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# Labor market conditions and charges of discrimination: Is there a link?

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**PRELIMINARY**

**Abstract**

This paper's goal is to determine whether the degree of labor market tightness affects the frequency of discrimination charges. State-level panel data on enforcement and litigation actions from the U.S. Equal Employment Opportunity Commission, along with disaggregated labor market statistics, allow us to assess the effects of labor market conditions on discrimination based on race or ethnicity, and how these effects vary across states and over time. Our findings have implications for how macroeconomic policies might be used to promote equal opportunity in the labor market.

Keywords: Labor market conditions, discrimination, EEOC, macroeconomic policy

JEL classification: J15, J63, J71, E61, Z13

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# Labor market conditions and charges of discrimination: Is there a link?

## 1 Introduction

This paper looks at race-based employment discrimination and how it depends on labor market conditions, specifically the degree of labor market tightness. To measure discrimination, we use state-level panel data on enforcement and litigation actions from the U.S. Equal Employment Opportunity Commission (EEOC).

*Ex ante*, it is reasonable to assume that discrimination would be less prevalent in a tight labor market, simply because firms will not be able to afford to discriminate if they are having to compete for workers. In the context of a search model, for example, the cost to an employer of passing on a qualified minority job candidate, or treating her in such a way that would increase the likelihood of separation, would be an increasing function of the expected time it would take to fill the vacancy, which would be longer when unemployment is low.

Discrimination is not directly observable, however; all we have are data on charges filed with the EEOC. The relationship between reported discrimination and labor market conditions is more complicated. On one hand, in a slack market, an unsuccessful job applicant might be more likely to make a charge if she perceived discrimination was the reason not getting the job—even if she was turned down for some other reason. A current employee may be less likely to file a charge, on the other hand, fearing that the employer could make life unpleasant if she did so—even though retaliation is strictly prohibited.

Our analysis of labor market conditions and charges of discrimination builds on related work analyzing labor market outcomes and the business cycle, labor market discrimination, and labor market anti-discrimination policy.

One related set of studies has looked at the effects of the business cycle on labor market outcomes. Research on this topic has uncovered a large and counter cyclical racial gap in unemployment. For example, Hoynes *et al.* (2012) and Cajner *et al.* (2017) both showed that Blacks and Hispanics are more negatively affected by recessions than other groups. Rodgers (2008) documented a similar pattern during downturns caused by contractionary monetary policy.

Other research has focused on labor market discrimination as an explanation of the racial gap in unemployment. While experimental studies and narrative methods conclude unambiguously that there is extensive racial discrimination in hiring, empirical models have not fully explained the observed differences in unemployment (Neumark, 2018; Darity and Mason, 1998; Lang and Lehman, 2012).

The EEOC dataset employed in our paper has also been used in other research on discrimination. Miller (2017), for example, used it to assess the effects of affirmative action. It has also been used by Oyer & Schaefer (2002) to look at wrongful termination, and by Hersch (2011) in a study of sexual harassment.

In this paper, we examine two dimensions of the relationship between labor market conditions and discrimination, using the data on race-based discrimination charges filed with the EEOC. Section 2 describes the data on charges and the labor market data used in the analysis. In section 3, we use panel data to assess the degree to which reported discrimination within states varies over time, as a function of the unemployment rate. Section 4 uses cross-sectional analysis to look at the variation between states in reported discrimination.

To preview, our panel analysis reveals a strong countercyclical pattern in discrimination, with falling unemployment associated with a decrease in the number of charges filed. Moreover, discrimination charges are disproportionately responsive to the Black/African-American (AA) and Hispanic/Latino-specific unemployment rates. In the cross-sectional analysis, we find that occupational mix and the demographic composition of the labor force explain most of the variation across states in the discrimination charge rate. These findings are consistent with the view that employers's decisions to discriminate are sensitive to the economic costs attendant upon them.

# 2 Data

## 2.1 EEOC charges

Our discrimination data come from the U.S. Equal Employment Opportunity Commission (EEOC), the federal agency charged with enforcing laws against workplace discrimination.[1] The EEOC reports the number of discrimination charges filed for six different categories: race, sex, age, national origin, religion, and color.[2] This paper focuses exclusively on race-based charges. Unfortunately, the race category is not broken down into subgroups (e.g. Black/AA, Hispanic/Latino and Asian), so we will not be able to look at the incidence of discrimination against those in specific groups.

By way of background, a charge of discrimination is a signed statement filed with the EEOC asserting that an employer, union, or labor organization engaged in employment discrimination in the workplace and requests that the EEOC take remedial action.[3] The law requires the EEOC to accept charges alleging employment discrimination and gives it authority to investigate. The EEOC uses the investigation's findings to determine the course of action, which may range from

[1] In general, firms with fewer than 20 employees are exempt.
[2] The data are from the Enforcement and Litigation Statistics, https://www.eeoc.gov/eeoc/statistics/enforcement/.
[3] Only violations of the Equal Pay Act do not require a charge to be filed.

voluntary remediation to a full-blown lawsuit.

In theory, retaliation against employees who file charges is strictly forbidden. Retaliation is common in practice, however. Over the past decade retaliation is the most alleged issue by federal employees and the most common discrimination finding among federal sector cases. In most cases the original discrimination allegation doesn't establish a violation of the law but the subsequent retaliation allegation does.

The EEOC's administrative data are a potentially valuable source of inflation on the incidence of discrimination. An attractive feature is that, because the EEOC is legally obligated to accept all charges filed, the numbers will not be affected by differences, either across states or over time, in the criteria used by the EEOC to decide whether and how to proceed with enforcement actions. It is not a perfect measure of workplace discrimination, however, as it requires a worker to file a charge, which is costly (from lost time and inconvenience, at a minimum; and quite often retaliation). Consequently, it reflects an individual's decision to file an application, which depends on the worker's assessments of the costs and benefits; and these are likely to be related to worker characteristics (Oyer and Schaefer, 2002).

### 2.2 Other data

Our analysis relies on labor market data from two other sources. We use labor force data from the Bureau of Labor Statistics (BLS), broken down by demographic groups and states, to calculate the discrimination charges filed as a share of the relevant demographic group. The BLS is also the source of unemployment rates disaggregated by state and race/ethnicity.[4] The analysis in section 4 makes use of EEOC data on employment by occupation, also broken down by demographic group and state.[5] The EEOC provides figures for ten different occupations; but as discussed below, we will use a coarser two-way distinction between low-wage blue-collar jobs and those with more professional or technical characteristics.[6]

The availability of the EEOC data limits the time period of our analysis to 2009–17. In addition, we drop states with any missing data and those with an average of fewer than 30 charges.[7] The reasons for excluding these states are twofold. First, the missing data are typically for the most recent years. This would skew the average unemployment and charge rates, since the un-

[4]The data are from the Local Area Unemployment Statistics, available at https://www.bls.gov/lau/ex14tables.htm.

[5]The data are from the *Job Patterns for Minorities and Women in Private Industry report*, available at https://www.eeoc.gov/eeoc/statistics/employment/jobpat-eeo1/index.cfm.

[6]The blue-collar occupations are Clerical, Craft, Operator, Laborer and Service. The other categories are Senior Office, Professional, Middle Management, Technical, and Sales.

[7]The states with missing values are Alaska, Hawaii, Idaho, Iowa, Maine, Montana, Nebraska, New Hampshire, North Dakota, Oregon, South Dakota, Utah, Vermont, Wyoming and West Virginia. Rhode Island is the one state with non-missing data but fewer than 30 charges.

employment rate has been steadily falling since 2011. Second, the data for states with very few charges (e.g. Wyoming and Alaska) tend to be noisy, and may be unrepresentative of patterns in the rest of the country. There is a lot of overlap between these two sets of states, and dropping those with missing data eliminates all but one of those with fewer than 30 claims. Table 1 displays the descriptive statistics for the variables used in the analysis.

## 3 Discrimination over time

This section examines the degree to which fluctuations over time in reported discrimination charges depend on changes in labor market tightness. Figures 1a and 1b plot the time series of the race-based charges rate (per 1,000 workers) and the Black unemployment rate for Mississippi and California, respectively. The plots clearly show that in both states, high unemployment rates are associated with a high rate of charge filing.

Our econometric approach is to estimate standard fixed-effects panel regressions of the following form:

$$Y_{i,t} = a_i + b_t + \mathbf{U}'_{i,t}\,\mathbf{c} + e_{i,t} \tag{1}$$

where $i$ indexes the state and $t$ is the year. The $a_i$ and $b_t$ are state and year fixed effects.

The dependent variable, $Y$, is the number of reported race-based discrimination charges, divided by the combined of the Black/AA and Hispanic/Latino labor force. The $\mathbf{U}$ is a vector of unemployment rates for various demographic groups. We use the labor force instead of employment in the denominator of $Y$ to eliminate the possibility of a mechanical linkage from the unemployment rate to the charge rate, resulting from employment appearing on both sides of the equation.

We estimate equation 1 using OLS, on the assumption that the error term is orthogonal to the regressors (the demographic group-specific unemployment rates). This rules out feedback from the frequency of discrimination charges to the unemployment rate. This would be invalid if employers used the likelihood of a worker filing a discrimination complaint as a consideration in the hiring decision. The assumption would also be invalidated by the omission of a variable that affected discrimination charges, was correlated with unemployment, and not absorbed by the time and state fixed effects.

The results are presented in Table 2, for our balanced panel of 34 states over the 2009–17 time period. The first column shows the estimates for a very simple specification with only the state-level unemployment rate and state fixed effects, but no time fixed effects. The results show that discrimination is highly countercyclical, rising during economic contractions and falling during expansions. The coefficient on unemployment indicates that a one percentage point decline in the unemployment rate is associated with a decrease of 0.07 in the reported discrimination rate, significant at the 0.001 level. To put that into perspective, the estimate implies that the roughly five percentage point drop in unemployment from 2009 to 2017 accounts for a 0.35 reduction in the rate of charge filing.

However, as shown in the second column of the table, the unemployment rate drops out when time fixed effects are included in the model. Consequently, we cannot attribute state-specific fluctuations in discrimination to labor market conditions in the state, as opposed to aggregate economic conditions.

The regression in the third column reports the results from a regression in which the unemployment rate is broken down into White, Black/AA and Hispanic/Latino categories, plus state fixed effects. The increase in the adjusted R-squared indicates that the disaggregation by race/ethnicity improves the model's fit relative to the specification with only state-level aggregate unemployment.

The results show that the effects of labor market conditions differ sharply across groups. The most pronounced impact is for the Black/AA group, with a highly significant coefficient of 0.022. This is smaller than the coefficient on overall unemployment in the first regression; but because the drop in Black/AA unemployment was considerably more pronounced (nine percentage points versus five), the contribution to the observed reduction in charge filing remains quite large. The statistically significant coefficient of 0.0163 on the Hispanic/Latino unemployment rate shows that labor market conditions disproportionately affect that group as well. Not surprisingly, White unemployment has no effect on discrimination charges.

The fourth column of Table 1 adds time fixed effects to the model. The key result is that the coefficients on Black/AA and Hispanic/Latino unemployment rates remain statistically significant, albeit somewhat reduced in magnitude and statistical significance. The negative coefficient on the White unemployment rate hard to interpret, as it suggests that higher unemployment is associated with fewer charges; but this may be picking up state-level labor market conditions not adequately captured by the included aggregate fixed effects.

Overall, the results strongly support the hypothesis that labor market conditions affect discrimination in a way that is consistent with a search model of employment. In a slack labor market, firms can afford to discriminate by passing up qualified minority job applicants, for example; or by treating existing employees in a way that would increase the likelihood of separation. One has to be a little careful, however, as the observed positive relationship between the unemployment rate and the rate of charge filing could also be driven by an increased tendency of workers to file charges in a slack labor market, even with no actual increase in discrimination.

## 4 Discrimination across states

We turn next to the question of what accounts for differences across states in reported discrimination. Figure 2 shows the average race-based charge rates for the 34 states we study. The figure reveals stark differences in the frequency of filing discrimination charges. At one end are Alabama, Indiana and Arkansas, with charge rates of 2.55, 2.46 and 2.16 per thousand, respectively. Connecticut, Massachusetts and California are at the other end of the spectrum, with charge rates of only 0.19, 0.20 and 0.28.

Differences in labor market conditions could explain some of these discrepancies, to the extent that slack conditions reduce employers' opportunity cost of discrimination, as discussed previously. Average unemployment rates do not vary *that* much across states, however; nor is there a clear relationship between unemployment and charge rates. Alabama's charge rate is nine times that of California, despite having a lower average unemployment rate. Factors other than labor market slack are therefore likely to be playing a role.

Occupational mix is another candidate explanation for cross-state differences in discrimination charges. For example, if clerical workers were more often the target of discrimination than those in technical occupations, then more discrimination claims will be filed in states with relatively more clerical workers.

The demographic composition of the labor force could be another factor. A higher share of Black/AA or Hispanic/Latino workers would not directly affect the incidence of discrimination, since charges are expressed as a share of the relevant subset of the labor force. There could be indirect effects, however. Again in the context of a search model, having a large share of minorities in the labor force would increase the cost of discrimination, if the scarcity of white workers meant it took longer for employers to find suitable non-minority workers.

Finally, discrimination may arise from longstanding cultural or social factors. Some (though surely not all) may be related to the history of slavery and segregation, and thus be more prevalent in the southern states.

To explore these possibilities, we estimate a cross-sectional regression using time averages of the state-level data. Essentially, what we are trying to get at is the source of the state fixed effects in the panel regressions presented in the previous section. The cross-sectional approach is appropriate here since the candidate explanatory variables are constant or change only gradually over time.

We use the following model specification

$$Y_i = \text{intercept} + \mathbf{U}_i'\mathbf{a} + \mathbf{L}_i'\mathbf{b} + + \mathbf{X}_i'\mathbf{c} + dD_i + e_i. \tag{2}$$

in which $Y$ is again the number of race-based discrimination charges (per thousand) in the relevant subset of the labor force, $\mathbf{U}$ is a vector of unemployment rates, $\mathbf{L}$ is a vector of labor force characteristics, with coefficient vectors $\mathbf{a}$ and $\mathbf{b}$ respectively. The $\mathbf{X}$ represents a vector of variables characterizing the mix of occupations, and the $\mathbf{c}$ is the vector of coefficients on those variables, and $D$ is a dummy variable equal to 1 for the states belonging to the Confederacy.

Table 3 displays the results from estimating equation 2, for the 34 states in our sample. In the regression in the first column, the $\mathbf{U}$ in equation 2 corresponds to the White, Black/AA and Hispanic/Latino unemployment rates. The $\mathbf{L}$ includes the Black/AA and Hispanic/Latino shares of the total labor force, and $\mathbf{X}$ includes the shares of the White, Black/AA and Hispanic/Latino workforce engaged in low-wage blue collar occupations. (The use of a finer breakdown is precluded by the relatively small number of observations.) The adjusted R-squared (0.739) is more than respectable. Only the share of White workers in blue collar occupations and Hispanic unemployment rates are significant at the 0.05 level. However, the three blue collar shares are very highly correlated, making the estimates on those two variables very imprecise. A formal statistical test does not reject the hypothesis that the three coefficients are equal.

For the regression in the second column, the Black/AA, Hispanic/Latino and White blue collar shares are consolidated into a single variable, representing the overall share of blue collar workers in total employment. The adjusted R-squared falls only slightly, to 0.736. With the multicollinearity problem eliminated, the blue collar share variable is highly statistically significant. It is also economically significant: the parameter estimate of approximately 5 implies that a 1 standard deviation increase in the blue collar share (0.06) is associated with an increase of 0.3 in the rate of charge filing. This corresponds to going from an "average" state with a charge rate of 1.10 per thousand (e.g. Illinois, with 1.09) to one with a rate of 1.31 (e.g. Ohio, 1.32). The Hispanic/Latino unemployment rate remains statistically significant, while the White and Black/AA rates are not. It also includes the Confederate dummy, whose coefficient is positive, but not statistically significant.[8]

The regression in the third column drops the insignificant Black/AA and White unemployment rates, and the Confederate dummy. The parameter estimates are very similar to the previous regression, and the adjusted R-squared falls slightly, to 0.717. Figure 3 shows that this model does a surprisingly good job of capturing cross-state differences in the rate of filing charges. A conspicuous outlier is Alabama (the right-most bar in the chart with a charge rate of 2.5), whose rate of charge filing is significantly under-predicted. Figure 4 is the partial residual plot, showing the contribution of each of the regressors to the fitted relationship.

[8] An alternative "deep south" dummy, corresponding to the first seven states to secede from the Union, fares no better.

Two important results emerge from this analysis. One is that the occupational mix matters: states with relatively more workers in blue-collar occupations tend to report more discrimination. A candidate explanation is that it is relatively easy to replace workers for low-end jobs (e.g. clerical or service), than it is for professional jobs (e.g. managerial or technical). In the context of a search model of employment, the opportunity cost (i.e. the additional time the vacancy would remain unfilled) firing a worker of failing to hire an applicant would be less costly in the former case than in the latter.[9]

The second important result is that Black/AA and Hispanic/Latino labor force shares are negatively associated with our charges-based measure of discrimination. This is consistent with the hypothesis, articulated above, that a larger share of minorities in the labor pool increases employers' opportunity cost of discrimination.

One slightly puzzling result is the negative estimated coefficient on the Hispanic/Latino unemployment rate. This is due to the fact that three of the states with the lowest rates of reported discrimination (California, Massachusetts and Connecticut) also have some of the highest rates of Hispanic/Latino unemployment (12.7, 11.3 and 10.5 percent respectively). The result goes away if these three states are dropped.[10] A conjecture is that the variable is picking up something related to occupational composition, inadequately captured by the binary blue-collar designation.

## 5 Conclusions

Using charges filed with the EEOC as an indicator, we found that race-based employment discrimination varies systematically over the business cycle and across states, in ways that are consistent with employers weighing Becker's (1971) "tastes for discrimination" against the opportunity cost of indulging those tastes.

Examining the cyclicality of discrimination charges in a panel of states in section 3, we found that the incidence of reported discrimination charges depends on the state of the labor market, with increases in unemployment leading to more frequent charges. Moreover, the unemployment rates for Black/AA and Hispanic/Latino workers affect race-based discrimination charges, even controlling for overall labor market conditions.

Looking across states in section 4, we found that slack labor market conditions, measured by the unemployment rate, are not generally associated with an increased incidence of race-based discrimination charges. The occupational mix of jobs matters more, as states with more blue-collar jobs, on average, experiencing a higher incidence of race-related discrimination charges.

[9] A caveat is that the blue-collar share variable may be picking up the effects of an omitted variable, such as personal income.

[10] Nevada and Washington also have below-average charge rates and high rates of Hispanic/Latino unemployment.

Fewer discrimination charges are filed in states with relatively larger shares of minority workers.

Our analysis can be directly extended in a number of different ways. One is to determine whether charges of retaliation, which are also reported to the EEOC, exhibit patterns similar to the ones documented in this paper. Second, by disaggregating the unemployment rate by gender, we should be able to see whether discrimination charges are more closely tied to male or female unemployment. Third, we can use a similar framework to examine gender- and age-based discrimination. Finally, we can see whether other factors, such as unionization rates, can help explain cross-state differences in discrimination.

Our findings have important macroeconomic implications. Broadly speaking, they show that the reduction in discrimination should not be overlooked as a benefit of a strong economy. Monetary and fiscal policymakers should take this into account when weighing the benefits of expansionary policy against the costs (e.g. higher inflation). Recent speeches by Yellen (2014) and Brainard (2017) are signs that Federal Reserve officials have in recent years become increasingly attuned to this dimension of economic performance.

Moreover, the relevant policy objectives extend beyond the Fed's traditional mandate of output and inflation stabilization to encompass equal economic *opportunity*.[11] As Brainard (2017) observed:

> "To the extent that disparities in income and wealth across race, ethnicity, gender, or geography reflect such disparities in opportunity, families and small businesses from the disadvantaged groups will then underinvest in education or business endeavors, and potential growth will fall short of the levels it might otherwise attain."

Thus, macroeconomic policies that reduce discrimination in the near term are likely to enhance the economy's long-term growth prospects.

[11] See Roemer & Trannoy (2016) for a wide-ranging discussion of equality of opportunity.

Table 1: Descriptive Statistics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Race-based claims | 940.8 | 740 | 64.4 | 3155 |
| Claims/labor force | 1.10 | 0.64 | 0.19 | 2.55 |
| Overall unemployment | 7.06 | 0.99 | 5.27 | 9.46 |
| White unemployment | 6.12 | 1.01 | 4.47 | 8.83 |
| Black unemployment | 12.43 | 2.07 | 8.94 | 17.68 |
| Hispanic unemployment | 8.72 | 1.68 | 5.46 | 12.73 |
| White labor force share | 0.79 | 0.08 | 0.62 | 0.90 |
| Black labor force share | 0.14 | 0.09 | 0.03 | 0.34 |
| Hispanic labor force share | 0.12 | 0.11 | 0.03 | 0.43 |
| Blue-collar share | 0.54 | 0.06 | 0.43 | 0.68 |
| Black blue-collar share | 0.69 | 0.05 | 0.55 | 0.77 |
| Hispanic blue-collar share | 0.75 | 0.06 | 0.60 | 0.88 |
| White blue-collar share | 0.46 | 0.07 | 0.35 | 0.59 |

*Note:* The 15 states with missing data are excluded, Rhode Island is also dropped due to the very small number of race-based discrimination claims. The total number of states is 34, and the sample covers the 2009–17 period.

Table 2: Panel regression results

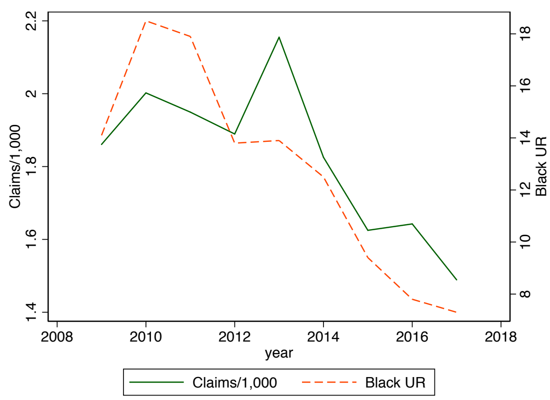
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Total | 0.0729*** | -0.0132 | | |
| | (13.19) | (-0.92) | | |
| White unemployment rate | | | 0.0144 | -0.0565** |
| | | | (1.00) | (-3.21) |
| Black/AA unemployment rate | | | 0.0220*** | 0.0116* |
| | | | (4.20) | (2.14) |
| Hispanic/Latino unemployment rate | | | 0.0163* | 0.0146* |
| | | | (2.28) | (2.14) |
| Constant | 0.586*** | 1.377*** | 0.598*** | 1.363*** |
| | (14.49) | (10.26) | (15.48) | (10.22) |
| State effects? | Yes | Yes | Yes | Yes |
| Time effects? | No | Yes | No | Yes |
| $R^2$ | 0.391 | 0.482 | 0.420 | 0.506 |
| Adjusted $R^2$ | 0.315 | 0.399 | 0.343 | 0.422 |

*Notes:* The dependent variable is the number of race-based discrimination claims divided by the labor force, expressed in claims per 1,000 workers. The sample consists of the 34 states with complete data for the 2009–17 period, and excluding Rhode Island due to the small number of claims filed in that state. The total number of observations is 306. Parentheses contain $t$ statistics, and asterisks indicate statistical significance: $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

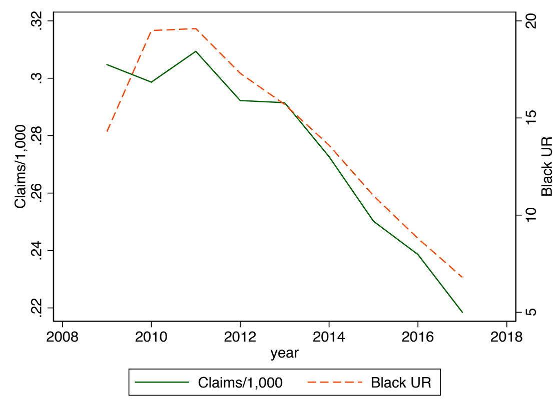
Table 3: Cross-section regression results

| | (1) | (2) | (3) |
|---|---|---|---|
| Black share in labor force | -0.652 | -2.706$^{*}$ | -1.982$^{*}$ |
| | (-0.69) | (-2.40) | (-2.32) |
| Hispanic share in labor force | -2.239 | -3.364$^{***}$ | -3.283$^{***}$ |
| | (-1.97) | (-3.87) | (-5.22) |
| White blue collar share | 5.462$^{*}$ | | |
| | (2.54) | | |
| Black blue collar share | -3.800 | | |
| | (-1.00) | | |
| Hispanic blue collar share | 2.346 | | |
| | (1.26) | | |
| White unemployment rate | 0.0155 | 0.00425 | |
| | (0.14) | (0.04) | |
| Black unemployment rate | 0.0277 | 0.0204 | |
| | (0.61) | (0.45) | |
| Hispanic unemployment rate | -0.156$^{*}$ | -0.138$^{*}$ | -0.143$^{**}$ |
| | (-2.51) | (-2.17) | (-3.46) |
| Share of blue collar workers | | 5.068$^{**}$ | 5.770$^{***}$ |
| | | (3.57) | (5.03) |
| Confederate dummy | | 0.254 | |
| | | (1.22) | |
| Constant | 0.737 | 0.00198 | -0.0801 |
| | (0.41) | (0.00) | (-0.11) |
| Observations | 34 | 34 | 34 |
| $R^2$ | 0.739 | 0.736 | 0.717 |
| Adjusted $R^2$ | 0.656 | 0.665 | 0.678 |

*Note:* The dependent variable is the number of race-based discrimination claims divided by the labor force, expressed in claims per 1,000 workers. The sample consists of the 34 states with complete data for the 2009–17 period, and excluding Rhode Island due to the small number of claims filed in that state. Parentheses contain $t$ statistics, and asterisks indicate statistical significance: $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.




(a) Mississippi




(b) California

Figure 1: Time series of race-based charges for two states

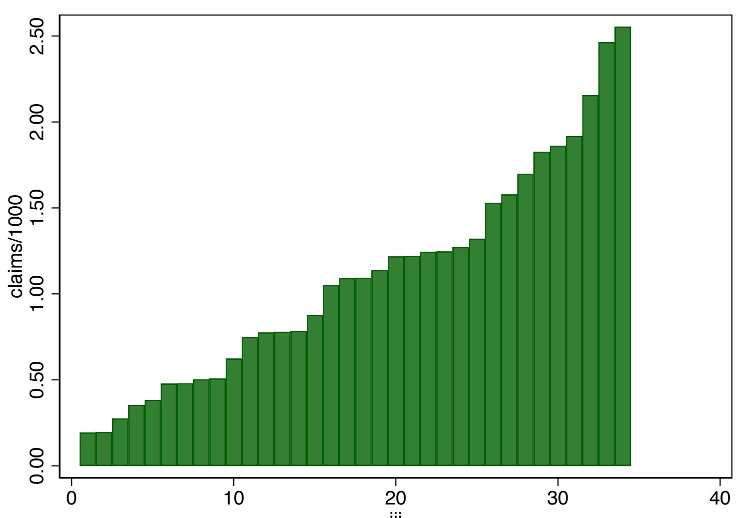



Figure 2: Distribution of race-based charges

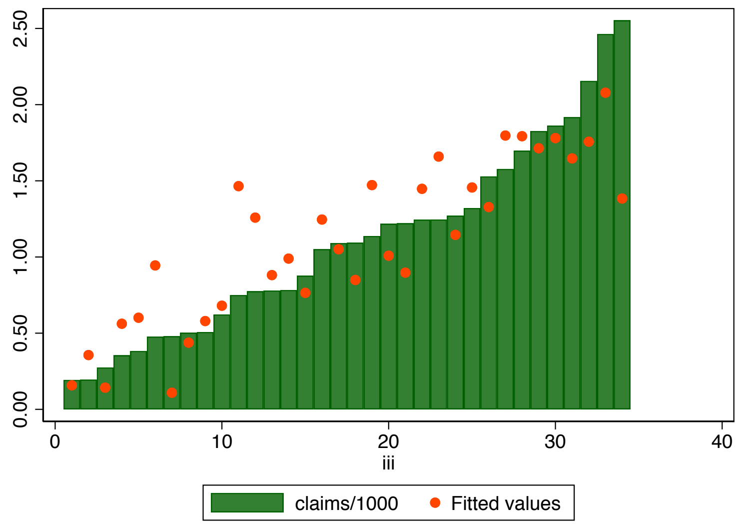



Figure 3: Actual and fitted values of race-based charges

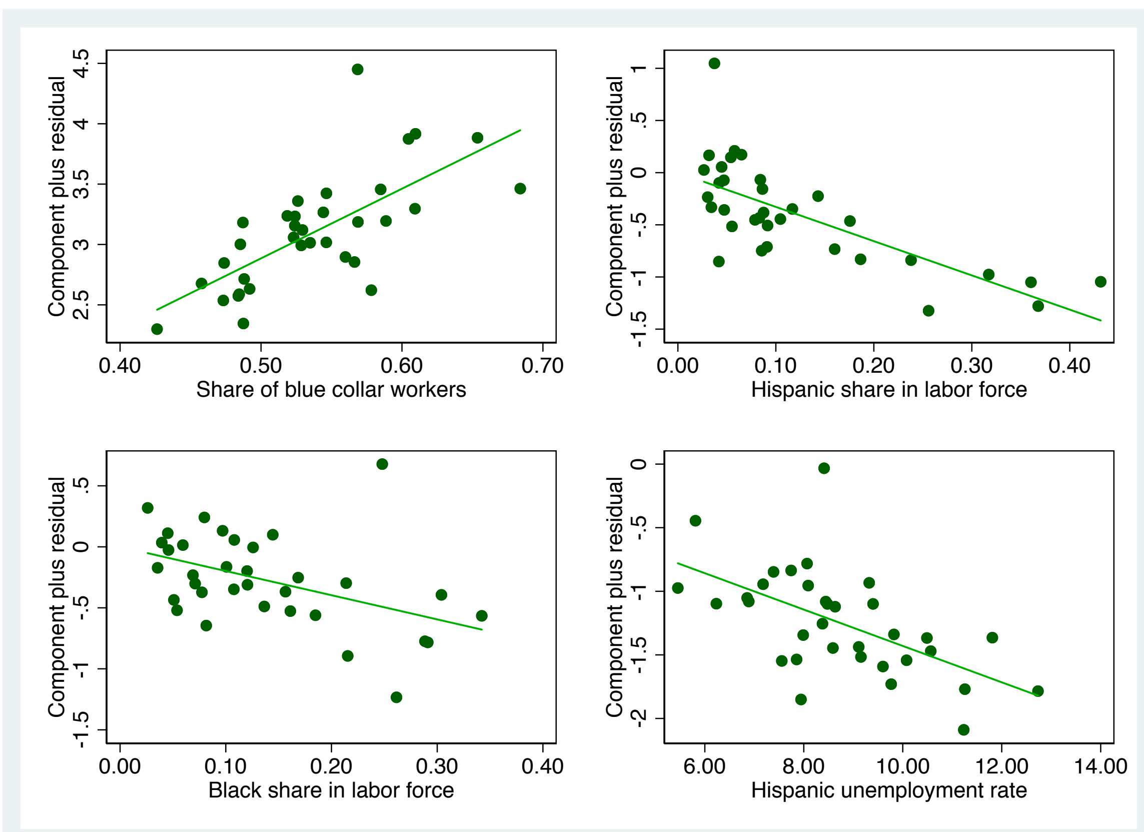



Figure 4: Contributions of regressors to fitted relationship

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