to two other areas of research—representative bureaucracy and polarization. Representative bureaucracy theory argues that if a bureaucracy has similar characteristics as its constituents—in terms of sex, race, ethnicity, socioeconomics, etc.—the bureaucracy will act in ways to benefit their constituents (Meier, 1993; Kennedy, 2014). My findings in the public housing authority experiment show that SLBs in Democratic/Republican areas are more likely to respond to liberal/conservative clients. The favoritism displayed in these results are similar to representative bureaucracy theory. Unfortunately, however, when bureaucrats and bureaucracies are acting in ways to favor their constituents with whom they share characteristics (in this case political beliefs), they are disfavoring those in their constituency who are do not share these characteristics. If bureaucracies are ‘playing favorites’ in this way there will inevitably be inequalities for how constituents are treated.

In instances when I do find discrimination, such findings could be indicative of the present polarization of American politics. In America, the amount of people who hold ascribe to a mixture of conservative and liberal values has been decreasing—a phenomenon known as political polarization (Heltzel and Laurin, 2020). American political polarization has reached very high levels in recent years (Heltzel and Laurin, 2020). My results that do show evidence of political discrimination could be a result of the political polarization in America as more and more Americans are sorting into politically isolated camps. It could be possible that if this study had been done at times of lesser polarization, there may have been little evidenced of political discrimination. SLBs may have generally held more politically heterodox views in Democratic- and Republican-majority areas.

Conclusion

The findings of my dissertation have important implications for public servants, public managers, and public administration scholars. My findings may also be representative of the current political moment of high polarization in the US. While I find evidence of political discrimination—I also find evidence of equal treatment. Both have important implications for the efforts made by SLBs to deliver public services in a fair and impartial manner.

CHAPTER 7

CONCLUSION

In this dissertation, I explore whether street-level bureaucrats (SLBs) discriminate against clients based on their client's political ideology. I draw from previous literature on SLB discrimination. I also draw on the Ideological-Conflict Hypothesis (Brandt et al., 2014). The Ideological-Conflict Hypothesis holds individuals will discriminate against people who have opposing political viewpoints. I test whether SLBs in US local governments discriminate against public service recipients based on political ideology. I also test if political discrimination varies for SLBs providing universal public services and SLBs providing needs-based public services. In addition to these hypotheses, I test if community characteristics influence the level of political discrimination among SLBs. Finally, based on previous empirical evidence, I test for evidence of sex discrimination by SLBs.

To explore these questions, I carry out two audit experiments. The first experiment tests for discrimination amongst SLBs providing a universal public service. I send email inquiries to municipal parks departments in cities where at least 60% of citizens voted for the Democratic or Republican candidate in the 2020 Presidential Election. I perform an identical experiment on a sample of public housing authorities.

The parks department experiment shows a little evidence of political discrimination. By and large, however, I find inconsistent evidence of political bias. My public housing authority experiment finds more evidence of political bias. SLBs in Democratic-majority counties are more likely to respond to emails from liberal clients.

Similarly, SLBs in Republican-majority counties are more likely to respond to emails from conservative clients.

The experiments show little and inconsistent evidence that community characteristics—population, income, and racial diversity—influence political discrimination by SLBs. The experiments also show little evidence that SLBs delivering a needs-based public service are more likely to politically discriminate than SLBs providing a universal service. There may be other social forces that could predict whether ideological discrimination may occur. Future empirical work could examine other factors such as organizational culture, team dynamics, and personal ethics.

Contrary to my expectations (and previous empirical evidence), I find that SLBs do discriminate based on sex. Female clients are more likely to receive a response than male clients. Female clients are also more likely to receive more helpful—yet slower—responses than male clients. I also found (somewhat weak) evidence that SLBs in Republican-majority counties were more likely to respond to female, conservative clients than the control group. Since these findings go against previous empirical evidence of SLB sex discrimination, future scholarship could explore how male and female clients are treated differently in other bureaucrat-client settings.

The findings have important implications. My findings show that there are instances of political discrimination by SLBs. This shows that SLBs are not fulfilling their duty to treat citizens equally in distributing public services. My findings show the need for governments and researchers to investigate how to make public service delivery fair and equal for all the people they serve—regardless of political ideology.

Researchers can also look for additional factors that may be contributing to political bias in public service delivery. For example, an organization’s leadership or ethical climate may predict the likelihood of political discrimination. Many other factors could be researched as predictors of discrimination at the individual level—such as SLB attitudes, experiences, and education.

Future scholarship should also examine if political discrimination is found in other public service contexts. My work shows evidence for discrimination in public housing assistance—and weaker evidence in parks departments. There may be other public services where ideological discrimination is prevalent. Future scholarship could test for political bias in tax collection, policing, teaching, social work, and many other fields. I hope this dissertation will help governments, street-level bureaucrats, and researchers will look for ways to reduce political bias in public service delivery.

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APPENDIX A

EXPENSES

Table A1: Expenses

Item	Cost	Description
Yet Another Mail Merge	$50	Cost of one-year, professional subscription
Payment for Mturk participants	$75	300 participants take a 1 minute survey @ rate of $15/hr