Racial Inequality in Firms: Spillover of Affirmative Action Bans

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Abstract

This paper suggests that affirmative action bans in the US public sector may influence racial inequality in the private sector. Since the 1990s, nine states have banned affirmative action practice in public universities and state governments. Though these bans have no legal jurisdiction over private-sector firms, I theorize that they could influence such firms normatively. Executives who have been skeptical about EEO policies may feel more normatively licensed to reduce commitment to EEO practices after such a ban. Using a difference-in-differences estimation on 11,311 firms from 1985 to 2015, I find that the bans are indeed associated with slower racial progress in private-sector firms: after a state adopts the affirmative action ban, growth in the proportion of Black managers in establishments with corporate headquarters in that state slows down by more than 50 percent and this slowdown is mostly concentrated in firms with politically conservative CEOs. These findings suggest a mechanism for the persistence of racial inequality and show that regulations can influence actors well beyond legal jurisdictions.

Keywords: inequality, diversity, race, regulation, law, organizational norm, CEO

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In the United States, normative support for racial equality in organization has been growing. Mainstream media and the public discourse have become increasingly vocal about having more underrepresented racial minorities in management, which has increasingly pressured firms to improve the representation of these groups (Dobbin and Kalev 2019; Dobbin, Kim, and Kalev 2011; Zhang 2021). Some progress has been made, but Black, Hispanic, and Asian employees continue to be heavily underrepresented in managerial roles and occupy lower positions in the occupational hierarchy (Huffman and Cohen 2004; Stainback, Tomaskovic-Devey, and Skaggs 2010). For example, Black employees today are still over 50 percent less likely than White employees to be managers (Zhang 2021). If norms shape organization behaviors, why have we not seen greater progress in racial equality?

This paper suggests that the growing normative support for racial equality could be countered by certain events—what I call counternormative events—that legitimize political stances in opposition to the norm. These events may be limited in scope and cannot alter the norm, but by lending legitimacy to opposing voices, they could be perceived as permission to discount it. To demonstrate this process, I study the consequences of one such event: the banning of affirmative action in the public sector. In recent decades, several states have banned affirmative action practices in state universities and other public-sector organizations. On the surface, these bans do not appear to be consequential for workplace inequality because they have no legal jurisdiction over private-sector firms.[1] I argue, however, that private-sector executives who have been skeptical about Equal Employment Opportunity (EEO) policies may perceive the bans as a normative license to reduce their firms' commitment to EEO practices. Banning affirmative action in the public sector could therefore help stall racial progress in private-sector firms, especially when firm leaders are skeptical of EEO policies.

I examine this hypothesis using a large dataset of 11,311 firms accounting for 34,353

[1] "Private sector" refers to the part of the national economy that is not under direct government control. It includes both publicly traded and privately owned firms.

business establishments from 1985 to 2015.[2] I use a difference-in-differences approach to measure how racial inequality in an establishment changes after an affirmative action ban. To account for unobserved heterogeneity between states, my empirical strategy matches establishments with similar characteristics and in the same county and industry but headquartered in different states. Assuming that executives at headquarters shape firm-wide practices, this method compares changes in racial inequality between two highly similar establishments, one headquartered in a state that has experienced a ban and the other headquartered in a state that has not.

I find evidence consistent with my hypothesis: after a state bans affirmative action in the public sector, private-sector firms headquartered in that state experience slower growth in the representation of Black managers, especially that of Black women managers. The 10-year increase in the proportion of Black managers at those firms is only at 0.8 percentage points after the ban, much lower than the 1.95 percentage points experienced by similar firms in states without a ban. This pattern appears to be quite strong in firms run by conservative CEOs but is less evident in firms with liberal CEOs. Additionally, this pattern does not apply to firms that are under federal contracts and therefore remain subject to federal affirmative action standards. I entertain various alternative explanations and conduct robustness checks, including examining, as a placebo test, states that had almost adopted affirmative action bans. I also replicate the findings in a sample of establishments that were all in states without a ban but varied in whether the state of their corporate headquarters had adopted a ban. In the end, results suggest that affirmative action bans in the public sector are associated with slower racial progress in private-sector firms.

This paper shows that certain events—such as affirmative action bans—can slow racial progress in the workplace. These events may appear minor amidst the broader sociopolitical climate that increasingly advocates for racial equality and they do not reverse the growing normative support for it. Nonetheless, firm leaders who are skeptical of EEO

[2] A business establishment is a part of a firm defined by having a particular location. For example, a firm with an office in San Francisco and an office in Boston would have two business establishments.

practices may perceive these events as lending legitimacy to their stance and providing a normative license to deviate from the growing equality norm. These dynamics could explain, in part, the persistence of racial inequality despite a growing normative pressure to reduce it.

More broadly, this paper shows that laws and regulations can normatively influence organizations outside their jurisdiction. It is well known that regulations impact organizations through both direct sanctions and the threat of sanction, but this study suggests that regulatory influence extends even further. Through a normative influence, organizations not governed by a regulation or law might nevertheless change their behavior.

REGULATORY SPILLOVER

Organization scholars have long been interested in how regulations shape organizations. There are two major perspectives, differentiated by the enforcement mechanism: the materialist approach sees law as shaping organizational behavior by creating material incentives and penalties, whereas the culturalist approach suggests that organizations adopt certain practices which the legal environment has constructed as proper and legitimate (Edelman and Suchman 1997). Culturalists thus place less emphasis on the role of legal sanctions in deterring undesirable behavior and more on the role of legal symbols in inducing desirable normative commitments. This approach has been widely used to explain the relationship between regulations and organizational inequality. For instance, studies of EEO laws in the United States find that these laws pushed the adoption of diversity practice not through direct sanctions but through normative influences (e.g., Dobbin and Sutton 1998). This perspective helps explain why regulations with weak enforcement power often have a strong influence: such regulations can still set the appropriate cultural norms.

But I suggest that the culturalist approach could have another implication: regulations could affect organizations far beyond their jurisdiction. A law could guide cultural norms on the appropriate organizational behavior, which could influence organizations not under the law's coverage. For instance, many countries have set gender quotas in their parliaments, which could potentially signal gender norms and expectations for organizations and thus shape gender inequality in private firms without legally requiring or enforcing it. This paper explores that kind of regulatory spillover by focusing on affirmative action bans in the United States.

EEO Laws in the Private Sector

In the 1960s, federal regulators responded to the persistent racial gap in the United States by issuing two types of regulation. The first was an affirmative action requirement for federal contractors. In 1961, John F. Kennedy's Executive Order 10925 encouraged federal contractors to take "affirmative action" to reverse the effects of past discrimination and, in 1965, Lyndon Johnson's Executive Order 11246 expanded Kennedy's order and created the Office of Federal Contract Compliance Programs (OFCCP) to enforce it. Johnson's order also required contractors to prepare annual written affirmative action plans specifying goals and timetables. The OFCCP can choose to review any federal contractor at its discretion; it tends to target firms in which racial minorities and women are significantly underrepresented (Kalev and Dobbin 2006).

A second federal-level regulation instituted antidiscrimination laws to which all employers were subject. In 1964, Title VII of the Civil Rights Act prohibited all private employers from discriminating based on race, color, religion, sex, or national origin, a law enforced by the subsequently established Equal Employment Opportunity Commission (EEOC) (Dobbin and Sutton 1998; Edelman 1990). Sanctions were rare and the law's impact was limited in the 1960s, but enforcement significantly increased in the early 1970s. As a result, the number of discrimination lawsuits skyrocketed, from several hundred a year in the early 1970s to over 5,000 a year in the late 1970s (Dobbin and Sutton 1998).

However, neither Kennedy nor Johnson defined "affirmative action" in their orders and there were no established practical guidelines for compliance. Similarly, Title VII made discrimination illegal but did not define it. To further complicate the issue, the affirmative action orders and discrimination prohibition are often seen as contradictory because, by giving preference to underrepresented racial minorities, employers are making race-conscious—in effect, discriminatory—decisions (Edelman et al. 1991). These legal ambiguities have been reflected in court decisions, as courts repeatedly flip-flopped on compliance standards. Judges interpreted EEO laws differently, depending on their personal beliefs and understanding, and decisions on both sides were often reversed by higher courts (Dobbin and Sutton 1998).

Given the legal ambiguity, executives, who are ultimately charged with setting the direction for their firms' EEO practices, are often influenced by normative discourse. Below, I describe a growing normative pressure for firms to hire and promote more underrepresented racial minorities.

[insert Figure 1 about here]

Growing Normative Pressure

To deal with the ambiguity in EEO laws, executives often sought advice from professionals—including human resources specialists, labor lawyers, and diversity consultants—to develop compliance strategies (Edelman 1990, 1992). To grow their own influence and secure jurisdiction over the domain of employment relations, these professionals often exaggerated the regulatory risk and became strong advocates of EEO practices (Edelman 1992; Sutton and Dobbin 1996). They developed various compliance strategies for EEO laws, such as diversity trainings, mentoring programs, grievance procedures, and affirmative action programs (Edelman, Uggen, and Erlanger 1999), and encouraged firms to adopt these EEO practices by emphasizing the business value of having more racial and gender diversity in the workplace (Kelly and Dobbin 1998). Through publications, conventions, and workshops, these professionals helped create a normative environment in which firms are expected to take actions to increase the presence of underrepresented racial minorities (Edelman et al. 1991;

Edelman 1992; Dobbin and Sutton 1998; Kelly and Dobbin 1998).

At the same time, activist groups and the media have been increasingly vocal about the issue of racial inequality in the workplace (Edelman, Fuller, and Mara-Drita 2001). Figure 2 plots the amount of media discourse about racial equality from 1980 to 2015: the proportion of news articles advocating for workplace racial equality increased sixfold and the proportion of firm press releases covering race-related issues increased over threefold. Correspondingly, the number of nonprofit organizations and activist groups focused on race-related issues has grown significantly (Rojas 2006). Thus, firm leaders have felt a greater pressure to show support for racial equality (Dobbin, Schrage, and Kalev 2015; Dobbin and Kalev 2019; Kalev, Dobbin, and Kelly 2006). In 1980, 25 percent of firms in the US self-advertised as EEO employers and, by 2000, this number had reached nearly 70 percent (Dobbin, Kim, and Kalev 2011).

[insert Figure 2 about here]

Since norms guide and shape organizational behavior, such a strong normative pressure should push firm leaders to hire and promote more underrepresented racial minorities. Additionally, regulatory pressure has not weakened. In fact, reports from the US Department of Justice show that employment discrimination lawsuits filed in US district courts have increased significantly in the past few decades (Skaggs 2009). Given the growing normative *and* legal pressure, why has the racial gap in the labor market declined only slowly?

Organizational scholars often explain this persistence by drawing from institutional theory, arguing that firms implemented various EEO practices only symbolically, which allowed them to respond to the normative pressure without actually reducing racial inequality (Edelman 1990, 1992; Dobbin and Kalev 2019). For instance, firms claim in their job postings to be pro-diversity employers while not changing their discriminating practices (Kang et al. 2016). The core assumption is that firms do not want to disrupt their routines, so they make symbolic gestures that do not affect their actual practices, a process referred to as "decoupling" (e.g., Meyer and Rowan 1977; Westphal and Zajac 2001). However, empirical evidence suggests that not all firms decouple (see Dobbin and Kalev 2019 for a discussion on this). For instance, while some EEO practices, such as diversity trainings, are indeed ceremonial, many others, such as diversity taskforces, do substantially improve racial and gender equality (Kalev, Dobbin, and Kelly 2006). Similarly, studies find significant improvement in a firm's managerial diversity during times of flux—for example, immediately following a lawsuit—suggesting that firms can make substantive organizational changes when necessary (Kalev and Dobbin 2006; Skaggs 2009; Zhang 2021). Thus, the decoupling argument does not fundamentally explain the persistence of racial inequality, as it remains unclear why some firms decouple their EEO practices while others do not.

Affirmative Action Bans

This study suggests that counternormative events—events that challenge the norms surrounding EEO practices—could shape how firm leaders approach EEO practices. One such counternormative event is the banning in several states of affirmative action in the public sector. The EEOC requires federal contractors to have affirmative action plans and surveys show that by 2000, over 60 percent of firms in the United States had adopted some form of affirmative action practice (Kalev, Dobbin, and Kelly 2006). Critics of affirmative action argue that by giving preference to racial minorities, affirmative action practices impede progress toward a race-blind society. This view gained legal legitimacy in the mid-1990s, when a number of states banned affirmative action in the public sector. In 1996, California issued a ban that prohibits the state government and its affiliates, including public universities and state government agencies, from considering race, sex, or ethnicity in employment, education, and contracting decisions. In the two decades since, nine states in total have, at some point, banned race-based affirmative action (see Table 1): California (1996), Washington (1998), Michigan (2006), Nebraska (2008), Arizona (2010), and Oklahoma (2012) adopted their bans via ballot initiative or legislative referendum; Florida (1999) via an executive order; and New Hampshire (2011) via the state legislature. In a 1996 ruling that only Texas was required to implement, the Fifth Circuit Court banned race-based affirmative action, but its decision was overturned by the Supreme Court in 2003.

[insert Table 1 about here]

These affirmative action bans apply only to public-sector employers and have no jurisdiction over private-sector firms, so, from a legal standpoint, they should have no effect on racial inequality in the private sector. The bans also do not appear to have affected EEO enforcement, as EEOC activities have not lessened in the affected states (Skaggs 2009), nor have the bans significantly altered the normative discourse on race, as evidenced by the growing normative support for racial equality in the past few decades (Dobbin, Kim, and Kalev 2011). This paper suggests that these bans could nonetheless shape workplace racial dynamics by providing legitimacy to voices opposing EEO practices.

Offering Normative Permission

Social norms are the informal rules that govern behavior in groups and societies. They shape individual action by dictating what is and is not acceptable in a given society (Weber 1978). Similarly, norms influence organizations' actions by defining the appropriate organizational structures and practices (Meyer and Rowan 1977). However, norms do not match every actor's private preferences and values; in fact, many norms are widely unpopular (Kim 2017). Nonetheless, people and organizations still follow most norms—including those they do not support—for fear of social sanctions. But the cost of deviation is often ambiguous; in many cases, actors can only deduce the consequences from external cues (Coleman 1994). If everyone follows a norm closely and there is little support for alternative norms, then actors may perceive—without having actually seen—severe consequences of violation and will be less likely to deviate. But if certain events grant legitimacy to counternormative behavior, then actors may perceive less risk from norm violation and feel more licensed to deviate.

Although there has been growing normative pressure for firms to adopt EEO practices, not everyone actually agrees and there is a clear bipartisan divide. For instance, the

2018 General Social Survey (GSS) found that almost 70 percent of Republican respondents strongly disagree with using affirmative action in employment and only 34 percent feel that we need to do more to improve racial equality (see Figure 3). Democratic respondents are much more supportive of EEO practices; only 29 percent strongly disagree with them and over 70 percent support doing more to improve conditions for Black Americans. The views of managers and executives in GSS are quite similar to those of the population overall. Although the support for affirmative action and improving conditions for Black Americans has increased from previous years, [3] these numbers still show strikingly divergent views toward EEO policies (Kim 2017).

Nevertheless, even those executives who are skeptical of EEO policies may commit to them for fear of legal risks and possible backlash from peers, the public, and other stakeholders. The extent to which executives embrace such policies depends on their interpretation of the normative environment. For years, diversity advocates have tried to exaggerate the negative consequences of not following EEO practices, a warning frequently reinforced by federal government orders and the mainstream media (Dobbin and Sutton 1998; Sutton and Dobbin 1996). As a result, many executives perceived EEO practices as taken-for-granted, such that failing to follow them could lead to costly lawsuits (Kalev and Dobbin 2006; Skaggs 2009), damaged reputation (McDonnell and King 2013), and perceived illegitimacy (Dobbin and Kelly 2007; Dobbin and Kalev 2019).

However, a regulatory change could shift people's perception of the normative environment. The state and its regulatory agencies are an important source of legitimacy and play a key role in defining what is and is not appropriate (Scott and Meyer 1982). When a regulatory change is inconsistent with the norm, it could serve as a jolt, prompting people to reassess the normative environment (Battilana, Leca, and Boxenbaum 2009; Greenwood, Suddaby, and Hinings 2002). In the case of workplace equality, although there had been some discourse against affirmative action and other EEO regulations all along, these views

[3] For example, the proportion of Americans supporting affirmative action has increased by roughly 20 percent from 2010 to 2018.

did not frequently appear in mainstream media and were seldom endorsed by government bodies. Affirmative action bans lent, for the first time, significant legitimacy to the opposing view, as these were government-endorsed actions that directly contradicted EEO regulations. These bans could push firms to reconsider both the legitimacy of EEO practices and the consequences of abandoning them.

In the private sector, affirmative action bans could be seen as an ambiguous signal. On the one hand, these notable local events received much media attention and were popular topics of discussion in the affected states (Baker 2019; Chan and Eyster 2003). They could signal that it is culturally acceptable to challenge EEO practices. On the other hand, these bans did not cover the private sector and did not appear to affect the overall normative discourse on race, which continued to grow more supportive of EEO practices (Dobbin and Kalev 2019). It is thus also possible that people would simply interpret these events as a small and largely inconsequential pushback within the broader normative environment.

Decades of research in social psychology have shown that people are more likely to notice and follow events that are consistent with their personal beliefs and values (see Nickerson 1998 for a review). People are more likely to pay attention to such events and rely on them for decision making, while ignoring or downplaying events that contradict their personal values (Strang and Macy 2001). This confirmation bias applies, in particular, to managers and executives (Chin, Hambrick, and Treviño 2013; Dearborn and Simon 1958; England 1967). Affirmative action bans could therefore have different effects on different private-sector firms depending on their members' stance toward EEO practices. Managers and employees who support EEO practices may not give these bans much weight, as the bans would not significantly alter their understanding of the normative environment. However, those managers and employees who have been skeptical about EEO practices may see the bans as validating their beliefs and offering legitimacy to their stance. They may perceive the bans as an indication that EEO practices have gone too far and that it would be acceptable to reduce one's commitment to them.

How would these dynamics affect racial inequality in private-sector firms? The normative influence of the bans could reach managers and employees at all levels, affecting their approaches to race in the workplace. But their effect on executives may have the broadest impact. Executives play an important role in setting firm-wide practices and agendas (Chin, Hambrick, and Treviño 2013; Gilbert and Ivancevich 2000; Gupta, Briscoe, and Hambrick 2018); in particular, in allocating resources toward and executing EEO practices (Baron, Mittman, and Newman 1991; Cockburn 1991). After a ban, executives who have been skeptical of EEO practices may feel normatively licensed to reduce their commitment to EEO-related programs and initiatives, put less pressure on middle managers to follow EEO guidelines, and even implement firm-wide practices that inadvertently disadvantage racial minorities. These changes could decrease the upward opportunities for racial minorities and slow down the growth of their representation in management, in both the short and long term. Therefore, I hypothesize that affirmative action bans in the public sector will slow down racial progress in private-sector firms, especially in firms whose executives are less supportive of EEO practices.

DATA AND ANALYSIS

I tested the hypothesis using a large dataset of US firms from 1985 to 2015. The data come from EEO-1 surveys (defined below) and are made up of panel observations at the establishment level, with "establishment" defined as an economic unit—such as an office, store, or factory—which produces goods or services. The EEOC began to collect demographic workforce data on private-sector firms in the late 1960s. Before 1982, all private-sector firms with at least 50 employees, as well as federally contracted firms with at least 25 employees, were required to submit EEO-1 forms annually.[4] In 1982, the cutoff was raised to 100 employees for nonfederal contractors and 50 for federal contractors, a stipulation that remains

[4]Government contractors are those private-sector firms with more than $50,000 worth of government contracts.

today. Firms meeting these criteria are required to file a separate form for each establishment that has at least 50 employees. Each EEO-1 survey form contains a matrix of occupational classifications and race/sex combinations into which employers enter counts of employees. The form also collects identifying information for each establishment, such as its location, industry, and parent firm. Past studies comparing EEO-1 reports to other datasets find their quality comparable to that of US Census or Current-Population-Survey–based sources (Tomaskovic-Devey et al. 2006; Robinson et al. 2005). Data from 1971 to 2015 were obtained for research purposes through an Intergovernmental Personnel Act agreement. For this study, I used data from 1985 to 2015.

The primary goal being to explore the racial gap for Black Americans, I limit the sample to establishments in counties in which at least three percent of the labor force is Black. County-level demographic data come from the Decennial Census. A robustness check reveals that removing this criterion does not substantively change the results.

Although the EEO-1 data have become the gold standard in studying organizational racial inequality, they have several limitations (Ferguson and Koning 2017; Tomaskovic-Devey et al. 2006). First, EEO-1 reports are only required of private-sector firms with at least 100 employees, which account for approximately 60 percent of all employment (Hollister and Wyper 2013). Thus, the sample is only representative of medium- to large-sized firms and excludes small businesses. Second, the EEO-1 report only provides annual employment totals for each racial category in each establishment, not information about individual workers. This prevents us from capturing all personnel changes within an establishment, since the data will not identify situations in which one employee leaves and an employee with the same demographic background and occupation is hired as a replacement. Third, the report does not include wage data, so we can only measure racial inequality based on each group's occupational attainment. Lastly, a larger-than-usual cohort of establishments entered the dataset in 2007, when the EEOC began collecting data on a voluntary basis from establishments smaller than the mandatory reporting threshold (Ferguson and Koning

2017). Robustness checks showed that those smaller establishments do not substantively influence the results of this study.

Occupational Categories

The EEO-1 data provide information on the occupational composition of each demographic group. Below, I use this information to measure racial inequality within each establishment. There are nine occupational categories on the EEO-1 form: managers, professionals, technicians, sales workers, office and clerical workers, craft workers, operatives, laborers, and service workers. Although this categorization is rather broad (Tomaskovic-Devey et al. 2006), it has remained constant over the years, unlike those of many other national surveys. The EEO-1's consistency in occupational definition ensures that observed changes are not driven by a shift in the coding system (Kalev 2014; Wilson and McBrier 2005).

Dependent Variable: Racial Minorities in Management

The outcome variable is the proportion of Black managers in an establishment, defined as the number of Black managers divided by its total number of managers. The EEO-1 report includes five racial groups: White, Black, Asian, Hispanic, and Native American. I excluded Native American employees from the analyses because most establishments have none. I conducted separate analyses on the four remaining racial groups, but I focused specifically on Black employees because past studies suggest that affirmative action has its strongest impact on them (Kurtulus 2012; 2016; Miller 2017). I examined racial minorities' representation in management—the highest level on the EEO-1 report's occupational ladder—because it best reflects an establishment's level of racial inequality (Kalev, Dobbin, and Kelly 2006; Ferguson and Koning 2017; Zhang 2021), there being little equality in an establishment in which most racial minority employees occupy low-paying, nonsupervisory positions, even if the overall workforce is highly diverse.

One concern with this measure is that adding a few managers may have a large effect on establishments with few managers. As a robustness check, restricting the sample to establishments with at least 10 managers reduces the estimated coefficients but produces substantively similar conclusions.

Figure 1a plots the trend for the dependent variable. The graph shows clearly that the proportion of racial minorities in management has been on the rise, although the racial gap remains significant. Part of this growth in racial minority managers is attributed to simply having more racial minorities entering the labor force. Figure 1b—plotting the proportion of managers among all employees in each racial group—indicates a slower progress: Black and Hispanic employees' likelihood of becoming managers has improved slowly in the past few decades. In 2015, White employees were still more than twice as likely as Black and Hispanic employees to be managers.

Executive Ideology: CEOs' Political Orientation

An important mechanism in my theoretical framework is executives' ideology: affirmative action bans are more likely to resonate with executives skeptical of EEO practices. I focused on CEOs, who tend to have the most influence on firm-wide racial practices (Cockburn 1991; Hambrick and Mason 1984). Political orientation is a strong determinant of one's attitude toward EEO policies; political conservatives are much more likely than liberals to disapprove of affirmative action, often by a factor of three or four (DiTomaso 2013; Klineberg and Kravitz 2003; see Figure 3). I therefore used CEOs' political orientation to proxy for their attitude toward EEO practices. Since CEO information is available only for a subsample of the firms, the sample is smaller in models that take executive ideology into account.

[insert Figure 3 about here]

Construction of the political-orientation variable was a two-step process. First, I identified CEO names using the Standard and Poor's (S&P) ExecuComp database, which provides basic CEO information for firms in the S&P 1500 Index from 1992 onward. With a trained research assistant's help, I used online pictures and biographies to hand-code each

CEO's basic observable demographic characteristics—such as observer-reported race and gender—and manually merged this database with the EEO-1 database based on firm name and year.

Second, I identified each CEO's political orientation based on personal political contributions (Briscoe, Chin, and Hambrick 2014; Carnahan and Greenwood 2018; Chin, Hambrick, and Treviño 2013; Gupta, Briscoe, and Hambrick 2018). Individual political contributions are tracked by the Federal Election Commission (FEC), as required by the Federal Election Campaign Act, and records of all contributions of $200 or above are available on the FEC website (Christensen et al. 2015). With a colleague's assistance, I collected CEOs' political contributions to Senate, House, and presidential candidates between 1991 and 2015. These data are stored in the FEC's "detailed files," which also list the donors' full names, employer names, and job titles. We then used a computer-based algorithm to match donors in the FEC data with CEOs in the ExecuComp database and manually inspected those matches that had imperfect matching scores to validate their accuracy.

I constructed each CEO's liberal orientation by taking the dollar value of his/her total contributions to Democratic candidates in those races and dividing it by the total dollar value of his/her contributions in those races. Because most CEOs donate only once every few years, I took each CEO's total donations over the entire time period (Christensen et al. 2015). Using this method, I identified the political orientation of 2,052 CEOs representing 1,389 firms. Among those CEOs, 23.8 percent (coded as liberal CEOs) had donated the majority of their contributions to Democrats and 76.1 percent (coded as conservative CEOs) to Republicans. I set the liberal orientation of CEOs who do not appear in the FEC database at 0.5; removing them from the sample does not substantively change the results. I excluded firms that replaced a conservative CEO with a liberal one, or vice versa, during the study period (10 years before and after the headquarters state ban).[5] These firms account for about 15 percent of the sample and including them does not substantively change the results.

[5]Such changes are not significantly associated with affirmative action bans.

Analytic Strategy and Matched Samples

A straightforward analytic strategy would be to examine the direct correlation between affirmative action bans and managerial-level racial composition. Since the bans are adopted at the state level, this approach would directly compare establishments in different states. I will show these results, but they should be taken with caution because of unobserved differences between states. The proportion of racial minority managers is highly dependent on the local labor market, which varies significantly over time and across states (see Online Appendix Figure A.1. For example, California, which banned affirmative action in 1996, experienced a large influx of Asian and Hispanic immigrants throughout the 1990s. Due to the timing of this population shift, we may observe a positive correlation between the affirmative action ban and the proportion of Asian and Hispanic managers, though the ban may not have directly affected firms' treatment of Asian and Hispanic employees.

To address this concern, I exploited the fact that two establishments in the same geographic area could be headquartered in different states. Specifically, I compared establishments that are in the same county and industry and of similar firm size but are headquartered in different states. While affirmative action bans could certainly influence middle managers and lower-level employees, my theoretical framework focuses on the bans' impact on executives, who, unlike middle managers and rank-and-file employees, play a major role in determining the firm's overall policies on race issues (Baron, Mittman, and Newman 1991; Zhang 2019). According to past research, a firm headquarters' local community—where most executives presumably reside—has an important influence on them and their decision making (Palmer, Friedland, and Singh 1986; Marquis, Glynn, and Davis 2007). I therefore expect a firm's headquarters location to play an important role in determining firm-wide race-based practices that would then influence the local establishments.

To empirically demonstrate the importance of firm-wide practices, Online Appendix Table A.1 shows the level of co-movement in inequality across establishments within the same firm. Specifically, I used the proportion of Black managers in other establishments (of the same firm) to predict the proportion of Black managers in the focal establishment, controlling a wide range of time-variant establishment characteristics and adding fixed effects on establishment, county-year, and industry-year. Depending on model specification, I find that when other establishments increase their proportion of Black managers by 1 percentage points, the focal establishment increases it by 0.09 to 0.14 percentage points. This result suggests considerable co-movements in inequality across establishments within the same firm, underscoring the role of firm executives in setting firm-wide practices that shape inequality.

I used a dynamic difference-in-differences design in which I compared establishments with corporate headquarters in states that banned affirmative action (treatment) to those with corporate headquarters in non-ban states (control). I implemented a matched sampling procedure: focusing specifically on the year before the event (the year before the headquarters state implemented the affirmative action ban), I matched every treatment establishment with up to two randomly selected control establishments from that same year. I required the control establishments to satisfy the following criteria in relation to the treatment establishment: (a) they were in the same county; (b) they had the same three-digit Standard Industry Classification (SIC) code;[6] (c) they were in the same quartile of firm size (measured by number of employees); and (d) their headquarters state had never adopted an affirmative action ban. Each treatment establishment was matched with at least one control establishment; those treatment establishments that could not be matched were dropped. To give an example, this matching would result in a comparison of two grocery stores in DeKalb County, Illinois, whose parent firms each had more than 30 thousand employees and were headquartered in different states.

I set the window of observation at 20 years—10 years before the event (adoption of the ban) to 10 years after—and excluded other years of observation from the sample. The 10-year pre-event period allows us to observe the parallel trend assumption and the 10 post-event period should provide sufficient time to observe resultant change, even if it is not

[6] I used three-digit SIC codes because a large number of firms have missing four-digit SIC codes in the EEO-1 report.

immediate.

Using this method, I collected two sets of samples. The main sample comprises all private-sector firms in our matches sample, which includes 11,311 firms and 34,353 establishments, accounting for 282,359 establishment-year observations. On average, a firm lasts 9.7 years in the sample and an establishment lasts 8.3 years. Table 3 shows the mean of key covariates between the treatment and control sample one year prior to an affirmative action ban. Compared to the nonmatched sample, the treatment and control establishments in the matched sample are much more aligned across most key covariates, such as firm age, establishment size, occupational composition, and the proportion of Black managers, professionals, and employees. For the analysis with CEO ideology, I gathered a second sample that covers firms in the S&P 1500 index and includes 1,805 firms and 19,263 establishments, accounting for 124,356 observations.[7]

[insert Table 3 about here]

Model Specifications

I examined changes in racial inequality at the establishment level by estimating the following model:

$$Y_{jt} = \sum_{p=-9}^{10} c_p T_{ip} + \sum_{p=-9}^{10} \beta_p T_{ip} \times Treatment_i + \gamma \cdot X_{it} + E_i + CY_t + \epsilon_{it}, \tag{1}$$

where Y_{jt} is the outcome variable at establishment j in year t. p is the number of years relative to the event (the headquarters state's implementation of the ban); specifically, I set year 1 to be the first year after the event. T_{ip} is a dummy variable indicating p years after the event. The coefficient of interest is β_p, which captures the average difference in the outcome variable between treatment and control establishments when $T = p$.

I also used a simpler model, grouping T_{ip} into pre- and post-event periods:

$$Y_{it} = c \cdot Post_i + \beta \cdot Post_i \times Treatment_i + \gamma \cdot X_{it} + E_i + CY_t + \epsilon_{it}, \tag{2}$$

[7] Detailed information on data construction and replication is available at www.letianzhang.com.

where $Post_i$ is 1 for post-event years and 0 for pre-event years.

Although the unit of observation is an establishment, many organizational practices are presumably decided at the firm level. Standard errors are therefore clustered at the firm level. Results are qualitatively similar whether or not establishment sizes are included as weights; for simplicity, I present models without weights.

These models assume that racial inequality in treatment and control establishments would have followed parallel trends had affirmative action bans not been adopted. That is, in the absence of the bans, the difference between the treatment and control establishments is constant over time (an increase at similar rates in the proportion of Black managers). Admittedly, affirmative action bans are not exogenous events; they could be influenced by factors that are correlated with the dependent variables. In this case, identification would be a concern if establishments' headquarters states are more likely to ban affirmative action when these establishments are on the verge of increasing their racial inequality (relative to control establishments). Since I cannot rule out this concern, I try to minimize it by including many fixed effects and controls.

First, I include establishment-level fixed effects, E_i, to control for time-invariant establishment traits. This allows us to observe changes within each establishment, rather than differences between establishments. I also include calendar-year fixed effects, CY_t, to control for the macro environment, as well as leads and lags around the event time, T_{ip}.

Second, X is a set of control variables that capture time-variant establishment- and firm-level characteristics, including the number of workers in each establishment and the number of establishments in the firm, as demographic inequality could be a function of firm size. I also include the occupational composition—including the proportion of managers, professionals, back-office workers, blue-collar workers, and service workers in the establishment—as occupational composition could influence racial minorities' hiring and promotion. To account for the political climate in each firm's headquarters state, I control for the majority party in its legislature and the political affiliation of its governor. I control for each firm's federal contractor status, since federal contractors are legally subject to EEOC's affirmative action policies. Finally, to distinguish inequality from overall workforce diversity, my models control for the proportions of five demographic groups—White, Black, Hispanic, Asian, and women—among nonmanagerial workers in the establishment and their proportions in the local labor force. Since the proportion of managers is higher in establishments with more professional workers, I control for each group's proportion among professional workers in the establishment. Data on local labor market demographics come from Decennial Census' county-level data, linearly extrapolated to obtain annual estimates.

RESULTS

Results show that banning affirmative action in the public sector is associated with slower growth in the proportion of Black managers in the private sector, especially that of Black women managers. This association varies depending on CEOs' political orientation: while firms with liberal CEOs did not experience a major change following an affirmative action ban, growth in the proportion of Black managers slows down by more than 50 percent in firms with conservative CEOs.

Preliminary Analyses

Table 2 presents straightforward regression models without matching. I directly examine the association between affirmative action bans and the proportion of Black managers in the establishment, using establishment and year fixed effects and controlling for time-invariant firm-level characteristics. Because California experienced major demographic shifts during the study period, I run models both including and excluding establishments in California. These models show that after a state bans affirmative action, the proportion of Black managers in establishments in that state is 0.3 percentage points less than in establishments in other states (see Model 1). In comparison, the annual growth in the proportion of Black managers in the entire sample is only 0.1 percentage points. The correlation is more negative for women than for men; after a ban, the drop is 0.2 percentage points for Black women managers and 0.1 percentage points for Black men managers (see Models 2 and 3). It is important to note that the proportion of Black managers in the overall sample is increasing (which is absorbed by year fixed effects), hence the negative coefficients associated with the bans indicate slower progress toward racial equality as opposed to increases in racial inequality.

Results of models predicting changes for other racial groups are more mixed. Using the full sample, the bans are associated with positive changes for Hispanic and Asian managers and negative changes for White managers, relative to establishments not affected by the bans (see Models 5, 7, and 9). However, after excluding California, the bans are associated with positive change in the proportion of White managers and negative changes in the proportion of Asian managers (see Models 6, 8, and 10). As mentioned earlier, these results should be interpreted with caution when comparing across states because of potential confounders—particularly, demographic shifts within states during this period. The different results based on the inclusion of California illustrate this point. In the following, I conduct more robust analyses using matching and difference-in-differences.

[insert Table 2 about here]

Main Analyses

I now present the main analyses, comparing establishments in the same county and industry and with similar firm size but headquartered in different states. Consistent with the hypothesis, an establishment experiences a significantly slower growth in the proportion of Black managers after its headquarters state bans affirmative action. This pattern can be seen from the descriptive trend in Figure 4: the proportion of Black managers in an establishment increases on average, but after the ban, establishments of firms headquartered in a state with a ban (the treatment group) see a significant slowdown in that growth, while establishments of firms headquartered elsewhere continued to see a similar growth rate. Table 4 displays these descriptive patterns across all racial groups, finding that the post-ban change is most salient for Black and White managers.

[insert Figure 4 about here]

[insert Table 4 about here]

Table 5 uses OLS models to illustrate this pattern. Affirmative action bans are associated with a 0.63-percentage-point drop in the proportion of Black managers (relative to control establishments) and this association is stronger for women: a 0.48-percentage-point drop for Black women managers versus a 0.15-percentage-point (statistically insignificant) drop for Black men managers.[8] At the same time, the bans are associated with a higher proportion of White men managers (relative to control establishments) and have slightly negative but statistically insignificant associations with the proportions of Hispanic and Asian managers. Overall, it appears that the bans mostly predict a change in the Black-White racial gap. These findings are consistent with past research suggesting that affirmative action has a strong effect on Black employees but limited impact on Hispanic and Asian employees (Kurtulus 2012; Miller 2017).

[insert Table 5 about here]

Figure 5 visually displays Black employees' representation in management before and after an affirmative action ban. The use of year fixed effects in Table 5 masks the overall trend: affirmative action bans are associated with slower progress rather than reversal. Figure 5a shows this point clearly: it estimates Table 5's Model 1 (Equation 1) without year fixed effects and plots the control and treatment establishments separately. The control and treatment establishments experience similar growth in the proportion of Black managers prior to the ban, but that rate drops by more than 50 percent for treatment establishments after the ban.

[insert Table 5 about here]

[8] This is a sizeable difference considering that the proportion of Black women managers in the sample is smaller than the proportion of Black men managers.

Figure 5b plots the estimated difference between control and treatment establishments with year fixed effects: about a year after the ban is adopted, the proportion of Black managers starts to drop for the treatment establishments relative to the control establishments. Compared to the pre-ban period, a treatment establishment's proportion of Black managers is 6 percent (0.5 percentage points) lower than a control establishment's two years after the ban and 13 percent (1 percentage point) lower five years after the ban, after which the gap stops growing. This gradually increasing gap could be an indication that the bans led to changes in firms' long-term EEO practices.

Figures 6a and 6b break down the trend by gender. Compared to the control establishments, managerial representation in the treatment establishments dropped only moderately for Black men after a ban, but dropped significantly for Black women. These patterns are consistent with Table 5 and may indicate that EEO practices affect Black women more than Black men, suggesting in turn the intensified consequences of these bans for those at an intersection of marginalized identities.

[insert Figure 6 about here]

Finally, I examine the association between affirmative action bans and the racial composition of the nonmanagerial workforce. High racial diversity in the workforce does not necessarily reflect racial equality because a firm could hire racial minorities disproportionately into low-paying, nonsupervisory positions. Nevertheless, it may be worthwhile to know if the bans are associated with any change in nonmanagerial workforce diversity. Controlling for local demographics, I find no such association (see Online Appendix Table A.3), suggesting that the influence of these bans is limited to managerial recruiting and promotion.

Conservative versus Liberal CEOs

Table 6 and Figure 7 examine how CEOs' political orientation moderates the post-ban change in racial inequality. As illustrated by Figure 7, I conduct split-sample analyses, dividing the sample into two groups: CEOs who donated more to Republicans than to

Democrats (conservative CEOs) and vice versa (liberal CEOs). These split-sample analyses show that in firms with conservative CEOs, an affirmative action ban is associated with a 0.97-percentage-point reduction in the proportion of Black managers (relative to the control establishments) (see Figure 7 and Table 6 Models 3 and 4). In firms with liberal CEOs, such a ban is associated with a statistically insignificant 0.37-percentage-point reduction (see Table 6 Models 5 and 6).

[insert Table 6 and Figure 7 about here]

The results of these split-sample analyses are consistent with those of the full model, in which I interact CEOs' political orientation with the treatment (see Models 1 and 2). In the full model, *Liberal CEO* is a continuous variable that measures the proportion of donations to Democrats and which has a value of 0.5 for those who did not donate to candidates of either party. Using a three-way interaction (*HQ in Banned States* x *Post Ban Period* x *Liberal CEO*), this model provides consistent evidence that the association between bans and inequality is much stronger in establishments of firms with conservative CEOs. As a robustness check, I included additional interaction terms to ensure that the moderating role of CEOs' political orientation is not confounded by other CEO or firm characteristics. In particular, I added CEOs' age, race, and gender as additional interaction terms; this did not substantively change the moderating coefficient for CEOs' political orientation. I also found that those CEOs who did not donate to either party behave similarly to liberal CEOs in that affirmative action bans are, for them, associated with statistically insignificant changes. In sum, these results suggest that the influence of affirmative action bans is mostly concentrated in firms with politically conservative leadership.

To address the possibility that this pattern is not driven by CEOs' ideology but rather by their employees' ideology, since the two are likely to be correlated, I constructed a separate variable measuring the average donation of each firm's non-executive employees, as the FEC donation database contains information on each donor's employer. Including this measure as an additional moderator (*HQ in Banned States* x *Post Ban Period* x *Liberal*

Employees) does not substantively change the coefficient of the main moderating coefficient (*HQ in Banned States* x *Post Ban Period* x *Liberal CEO*) and this additional three-way moderator has a small and statistically insignificant coefficient, suggesting that it is not employees' ideology mainly driving the results.

It is worth noting that CEOs' race, gender, and age do not appear to significantly affect how their firm reacts to affirmative action bans (see Online Appendix Table A.4). Intuition may suggest that minority, women, and younger CEOs are more supportive of EEO practices than White, male, and older CEOs. However, using firm fixed-effects models, I did not find a CEO's race, gender, or age to be associated with racial inequality in the firm; the only CEO characteristic significantly associated with racial inequality is political orientation (see Online Appendix Table A.5). However, it is possible that this result is simply driven by the small number of racial minority and women CEOs in the sample.

Federal Contractors versus Noncontractors

Table 7 shows that the association between affirmative action bans and slowed racial progress does not apply to federal contractors. Unlike typical private-sector firms, firms under federal contracts are required to enforce federal affirmative action practices. These contractors must write affirmative action plans and reports and their progress on racial equality is monitored by the OFCCP (Kurtulus 2012; Miller 2017). As predicted, I find that for federally contracted firms, the bans are associated with only a statistically insignificant 0.09-percentage-point drop in the proportion of Black managers (relative to control establishments), in contrast to the 1-percentage-point decrease for noncontracted firms (see Table 7 Model 1).

[insert Table 7 about here]

Results by State

Table 8 shows how the association between affirmative action bans and slower racial progress varies across states. I followed the same matching procedure and model specification as in the main analysis except treating each state ban one at a time. As the table shows, the bans in Texas (1996), Michigan (2006), Nebraska (2008), and Arizona (2010) predict the biggest slowdown in the growth of Black managers, whereas the bans in California (1996), Washington (1998), and Florida (1999) are associated with little change. As the former set of states are on average more politically conservative than the latter, this pattern is consistent with the idea that the bans would slow down racial progress the most in areas where more people are skeptical of EEO practices.

[insert Table 8 about here]

A Placebo Test

A state's adoption of an affirmative action ban could be correlated with public aversion toward EEO policies. Could that popular opposition, rather than the actual regulatory ban, be responsible for the slower racial progress? To alleviate this concern, I conducted a placebo test by examining firms headquartered in Colorado, Missouri, and Utah, where affirmative action bans were proposed but ultimately failed to pass. The initiative in Colorado (2008) was especially close, defeated in a 49-percent to 51-percent popular vote, whereas initiatives in Missouri (2008) and Utah (2010) failed to qualify for the ballot. All three initiatives gained substantial popular support in their states before being dropped, making these states comparable to the nine in which the bans did pass. If the observed slowdown in racial progress is in fact the result of a state's rising popular sentiment against EEO practices, then we should expect a similar slowdown for firms headquartered in those three states. However, if, as my theory suggests, the slower racial progress comes from regulatory changes, then we should not observe any significant change in racial progress in those three states.

In the placebo test, I treated the three placebo states in the same way that I treated the other nine states that did pass the ban: I identified establishments of firms headquartered in these three states and matched them with establishments in the same county and industry and of similar firm size but headquartered in a non-ban state. As Table 8 shows, the placebo bans in these three states show a positive coefficient in predicting the proportion of Black managers, although the point estimates are close to zero and far from statistical significance, suggesting no systematic differences between establishments with corporate headquarters in these three states and those with corporate headquarters in other non-ban states. These results further support the hypothesis that the observed change comes from the adoption of affirmative action bans, not from shifts in popular sentiment.

Robustness Checks and Alternative Explanations

My analyses compare establishments in the same county but headquartered in different states. A more restrictive sample would include only establishments in states that never adopted a ban but varied in whether the state of their corporate headquarters adopted a ban. Using this more restricted sample produces substantively similar conclusions, adding support to the main results (see Online Appendix Table A.2).

One alternative explanation is that an affirmation action ban somehow reduces that state's EEOC enforcement in the private sector, allowing firm executives to relax their EEO commitment. I therefore investigate whether there was any association between the bans and the number of discrimination lawsuits. To identify EEO lawsuits, I searched major newspapers and looked for racial and gender discrimination lawsuits against private-sector firms. I found 217 racial discrimination and 117 gender discrimination lawsuits from 2000 to 2015. I run OLS regressions at the firm level to see whether an affirmative action ban in a firm's headquarters state is associated with fewer discrimination lawsuits against that firm. My analysis shows no such association: the coefficient is close to zero and far from statistical significance (see Online Appendix Table A.6). Based on this analysis, it does not appear that affirmative action bans weakened EEOC enforcement in the private sector.

Regarding supply-side explanations, my analytical strategy of comparing similar establishments in the same county helps address many of them. For example, the bans may reduce Black enrollment in public universities, especially the more selective ones, which could lead to fewer qualified Black candidates for managerial positions in the private sector. Similarly, Black employees may migrate from the public to the private sector or vice versa after the bans. By comparing similarly located workplaces, my models account for such differences across local labor supplies.

A possible supply-side explanation is that after a state bans affirmative action, Black jobseekers or employees may voluntarily avoid or leave firms headquartered in that state, even though the firms in which they worked or sought work may not have been affected by the ban. I expect such supply-side reactions to be strongly moderated by the unemployment rate and macro-economic conditions. When the unemployment rate is high and/or the economy is doing poorly, jobseekers and employees have fewer options and should therefore be less likely to voluntarily avoid or leave firms, even those headquartered in states with bans they find objectionable. I examine this possibility by obtaining annual state-level unemployment data from the Current Population Survey, county-level decennial unemployment data from the Census Bureau, and the macro-level economic recession indicator from the National Bureau of Economic Research. The decennial unemployment data are linearly extrapolated to the approximate annual rate. I include these three variables as moderators in separate models and find that none significantly moderates the relationship between the ban and racial inequality, indicating that the influence of affirmative action bans does not vary significantly based on unemployment rate or macro-economic conditions. These findings are inconsistent with a supply-side explanation. It is still possible, however, that affirmative action bans have some kind of behavioral impact on jobseekers and employees.

DISCUSSION

This study suggests that bans on state-level affirmative action, which legally apply only to the public sector, could nevertheless normatively shape racial inequality in private-sector firms. Examining 11,311 firms, I find that after a state passes an affirmative action ban, growth in the proportion of Black managers in firms headquartered in that state slows by more than 50 percent. After the ban, the proportion of Black managers in such firms is 8.4 percent smaller than that of comparable firms not headquartered in that state. This slowdown in growth is mostly concentrated in firms with CEOs who hold a conservative political ideology: such firms see a 13-percent gap between treatment and control while this gap is less than 5 percent for firms with liberal CEOs. In addition, the bans do not predict a significant change in racial inequality for firms under a federal contract, which are still subject to federal affirmative action requirements. These results support the hypothesis that affirmative action bans in the public sector are associated with slower racial progress in private-sector firms, especially in those with conservative CEOs.

Regulatory Influence beyond Jurisdiction

This study suggests that laws and regulations can influence audiences outside their jurisdiction. In a culturalist framework, laws could influence organizational actors' cognitive framework and institute normative guidelines for appropriate organizational behavior. Neo-institutional theory follows this tradition: laws not only have the power to directly sanction organizational behavior, but also can normatively shape it by granting legitimacy to certain organizational forms (Meyer and Rowan 1977). This view of law as a cultural carrier has two important implications: (a) regulations with weak enforcement power can nonetheless have a strong normative impact on organizations and (b) regulations can have normative consequences well beyond their designated jurisdiction. This first point has been well documented: many studies have shown that EEO regulations in the US, despite their weak enforcement power, have significantly shaped organizational approaches to racial inequality (e.g., Dobbin and Sutton 1998). The second implication—the spillover effect of regulations—has seldom been mentioned. One contribution of this study is to provide empirical evidence of such a spillover. In doing so, I also show that it is highly contingent on organizational leaders' individual ideologies and beliefs.

This regulatory spillover could apply to many contexts. In fact, it is often easier for governments to implement regulations in the public sector than in the private sector. For example, the US government has specific employment rules that apply only to public agencies. However, it is possible that these rules, when widely publicized, could have normative consequences for private-sector organizations. Similarly, when Canadian Prime Minister Justin Trudeau introduced a gender-balanced cabinet in 2015, some observers argued that this move, while applying only to his cabinet, "sets new expectations that should land women more prominent roles in everything from governments to corporations to sports organizations" (Toronto Star 2015). This kind of spillover dynamic may be especially salient in authoritarian regimes in which private firms are more reliant on the government for various resources. Anecdotal evidence suggests that the Chinese government often influences firm behavior by imposing regulations on state-run organizations, knowing that most private firms will interpret this as a normative shift and follow suit.

Explaining the Persistence of Racial Inequality

The establishment of EEO regulations in the 1960s was supposed to reduce racial gaps in the workplace, but, after some initial success, the progress slowed down. In particular, Black Americans have not gained significant inroads into managerial positions since the late 1990s, which is puzzling because, over the last few decades, normative support for racial equality and EEO practices has grown significantly. While several factors—including persistent racial segregation and continued disparity in education—could be responsible (Stainback, Tomaskovic-Devey, and Skaggs 2010), I argue that counternormative events played a part as well. For instance, Ronald Reagan's election to the presidency and his stance on racial issues could have sent a negative signal about the importance of EEO practices. These events do not appear to have altered the growing normative support for racial equality (Dobbin, Schrage, and Kalev 2015; Dobbin, Kim, and Kalev 2011; Kalev, Dobbin, and Kelly 2006), but they offered important legitimacy to voices opposing EEO practices and provided a normative license for firms to dial back their EEO commitment. This interpretation complements the current "decoupling" explanation, which states that firms adopt purely symbolic EEO practices in order to alleviate normative pressure without having to implement real change. It is possible that affirmative action bans and other counternormative events have encouraged firms to decouple their EEO practices.

Counternormative Events

My findings demonstrate how norms shape organizational behaviors. If people's private beliefs run counter to a social norm, they will be particularly attentive to events and signals that provide legitimacy for opposition to that norm. These counternormative events may be important in validating such beliefs and making the individuals feel more normatively licensed to discount or defy the norm. This dynamic may be especially salient for sensitive issues such as EEO practices, which have gained increasing normative acceptance but are also questioned by many. Counternormative events help explain why growing normative pressures do not always translate into substantive changes in organizational behavior.

It is important to differentiate counternormative events from two related concepts. First, these events do not involve or imply deinstitutionalization. In this case, affirmative action bans may have temporarily pushed back the growing normative support for racial equality in some states, but have not so far reversed it. Counternormative events, even when widely publicized, may not garner much support from the mainstream media and the general public. Second, the concept of counternormative events may seem similar to the idea of plural institutional logics: organizations sometimes face competing normative pressures (Greenwood et al. 2011). When different normative demands are imposed on organizations, they need to devise strategies to address the competing expectations. But counternormative events do not impose pressure on organizations; it is difficult to imagine any private-sector firm leaders feeling pressure to ban affirmative action. Instead, counternormative events offer a normative license for organizational actors to engage in and feel justified about a certain behavior. Unlike normative pressure, a normative license gives organizations more agency and could lead to substantial heterogeneity in how firms respond to it.

Counternormative events are common. For instance, although the more politically liberal regions of the United States have seen a steady increase in the acceptance of immigrants, events such as Donald Trump's election could lend normative legitimacy to anti-immigrant behaviors. In fact, after Trump became President, there was a sudden increase in anti-immigrant activities even in the more liberal regions (Flores 2018). This concept of counternormative events shows how critical moments could have long-lasting impact on institutions and organizations. Recent work in organizational theory has begun to pay closer to attention to the role of major events in transforming organizational structures. For example, Tilcsik and Marquis (2013) show that mega-events and natural disasters interact with local communities to affect firm's philanthropic spending. Events like mergers and acquisitions could shape a firm's future approaches toward racial and gender inequality (Zhang 2021). This study contributes to that line of work by underscoring how local events and leader ideology interact to selectively influence firm behavior.

Understanding the Consequences of Affirmative Action Bans

This study also deepens our understanding of how affirmative action bans influence racial inequality. Since California introduced its ban in 1996, affirmative action bans have received much public scrutiny. A natural question is whether or not they exacerbate racial inequality. Since these bans target the public sector—notably, public universities—past scholarship has mostly focused on racial gaps in education. But extensive research has found no clear evidence that the bans lead to greater racial disparity in education (Antonovics and Backes 2013; Brown and Hirschman 2006; Chan and Eyster 2003; Hinrichs 2014; Howell 2010). Thus, for scholars concerned about labor market inequality, these bans may appear to have limited impact. Education gaps would logically contribute to workplace gaps, but since there is no strong evidence for a widened education gap, there has been little reason to believe that the bans would influence workplace racial inequality. My study suggests that affirmative action bans may nevertheless contribute to racial gaps in the workplace—not through changes in university enrollment, but by influencing executives' approach to EEO practices. This finding illustrates a different—perhaps unintended—consequence of affirmative action bans.

Limitations

Some limitations of this study provide opportunities for future research. Empirically, the biggest limitation is potential endogeneity. Firms headquartered in states that adopted affirmative action bans could be systematically different from those headquartered in non-adopting states. Matching and a placebo test help alleviate this concern but cannot entirely eliminate it. Similarly, a firm's choice of CEO is not random, so firms with conservative CEOs may systematically differ from those with liberal CEOs. While I tried to control for many possible confounders, any causal interpretation should be treated with caution.

Another empirical limitation is that I do not observe micro-mechanisms underlying a regulatory spillover. For example, I do not directly measure how CEOs feel about EEO practices or how they interpret affirmative action bans. Instead, I make inferences based on macro-level patterns. Future work could use experimental approaches to better identify mechanisms whereby regulatory events influence decision makers beyond their jurisdiction.

In terms of context, this study focuses on how affirmative action bans normatively shape executives' decision making. Although executives play a key role in both setting and executing EEO practices, other members of the organization, including diversity officers, lawyers, and middle managers, could also shape racial dynamics in the workplace. Unfortunately, understanding the impact of the bans on non-executives is empirically difficult, since comparing organizations in different states could lead to numerous endogeneity issues (see Table 2). Thus, the empirical question of how counternormative events influence others in the organization remains unclear.

CONCLUSION

Laws and regulations have far-reaching consequences. Their power rests as much in setting normative guidelines as in threatening or delivering direct punishment. Consequently, laws and regulations could have an impact well beyond their legal jurisdictions. This study underscores these interesting dynamics: affirmative action bans in the public sector appear to have slowed down racial progress in the private sector. This spillover is perhaps unexpected to both advocates and opponents of these bans, suggesting the unintended consequences of regulations. By demonstrating this process, I suggest a mechanism that explains why racial inequality persists despite increasing normative pressure to reduce it. Certain events, though not powerful enough to shift the norm, could serve as a license for firms to deviate from it.

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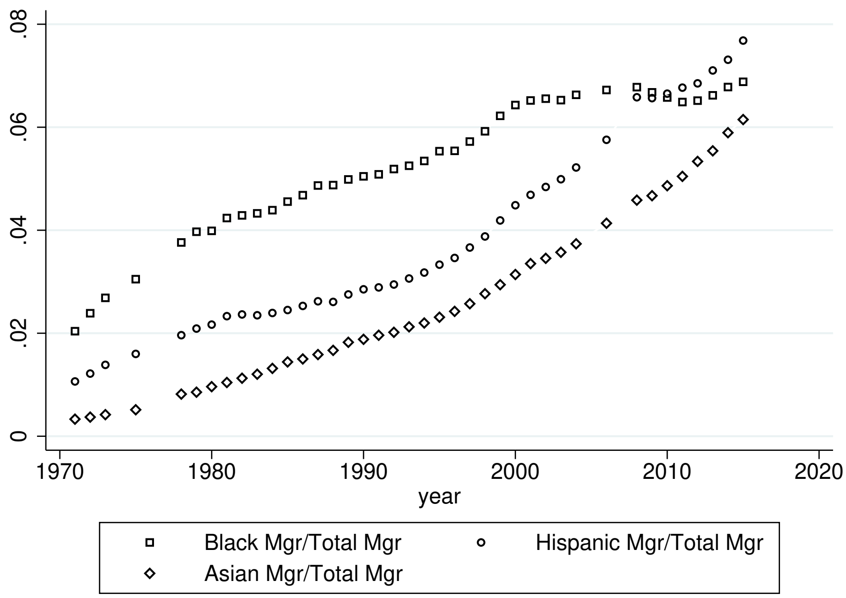
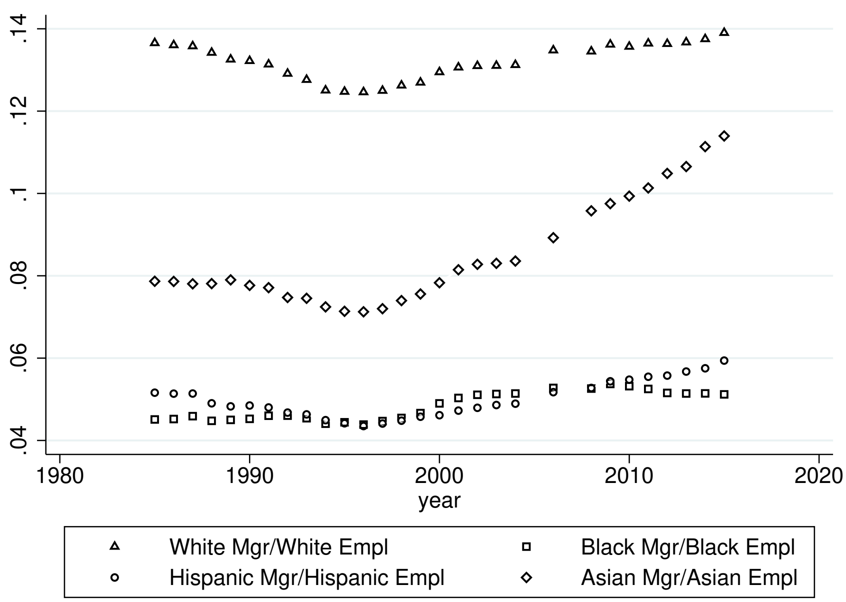
FIGURES AND TABLES



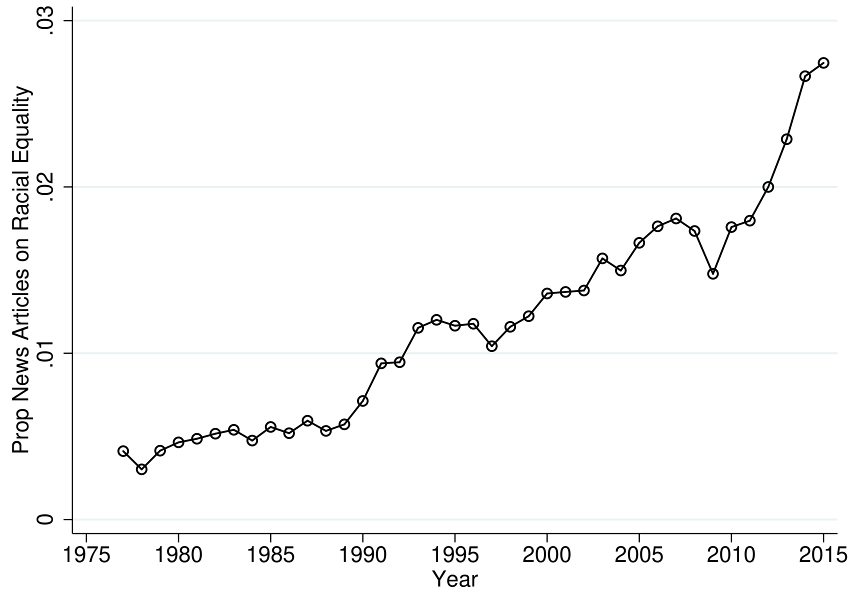
(a) Prop of Racial Minority Managers



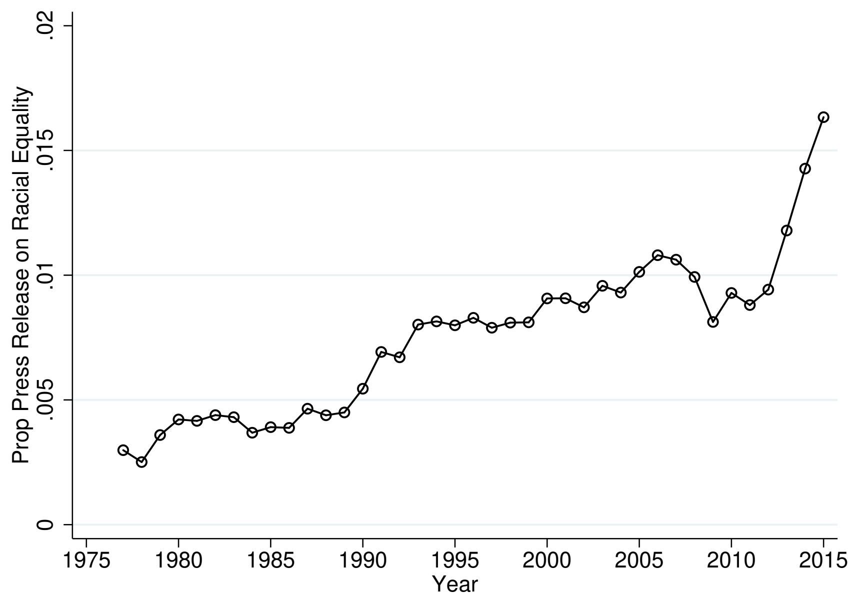
(b) Prop of Managers within Each Group

Figure 1: Trend in Racial Inequality in Private-Sector Firms

Notes: The figures show the descriptive trend managerial representation. Figure a shows the proportion of racial minorities in management (which is the dependent variable in my models). Figure b shows the proportion of employees who are managers in each racial group. Data come from the EEO-1 database, covering all private-sector US firms with more than 100 employees.



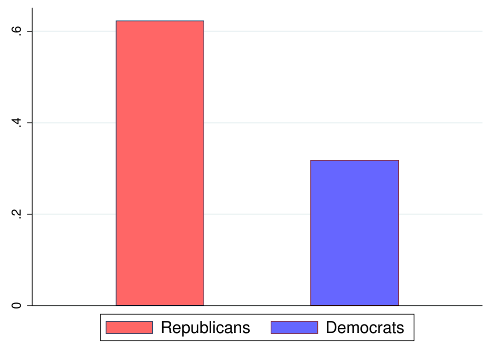
(a) News Articles



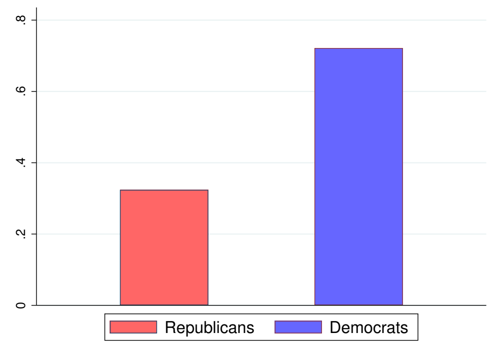
(b) Press Releases

Figure 2: Growing Normative Acceptance of Racial Equality

Notes: These graphs use media data from Factiva to show the growing normative support for racial equality in the United States. Figure (a) shows the proportion of all firm-related news articles that advocate for racial equality / diversity. Figure (b) shows the proportion of all firm press release that mentions race and diversity issues.



Do you strongly oppose giving preference to Black Americans in hiring and promotion?



Are we spending too little in improving the conditions of Black Americans?

Figure 3: Attitudinal Differences between Republicans and Democrats

Notes: These charts use data from General Social Surveys 2016 and 2018. The first question asks "are you for or against preferential hiring and promotion of blacks?". The chart shows the proportion of respondents who answered "strongly oppose." The second question asks "are we spending too much, too little, or about the right amount on improving the conditions of blacks?". The chart shows the proportion of respondents who answered "too little." The proportions are highly similar even I restrict the sample to just managers.

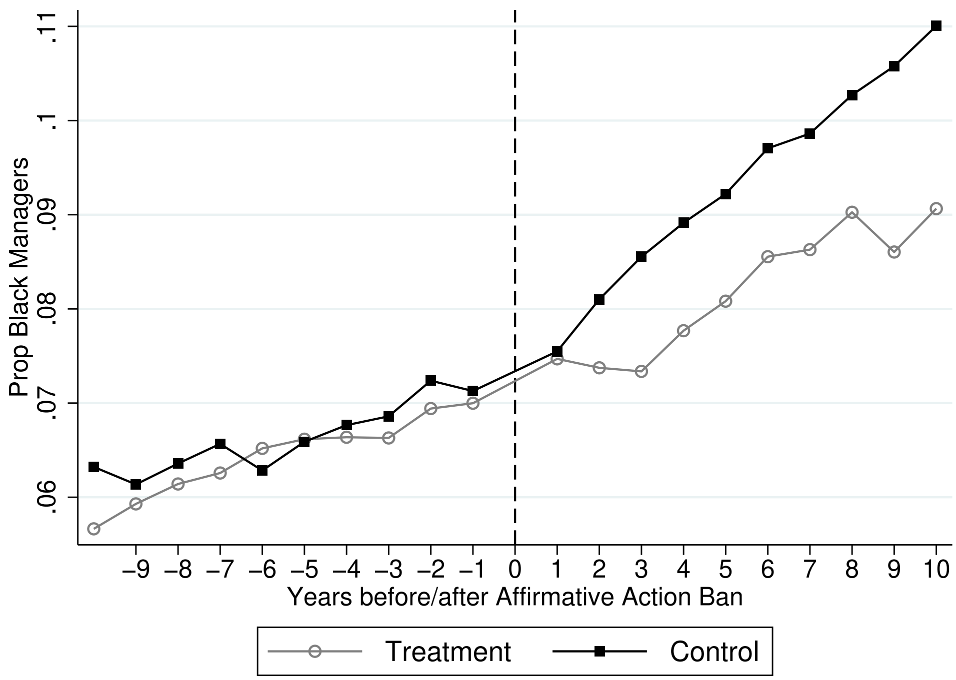
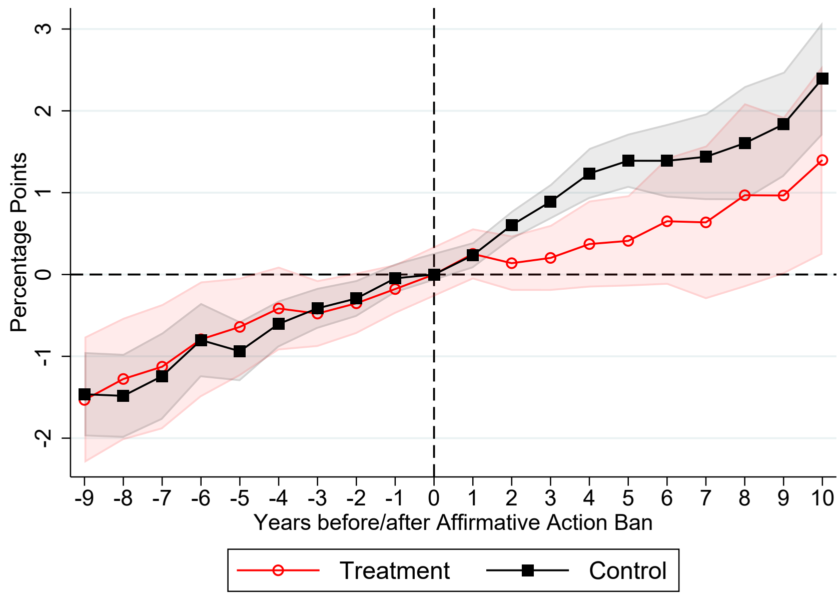
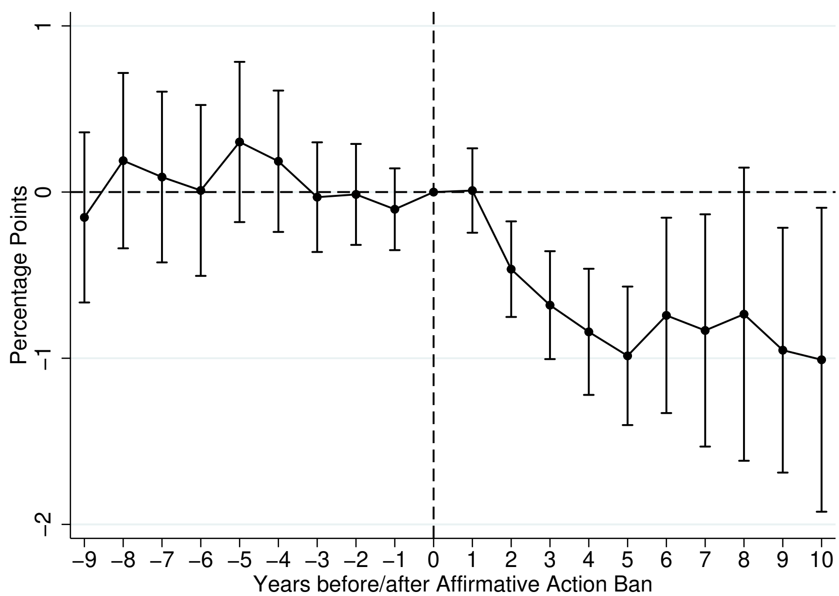


Figure 4: Descriptive Trend: Prop of Black Managers

Notes: This graph descriptively shows the proportion of Black managers, before and after the firm's HQ state implemented an affirmative action ban. Treatment establishments include those headquartered in a banned state and control establishments are headquartered in a state that never received a ban. I used establishment-level data from EEO-1 from 1985 to 2015.



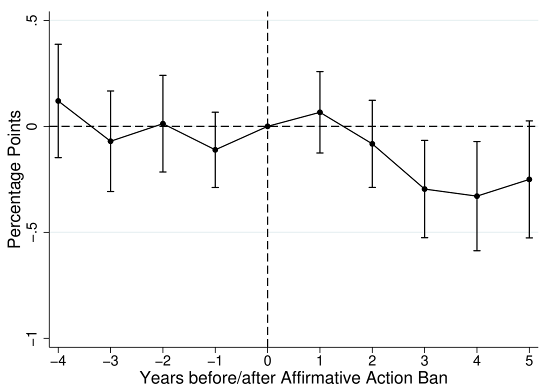
(a) Plotting Treatment and Control Separately



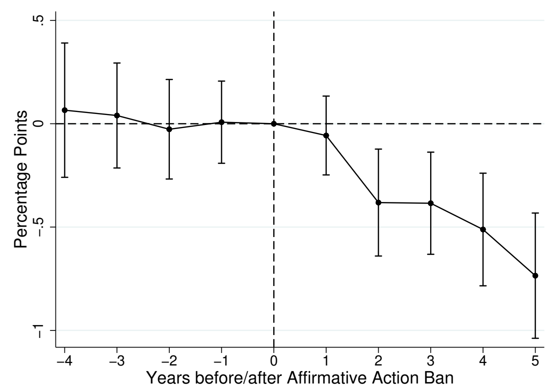
(b) Plotting Difference between Treatment and Control

Figure 5: Estimated Changes After Affirmative Action Bans: Prop of Black Managers

Notes: These graphs show estimated level of change in the proportion of Black managers, relative to the control group, before and after the firm's HQ state implemented an affirmative action ban. Figure a does not include year fixed effects and plots the treatment and control establishments separately. Figure b includes year fixed effects and plots the estimated difference between the treatment and control establishments. I used establishment-level data from EEO-1 from 1985 to 2015. Model specifications are based on those in Table 5.



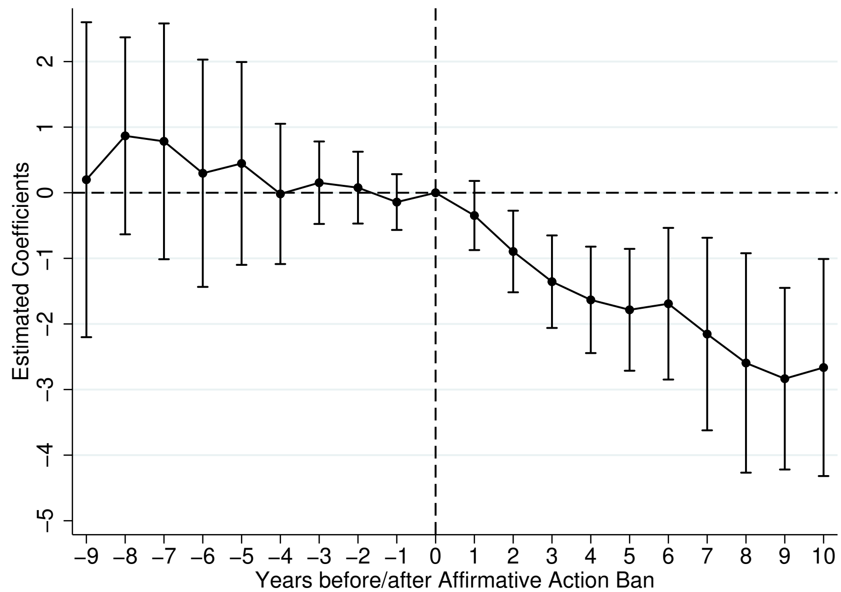
(a) Pct Black Men Managers



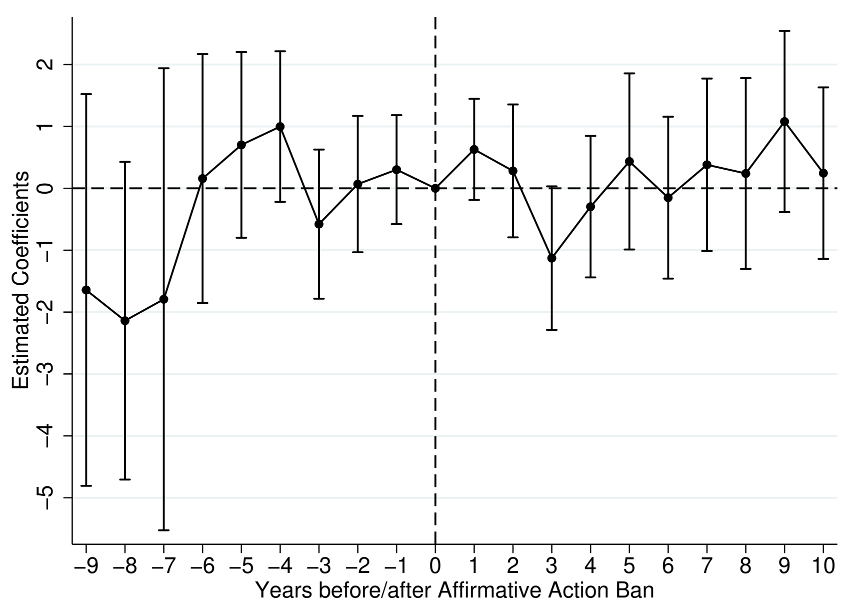
(b) Pct Black Women Managers

Figure 6: Estimated Changes After Affirmative Action Bans: Sorted by Gender

Notes: These graphs show estimated level of change in the proportion of Black managers, relative to the control group, before and after the firm's HQ state implemented an affirmative action ban. I used establishment-level data from EEO-1 from 1985 to 2015. Model specifications are based on those in Table 5.



(a) Firms with Conservative CEOs



(b) Firms with Liberal CEOs

Figure 7: Estimated Changes After Affirmative Action Bans: Sorted by CEO Ideology

Notes: These graphs show estimated level of change in the proportion of Black managers, relative to the control group, before and after the firm's HQ state implemented an affirmative action ban. I split the sample based on CEO's political ideology and excluded those firms that had switched from a politically liberal to a politically conservative CEO or vice versa during this period. Model specifications are based on those in Table 6.

Table 1: Time Table for Statewide Affirmative Action Bans

State Name	**Year of Ban**	**Notes**
California	Nov 5, 1996	Enacted by public vote through Proposition 209
Texas	Mar 18, 1996	Passed through lower court order, but the ban was revoked in June 23, 2003 by the U.S Supreme Court through case, Grutter v. Bollinger, 539 U.S. 306
Washington	Nov 3, 1998	Enacted by public vote through Initiative 200, a Washington State statute
Florida	Nov 9, 1999	Issue by governor, Jeb Bush through an executive order
Michigan	Nov 7, 2006	Enacted by public vote through the Michigan Civil Right Initiative
Nebraska	Nov 4, 2008	Enacted by public vote through the Nebraska Civil Rights Initiatives (Initiative 424)
Arizona	Nov 2, 2010	Enacted by public vote through Proposition 107
New Hampshire	Jun 30, 2011	Passed through House Bill 0623 by the State Legislature
Oklahoma	Nov 6, 2012	Passed through a legislatively referred constitutional amendment (State Question 758)

Table 2: Linear Estimation without Matching (Preliminary Models): Predicting Managerial Composition

	Pct Black				Pct White		Pct Hispanic		Pct Asian	
	(1) All	(2) Men	(3) Women	(4) All	(5) All	(6) All	(7) All	(8) All	(9) All	(10) All
Establishment in Banned States	-0.300***	-0.103*	-0.197***	-0.226**	-0.435***	0.229*	0.465***	0.0854	0.270***	-0.0889*
	(0.0751)	(0.0410)	(0.0557)	(0.0863)	(0.113)	(0.111)	(0.0682)	(0.0732)	(0.0481)	(0.0358)
Pct Managers	4.599***	0.923**	3.676***	5.150***	-10.66***	-10.32***	2.813***	2.459***	3.250***	2.713***
	(0.786)	(0.348)	(0.615)	(0.863)	(0.969)	(0.988)	(0.348)	(0.306)	(0.357)	(0.281)
Pct Professional Workers	0.1000	-0.530	0.630	0.313	-0.624	-0.873	0.139	0.165	0.385	0.395*
	(0.608)	(0.284)	(0.408)	(0.664)	(0.750)	(0.810)	(0.268)	(0.249)	(0.215)	(0.181)
Pct Backoffice Workers	0.723	-0.423	1.146**	0.917	-1.242	-1.211	0.255	0.135	0.263	0.160
	(0.641)	(0.291)	(0.418)	(0.704)	(0.788)	(0.854)	(0.260)	(0.236)	(0.211)	(0.168)
Pct Blue Collars	0.235	0.267	-0.0321	0.332	0.0369	0.0421	-0.377	-0.423	0.106	0.0484
	(0.683)	(0.270)	(0.480)	(0.741)	(0.858)	(0.917)	(0.307)	(0.275)	(0.158)	(0.137)
Total Num Workers (log)	0.410***	0.145***	0.265***	0.446***	-0.851***	-0.835***	0.288***	0.256***	0.153***	0.132***
	(0.0558)	(0.0339)	(0.0354)	(0.0602)	(0.0657)	(0.0703)	(0.0300)	(0.0297)	(0.0318)	(0.0305)
Total Num Establishments (log)	0.0472*	0.0196	0.0276	0.0528*	-0.0908**	-0.0888**	0.0312*	0.0226	0.0124	0.0133
	(0.0232)	(0.0122)	(0.0224)	(0.0256)	(0.0337)	(0.0337)	(0.0150)	(0.0130)	(0.0146)	(0.0129)
Federal Contractor	0.0260	0.0179	0.00816	0.0208	-0.0774	-0.0524	-0.00825	-0.0154	0.0596*	0.0469
	(0.0898)	(0.0393)	(0.0587)	(0.0995)	(0.103)	(0.110)	(0.0397)	(0.0342)	(0.0294)	(0.0308)
State Governor: Democratic Party	-0.107***	-0.0667***	-0.0402*	-0.114**	-0.0333	0.121**	0.0664**	-0.0373*	0.0738***	0.0298
	(0.0311)	(0.0189)	(0.0200)	(0.0355)	(0.0469)	(0.0464)	(0.0208)	(0.0149)	(0.0169)	(0.0161)
State Legislature: Democratic Party	-0.548***	-0.260***	-0.288***	-0.537***	0.208	0.261*	0.0248	-0.00485	0.315***	0.281***
	(0.110)	(0.0425)	(0.0798)	(0.110)	(0.125)	(0.127)	(0.0340)	(0.0352)	(0.0265)	(0.0263)
Observations	3673094	3673094	3673094	3318233	3673094	3318233	3673094	3318233	3673094	3318233
R^2	0.742	0.646	0.711	0.747	0.783	0.776	0.758	0.752	0.749	0.720
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estab. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workers' Demo.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded California				Yes		Yes		Yes		Yes

Notes: The table shows post-ban changes in managerial composition at the establishment level without matching. Dependent variables are the proportion of managers of a particular demographic group among all managers in an establishment. For example, *Pct Black: All* is the number of Black managers over the number of managers in an establishment. *Pct Black: Women* is the number of women Black managers over the number of managers in an establishment. *Establishment in Banned States* is the key independent variable: it is 1 if an establishment is in one of the nine banned states and the state has already implemented the ban. Workers' demographics include the proportion of Black, White, Asian, Hispanic, and women employees. Local demographics include the proportion of Black, White, Asian, Hispanic, and women residents in the county. Data come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Summary Statistics on Key Variables

	Matched Sample		**Nonmatched Sample**
	Treatment	**Control**	
Firm Age	19.663	19.294	17.639
Num Employees in Est. (log)	4.637	4.497	3.896
Prop Black Managers	0.070	0.071	0.063
Prof Black Professionals	0.071	0.079	0.060
Prof Black Employees	0.131	0.137	0.120
Prop White Managers	0.845	0.836	0.853
Prof White Professionals	0.796	0.778	0.828
Prof White Employees	0.698	0.690	0.728
Prop Managers	0.142	0.141	0.133
Prop Professionals	0.220	0.216	0.114

Notes: The table shows summary statistics for the key variables. The matched sample shows summary statistics for control and treatment establishments one year prior to the bans. Treatment establishments are those headquartered in a banned state and control establishments are those headquartered elsewhere. Data come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Descriptive Summary Before/After Affirmative Action Bans

	Prop Black Managers		
	Treatment	**Control**	**Δ (Treatment - Control)**
Pre-Ban	6.57	6.76	-0.19
Post-Ban	8.00	9.01	-1.01
	Prop White Managers		
	Treatment	**Control**	**Δ (Treatment - Control)**
Pre-Ban	85.74	85.34	0.40
Post-Ban	81.60	80.35	1.25
	Prop Hispanic Managers		
	Treatment	**Control**	**Δ (Treatment - Control)**
Pre-Ban	4.99	5.09	-0.10
Post-Ban	6.94	7.11	-0.17
	Prop Asian Managers		
	Treatment	**Control**	**Δ (Treatment - Control)**
Pre-Ban	2.70	2.81	-0.11
Post-Ban	3.46	3.53	-0.07

Table 5: Linear Estimation with Matching (Main Models): Predicting Managerial Composition

	Pct Black			Pct White			Pct Asian	Pct Hispanic
	(1) All	(2) Men	(3) Women	(4) All	(5) Men	(6) Women	(7) All	(8) All
HQ in Banned States x Post Ban Period	-0.626*	-0.148	-0.478*	0.712*	1.082	-0.370	0.0294	-0.115
	(0.254)	(0.122)	(0.196)	(0.346)	(0.577)	(0.400)	(0.116)	(0.182)
Pct Managers	3.712	0.948	2.764*	-10.99***	-18.30***	7.312**	2.782***	4.500***
	(1.954)	(1.253)	(1.092)	(2.204)	(2.100)	(2.225)	(0.571)	(0.834)
Pct Professional Workers	0.517	-0.222	0.739	-0.502	2.301	-2.803	-0.648	0.633
	(1.824)	(1.170)	(0.971)	(2.019)	(1.631)	(1.848)	(0.419)	(0.657)
Pct Backoffice Workers	0.818	-0.111	0.928	-1.749	0.390	-2.139	-0.319	1.251*
	(1.936)	(1.228)	(0.986)	(2.109)	(1.516)	(1.890)	(0.360)	(0.597)
Pct Blue Collars	-0.450	-0.000200	-0.450	1.477	4.141*	-2.663	-0.568	-0.459
	(1.830)	(1.097)	(1.098)	(2.062)	(2.016)	(1.820)	(0.400)	(0.664)
Total Num Workers (log)	0.234*	0.124	0.110	-0.649***	-1.352***	0.702***	0.146*	0.270***
	(0.103)	(0.0708)	(0.0704)	(0.142)	(0.196)	(0.178)	(0.0601)	(0.0811)
Total Num Establishments (log)	0.0427	0.000812	0.0419	-0.00820	-0.487***	0.478***	-0.0248	-0.00972
	(0.0469)	(0.0322)	(0.0346)	(0.0746)	(0.142)	(0.118)	(0.0300)	(0.0436)
Federal Contractor	0.0451	0.0661	-0.0209	-0.109	-0.0817	-0.0269	0.0315	0.0320
	(0.143)	(0.0891)	(0.108)	(0.234)	(0.276)	(0.214)	(0.0729)	(0.100)
HQ State Governor: Democratic Party	0.0594	0.0231	0.0363	-0.0302	0.246	-0.276	-0.0225	-0.00667
	(0.137)	(0.0667)	(0.102)	(0.168)	(0.311)	(0.233)	(0.0560)	(0.0871)
HQ State Legislature: Democratic Party	-0.235	-0.0520	-0.183	0.0544	-0.0347	0.0890	0.190**	-0.00874
	(0.191)	(0.0745)	(0.168)	(0.253)	(0.402)	(0.271)	(0.0689)	(0.115)
Post Ban Period	0.515**	0.0572	0.458**	-0.538*	-0.696	0.158	-0.0954	0.118
	(0.177)	(0.105)	(0.148)	(0.231)	(0.366)	(0.258)	(0.0787)	(0.138)
Observations	282359	282359	282359	282359	282359	282359	282359	282359
R^2	0.716	0.613	0.662	0.747	0.774	0.748	0.698	0.736
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estab. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workers' Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows post-ban changes in managerial composition at the establishment level after matching. Dependent variables are the proportion of managers of a particular demographic group among all managers in an establishment. *HQ in Banned States x Post Ban Period* is the key independent variable: *HQ in Banned States* is 1 if an establishment's headquarter is in one of the nine banned states and *Post Ban Period* is 1 after the ban is announced. Coefficients for *Post Ban Period* should be interpreted with caution because year fixed effects affect its magnitude. Descriptive graphs without year fixed effects in Figure 5a are more informative in displaying the broader trend. Workers' demographics include the proportion of Black, White, Asian, Hispanic, and women employees. Local demographics include the proportion of Black, White, Asian, Hispanic, and women residents in the county. Data come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Conservative versus Liberal CEOs: Predicting Proportion of Black Managers

	Full Sample		Conservative CEOs		Liberal CEOs		Non-Donating CEOs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HQ in Banned States	-0.936*	-0.994*	-0.975**	-1.379**	-0.367	-0.428	0.391	0.501
x Post Ban Period	(0.400)	(0.414)	(0.339)	(0.434)	(0.500)	(0.504)	(0.423)	(0.464)
HQ in Banned States	1.948**	2.083**						
x Post Ban Period x Liberal CEO	(0.719)	(0.742)						
Observations	124356	124356	70096	70096	11887	11887	42373	42373
R^2	0.763	0.763	0.766	0.759	0.807	0.803	0.807	0.800
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workers' Demographics	Yes		Yes		Yes		Yes	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows post-ban changes in Black managers at the establishment level sorted by firm CEO characteristics. Dependent variable is the proportion of Black managers: the number of Black managers over the number of managers in an establishment. CEOs' political ideology is calculated based on their donation record. Control variables include: *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Federal Contractor*, *Return on Asset*, *Tobin's Q (log)*, *CEO Age*, *Women CEO*, *Racial Minority CEO*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, *Post Ban Period*, *Post Ban Period x Liberal CEO*, and *HQ in Banned States x Liberal CEO*. Demographic data come from the EEO-1 database, covering all US firms with more than 100 employees. CEO information comes from the Compustat ExecuComp database and self-coding, covering S&P 1500 firms. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Federal Contractors versus Non-Contractors: Predicting Proportion of Black Managers

	Non-Contractors		Federal Contractors	
	(1)	(2)	(3)	(4)
HQ in Banned States	-0.980**	-1.032*	-0.184	-0.151
x Post Ban Period	(0.367)	(0.424)	(0.211)	(0.246)
Observations	151944	151944	127398	127398
R^2	0.705	0.699	0.733	0.726
Year Fixed Effects	Yes	Yes	Yes	Yes
Establishment Fixed Effects	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes
Workers' Demographics	Yes		Yes	
Control Variables	Yes	Yes	Yes	Yes

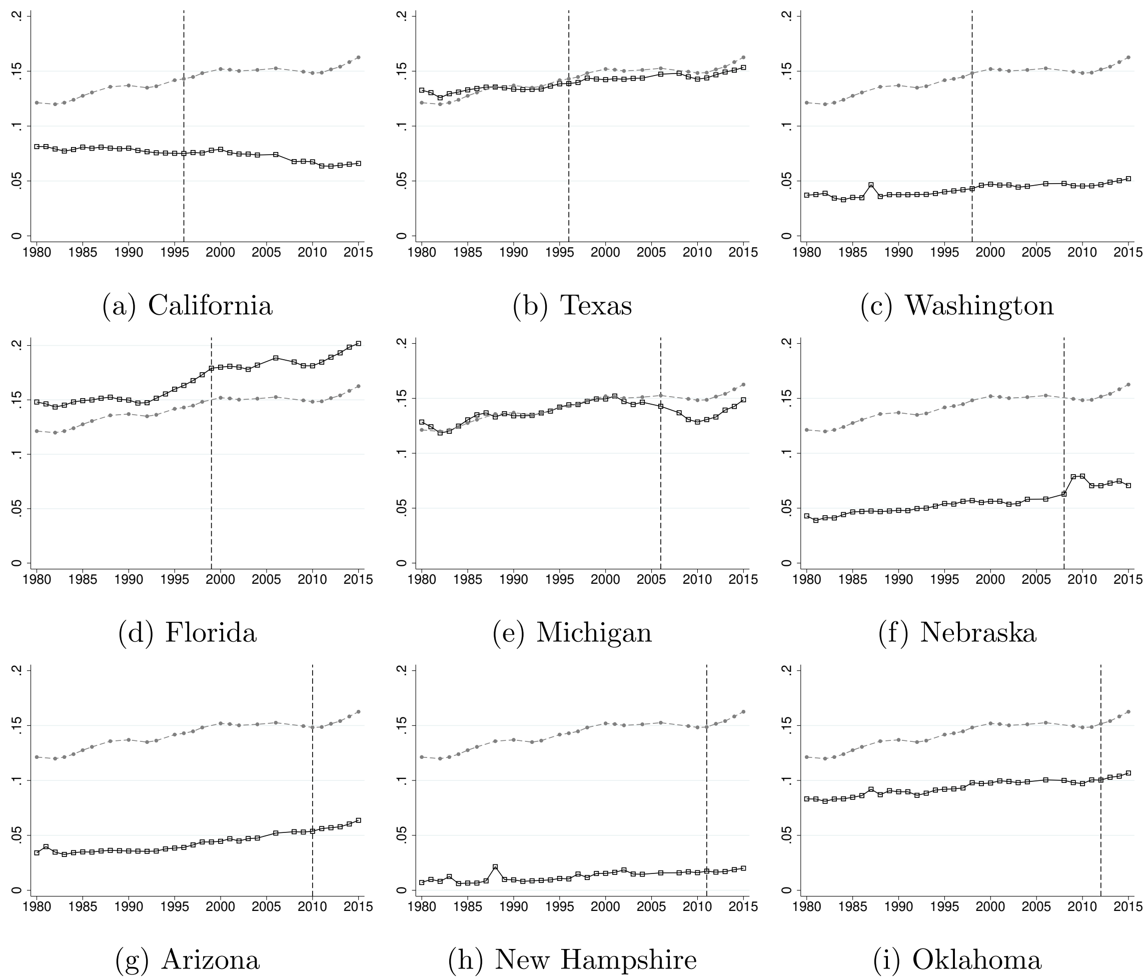
Notes: The table shows post-ban changes in Black managers at the establishment level sorted by federal contractor status. Dependent variable is the proportion of Black managers: the number of Black managers over the number of managers in an establishment. Controls include: *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Return on Asset*, *Tobin's Q (log)*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, and *Post Ban Period*. Demographic data and federal contractor information come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Breaking Down the Post-Ban Change in Racial Inequality by State

State	**Effect Size**	**Event Year**	**Num Estab.**	**Num Firms**
California	0.14	1996	2,983	1,158
	(0.27)			
Texas	-0.72	1996	2,531	820
	(0.30)			
Washington	-0.02	1998	530	171
	(.38)			
Florida	0.14	1999	1,674	425
	(0.64)			
Michigan	-0.81	2006	3,545	603
	(0.54)			
Nebraska	-1.16	2008	707	173
	(0.80)			
Arizona	-0.56	2010	1,523	460
	(0.45)			
New Hampshire & Oklahoma	-0.44	2011 & 2012	782	317
	(0.49)			
Colorado, Missouri, & Utah	0.15	2008 & 2010	4,379	1,124
(placebo test)	(0.19)			

Notes: The table shows post-ban changes in Black managers at the establishment level sorted by state. Dependent variable is the proportion of Black managers: the number of Black managers over the number of managers in an establishment. I used the same matching procedure and model specification as in Table 5, except examining each state ban one at a time. The effect size refers to the coefficient for *HQ in Banned States x Post Ban Period* in the models. Data come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses.

APPENDICES



(a) California (b) Texas (c) Washington

(d) Florida (e) Michigan (f) Nebraska

(g) Arizona (h) New Hampshire (i) Oklahoma

Figure A.1: Proportion of Black Employees in Banned States

Notes: These graphs show the proportion of Black employees in each of the banned states (and compared to that in the non-banned states). The gray dash line represents the average proportion of Black employees across all non-banned states, and the darker solid line is the average proportion of Black employees in the banned state. The dashed vertical line indicates the year when the affirmative action ban took place in that state. Data come from the EEO-1 database, covering all private-sector US firms with more than 100 employees.

Table A.1: Linear Estimation on Firm-Wide Co-Movement: Predicting Prop of Black Managers

	(1)	(2)	(3)	(4)
Prop Black Managers	14.39***	12.76***	11.75***	9.127***
in Other Establishments	(1.693)	(1.410)	(1.297)	(1.051)
Observations	3171637	3171637	3022273	2781116
R^2	0.733	0.737	0.724	0.732
Year Fixed Effects	Yes	Yes		
Estab. Fixed Effects	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes
Workers' Demographics	Yes	Yes	Yes	Yes
County-Year Fixed Effects			Yes	Yes
SIC3-Year Fixed Effects				Yes

Notes: The table examines co-movement in racial inequality across establishments within the same firm. It uses OLS models to predict the proportion of Black managers in an establishment. *Prop Black Managers in Other Establishments* is the proportion of black managers in other establishments within the same firm. For example, Model 1 shows that when other establishments' prop of Black managers increase by 1 percentage point, the focal establishment's proportion of Black managers increases by 0.14 percentage points. Control variables include *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Federal Contractor*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*. Data come from the EEO-1 database. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Limiting to Establishments in States that Never Adopted a Ban: Predicting Proportion of Black Managers

	Conservative CEOs		Liberal CEOs	
	(1)	(2)	(3)	(4)
HQ in Banned States	-1.161*	-2.000**	0.395	0.388
x Post Ban Period	(0.512)	(0.736)	(0.889)	(0.909)
Observations	26799	26799	9048	9048
R^2	0.808	0.799	0.772	0.768
Year Fixed Effects	Yes	Yes	Yes	Yes
Establishment Fixed Effects	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes
Workers' Demographics	Yes		Yes	

Notes: The table shows post-ban changes in states that never adopted an affirmative action ban. Dependent variable is the proportion of Black managers: the number of Black managers over the number of managers in an establishment. Controls include: *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Return on Asset*, *Tobin's Q (log)*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, and *Post Ban Period*. Demographic data and federal contractor information come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Linear Estimation with Matching: Predicting Non-managerial Workforce Composition

	Pct Black		Pct White		Pct Asian		Pct Hispanic	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women	(7) Men	(8) Women
HQ in Banned States	-0.137	0.154	-0.0911	0.296	-0.0223	0.0218	-0.0397	-0.105
x Post Ban Period	(0.193)	(0.310)	(0.246)	(0.505)	(0.0949)	(0.0928)	(0.0512)	(0.0554)
Observations	294922	294922	294922	294922	294922	294922	294922	294922
R^2	0.877	0.906	0.911	0.905	0.926	0.894	0.841	0.831
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estab. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workers' Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows post-ban changes in nonmanagerial employee composition at the establishment level. Dependent variables are the proportion of nonmanagerial employees of a particular demographic group among all nonmanagerial employees in an establishment. Local demographics include the proportions of Black, White, Asian, Hispanic, and women residents in the county. Controls include: *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Return on Asset*, *Tobin's Q (log)*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, and *Post Ban Period*. Data come from the EEO-1 database, covering all US firms with more than 100 employees. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Predicting Proportion of Black Managers: Interacting with Various CEO Traits

	Pct Black
HQ in Banned States x Post Ban Period x Liberal CEO	1.948**
	(0.719)
HQ in Banned States x Post Ban Period x CEO Age	0.00599
	(0.0330)
HQ in Banned States x Post Ban Period x Women CEO	0.966
	(1.412)
HQ in Banned States x Post Ban Period x Black CEO	-2.496
	(2.752)
HQ in Banned States x Post Ban Period x Other Minority CEO	0.00535
	(0.699)
Observations	124356

Notes: The table shows how various CEO traits moderate the post-ban changes in the proportion of Black managers at the establishment level. The dependent variable is the proportion of Black managers: the number of Black managers over the number of managers in an establishment. I used the same model specification as in Model 1, Table 6. I ran each three-way interaction term separately (*HQ in Banned States x Post Ban Period x CEO Trait*), using the model specification in Table 6's Model 1. Data come from the EEO-1 database and the Compustat ExecuComp database, covering S&P 1500 firms. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.5: CEO Characteristics and Firm Inequality: Predicting Managerial Composition

	Pct Black		Pct Hispanic		Pct Asian		Pct Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Liberal CEO	0.235*	0.209*	0.0985	0.0231	0.309	0.0283	0.149	0.209
	(0.101)	(0.0899)	(0.123)	(0.110)	(0.220)	(0.144)	(0.286)	(0.268)
Women CEO	-0.104	-0.149	0.0506	-0.0374	0.540	0.206	0.216	0.119
	(0.149)	(0.148)	(0.228)	(0.195)	(0.716)	(0.340)	(0.523)	(0.505)
Black CEO	0.514	0.286	-0.132	-0.114	-0.370	-0.0997	0.224	0.0140
	(0.488)	(0.451)	(0.397)	(0.350)	(0.612)	(0.464)	(0.898)	(0.831)
Asian CEO	0.114	0.125	-0.342	-0.233	2.998**	1.658**	-0.504	-0.0643
	(0.155)	(0.132)	(0.180)	(0.167)	(1.155)	(0.574)	(0.581)	(0.567)
Hispanic CEO	0.156	-0.0231	-0.0198	-0.0391	-0.107	-0.351	0.241	0.0341
	(0.225)	(0.235)	(0.271)	(0.277)	(0.391)	(0.393)	(0.761)	(0.735)
CEO Age	0.000924	0.00116	-0.00648	-0.00716	0.00560	0.0131**	-0.00762	-0.00898
	(0.00381)	(0.00335)	(0.00427)	(0.00390)	(0.00563)	(0.00443)	(0.0102)	(0.00967)
Observations	25886	25706	25886	25706	25886	25706	25886	25706
R^2	0.894	0.907	0.885	0.900	0.942	0.959	0.951	0.953
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Workers' Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows how various CEO traits are associated with managerial composition at the firm level. Dependent variables are the proportion of managerial employees of a particular demographic group among all managerial employees in a firm. Control variables include: *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Return on Asset*, *Tobin's Q (log)*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, and *Post Ban Period*. Data come from the EEO-1 database and the Compustat ExecuComp database, covering S&P 1500 firms. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6: Affirmative Action Bans and EEO Enforcement: Predicting the Likelihood of Major EEO Lawsuits

	Race-Related Lawsuit		Gender-Related Lawsuit	
	(1)	(2)	(3)	(4)
HQ in Banned States	-0.00138	0.00427	-0.000407	0.000186
x Post Ban Period	(0.00156)	(0.00380)	(0.00135)	(0.00285)
Liberal CEO	-0.000770	-0.00274	0.000684	0.00564*
	(0.00203)	(0.00378)	(0.00152)	(0.00287)
Women CEO	0.00130	0.00317	-0.000136	0.00307
	(0.00387)	(0.00518)	(0.00245)	(0.00413)
Black CEO	-0.0123***	-0.0218	-0.00643**	-0.00873
	(0.00353)	(0.0119)	(0.00197)	(0.00846)
Asian CEO	0.00256	0.000849	0.00152	0.00362
	(0.00224)	(0.00316)	(0.00185)	(0.00271)
Hispanic CEO	-0.00366	-0.00637	-0.00137	-0.000629
	(0.00218)	(0.00356)	(0.00196)	(0.00433)
CEO Age	0.0000667	0.000168	0.0000275	0.000105
	(0.0000717)	(0.000119)	(0.0000581)	(0.0000787)
Observations	25889	25707	25889	25707
R^2	0.021	0.161	0.011	0.147
Year Fixed Effects	Yes	Yes	Yes	Yes
Establishment Fixed Effects		Yes		Yes
Local Demographics	Yes	Yes	Yes	Yes
Workers' Demographics		Yes		Yes
Control Variables	Yes	Yes	Yes	Yes

Notes: The table uses OLS models to examine post-ban changes in EEO enforcement. Dependent variables (binary) are whether or not a firm in a given year was involved in a major EEO lawsuit. This information is hand-coded from various newspaper sources and covers most firms in the S&P 1500. Control variables include *Pct Managers*, *Pct Professional Workers*, *Pct Backoffice Workers*, *Pct Blue Collars*, *Total Num Workers (log)*, *Total Num Establishments (log)*, *Return on Asset*, *Tobin's Q (log)*, *HQ State Governor: Democratic Party*, *HQ State Legislature: Democratic Party*, and *Post Ban Period*. Demographic data come from the EEO-1 database and CEO information come from the Compustat ExecuComp database. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.