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Age Discrimination across the Business Cycle

Abstract

A key prediction of discrimination models is that competition in the labor market serves as a moderating force on employer discrimination. In the presence of market frictions, however, recessions create excess labor supply and thus generate opportunities to engage in discriminatory behaviors far more cheaply. A natural question arises: does discrimination increase during recessions? We focus on age discrimination and test this hypothesis in two ways. We first use employee discrimination charges filed with the Equal Employment Opportunity Commission (EEOC), along with an objective measure of the quality of those charges. For each one percentage point increase in a state-industry's monthly unemployment rate, the volume of age discrimination firing and hiring charges increases by 4.8% and 3.4%, respectively. Even though the incentive to file weaker claims is stronger when unemployment is high, the fraction of meritorious claims also increases significantly when labor market conditions deteriorate. This is a sufficient condition for real (versus merely reported) discrimination to be increasing under mild assumptions. Second, we repurpose data from a correspondence study in which fictitious resumes of women were randomly assigned older versus younger ages and circulated across different cities and time periods during the recovery from the Great Recession. Each one percentage point increase in the local unemployment rate reduces the relative callback rate for older women by 14%.

JEL-Codes: J710, J640, J230.

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1 Introduction

Starting with Becker (1957), economists have argued that taste-based discrimination–or the preference for a certain class of workers based on characteristics unrelated to productivity–is costly, and hence, unsustainable in a competitive market. But if substantial frictions exist, any shock that produces slackness in the labor market will create opportunities for employers to indulge in their discriminatory preferences without incurring as large a productivity tradeoff.[1] For example, if downwardly rigid wages necessitate layoffs, discriminatory firms can fire equally productive but less preferred workers without harming profits. Likewise, a larger pool of unemployed workers lowers hiring search costs so that discriminatory firms need not subjugate profit considerations to subjective, animus-based ones.

We employ two unique data sources and approaches to test whether, consistent with theory, firing and hiring discrimination rise as labor market slackness makes them less costly. Any evidence of increased firing discrimination, in particular, is less likely to be explained by models of statistical discrimination, since firms will have learned about productivity for already employed workers (Altonji and Pierret, 2001).

In this paper, we focus on the incidence of age discrimination over the business cycle. A key reason is that age discrimination must be shown to be intentional to be illegal under the Age Discrimination in Employment Act (ADEA), so our analysis concerns conscious decisions to discriminate. This is in contrast to other classes, such as race or gender, which are protected under Title VII of the Civil Rights Act of 1964, where unintentional discrimination is also illegal.[2] Moreover, the Supreme Court has ruled that older workers may be termi-

[1]Others have had this general insight. See, for example, Ashenfelter (1970); Baert et al. (2015); Freeman (1973); Shulman (1987); Biddle and Hamermesh (2013); Neumark and Button (2014); Knepper (2018); Boulware and Kuttner (2019).

[2]Disparate *treatment* is illegal under the ADEA, but disparate *impact* claims are not. As explained by Rozycki and Sullivan (2010), in disparate treatment cases, "plaintiffs must show that their employers treated them less favorably because of the employee's membership in a protected class, such as race, gender, or age. The employee must prove through direct or circumstantial evidence that the discrimination was intentional. In contrast, a disparate-impact claim does not require proof of an intention to discriminate. Instead, showing that a facially neutral employment practice has a disproportionately adverse impact on a protected group states a prima facie case of unlawful disparate-impact discrimination."

nated lawfully due to "reasonable factors other than age," such as wages and productivity, which may be correlated with age (see Section 2.2 for details). Age discrimination also has potentially significant consequences: a large and growing fraction of the labor force is older (Maestas et al., 2016), late-in-life involuntary job loss has severe adverse effects on physical and mental health (Gallo et al., 2000), and older workers have had a particularly difficult time getting rehired in the aftermath of the Great Recession (Johnson, 2012; Neumark and Button, 2014).

Measuring age discrimination, and indeed any type of workplace discrimination, is difficult. Direct, objective measures of discrimination are scarce and so scholarship has tended to lean on indirect ones, such as wage and employment gaps. Such outcomes, while likely to be adversely impacted by increases in discrimination, could also be due to productivity or costs which differ across age groups (Scott et al., 1995). This measurement challenge is complicated further by the presence of turbulent labor market conditions such as those engendered by the Great Recession. While unemployment spells lasted longer and hiring rates fell further for older workers during the Great Recession (Johnson and Butrica, 2012), the attribution of these adverse outcomes to discrimination is called into question by early claiming of Social Security (Hutchens, 1999) and early retirement (Bosworth, 2012).[3]

Our paper overcomes these challenges using two complementary analyses. The first investigation leverages direct measures of employment discrimination: ADEA charges filed with the Equal Employment Opportunity Commission (EEOC). We use state×industry×month variation in exposure to the Great Recession to test whether employers discriminate more against older workers when competitive forces are weakened. For each one percentage point increase in the unemployment rate, we find the volume of ADEA firing and hiring charges increases by 4.8% and 3.4%, respectively. These results point to an increase in the *reported* level of discrimination, but do not allow one to distinguish genuine employer misconduct

[3]Neumark and Button (2014) recognize this complication in their work: "Of course we do not actually know whether age discrimination was or is occurring. But we can ask whether these state protections reduced the adverse effects of the Great Recession on older workers relative to younger workers."

from elevated employee incentives to file a case. The reason is that as outside labor market opportunities recede, the opportunity cost of pursuing a claim will fall, and hence more marginal cases will be filed with the EEOC even if actual discrimination has not increased.

We address this potential confound by taking advantage of the EEOC's determination of whether a discrimination case has "merit" – a decision which involves a lengthy follow-up investigation as needed. Using this proxy for the quality of claims, we find the fraction of ADEA discrimination cases with merit *rises* in response to deteriorating labor market conditions. For each one percentage point increase in the unemployment rate, the probability a case has merit increases by a statistically significant 0.7%. Under relatively mild assumptions,[4] this is a sufficient condition which allows us to conclude that actual (as opposed to merely reported) age discrimination increased during the Great Recession. In a series of robustness checks, we probe a variety of alternative explanations.

The second analysis uses a correspondence study. A large literature has used this type of design to study levels of hiring discrimination for different groups.[5] More germane to our analysis, two papers have looked at how labor market tightness across occupations affects callback rates for ethnic minorities. Baert et al. (2015) finds that occupations with shorter vacancy durations discriminate more in Belgium. An alternative interpretation is that occupations with difficult to fill vacancies are less desirable and hence ethnic minorities face less competition from natives (Bulow and Summers, 1986). Carlsson et al. (2018) finds the opposite result using the native female callback rate as a measure of labor market tightness in Sweden; since this measure is potentially endogenous, they also use the vacancy-unemployment ratio by occupation and find marginally significant effects.

Our focus is on how the level of age discrimination varies over the business cycle. Fortu-

[4]Specifically, we require that holding constant the level of actual discrimination, the quality of marginally added cases falls during a recession. We also require the merit variable to only vary with the business cycle due to changes in the true quality of cases.

[5]For a sampling of correspondence studies using race, ethnicity, and immigration status, see Bertrand and Mullainathan (2004); Carlsson and Rooth (2012); Edo et al. (2019); Oreopoulos (2011); Rooth (2010). For age, see Bendick et al. (1997, 1999); Riach and Rich (2010), and for age by sex, see Farber et al. (2017); Lahey (2008); Neumark et al. (2019a,b). For broader surveys on labor market discrimination, see Bertrand and Duflo (2017); Neumark (2018).

itously, we are able to repurpose data from a correspondence study conducted by Farber et al. (2017) in the aftermath of the Great Recession. These authors sent out fictitious resumes for women applying to administrative support positions, to answer a different set of questions.[6] The resumes were assigned older versus younger ages (and other characteristics, depending on treatment) and circulated across a panel of 8 different cities from 2012-2014, generating ample across-city and across-time variation in unemployment. In the first three rounds of treatments, a pair of older or younger resumes were randomly sent to each employer. In the fourth round, four fictitious applications were sent to each firm, two with older ages and two with younger ages.

Our repurposed correspondence study analysis reveals the age callback penalty grows considerably in the presence of anemic labor market conditions. Each one percentage point increase in the local unemployment rate reduces the callback rate for older women by 1.7 percentage points (off a baseline 10.8% callback rate), relative to younger women. We interpret this as evidence that firms discriminate more as the number of hiring options increases due to an elevated unemployment rate (similar to the EEOC study). Using the fourth round of the study, we leverage the fact that the number of options available to the employer directly increases due to the experimental design. In the fourth round, older candidates directly compete with an additional two younger candidates compared to the first three rounds. All else equal, an older female is 6.8 percentage points less likely to receive a callback when she is competing against two additional younger female applicants, which translates to a 63% reduction relative to the mean.

The two analyses complement each other well, as each has unique strengths. The EEOC data cover the entire U.S. and capture age discrimination borne by real people during a recession. Equally important, our EEOC analysis allows us to study changes in discrimination on the firing margin, something which is not possible with a correspondence or experimental study. The firing margin is particularly noteworthy, both because it constitutes the bulk of

[6] In their paper, the authors investigate the effect of age, unemployment spell length, and low-level interim jobs on the callback rate.

these types of age discrimination cases (85% firing versus 15% hiring), and because losing a job is likely to impose greater costs compared to not being hired in the first place. The correspondence analysis has the advantage of random assignment of applicant age to otherwise comparable profiles, and requires no assumptions about reporting behavior during a recession. Interpreting our findings, the EEOC firing margin is more likely to be driven by taste-based discrimination, since the employer has good information about a worker's productivity.[7] For the EEOC and correspondence hiring results, both taste-based and statistical discrimination could play important roles.

Taken together, our two analyses provide compelling evidence that age discrimination rises as labor markets deteriorate. As far as we know, this is the first direct evidence for age discrimination varying with the business cycle, both for the firing and hiring margins. This accords with Becker's prediction that as competition for workers wanes, discrimination should increase. A related point is that the extent of measured discrimination depends crucially upon the labor market context during which that measurement happened. This is relevant when interpreting and comparing research documenting discrimination in different time periods or labor markets.[8]

The next section describes the EEOC's role in investigating employer misconduct and the details of federal ADEA laws. Section 3 describes both the EEOC and correspondence study data. Section 4 outlines a simple framework for discrimination reporting behavior and Section 5 details the empirical methodology. Section 6 presents the main results for our two complementary analyses. Section 7 summarizes and concludes.

[7] It is still possible that an employer is statistically discriminating based on expectations of future productivity based on age, however.

[8] For example, this is salient when comparing estimates of discrimination against ethnic minorities (Doleac and Hansen, 2020; Riach and Rich, 2002), women (Egan et al., 2017; Goldin and Rouse, 2000; Helleseter et al., 2018; Kuhn and Shen, 2012; Neumark et al., 1996), or workers whose nationality or race differs from that of their manager (Åslund et al., 2014; Giuliano et al., 2009, 2011).

2 The EEOC and Discrimination Reporting[9]

2.1 The EEOC's Historical Origin and Role

Taking up the mantle of his recently deceased predecessor, President Lyndon B. Johnson wielded his considerable political capital to help break the Senate filibuster detaining the landmark anti-discrimination bill that would go on to become one of his defining legislative achievements. The resulting Civil Rights Act of 1964 forbade discrimination in public accommodations and in federally-funded programs and activities. Title VII of the Act prohibited workplace discrimination on the basis of race, sex, color, religion, or national origin and commissioned funds to be used in the creation of the regulatory agency tasked with enforcing this ambitious initiative to ensure "justice and equality in the workplace."

Established in 1965, this Equal Employment Opportunity Commission (EEOC) has since evolved to administer not only the Civil Rights Act but also other federal laws protecting workers against employment discrimination. More specifically, the major types of discrimination covered by the EEOC include: age, disability, equal pay, genetic information, harassment, national origin, pregnancy, race, religion, retaliation, sex, and sexual harassment. As such, it has become the preeminent agency responsible for the enforcement of nearly all forms of illegal employment discrimination for firms with 15 or more employees (20 or more for age discrimination). Based on the distribution of firm size, we estimate that over 85% of all workers in the United States are covered by age discrimination laws.

Over time, the EEOC has expanded its operations out from its headquarters in Washington, D.C. to include over 2,000 employees across 53 field offices, each of which is responsible for processing and investigating the discrimination charges filed within their geographic area. Wide though its scope is, the EEOC does not enforce all laws prohibiting discrimination and oversee all workplace issues, which are instead covered by various other federal agencies.[10]

[9] This section draws on information from the EEOC website. For further details, see https://www.eeoc.gov.

[10] Such anti-discrimination laws include: Civil Service Reform Act of 1978, Immigration and Control Act of 1986, Executive Order 11246, Title VI of the Civil Rights Act of 1964, Title II of the Americans with

The EEOC enforces worker protections against discrimination for private employers, public employers, employment agencies, and labor unions. Certain states, counties, towns, and cities have implemented their own anti-discrimination laws, which can sometimes complement or even supersede those enforced by the EEOC. The organizations responsible for enforcing these laws, Fair Employment Practice Agencies (FEPAs), differ from the EEOC in that they can offer protection to additional classes of workers (e.g., sexual orientation, marital status), utilize different deadlines for filing a charge, apply varying standards to enforcement, and offer alternate forms of relief to victims. That said, many FEPAs have worksharing agreements with the EEOC so that whenever the charge's allegation is also covered by an EEO law, the FEPA will dual file the charge with the EEOC, and vice-versa. Additionally, dual filing ensures that charging party rights are protected under federal and state or local law, where applicable. To control for heterogeneity in the coverage and intensity of employment discrimination enforcement across states, we include state fixed effects and exclude FEPA charges from the analysis.

2.2 Federal Age Discrimination in Employment Act

The Age Discrimination in Employment Act (ADEA) was codified into federal law in 1967 with the explicit purpose of protecting workers against workplace discrimination on the basis of age. Issues covered include practices involving firing, hiring, promotion, layoff, compensation, harassment, etc. The youngest age above which an employee is eligible for protection under the ADEA is 40.

A primary purpose of the ADEA is to help counter the perception among employers that age adversely impacts ability. This is an important point, as it, along with prior evidence, suggests that much of the discrimination that persists in the workforce is attributable to statistical rather than taste-based discrimination (Neumark, 2018). Importantly, though,

Disabilities Act (ADA), Family and Medical Leave Act (FMLA), Occupational Safety and Health Act of 1970 (OSHA), Section 503, 504, and 508 of the Rehabilitation Act, Social Security Act, Fair Labor Standards Act, National Labor Relations Act, Section 1981 of the Civil Rights Act of 1866, Workers Compensation Law, and Title I of the Genetic Information Nondiscrimination Act.

the EEOC does not distinguish between taste-based and statistical discrimination in its enforcement activities; both are considered to be illegal under the law.

There is, however, an important question on the extent to which the law does or does not differentiate between cases arising due to age discrimination versus ability and/or costs. In the majority opinion written for the 2005 Supreme Court Case of *Smith v. City of Jackson, Miss.* (544 U.S. 228 (2005)), Justice Sandra Day O'Connor unequivocally asserts the right of employers to lawfully take actions that are inimical to the class of older employees, so long as they are based on a "reasonable factor other than age." Specifically, she writes:

> *...the Wirtz Report correctly concluded that–unlike the classifications protected by Title VII–there often is a correlation between an individual's age and her ability to perform a job. Wirtz Report 2, 11-15. That is to be expected, for "physical ability generally declines with age," Murgia, supra, at 315, and in some cases, so does mental capacity, see Gregory v. Ashcroft, 501 U. S. 452, 472 (1991). Perhaps more importantly, advances in technology and increasing access to formal education often leave older workers at a competitive disadvantage vis-a-vis younger workers. Wirtz Report 11-15. Beyond these performance-affecting factors, there is also the fact that many employment benefits, such as salary, vacation time, and so forth, increase as an employee gains experience and seniority. See, e.g., Finnegan v. Trans World Airlines, Inc., 967 F. 2d 1161, 1164 (CA7 1992) ("[V]irtually all elements of a standard compensation package are positively correlated with age"). Accordingly, many employer decisions that are intended to cut costs or respond to market forces will likely have a disproportionate effect on older workers. Given the myriad ways in which legitimate business practices can have a disparate impact on older workers, it is hardly surprising that Congress declined to subject employers to civil liability based solely on such effects....Congress' decision to limit the coverage of the ADEA by including the RFOA provision is consistent with the fact that age, unlike race or other classifications protected by Title VII, not uncommonly has relevance to an individual's capacity to engage in certain types of employment...This "reasonable factors other than age" (RFOA) provision "insure[s] that employers [are] permitted to use neutral criteria" other than age, EEOC v. Wyoming, 460 U. S. 226, 232-233 (1983), even if this results in a disparate adverse impact on older workers.*

This ruling is important for interpreting our findings. The ADEA allows for disparate impact in the hiring and firing of older workers, in contrast to other protected classes such as race or sex where it would be illegal (see footnote 2). The implication is that an ADEA claim in which older employees are fired based on cost or productivity considerations will not be considered meritorious, at least under the post-2005 interpretation of the law.[11] It is for this reason as well that our EEOC analysis sample begins in 2005.

2.3 Process for Filing and Resolving Discrimination Charges

Figure 1 lays out the process for filing and resolving discrimination charges. Individuals are typically required to file a charge within 180 days of the alleged discriminatory action. The employer is then notified of the receipt of the charge within 10 days of the filing date. Normally the case is first referred to mediation, during which a neutral third party will attempt to assist the two parties in reaching a voluntary resolution to the charge. The average time to resolution for mediated cases is less than three months.

If instead either the employer or employee decides against mediation, the EEOC begins its investigation by first asking the employer to provide a written answer to the discrimination charge, after which the EEOC may hold interviews, gather documents, and interview witnesses. This process takes approximately 10 months on average. At any time during the investigation, the charging party and respondent may reach a negotiated settlement or the charging party may withdraw the case after receiving desired benefits from the employer. These are both considered to be "merit resolutions" by the EEOC, as they imply an outcome favorable to the charging party.

Following the investigation, the EEOC determines whether they have reasonable cause to believe that the alleged discrimination occurred according to the evidence collected. If no reasonable cause is determined, the charging party may still exercise the right to sue. If instead a reasonable cause is determined (i.e., the case has "merit"), the EEOC will again

[11] Section 4(f)(2) of the current version of the ADEA confirms that reasonable factors other than age are allowable. To clarify, it would still be illegal to fire a worker based on expected future declines in productivity based on their age as this is a form of statistical discrimination.

attempt to negotiate a voluntary agreement with the employer and charging party, resulting in either a successful or unsuccessful conciliation. If efforts to conciliate the charge are unsuccessful, the EEOC will then refer the case to its legal staff to determine its suitability for litigation.

Figure 1 displays the fraction of cases with different outcomes for ADEA hiring plus firing charges in our baseline sample. Combined merit resolutions are significantly rarer (17%) than are cases dismissed due to not having had reasonable cause (68%). The remaining category is administrative closures, which are charges for which the resolution cannot be determined (15%).[12] Only a small number (0.3%) of all initially filed charges are litigated.

3 Data

This paper combines a unique source of EEOC administrative data on charges with local area estimates of employment produced by the Bureau of Labor Statistics (BLS). This enables us to examine the relationship between the Great Recession and self-reported, but quality-validated, workplace discrimination charges filed by older employees. Additionally, we use data from a correspondence study of job applications for older and younger women to assess whether increases in local unemployment rates exacerbate age discrimination. In the following subsections, we describe the primary data elements subsumed in each.

3.1 EEOC Charge Data

Our EEOC analysis uses the universe of roughly 80,000 ADEA firing and hiring charges filed with the EEOC from 2005 through 2015 (approximately 8,000 annual filings).[13] These are further partitioned into 51 issues (e.g., Sexual Harassment, Discharge, Hiring, etc.) and 105 bases (e.g., Sex-Female, Race-Black, Age, etc.). Each observation in the EEOC dataset cor-

[12] These include scenarios where the charging party fails to respond to the letter, the EEOC does not have jurisdiction, the charging party files a private lawsuit, there is a failure to locate the charging party, etc.

[13] Data is unfortunately missing from October 2010 through September 2011.

responds to a particular charge, which may include multiple claims of types of discrimination. The average number of claims per charge is just over 4 for ADEA firing charges and just over 3 for ADEA hiring charges. For the purposes of this paper, we classify an observation as a firing charge if one of the issues was coded as "discharge" or "layoff" and as a hiring charge if one of the issues was "hiring." These charge types account for approximately 73% of all ADEA filings. Appendix Table A1 lists the most common basis categories in addition to age, and the most common additional issue categories. The table shows that retaliation and disability claims are commonly included in ADEA firing and hiring charges, and that terms and conditions and harassment are commonly included as additional issues.[14]

Appendix Table A1 also reports selected characteristics of the workers and firms. For both firing and hiring, the average age of the charging party is 56 years old, with over half being white and roughly one-quarter black. Interestingly, the gender composition skews more male in hiring charges. The share of plaintiffs retaining private legal counsel is far greater in ADEA cases of firing discrimination than in hiring discrimination (17% versus 7%), likely reflecting the monetary stakes being greater in grievances involving a discharge. Finally, the composition of private versus public firms differs by the type of charge filed; nine out of ten firms accused of firing discrimination are private, compared to just three-quarters of those accused of hiring discrimination.

Particularly important for our study, the EEOC data include information on how the charges are resolved, which results from a follow-up investigation conducted by the local EEO office. We transform the resolution into a binary variable that indicates if the agency determined the case to have had "merit," which serves as a useful proxy for the quality of the charge filed. The EEOC classifies as meritorious those cases resulting in settlements, withdrawals with benefits, and reasonable cause findings. Cases determined to have merit include both successful and unsuccessful final conciliation attempts. In general, merit resolutions are those charges for which the outcome is favorable to the charging party, either

[14]Note that a charge including a discharge can also involve a hiring issue, for example if an employee feels they were wrongly fired and not rehired for another position.

by way of monetary damages being exchanged or the EEOC concluding that the charge had reasonable cause following its lengthy investigation.

Table 1 provides a detailed breakdown of case resolutions for the ADEA firing and hiring charges separately. Notable differences between the two types of charges emerge; namely, ADEA firing cases are six times as common, 22% more likely to have had merit, and generate larger monetary damages. This makes sense in light of the fact that hiring discrimination is notoriously difficult to prove. In addition, a discriminatory firing is also more salient, as it deprives a worker of their current income stream.

3.2 State and Industry Unemployment Data

To measure local exposure to the Great Recession and subsequent recovery over the 2005-2015 period, we first calculate the number of unemployed individuals at the state-month level using the Local Area Unemployment Statistics series produced by the BLS. We also use variation in industry-specific exposure using unemployment statistics tabulated at the industry-month level by the BLS. We then impute state-by-industry specific unemployment rates at the monthly level, the details of which are made available in Section 5.

Appendix Figure A1 shows state variation in the unemployment rate at the height of the Great Recession (December 2009). There exists considerable cross-sectional variation; unemployment rates ranged from just over 4% in North Dakota to nearly 14% in Michigan. Appendix Figure A2 documents similarly wide variation across industries. Construction was shocked particularly hard, seeing a peak unemployment of 22%, whereas education and health services were relatively insulated, with unemployment reaching only 6%. While not shown, there is also variation in the speed of recovery across both states and industries.

3.3 Correspondence Study Data

Our second analysis uses data from Farber et al. (2017), who generated over 12,000 fictitious resumes and submitted them to 8 different cities over four time periods between 2012 and 2014. They explored how applicant characteristics (age, unemployment duration, and whether the applicant held a low-level interim job) affected the callback rate for administrative support jobs. We repurpose their data to see how differences in local unemployment affect callback rates of older workers. For context, all of the artificial applicants were college-educated females with significant work experience.

Consistent with standard methods used in correspondence studies, for each city and in each application wave, paired applications were submitted with just one differing characteristic. Importantly, in rounds 1-3, either two younger [35, 36, 37, 40, 41, or 42] or two older [55, 56, 57, or 58] applications were sent to each job posting, and so variation in age is generated across rather than within job postings. Round 1 compared the newly unemployed with those who had been randomly assigned an unemployment spell of 4, 12, 24, or 52 weeks. Round 2 was identical except that each applicant had been randomly assigned an unemployment duration of 0, 4, 12, 24, or 52 weeks. Round 3 precisely mirrored round 2 except that a low-level interim job had been assigned randomly at the application level, within matched-pairs. Finally, round 4 added to round 3 the modification that each posting received an application from both a younger and older pair of workers. Round 4, then, differs from the first three in that older workers directly compete against their younger counterparts.

Table 2 shows the number of applications submitted during each round of applications–03/2012-05/2012, 07/2012-09/2012, 11/2013-4/2014, and 04/2014-08/2014–and for each of the 8 cities–Charlotte, Chicago, Dallas, Omaha, Pittsburgh, Portland (ME), Sacramento, and Tampa Bay.[15] As Farber et al. (2017) note, they intentionally picked 4 low unemployment cities and 4 high unemployment cities. This feature, along with the fact that each successive round of applications was submitted as labor markets continued to recover from the Great Recession, generates meaningful across-city and across-time variation, as illustrated in Figure 2.

[15] Portland, ME was omitted in rounds 1 and 3 of the survey.

4 Actual versus Reported Discrimination

Before turning to our empirical models, we briefly discuss how a recession is predicted to impact both actual and reported age discrimination. We start with a framework described by Biddle and Hamermesh (2013) and Baert et al. (2015) where (i) some firms have a taste for discrimination, i.e., a preference for equally productive younger versus older workers in our setting and (ii) the tightness of the labor market imposes a tradeoff between profits and discrimination for monopsonistic firms. The tradeoff arises because there are search costs to finding and retaining qualified workers.

When the economy is doing well and the supply of workers thin, not retaining or not hiring qualified older workers reduces profits through these higher search costs. Now consider what happens during a recession. Discriminatory firms which need to lay off workers will want to fire their older workers first, absent any legal costs of doing so. Similarly, discriminatory firms that are hiring during a recession face lower search costs for finding a young worker among the enlarged pool of those looking for work. The goal of this paper is to test whether actual discrimination moves countercyclically, and this model provides one possible explanation for why it might.[16]

But one cannot distinguish between actual and reported discrimination without characterizing a worker's incentives to file a charge. Older workers who are fired from their jobs (or not hired in the first place) have the option to pursue a legal claim of discrimination to receive both monetary payments and a potential restoration of their job. A worker's firing may have been linked to age discrimination, but it could also have been due to lower productivity/higher costs relative to retained workers and hence perfectly legal. How strong a case the worker has influences their chances of winning, and therefore their likelihood of filing an EEOC charge.

The worker's reporting threshold will also respond to labor market conditions, both due

[16] Other models are possible as well (see Carlsson et al. (2018)), and can even lead to the opposite prediction if age is a proxy for characteristics not observed by the employer (a situation more relevant to the hiring margin than the firing margin).

to the time costs of filing a charge and the difficulty of finding new employment at a similar wage. During good economic times, the opportunity cost of filing a claim is higher and the potential benefits lower, as it is easier to find a new job quickly. Conversely, as the job market weakens, workers have an incentive to file more marginal claims. Hence, for a given level of actual discrimination, we assume that during a weak labor market the volume of charges will be higher while average claim quality (merit) will be lower.

This simple framework makes clear that during a recession, the volume of hiring and firing charges could go up for two different reasons: an actual increase in discrimination and a reported increase in discrimination. Therefore, a jump in EEOC charges during a recession does not, by itself, necessarily imply an increase in actual age discrimination. We can, however, arrive at such a conclusion if the quality of discrimination charges filed weakly increases. In this case, the rise in actual discrimination more than offsets the increased filing of weaker cases. This interpretation is valid so long as (i) holding constant the level of actual discrimination, the merit of marginally added cases falls during a recession, and (ii) the merit variable is an objective measure of case quality whose mean varies with the business cycle only due to changes in the true quality of cases. As robustness checks, later in the paper we explore and rule out several alternative explanations for why merit might change during a recession.

The benefit of our EEOC data is that we have an independent measure of the quality of a case, which allows us to test whether the sufficient condition holds. Importantly, we are able to measure discrimination on the firing margin, something not possible with a correspondence study. The benefit of the correspondence data is that the issue of reporting does not even arise; moreover, we can directly test what happens when older job applicants face increased competition from younger applicants.

5 Empirical Models

5.1 EEOC Charge Model

To identify the effect of unemployment on discrimination, we adapt the empirical model outlined in Maestas et al. (2018). That paper leverages variation in unemployment across states and over time to study disability insurance claims. We augment their formulation by including imputed measures of monthly state exposure by industry. Such an enhancement is possible because industry is included in the EEOC data and especially useful because of the rich variation in unemployment exhibited across industries during the Great Recession (see Appendix Figure A2).

To exploit this additional layer of heterogeneity, we impute monthly industry-specific unemployment at the state level using weighted national unemployment shares by industry. Specifically, we first recognize the number of unemployed individuals in each state s in time period t, U_{st}, equals the weighted sum of industry-specific unemployment j within that state:

$$U_{st} = \sum_{j=1}^{J} w_{jst} U_{jst} \tag{1}$$

where the subscripts denote industries and the weights, w_{jst}, represent each industry's share of total state employment in a period. These employment shares can be directly calculated at the monthly-state level from the Quarterly Census of Employment and Wages (QCEW).

To impute U_{jst}, we assume that industry j's share of unemployment in state s in period t is equal to the corresponding share at the national level n, once reweighted by the relevant employment shares at the state and national level. This assumption can be expressed as:

$$w_{jst} \times \frac{U_{jst}}{U_{st}} = w_{jnt} \times \frac{U_{jnt}}{U_{nt}} \tag{2}$$

As all other variables are available from the QCEW or BLS's Current Employment Statistics, U_{jst} can be imputed by solving as a function of these known quantities.

Armed with these monthly state-industry measures of labor market tightness, we estimate two different types of models, one for hiring and firing volume, and one for hiring and firing merit. Our baseline model for the volume regressions collapses the number of ADEA charges to the industry-state-month level and takes the following form:

$$volume_{jst} = \beta U_{jst} + \gamma_j + \alpha_s + \theta_t + \epsilon_{jst} \tag{3}$$

where $volume_{jst}$ is the number of ADEA hiring or firing discrimination reports filed with the EEOC in a state-industry-month and γ_j, α_s, and θ_t are fixed effects for industry, state, and time. As in Maestas et al. (2018), we use the number unemployed as our measure instead of the unemployment rate to eliminate the confound introduced by industry-state-time differences in the size of the labor force on our outcome measures. The coefficient β can easily be rescaled to estimate the effect of a one percentage point increase in the national unemployment rate on the change in the number of ADEA discrimination claims filed. In robustness checks, we explore alternative measures for labor market slackness, and find similar results.

This baseline model implicitly assumes that past changes in unemployment do not induce contemporaneous discrimination charges. As an alternative, we allow for the possibility that discrimination charge filing behavior responds not just to current movements in the unemployment rate but to previous changes as well. In particular, we implement a polynomial distributed lag model similar to that in Maestas et al. (2018):

$$volume_{jst} = \beta(L) U_{jst} + \gamma_j + \alpha_s + \theta_t + \epsilon_{jst} \tag{4}$$

where the function $\beta(L)$ is a lag polynomial that measures the effects of current and past values of unemployment on volume. The sum of the individual lag weights represents the cumulative number of discrimination reports induced by current and previous changes in unemployment. The appropriate polynomial degree and number of lags are chosen by minimizing the Akaike Information Criteria (AIC)/Bayesian Information Criteria (BIC).

Our baseline model for the merit regressions uses noncollapsed data at the individual case level, so that we can control for relevant case characteristics. We model the dummy variable for whether case i was determined to have merit as:

$$merit_{ijst} = \beta U_{jst} + \gamma_j + \alpha_s + \theta_t + \pi X_{ijst} + \epsilon_{ijst} \tag{5}$$

where X_{ijst} is a vector of control variables associated with a case. We include the race, age, and sex of the charging party, along with the firm's sector (public or private). Time fixed effects implicitly account for the potential impact of changing resource constraints at the EEOC on case success rates. In a robustness check, we additionally include controls for the type of claim being filed (e.g., sexual harassment, wages, suspension) and the class of protected employees involved (e.g., race, sex, disabled); the results are similar, suggesting compositional changes are not driving our results. We also consider polynomial distributed lag models for merit which are analogous to equation (4).

Though state-industry-time differences in local labor market conditions constitute the source of identifying variation, we conservatively cluster our standard errors at the state level. Since charges are filed with one of the 53 local EEO offices, this also allows for arbitrary correlation across the decisions reached by any one local office.

5.2 Correspondence Study Model

For our correspondence study analysis, we estimate two types of regressions, one for rounds 1-3 and another when including rounds 1-4. As a reminder, rounds 1-3 sent either 2 older or 2 younger applications to each job posting. To estimate the effect of unemployment on callback rates for older female applicants using rounds 1-3 of the Farber et al. (2017) study, we use the following specification:

$$call_{ict} = \beta_1 UR_{ct} + \beta_2 older_i + \beta_3 (older_i \times UR_{ct}) + \alpha_c + \theta_t + W_i + \epsilon_{ict} \tag{6}$$

where $call_{ict}$ is an indicator for whether resume i in a given city c at time t received a callback, UR_{ct} denotes the unemployment rate, and $older_i$ indicates whether the applicant is over age 50. Additionally, α_c and θ_t represent city and time fixed effects, respectively, and W_i is a vector of other characteristics assigned to the resume (length of listed unemployment spell and having held a low-level interim job).

The coefficient of interest here is β_3, which tells us how much the callback rate changes for elderly applicants, relative to younger ones, for a one percentage point increase in the local unemployment rate. A negative coefficient would suggest that recessions exacerbate age discrimination on the entry margin. We cluster the standard errors at the city-round level, since that is the level of randomization.

When analyzing the results from Round 4, we add both an indicator for this round of treatment and its interaction with whether the fictitious resume was assigned an older age. We do this because, unlike in rounds 1-3, each employer receives two older applications and two younger applications, rather than just a single pair of either type. Thus, this interaction term captures how older female applicants fare when they are in direct competition with 2 additional younger female applicants, relative to when they are not.[17]

A negative coefficient on this latter interaction term would be consistent with the idea that increasing the number of younger employees applying to a firm increases the extent to which a firm can be selective/discriminatory without bearing as much of a cost. One way to increase the number of options an employer has is to increase the unemployment rate, since more individuals will be looking for a job; this is the source of variation we exploit for both rounds 1-3 and the EEOC analysis. In round 4 of the correspondence study, the options an employer has to choose from is instead experimentally increased by two additional younger applicants.

6 Results

In this section, we first present results using the EEOC data. We begin with a graphical overview, followed by our regression models and several robustness checks. We then report our findings using the correspondence data.

[17]Phillips (2019) makes the general point that spillovers can occur when multiple applications of different types are sent to the same job posting.

6.1 EEOC Charge Results

Graphical overview. Figure 3 provides an initial look at how the combined number of monthly ADEA hiring and firing discrimination charges evolves over the business cycle. Both total charges and merit charges increase by roughly 50% as unemployment rises from a low of 4.5% to a peak of 10%.[18] These aggregate trends, while informative, mask underlying heterogeneity by geography and sector. In the figures which follow, we show how different state and industry components correlate with the business cycle.

Figure 4 provides a state-level view of how both the volume and quality of ADEA hiring and firing claims moved during the pre versus post-recessionary periods.[19] Panels (a) and (b) show that the economies hit hardest by the contraction between 2005 and 2009 were also the ones for which total discrimination charges and their average quality increased most sharply. Likewise, in panels (c) and (d), each state's unemployment rate change between 2009 and 2015 is plotted against the corresponding change in the volume and quality of ADEA charges, respectively. It is clear from the graphs that the state economies that recovered least from the Great Recession were also the ones that sustained both the highest volume and average quality of claims.

Figure 5 presents a similar set of graphs, but this time using industry-specific changes in the unemployment rate. Industries more susceptible to the negative labor demand shocks perpetuated by the Great Recession, such as mining and construction, were also those that experienced the largest increase in the volume of charges between 2005-2009 (panel a). Conversely, industries recovering more fully exhibited the largest reduction in charges from 2009-2015 (panel c). And as with the nature of the geographic shocks, the countercyclical relationship of merit is borne of both an increase during bad times (panel b) and a curtailment in the wake of the recovery (panel d). The differently sized responses to these

[18]The number of merit charges drops following the break in the data near the end of 2011. We include time fixed effects in all of our regressions, which should capture this level difference. Our results are robust to only using the period prior to the break in the data.

[19]The periods are chosen based on the official NBER recession end date.

shocks indicate that the state and industry sources of variation are somewhat unique from one another. Combining both types of shocks, then, generates even richer variation in labor market conditions, and should yield greater precision in estimation.

Volume regressions. We now turn to regression results for the volume of discrimination charges at the industry×state×month level. Table 3 documents clearly the countercyclical nature of age discrimination hiring and firing volume over the business cycle. Start with column (1), which regresses the combined number of charges (firing and hiring) on the contemporaneous number of unemployed individuals as described in equation (3). The point estimate reveals that when the number of unemployed persons rises by 100,000, there will be 1.97 more age discrimination charges. This coefficient can be easily rescaled to estimate the effect of a one percentage point increase in the national unemployment rate.[20] The rescaled estimate, which we label in bold as the "effect of 1 pp ↑ unemp" in our tables, reveals that each one percentage point increase in the national unemployment rate generates 30.3 additional monthly ADEA discrimination charges off a baseline of 665.0 charges, or a 4.6% increase. Alternatively, the elasticity of charges with respect to the unemployment rate is 0.31.

Splitting the sample into firing and hiring cases makes clear that most of the increase in age discrimination is driven by the firing margin. This makes sense, as firing cases are much more common (85% of the sample). Table 3 indicates that a one percentage point increase in national unemployment leads to 27 additional monthly firing charges (column 3), compared to just 3.25 additional hiring charges (column 5). In percent terms, this is a 4.8% increase in firing charges and 3.4% in hiring charges.

It is possible that discrimination effects are dynamic, growing over the life-cycle of the recession. To allow for this, we turn to the polynomial distributed lag model of equation (4). The AIC and BIC both always select an optimal lag length of 6. Column (2) reports

[20] Specifically, we multiply the coefficient by 1 percent times the average size of the labor force over the sample period (154 million workers).

these estimates for the combination of hiring and firing. Most of the effect shows up contemporaneously, with little evidence of lagged unemployment mattering. Moreover, when we integrate the effects over all periods, we end up with a total effect which is similar to that found in the contemporaneous model of column (1). The same is also true when we examine the firing and hiring margins separately.

Thus, we can use either the contemporaneous or polynomial distributed lag estimates to make in-sample predictions for how the Great Recession induced hiring and firing discrimination reports. During that period, the national unemployment rate more than doubled from 4.5% to 10%, suggesting that ADEA firing discrimination claims increased by 149 per month, a 26% jump relative to the mean. ADEA hiring discrimination reports, on the other hand, are predicted to have increased by 18 per month, a 19% increase.

Merit regressions. While the increases in volume are important in their own right, in isolation they do not reveal whether actual employer misconduct rose, or whether the increase is driven by lower quality filings in the midst of a weak job market. A sufficient condition for elevated age discrimination during a recession is that average case quality does not decrease, a condition we discussed in Section 4 and test for using our merit variable.

Table 4 estimates the relationship between the number unemployed in a state-industry-month and the quality of ADEA firing and hiring charges. The dependent variable is whether a claimant's case was found to have merit. Both age and female are positive predictors of the success of an ADEA discrimination claim. Charges are also 4 percentage points more likely to be meritorious when filed against private versus public firms.

Somewhat remarkably, the quality of combined age discrimination charges (firing+hiring) *increases* during the Great Recession. The implied effect in column (1) is that each one percentage point increase in a state-industry's monthly unemployment rate engenders a 0.0012 increase in the fraction of claims with merit.[21] This is relative to an average merit

[21] To calculated the implied effect, we multiply the estimated coefficient by 1% times the average size of a state-industry's labor force (681,000).

rate of 0.167, and so translates to a 0.7% increase. Looking at separate merit regressions for firing and hiring in columns (3) and (5), a similar pattern emerges, although only the firing estimate is statistically significant at conventional levels. The polynomial distributed lag models have noisy estimates for individual time periods, but when integrated yield similar total implied effects.

Combining the volume and merit results, we conclude that the level of actual discrimination rose during the Great Recession. During that period, the national unemployment rate rose by 5.5 percentage points from trough to peak, implying the fraction of cases with merit rose by 0.67 percentage points, or a 4% increase relative to the mean.

Robustness and alternative hypotheses. Table A2 reports a variety of specification checks, both for the volume (top panel) and merit regressions (bottom panel). Mirroring the graphical analysis of Figures 4 and 5, in columns (1) and (2) we separately test for effects during the run-up (2005-2009Q2) and recovery from (2009Q3-2015) the Great Recession. While the volume effects of a 1 percentage point increase in unemployment are similar in either period (4.2% in the earlier subsample and 4.6% in the latter), the countercyclical response of merit is nearly three times stronger in the first half of the sample (1.3% increase versus a 0.5% increase).[22] Column (3) demonstrates that the volume and quality results are nearly the same when the sample is restricted to workers over the age of 50. In column (4), we replace the date of filing with the self-reported date of the discriminatory event; while the direction and precision of the estimated effects are similar, the coefficients for both volume and merit shrink somewhat.

The results are likewise robust to only using variation in unemployment at the state level (column (5)), with even larger percent changes for both volume (8.9%) and merit (1.0%). In column (6), we use the unemployment rate as the independent variable and for volume use the number of charges filed in a state-month divided by the size of the relevant

[22] If we instead use the time period before the missing-data break period (2005-October 2010), the estimates imply a 4.1% change effect for volume and a 0.9% change effect for merit.

labor force as the dependent variable (the merit variable remains the same as before). This rate-on-rate specification is less precisely estimated compared to column (5), but results in similarly-sized estimates. Finally, column (7) uses employment to population ratios instead of unemployment rates as a measure of state labor market tightness.[23] Each one percentage point drop in the employment to population ratio increases discrimination charges by 4.6% and increases merit by 2.1%. The relatively larger merit response makes sense given that (i) the employment to population ratio exhibits less variation compared to the unemployment rate, and (ii) the employment to population ratio dropped sharply in the run-up to the GR (the period where we find a larger effect on merit in column (1)) but changed little in its aftermath.

Table 5 explores a variety of alternative explanations for why merit increases during recessions.[24] One possibility is that other case characteristics that are correlated with ADEA charges, such as Americans with Disabilities Act (ADA) or retaliation claims, are driving the results. Column (1) controls for the presence of all other bases and issues raised (i.e., the types of case characteristics summarized in Table A1) yet finds the headline merit estimate unchanged. Another possibility is that the claimant employs more resources to improve their chances of winning when the job market languishes. As a partial test of this, we include a control for whether the charging party obtained outside legal representation in column (2). While legal representation increases the chance a claimant receives a merit ruling by 4 percentage points, the unemployment coefficient remains virtually unchanged. Neither is it the case that the retention of legal representation is more common during recessions.[25] It is also possible that employers are reluctant to hire (or quick to fire) older workers if they subscribe to the stereotype that they are incapable of handling tasks that require a

[23]To convert the volume of charges filed to a rate, we divide the number of charges by the size of each state's population. The merit variable remains the same as before.

[24]The level of resources the EEOC has at its disposal for investigating claims both over time and across geography is ruled out as an explanation with the inclusion of month and state fixed effects in our regressions.

[25]We estimate that each one percentage point increase in the national unemployment rate reduces the fraction of charging parties that privately obtain legal representation by a statistically insignificant 0.8 percentage points, off a 15.7% baseline.

high degree of technological sophistication (McCann and Keaton, 2013; Burn et al., 2019). Thus we test in column (3) whether merit increases in ADEA charges are driven by 27 high-tech industries–identified as those whose share of Science, Technology, Engineering, and Mathematics (STEM) jobs exceeds 2.5 times the national industry average–but find no evidence in favor of such a hypothesis.[26]

Another alternative is that merit increases countercyclically due to compositional changes in the skill level of workers that file claims during recessions.[27] The compensation awarded to successful claimants should, in theory, equal the value of the lost wages due to a firm's discriminatory firing. If wages are a reasonably good proxy for skill, the positive selection story would imply that the average compensation won by illegally discharged employees would be countercyclical over the business cycle. But column (5) finds a negligible impact of unemployment on the average damages awarded amongst those cases for which any compensation is provided, suggesting no change in the composition of cases by benefit level.

A different compositional explanation is that larger firms, against which discrimination claimants have less success (see Appendix Figure A3), are less likely to have been accused during recessions. However, we find that whereas the fraction of charges accounted for by larger firms was less than proportional to the share of workers employed by such firms prior to the Great Recession, larger firms contribute a more than proportionate share of ADEA charges in its aftermath.[28]

We also examine whether merit rulings reflect economic considerations–such as salary, benefits, and productivity–rather than the unequal treatment of an equally performing cohort

[26]This methodology was created by the BLS and is described here https://www.bls.gov/opub/btn/volume-7/high-tech-industries-an-analysis-of-employment-wages-and-output.htm?viewfull#edn3

[27]Consider, for example, a scenario in which only bad workers file claims when jobs are plentiful whereas more skilled workers simply switch jobs when they are terminated illegally due to age considerations. In the midst of a recession, however, even high-skilled older workers may fail in their job search and so would be more inclined to file discrimination claims. This would be consistent with the model proposed by Kroft et al. (2013), except that the act of filing a discrimination claim–rather than incurring a longer unemployment spell–during tight labor markets conveys the less noisy negative signal of worker quality.

[28]We further find that the effect of recessions on merit is not monotonically increasing in firm size. Relative to firms having 201-500 employees, the effect of a one pp increase in the unemployment rate on merit for the largest firms is 0, as compared to a positive 2.8 pp ($p<0.10$) for firms having 101-200 employees and a statistically insignificant negative 1 pp for firms with fewer than 100 employees.

of older workers. As a reminder, reasonable economic factors other than age are perfectly legal grounds for dismissal, even if they have a disparate impact on older workers (see Section 2.2), and so should not result in a merit ruling. To explore this empirically, we first make the observation that if workers are paid their marginal product, wage dispersion in an industry should reflect the underlying productivity distribution of its workers. This is especially true the more decentralized is the prevailing wage-bargaining system (Dahl et al., 2013). The relative absence of intra-industry wage dispersion then implies either that productivity is uniform or that differences in productivity are not easily observable. Furthermore, if recession-generated increases in merit rulings are driven by high wage-dispersion industries, this would call into question the notion that we are capturing firings unjustified by countercyclical upskilling or cost-conscious downsizing.

To test this, we use the 2004 BLS Occupational Employment Statistics (OES) to construct a measure of industry wage dispersion: the quartile coefficient of wage dispersion.[29] Among the low wage-dispersion industries are those found in food services and accommodation, retail, and transportation and utilities. We modify our merit regression to include a measure of wage dispersion at the 4-digit industry level (290 industries) and its interaction with the level of unemployment.[30] Column (4) of Table 5 finds a sizable negative coefficient on the interaction term, providing evidence that in slack labor markets, meritorious ADEA discharge claims are being filed in industries for which differences in output across workers are less pronounced.[31] The implication is that the recessionary uptick in merit is unlikely to

[29] The quartile coefficient of wage dispersion is defined as $(P_{75}-P_{25})/(P_{75}+P_{25})$, where P_{75} and P_{25} are the 75th and 25th percentiles. We obtain similar results if we use the 90th and 10th percentiles instead. We use measures of wage dispersion from the year 2004 so that they are uncontaminated by any recession-induced compression.

[30] In 7.5% of observations, the quartile coefficient of wage dispersion is not available at the 4-digit industry level either because the employment cell is too small to compute percentile wages or because the percentile wage is top-coded at $145,600 (in 2004 dollars). In either case, we replace the missing value with that of its 2-digit industry measure of wage dispersion.

[31] We limit the sample to firing cases for this analysis since productivity is more likely to be observed for those already employed. However, the results are robust to including hiring cases as well. To rule out the possibility that the dispersion interaction is instead capturing low-wage industries, which tend to have more compressed wage distributions, we additionally tried interacting unemployment with median industry wages. The measured wage dispersion interaction effect is insensitive to this modification.

have resulted from age-blind economic calculations.

6.2 Correspondence Study Results

We now shift focus to our complementary analysis using the correspondence study data, where we test whether older women have a harder time finding a job as the labor market deteriorates. We begin with a graphical view of the data. Figure 6 plots regression-adjusted callback rates for applications assigned older versus younger ages–i.e., the age penalty– against the local unemployment rate within each city and time period for rounds 1-3 of the Farber et al. (2017) data.[32] There is a clear negative slope, implying that weak labor markets exacerbate age discrimination.

For a more precise estimate of the relationship between recessions and the intensity of age discrimination against women, we present regression results based on equation 6. The key coefficient on the interaction term, $older \times unemployment\ rate_{ct}$, tells us how much the callback rate changes for older applicants, relative to younger ones, for each one percentage point increase in the local unemployment rate. Because federal, state, and local government employers are bound by additional regulations stipulating that all applicants receive a fair chance at employment, they are likely to have less discretion to respond to job inquiries in a discriminatory fashion.[33] To account for this, we control for the fraction of public employment in a city as well as an interaction term, $older \times public_{ct}$, which tells us the effect of a one percentage point increase in the size of the public sector on the likelihood that an older applicant receives a callback. This mainly impacts Sacramento, which is a state capital, and has a public sector which is approximately twice as large as the remaining 7 cities (see Appendix Figure A4).

The first column of Table 6 reports estimates without city or time fixed effects. The second column adds these fixed effects into the regression, and shows the estimates are similar.

[32] The regression-adjustment controls for other characteristics found on the resume, such as the length of the applicant's listed unemployment spell and whether or not the applicant held a low-level interim job.

[33] Consistent with this observation, using EEOC charge data, female ADEA hiring discrimination claims filed against private versus public companies are nearly 6 percentage points more likely to have merit.

Each one percentage point rise in the local unemployment rate reduces the callback rate for older applicants by 2.1 percentage points in the first three rounds of the correspondence study, off a baseline 11.6% callback rate. The estimate with fixed effects translates to an 18% decrease in the number of callbacks for older applicants. As anticipated, increases in the size of the public sector appear to reduce age discrimination as well. In column (3), we add an additional control for $public \times unemployment\ rate_{ct}$, which while an important callback predictor, has no measurable effect on our coefficient of interest.

Next, we add to our analysis the 4th round of the study. Recall the 4th round treatment is different from the first three as two "younger" and two "older" applications are submitted to each posting, as opposed to just one set or the other. Whereas the variation in the first three rounds emanates from differences in local labor market conditions over time and across cities, the fourth round additionally introduces within-job posting variation in age. Both treatments tell us something different about the effect of reduced labor market competition on outcomes for older applicants. Therefore, we include an interaction term for $older \times \mathbb{1}(competing)$, where $\mathbb{1}(competing)$ is a dummy variable for being an observation from the 4th round of the survey (and hence competing against an additional two younger applicants).

The first column of Table 7 does not include city or time fixed effects, while the second column does. Focusing on the second column, similar to what we found in Table 6, older applicants are relatively less likely to receive a callback in cities that recovered less successfully from the Great Recession. In percent terms relative to the mean, the effect size of -1.67 percentage points represents a 15% drop.

The interaction term $older \times \mathbb{1}(competing)$ tells us how older workers fare when they are in direct competition with two additional younger workers versus when they are not. The estimate in column (3) suggests that, all else equal, an older female applying to an administrative support position is 6.8 percentage points less likely to receive a callback when she is competing with two additional younger female applicants, a sizable 63% reduction relative to the mean. We interpret this latter result as alternative evidence that when an employer faces a lower search cost to hire younger workers, they tend to disfavor older applicants.

It would be interesting to extend this type of analysis using data from other existing correspondence studies on age discrimination. Unfortunately, either sample sizes are too small (Bendick et al., 1997, 1999; Riach and Rich, 2010), the number of cities across which the resumes were sent is too small (Lahey, 2008), or the variation in unemployment is too limited (Neumark et al., 2019a,b). While Neumark et al. (2019a) conducted a correspondence study across twelve different cities and Neumark et al. (2019b) across 50 states, they did so during 2015 or 2016, when even the worst labor markets were mostly recovered from the Great Recession. Hence, these two studies occurred during relatively tight labor markets and provide substantially less variation in unemployment. In the Farber et al. (2017) study we analyze, the mean unemployment rate across cities and time is 6.9%, with a variance of 3.0%. In comparison, Neumark et al. (2019a) has a mean of 5.3% and a variance of 0.6%, and Neumark et al. (2019b) has a mean of 4.4% and a variance of 0.9%.

7 Conclusion

This paper tests the Becker (1957) prediction that competition should reduce age discrimination, using economic recessions as a source of reduced labor market competition. We are able to separately test for countercyclical changes in firing and hiring discrimination using two complementary analyses.

In the first analysis, we deploy novel data on discrimination charge filings with the EEOC before, during, and after the Great Recession. Our estimates imply that from the trough to the peak in unemployment, age-related firing and hiring discrimination charges increased by 26% and 19%, respectively. We use a proxy for the quality of a claim to disentangle countercyclical employee filing incentives and genuine employer misconduct. We estimate that the Great Recession induced a 4% increase in the quality of firing and hiring discrimination claims. Under mild assumptions, these results are sufficient to conclude that both actual and reported discrimination against older workers increased during the Great Recession.

In our second analysis, we repurpose data from the correspondence study of Farber et al. (2017) to examine how older female job applicants fare when unemployment is higher. We find that a one percentage point increase in unemployment leads to an 18% decrease in the relative likelihood of receiving a callback. Moreover, when an older female is in direct competition with an additional two younger applicants, her callback rate falls by 63%.

Combined, these two analyses provide compelling evidence that negative labor demand shocks increase employment discrimination against both current and prospective older employees. The findings suggest that whatever power disparities exist between an individual and her employer, they grow during recessions so that firms may engage in discrimination against workers with relative impunity. From a policy perspective, this argues for increased support of deterrence efforts by guardians against corporate malfeasance–like the EEOC–during periods of economic malaise. A similar conclusion could be extrapolated to other federal watchdog agencies, such as the Occupational Safety and Health Administration (OSHA), as worker injury risk has been shown to increase during economic contractions (Boone et al., 2011).

In future work, it would be interesting to study how discrimination for other classes of workers evolves over the business cycle. However, one challenge to studying classes protected by Title VII (e.g., race or sex), is that employment practices that generate a disparate impact are illegal, complicating the interpretation of any findings. In contrast, the ADEA allows for firings based on cost or productivity considerations, even if they disproportionately affect older workers. It would also be useful to explore how other market shocks, such as changes in product market competition, affect discrimination in firing and hiring.[34]

[34] Along these lines, Black and Brainerd (2004) find that globalization reduces the scope for firm discrimination in wages.

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8 Figures

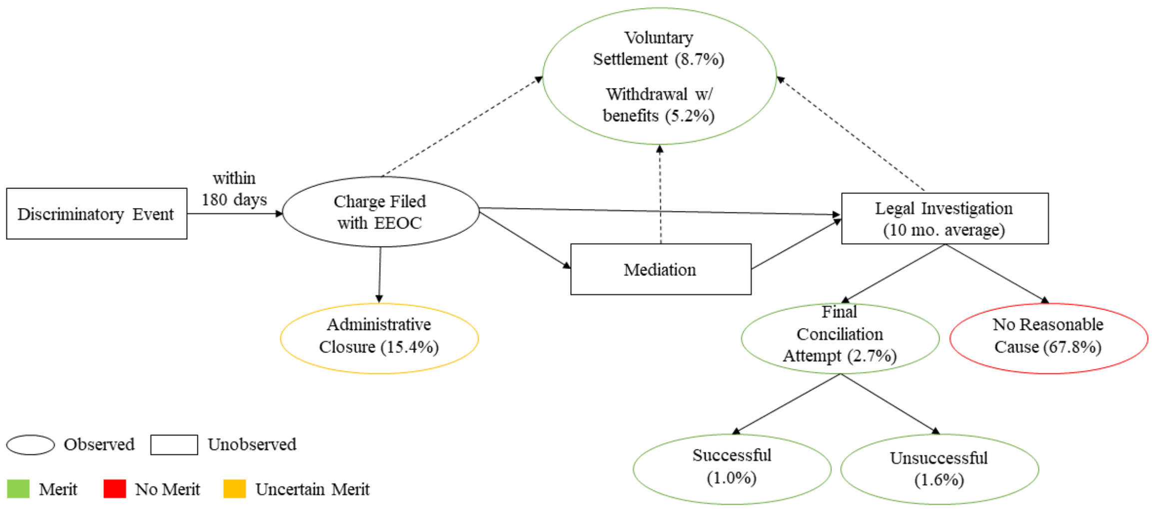

Figure 1: EEOC Charge Filing Process and Resolution

Flow chart describing the order of events, beginning with the discriminatory action and ending with the resolution of the EEOC discrimination charge. Percentages are shown for ADEA hiring and firing charges in our baseline sample. A small fraction of charges (0.3%) are resolved through EEOC-initiated litigation (not shown above).

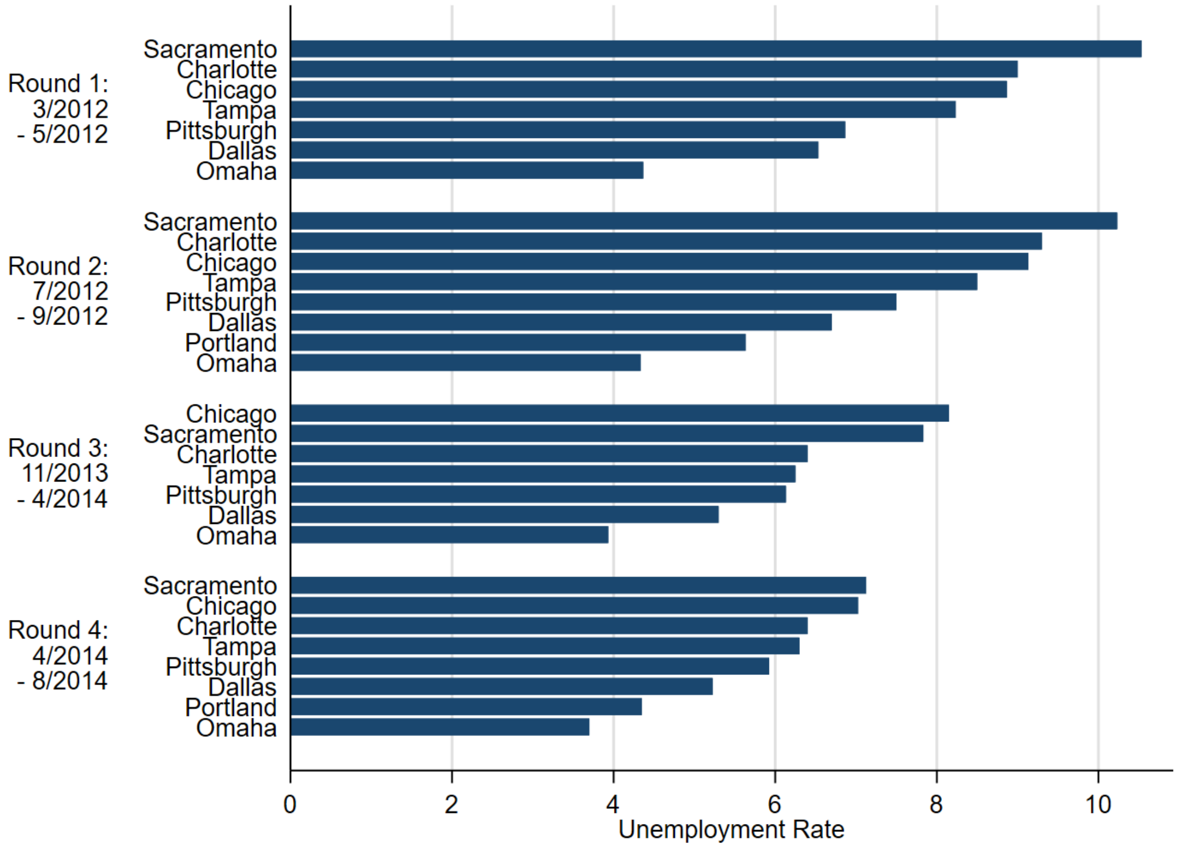

Figure 2: Local Unemployment Rates in Correspondence Study

Unemployment rates calculated at the MSA level for a city, averaged over the relevant time period in a round, for the Farber et al. (2017) data.

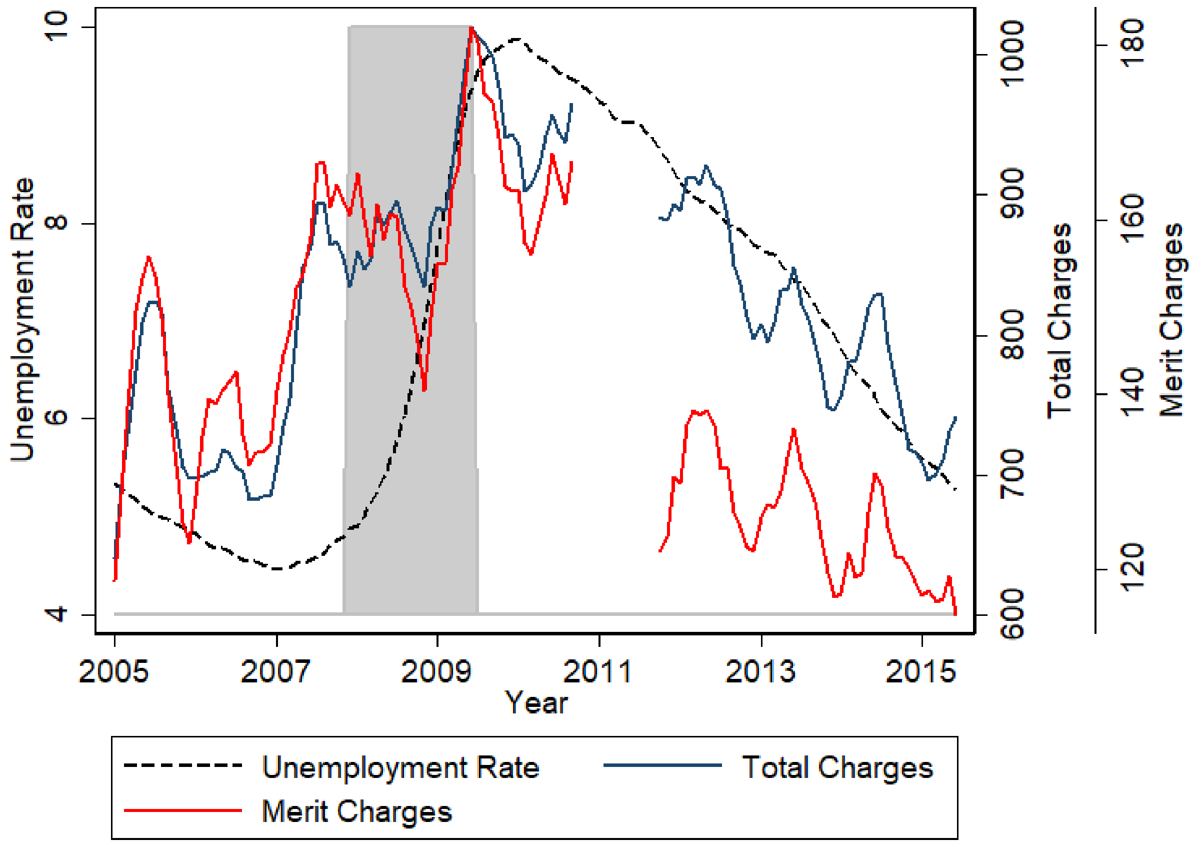

Figure 3: ADEA Hiring and Firing Discrimination Charges over Time

Seven-month smoothed monthly number of nationally aggregated hiring and firing ADEA discrimination charges filed with the EEOC, the smoothed number of those charges with merit, and the smoothed unemployment rate. Data is missing from November 2010 through September 2011. Shading indicates the Great Recession, as defined by the NBER.

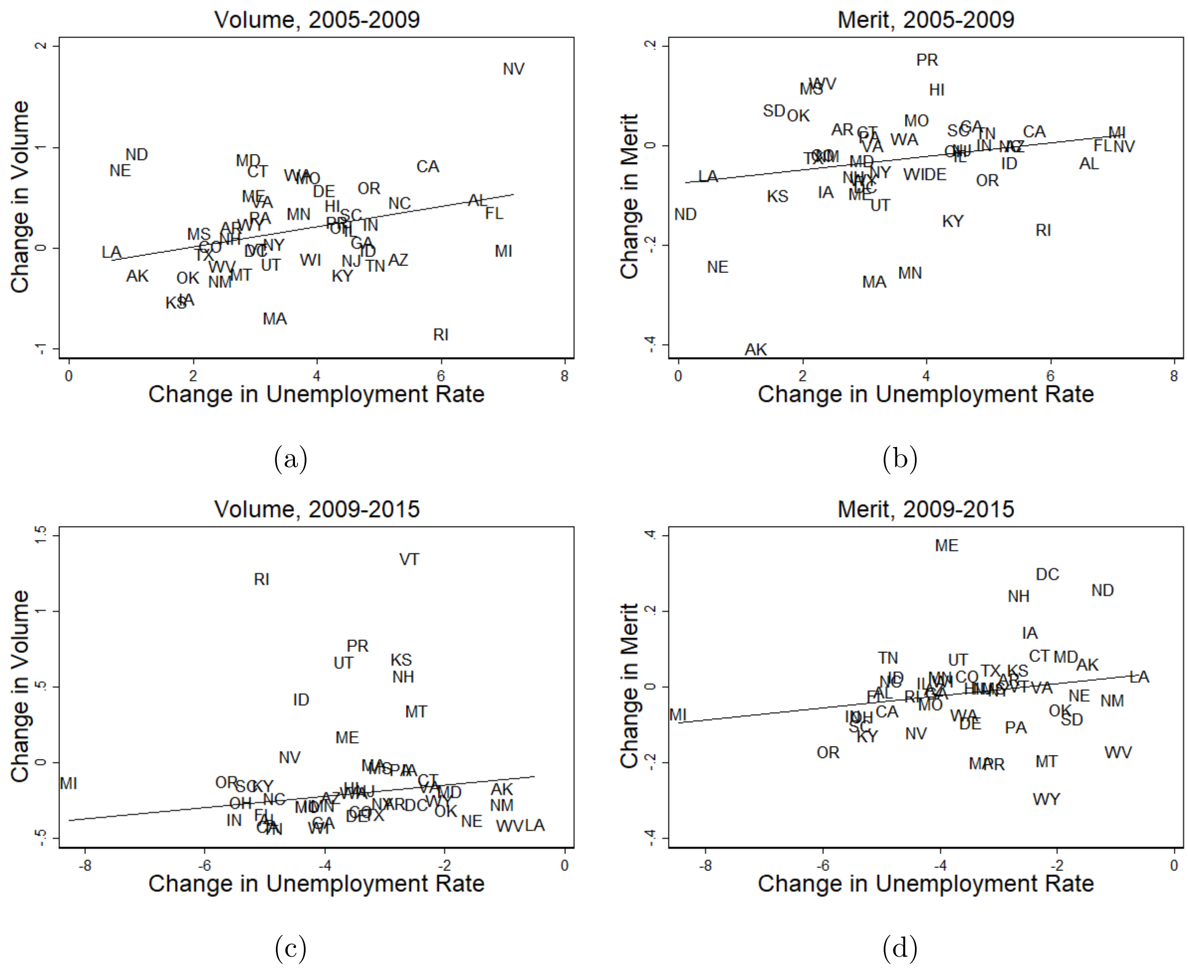

Figure 4: ADEA Firing + Hiring Charges Across the Great Recession (by State)

Change in volume is defined as the fractional change in charges relative to the size of each state's labor force. For visual clarity, the small state of ND is omitted from panel 4c; its changes in the unemployment rate and volume are -1.53% and 349%, respectively.

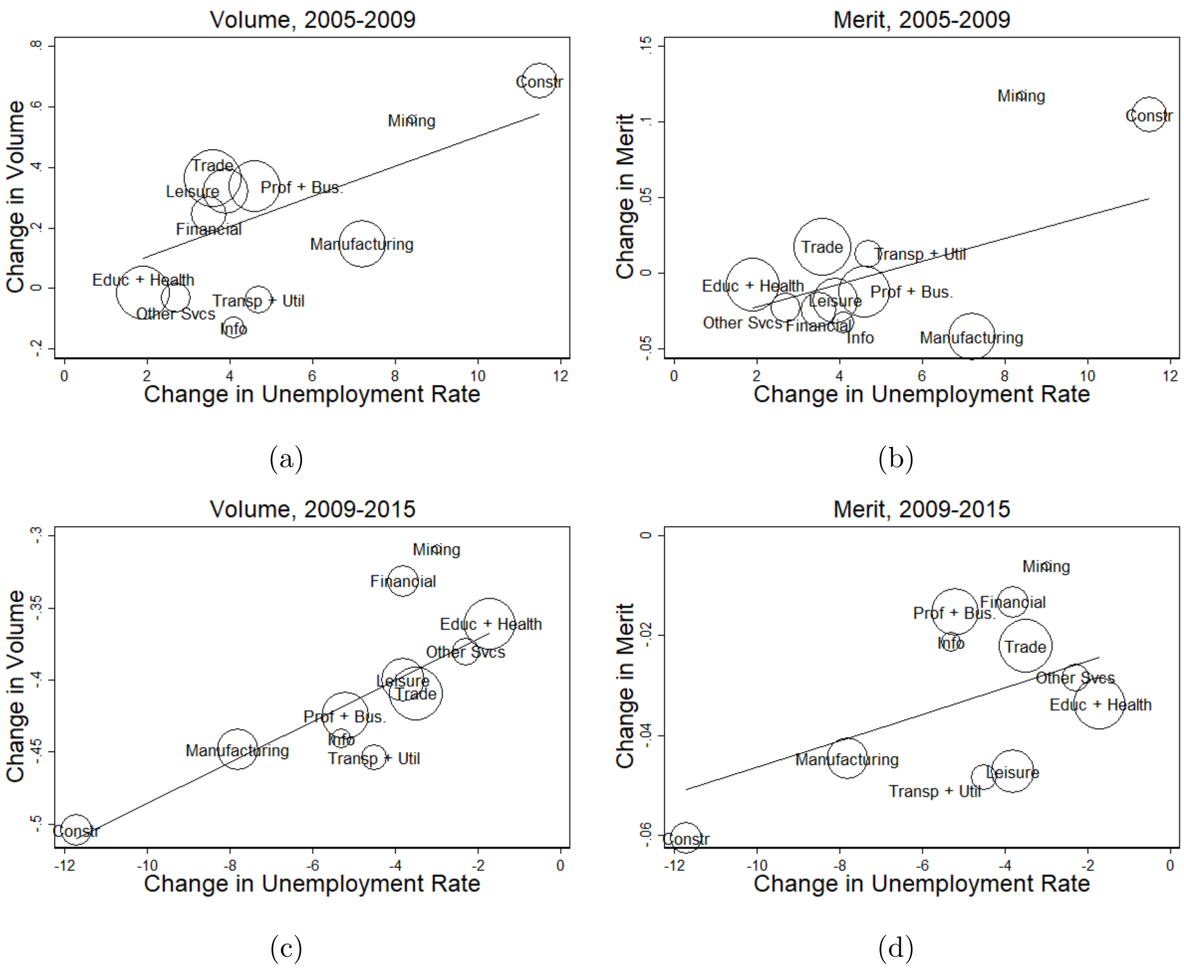

Figure 5: ADEA Firing + Hiring Charges Across The Great Recession (by Industry)

Change in volume is defined as the fractional change in charges relative to the size of each industry's labor force.

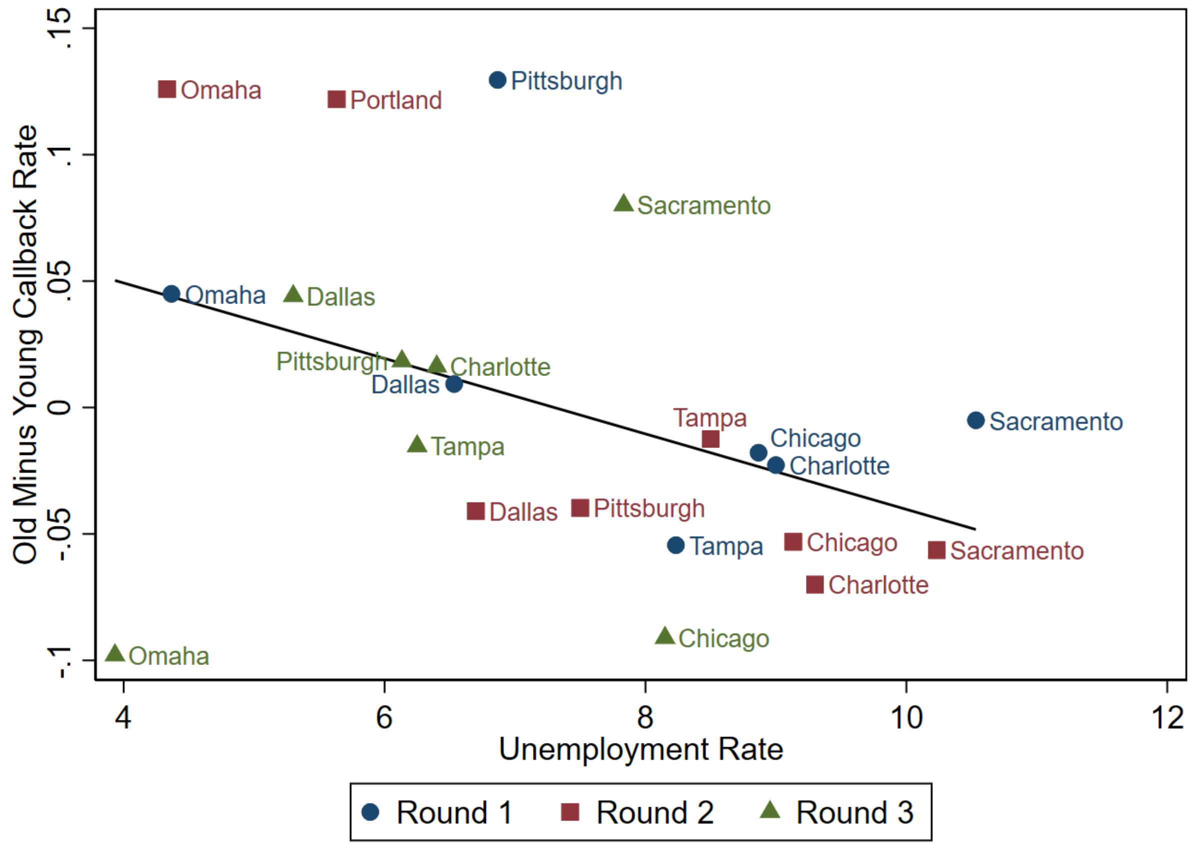

Figure 6: Age Callback Penalty by Local Unemployment Rate, Rounds 1-3

Markers are the regression-adjusted differences in average callback rates between older and younger applicants. The black line is the unweighted regression line through the markers.

9 Tables

Table 1: Resolution of ADEA Charges, 2005-2015

	Firing	Hiring
Resolutions by Type		
Merit	0.172	0.141
Settlement with benefits	0.091	0.067
Withdrawal with benefits	0.055	0.035
Reasonable cause	0.025	0.038
Successful conciliation	0.010	0.013
Unsuccessful conciliation	0.015	0.025
No Merit		
No reasonable cause	0.669	0.735
Uncertain Merit		
Administrative closures	0.159	0.125
Compensation Awarded		
Average damages awarded	$29,200	$21,929
Total monetary benefits	$280.8	$22.5
Charges	68,164	11,617

Average damages awarded is conditional on winning any compensation. Monetary benefits are in millions of dollars and exclude those obtained through litigation.

Table 2: Job Postings by City and Time Period in Correspondence Study

	Round 1: 03-05/2012	Round 2: 07-09/2012	Round 3: 11/2013-04/2014	Round 4: 04-08/2014	Total
Charlotte, NC	178	167	120	169	634
Chicago, IL	173	165	67	275	680
Dallas, TX	165	147	161	330	803
Omaha, NE	85	147	122	110	464
Pittsburgh, PA	145	156	157	149	607
Portland, ME	0	120	0	87	207
Sacramento, CA	110	156	93	170	529
Tampa, FL	171	157	114	228	670
Total job postings	1,027	1,215	834	1,518	4,594
Applications/posting	2	2	2	4	

Data collected by Farber et al. (2017). In rounds 1-3 either two younger or two older applications were sent to each job posting. In round 4, two younger and two older applications were sent to each job posting.

Table 3: Charge Volume and Unemployment

	Firing + Hiring		Firing		Hiring	
	Base	PDL	Base	PDL	Base	PDL
Dep. var. = # of charges	(1)	(2)	(3)	(4)	(5)	
$\text{unemployment}_{jst}$	1.97***	1.45***	1.76***	1.30***	0.21***	0.15
	(0.43)	(0.31)	(0.41)	(0.34)	(0.05)	(0.11)
$\text{unemployment}_{jst-1}$		0.06		0.25		-0.19
		(0.32)		(0.24)		(0.18)
$\text{unemployment}_{jst-2}$		0.02		-0.21		0.24*
		(0.25)		(0.25)		(0.13)
$\text{unemployment}_{jst-3}$		0.41		0.41*		-0.01
		(0.31)		(0.24)		(0.14)
$\text{unemployment}_{jst-4}$		-0.25		-0.23		-0.03
		(0.45)		(0.39)		(0.12)
$\text{unemployment}_{jst-5}$		0.33		0.42		-0.09
		(0.23)		(0.29)		(0.09)
$\text{unemployment}_{jst-6}$		-0.01		-0.16		0.15
		(0.35)		(0.37)		(0.09)
Effect of 1 pp ↑ unemp	**30.3**	**30.8**	**27.0**	**27.4**	**3.25**	**3.38**
Mean(# national charges)	665.0	665.0	568.6	568.6	96.3	96.3
% change	4.6	4.6	4.7	4.8	3.4	3.5
Elasticity	0.31	0.32	0.32	0.33	0.23	0.24
N (state-industry-months)	76,485	76,485	76,485	76,485	76,485	76,485
Polynomial degree		quadratic		quadratic		quadratic
AIC	321,274	321,113	300,064	299,924	139,744	139,682
R^2	0.143		0.432		0.118	

Industry-state-month level regressions for the volume of cases. The sample period spans 2005-2015. Regression coefficients show the change in charges filed per 100,000 increase in the number unemployed. Bolded 'Effect of 1 pp ↑ unemp' is the implied effect of a one percentage point increase in the national unemployment rate on the national monthly number of charges filed. The PDL model estimates the cumulative effect of previous and contemporaneous unemployment on current period charges using a polynomial distributed lag model; the total effect is the sum of coefficients across all lags. The AIC is used to choose the number of lags; while not shown, the BIC chooses the same lag structure. All regressions include state, time, and industry fixed effects. Standard errors clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Charge Quality and Unemployment

	Firing + Hiring		Firing		Hiring	
	Base	PDL	Base	PDL	Base	PDL
Dep. var. = $\mathbb{1}(merit)$	(1)	(2)	(3)	(4)	(5)	(6)
unemployment$_{jst}$	18.0***	-5.3	13.6**	-17.0	19.4	9.6
	(4.56)	(21.2)	(5.71)	(16.7)	(17.3)	(68.5)
unemployment$_{jst-1}$		25.4		27.3		30.5
		(30.9)		(30.8)		(86.4)
unemployment$_{jst-2}$		-15.9		12.4		-107*
		(42.2)		(56.8)		(53.5)
unemployment$_{jst-3}$		57.4**		6.43		234**
		(22.3)		(21.6)		(98.9)
unemployment$_{jst-4}$		-25.2		-4.70		-98.6
		(27.2)		(27.9)		(62.6)
unemployment$_{jst-5}$		10.4		43.9*		-166
		(24.1)		(23.4)		(115)
unemployment$_{jst-6}$		-29.6		-55.5		115
		(37.9)		(33.8)		(107)
age	0.0015***	0.0015***	0.0015***	0.0015***	0.0016***	0.0016***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
female	0.0184***	0.0184***	0.0149***	0.0149***	0.0301***	0.0301***
	(0.0024)	(0.0024)	(0.0026)	(0.0026)	(0.0061)	(0.0061)
private	0.0405***	0.0405***	0.0406***	0.0405***	0.0415***	0.0412***
	(0.0055)	(0.0055)	(0.0064)	(0.0065)	(0.0094)	(0.0093)
Effect of 1 pp ↑ unemp	**0.0012**	**0.0012**	**0.0009**	**0.0009**	**0.0013**	**0.0012**
Mean(merit)	.167	.167	.172	.172	.141	.141
% change	0.7	0.7	0.5	0.5	0.9	0.8
Elasticity	0.04	0.04	0.03	0.03	0.05	0.05
N (charges)	78,202	78,202	68,157	68,157	11,614	11,614
Polynomial degree		quadratic		quadratic		linear
AIC	67,660	67,654	60,533	60,528	8,431	8,430
R^2	0.017		0.018		0.042	

Individual level regressions for whether a case is determined to have merit. The sample period spans 2005-2015. Regression coefficients on 'unemployment' are multiplied by 10^{-8}. Bolded 'Effect of 1 pp ↑ unemp' is the implied effect of a one percentage point increase in a state-industry's monthly unemployment rate on the fraction of charges found to have had merit. The PDL model estimates the cumulative effect of previous and contemporaneous unemployment on current period charges using a polynomial distributed lag model; the total effect is the sum of coefficients across all lags. The AIC is used to choose the number of lags; while not shown, the BIC chooses the same lag structure. All regressions include state, time, and industry fixed effects. Standard errors clustered at the state level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Alternative Hypotheses for the Increase in Charge Quality

	$\mathbb{1}(merit)$				Log(benefit)
	(1)	(2)	(3)	(4)	(5)
$\text{unemployment}_{jst}$	17.7***	18.5***	18.1***	42.3***	-0.095
	(4.50)	(4.80)	(4.85)	(13.3)	(49.3)
legal representation		0.040***			
		(0.008)			
unemployment×high-tech			-2.00		
			(10.2)		
high-tech industry			0.009		
			(0.012)		
unemployment×dispersion				-100**	
				(43.1)	
dispersion				0.211***	
				(0.054)	
Effect of 1 pp ↑ unemp	**0.0012**	**0.0013**	**0.0012**	**0.0007**	**-0.0015**
Mean(dep. var.)	.167	.167	.167	.172	9.28
% change	0.7	0.7	0.7	0.4	-0.02
Elasticity	0.04	0.04	0.04	0.02	-0.001
Issue and Basis FEs	X				X
Discharges only				X	X
N (charges)	77,308	78,205	78,205	68,159	9,615
R^2	0.022	0.019	0.017	0.022	0.143

Regression specifications parallel those of Table 4. Bolded 'Effect of 1 pp ↑ unemp' is the implied effect of a one percentage point increase in a state-industry's monthly unemployment rate on the fraction of charges found to have had merit. Column 1 adds in fixed effects for the issues and bases included in a case, and column 2 adds in a variable for whether the claimant retained outside legal representation. Column 3 controls separately for 27 'high-tech' industries–identified as those whose share of STEM workers exceeds 2.5 times the national average–and its interaction with unemployment. In column 4, the variable 'dispersion' is the quartile coefficient of wage dispersion (mean = 0.315, sd = 0.063), and we evaluate the effect of a 1 pp increase in unemployment at the mean level of industry wage dispersion. Column 5 uses the natural log of monetary benefits in discharge cases for which the claimant receives positive compensation. All regressions include state, time, and industry fixed effects and controls for age, female, race, and private firm. Standard errors clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Callback Rates and Labor Market Conditions (Rounds 1-3)

Dep. var. = $\mathbb{1}(callback)$	(1)	(2)	(3)
older x unemployment rate$_{ct}$	-0.0219**	-0.0207**	-0.0207**
	(0.0091)	(0.0091)	(0.0091)
older	0.0068	-0.0005	0.0016
	(0.0634)	(0.0634)	(0.0630)
unemployment rate$_{ct}$	-0.0048	-0.0027	0.0592**
	(0.0048)	(0.0129)	(0.0239)
public$_{ct}$ x unemployment rate$_{ct}$			-0.3538***
			(0.1025)
public$_{ct}$	-0.412		
	(0.2539)		
older x public$_{ct}$	1.032***	1.0249***	0.9993**
	(0.3598)	(0.3601)	(0.3586)
Mean(callback rate)	.116	.116	.116
City FE		X	X
Time FE		X	X
Job postings	3,076	3,076	3,076
Resumes	6,152	6,152	6,152
City-rounds	22	22	22
R^2	.010	.022	.023

Correspondence study data originally collected by Farber et al. (2017) across 8 cities and 3 different time periods. In rounds 1-3 either two younger or two older applications were sent to each job posting. The variable 'older' is a dummy for whether the applicant is over age 50, 'unemployment rate$_{ct}$' is the city-round unemployment rate, and 'public$_{ct}$' is the fraction of the city's workforce employed in the public sector. Additional controls include the ficticious applicant's unemployment spell length and whether they held a low-level interim job. Standard errors clustered at the city-round level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Callback Rates and Labor Market Competition (All 4 Rounds)

Dep. var. = $\mathbb{1}(callback)$	(1)	(2)	(3)
older x $\mathbb{1}$(competing)	-0.0394*	-0.0681**	-0.0682**
	(0.0218)	(0.0260)	(0.0262)
older x unemployment rate$_{ct}$	-0.0139*	-0.0167**	-0.0167**
	(0.0077)	(0.0076)	(0.0077)
older	0.0286	0.0666	0.0666
	(0.0562)	(0.0623)	(0.0617)
unemployment rate$_{ct}$	-0.0029	-0.0189**	-0.0195
	(0.0050)	(0.0090)	(0.0278)
$\mathbb{1}$(competing)	-0.0073		
	(0.0164)		
public$_{ct}$ x unemployment rate$_{ct}$			0.0028
			(0.1148)
public$_{ct}$	-0.3844*		
	(0.1977)		
older x public$_{ct}$	0.5450*	0.5623*	0.5635*
	(0.3052)	(0.3021)	(0.3019)
Mean(callback rate)	.108	.108	.108
City FE		X	X
Time FE		X	X
Job postings	4,594	4,594	4,594
Resumes	12,224	12,224	12,224
City-rounds	30	30	30
R^2	.007	.017	.017

Correspondence study data originally collected by Farber et al. (2017) across 8 cities and 4 different time periods. In rounds 1-3 either two younger or two older applications were sent to each job posting. The variable '$\mathbb{1}$(competing)' is a dummy for being part of round 4, where two younger and two older applications were sent to each job posting. The variable 'older' is a dummy for whether the applicant is over age 50, 'unemployment rate$_{ct}$' is the city-round unemployment rate, and 'public$_{ct}$' is the fraction of the city's workforce employed in the public sector. Additional controls include the ficticious applicant's unemployment spell length and whether they held a low-level interim job. Standard errors clustered at the city-round level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10 Online Appendix

"Age Discrimination across the Business Cycle"
By Gordon Dahl and Matthew Knepper

Appendix Figures and Tables

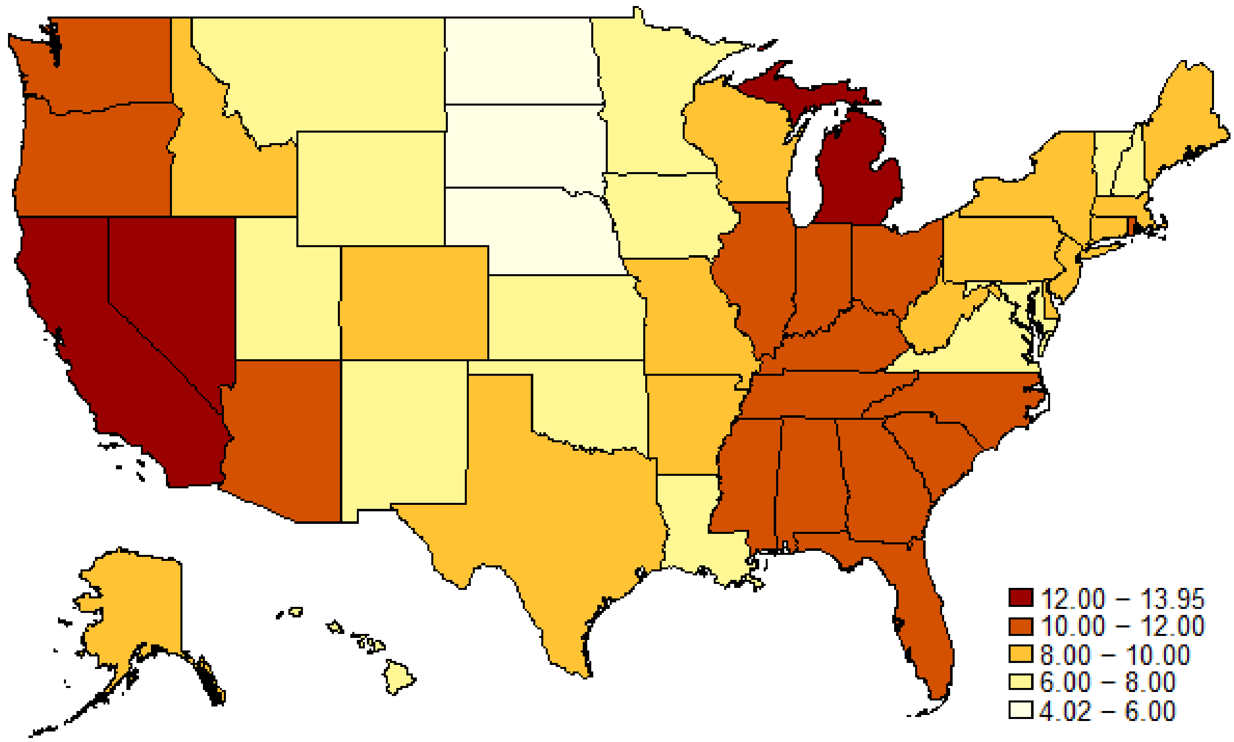

Figure A1: State Unemployment Rates at the Height of the Great Recession

Nonseasonally-adjusted monthly unemployment rates by state in December of 2009, split into quintiles.

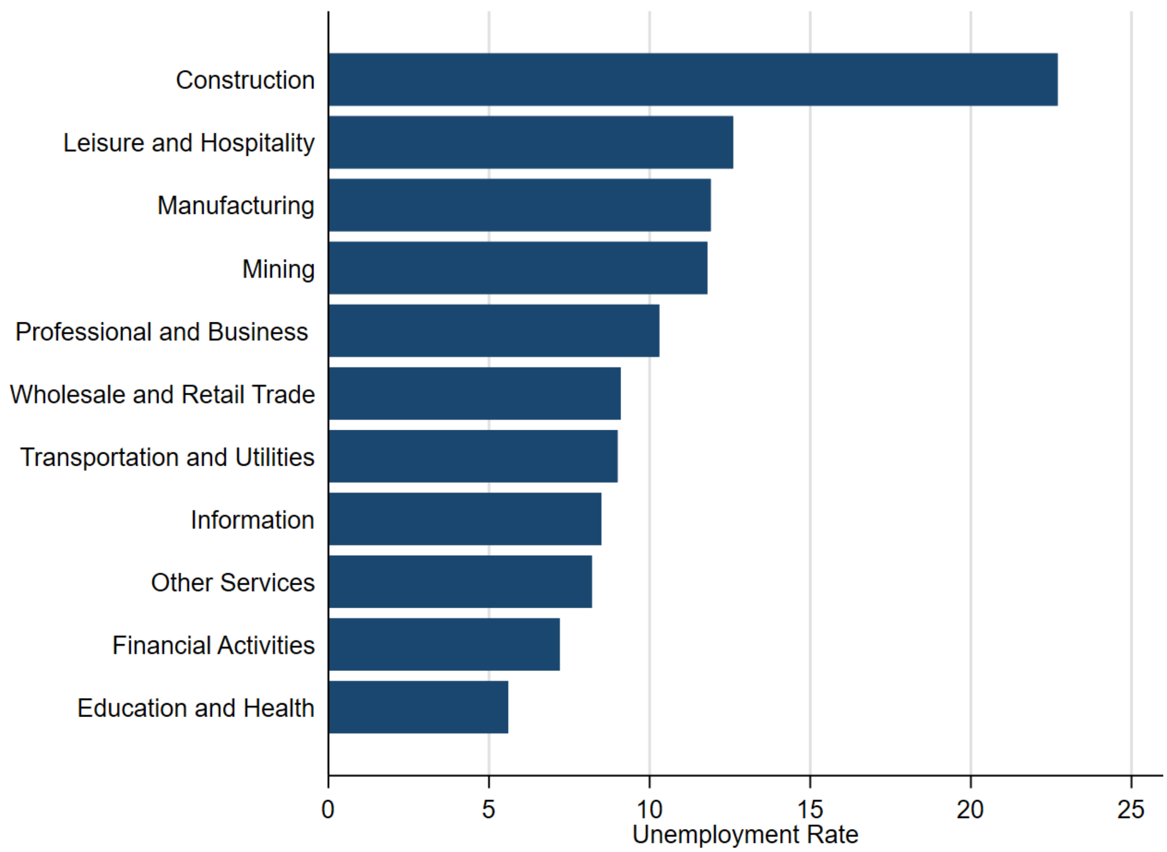

Figure A2: Industry Unemployment Rates at the Height of the Great Recession

Nonseasonally-adjusted monthly unemployment rates by industry in December of 2009.

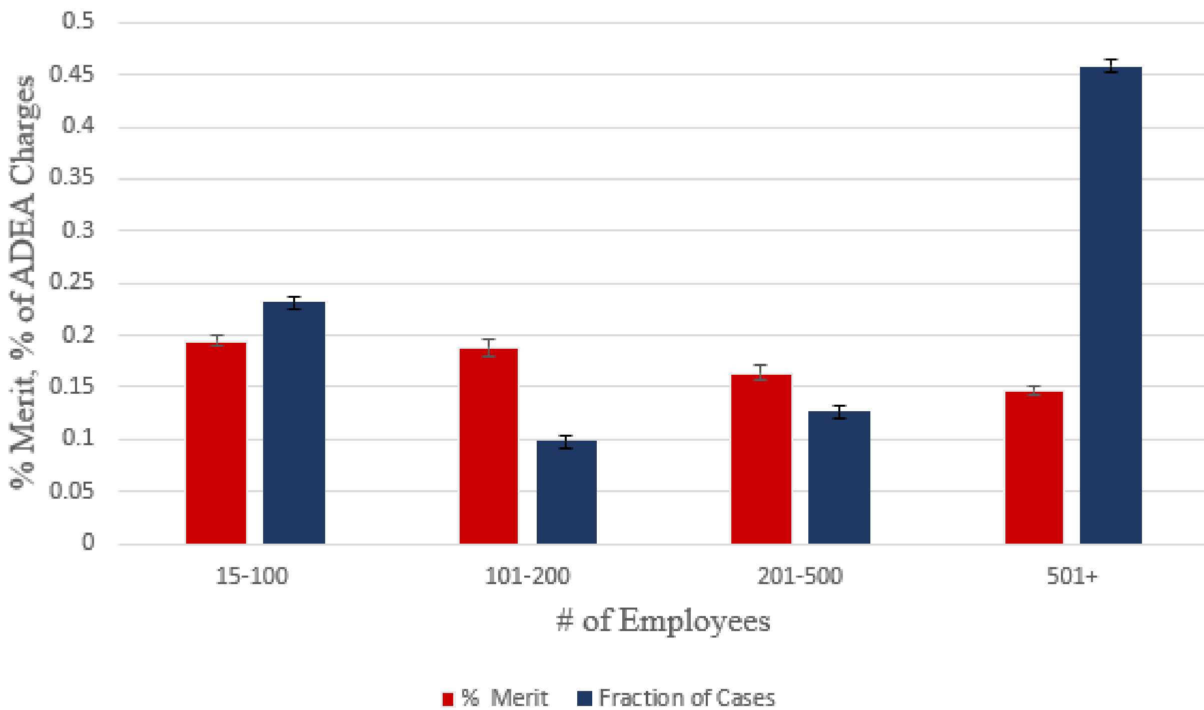

Figure A3: Charges Filed by Firm Size and Claim Quality

Note that firms with fewer than 15 employees are not covered under the ADEA.

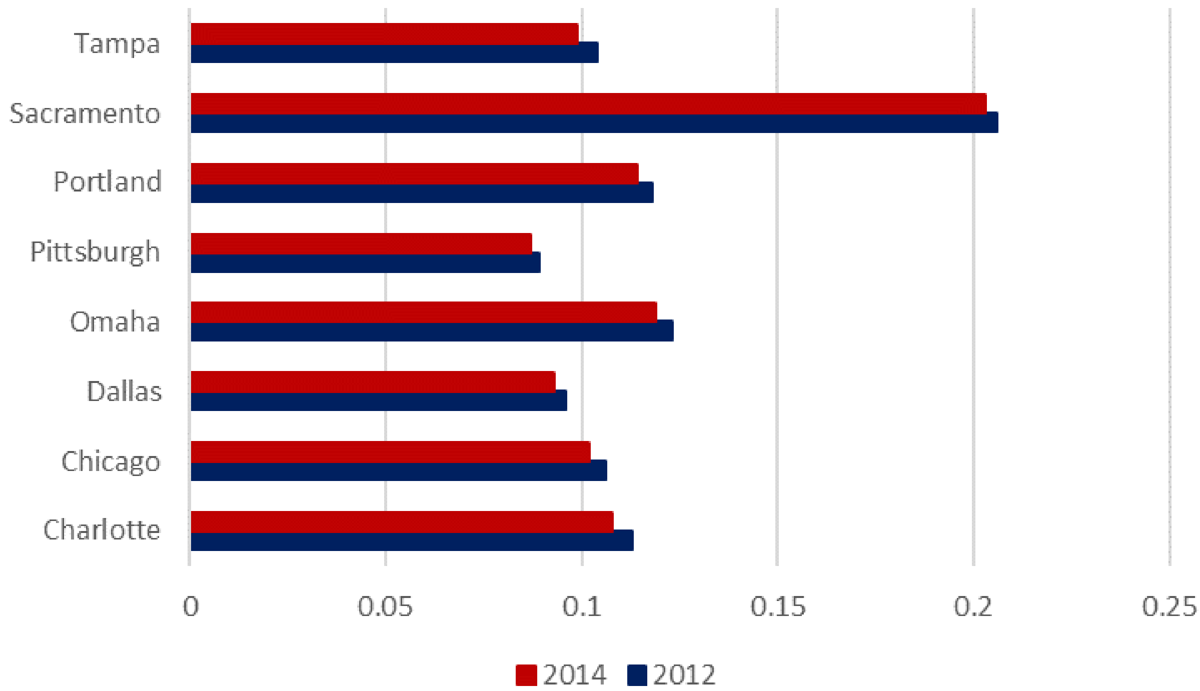

Figure A4: Size of Public Sector, by City and Year

The fraction of each city's workforce that is employed in the public sector based on BEA Regional Employment statistics.

Table A1: ADEA Charges by Type

	Firing	Hiring
Top Basis Categories		
Retaliation	0.286	0.157
Disability	0.233	0.167
Race-Black	0.161	0.179
Sex-Female	0.147	0.097
National Origin	0.088	0.100
Sex-Male	0.056	0.085
Top Issue Categories		
Discharge	1	0.135
Hiring	0.023	1
Terms and Conditions	0.197	0.072
Harassment	0.168	0.031
Discipline	0.115	0.013
Reasonable Accom.	0.059	0.016
Wages	0.040	0.015
Suspension	0.037	0.002
Promotion	0.036	0.037
Demotion	0.023	0.006
Sexual Harassment	0.020	0.004
Worker/Firm Characteristics		
Age	56.0	56.0
White	0.560	0.544
Black	0.241	0.256
Female	0.509	0.370
Legal representation	0.171	0.073
Private firm	0.908	0.756
Charges	68,164	11,617
Claims per charge	4.19	3.23

ADEA firing and hiring charges filed with the EEOC between 2005 and 2015. Only the most prevalent basis and issue categories are shown in this table. Because the number of claims per charge exceed 1, the fraction of all bases and of all issues need not sum to 1.

Table A2: Robustness checks, All ADEA Firing + Hiring Charges

				Volume			
Dep. var. = # of charges	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{unemployment}_{jst}$	1.79***	2.09***	1.51***	1.43***			
	(0.48)	(0.47)	(0.35)	(0.34)			
unemployment_{st}					3.86***		
					(0.79)		
$\text{unemployment rate}_{st}$						3.00*	
						(1.54)	
$\text{emp:pop ratio}_{st}$							-1.28**
							(0.64)
Effect of 1 pp ↑	**27.56**	**32.19**	**23.25**	**22.02**	**59.44**	**46.20**	**-30.50**
Mean(# national charges)	651.0	694.3	512.5	644.3	665.0	665.0	665.0
% change	4.2	4.6	4.5	3.4	8.9	6.9	-4.6
Elasticity	0.25	0.35	0.31	0.23	0.61	0.47	-2.76
N	32,235	44,250	76,485	79,103	6,240	6,240	6,120
R^2	0.408	0.463	0.422	0.294	0.912	0.702	0.693
Dep. var. = $\mathbb{1}(merit)$				**Merit**			
$\text{unemployment}_{jst}$	36.8**	9.93*	19.7***	15.9***			
	(13.9)	(5.05)	(5.15)	(4.03)			
unemployment_{st}					2.62**		
					(1.16)		
$\text{unemployment rate}_{st}$						0.170	
						(0.231)	
$\text{emp:pop ratio}_{st}$							-0.344*
							(0.178)
Effect of 1 pp ↑	**0.0024**	**0.0007**	**0.0013**	**0.0011**	**0.0016**	**0.0017**	**-0.0034**
Mean(merit)	.182	.155	.170	.165	.167	.167	.167
% change	1.3	0.5	0.8	0.7	1.0	1.0	-2.1
Elasticity	0.06	0.03	0.05	0.04	0.07	0.07	1.14
N (charges)	35,157	43,048	61,492	77,308	78,212	78,212	78,027
R^2	0.023	0.017	0.018	0.018	0.025	0.025	0.025
2005-2009Q2 sample	X						
2009Q3-2015 sample		X					
Age 50+ sample			X				
Event date used				X			

See notes to Tables 3 and 4. Columns 1-4 test sensitivity to different time periods, a different age sample, and using the event date in place of the filing date. Column 5 uses the number unemployed at the state-month level instead of the industry-state-month level. Columns 6 and 7 are rate-on-rate regressions at the state level, where the dependent variable is the number of charges divided by the size of each state's labor force and population, respectively, and the regressions are weighted by each state's labor force and population, respectively. The top-panel coefficients show the change in charges filed per 100,000 increase in the number unemployed (employed). Bolded 'Effect of 1 pp ↑ unemp' is the implied effect of a one percentage point increase in the national unemployment rate on the national monthly number of charges filed.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$