Do State Laws Protecting Older Workers from Discrimination Reduce Age Discrimination in Hiring? Experimental (and Nonexperimental) Evidence

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Abstract

We provide evidence from a field experiment — a correspondence study — on age discrimination in hiring for retail sales jobs. We collect experimental data in all 50 states and then relate measured age discrimination — the difference in callback rates between old and young applicants — to variation across states in antidiscrimination laws offering protections to older workers that are stronger than the federal age and disability discrimination laws. We do a similar analysis for nonexperimental data on differences across states in hiring rates of older versus younger workers. The experimental evidence points consistently to evidence of hiring discrimination against older men and, more so, against older women. However, the evidence on the relationship between hiring discrimination against older workers and state variation in age and disability discrimination laws is not so clear; at a minimum, there is not a compelling case that stronger state protections reduce hiring discrimination against older workers. In contrast, the non-experimental evidence suggests that stronger disability discrimination protections increase the relative hiring of older workers.

Citation


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Introduction

In the face of population aging, policy efforts to boost the labor supply of older Americans have focused on reforms to Social Security, including reducing benefits for those claiming at the early eligibility age of 62, increasing the full retirement age (with additional increases scheduled in the future), and reducing the taxation of earnings after Social Security benefits are claimed — which increases benefit claiming at earlier ages, but also increases labor supply post-claiming (Martin and Weaver 2005, Figinski and Neumark, forthcoming). Efforts to encourage people to work longer via these supply-side reforms may be thwarted, however, by age discrimination in labor markets. This potential for age discrimination can be doubly problematic: If businesses do not respond to the policy-induced larger labor supply by hiring older workers, it could lead to even harsher policy reforms for seniors with more adverse effects on older workers who are not actively seeking to work longer.

Thus, policies to increase employment of older workers need not be limited to supply-side reforms that increase incentives to work longer, but could also include stronger laws protecting older workers from discrimination in the labor market. Moreover, hiring of older workers is likely to be essential to significant lengthening of work lives, because many seniors transition to part-time or shorter-term “partial retirement” or “bridge jobs” at the end of their careers (Cahill et al., 2006; Johnson, 2014), or return to work after a period of retirement (Maestas, 2010).

In this paper, we study whether stronger laws protecting older workers from discrimination can boost hiring of older workers. We conduct a large-scale field experiment to measure age discrimination in hiring, with the specific goal of determining whether stronger antidiscrimination laws in some U.S. reduce hiring discrimination against older workers.

In addition to age discrimination laws, we also consider disability discrimination laws. As argued in Neumark, Song, and Button (2017) and Stock and Beegle (2004), disability discrimination laws may be important in protecting older workers, in particular, from discrimination. Disabilities that
can limit work and hence trigger protection by disability discrimination laws rise steeply with age, especially past age 50 or so (e.g., Rowe and Kahn, 1997). Correspondingly, employer expectations that a worker will develop a disability in the near future should also rise steeply with age. Indeed, disability discrimination laws may do more to protect many older workers than age discrimination laws. Many ailments associated with aging have become classified as disabilities (Sterns and Miklos, 1995). These ailments can give some older workers an option of pursuing discrimination claims under either the Age Discrimination in Employment Act (ADEA) or the Americans with Disabilities Act (ADA), or the corresponding state laws. The combined effect of potential coverage under both age and disability discrimination laws may be to increase protections. For example, the ADA does more to limit defenses against discrimination claims.¹ A disability discrimination claim does require proving a disability, but as we explain, doing so can be substantially easier under state disability discrimination laws than under the ADA.²

It may seem obvious that stronger discrimination protections for older or disabled workers will increase hiring of older workers. However, these laws may be ineffective at reducing or eliminating age discrimination in hiring. Enforcement relies in large part on potential rewards to plaintiffs’ attorneys. In hiring cases, it is difficult to identify a class of affected workers, which inhibits class action suits and thus substantially limits awards. In addition, economic damages can be small in hiring cases because one employer’s action may extend a worker’s spell of unemployment only modestly. Terminations, in contrast, can entail substantial lost earnings and pension accruals. Moreover, it could be worse: If age

¹ Unlike the ADEA, the ADA does not include an exception for bona fide occupational qualifications (BFOQs). BFOQ exceptions arise when age is strongly associated with other factors that pose legitimate business or safety concerns (e.g., Stock and Beegle, 2004; Posner, 1995; Starkman, 1992). Furthermore, age-related disabilities might be judged as amenable to “reasonable accommodation” by employers under disability discrimination laws, which usually require “reasonable accommodation” of the worker, making it much harder to justify an apparently discriminatory practice on the basis of business necessity (Gardner and Campanella, 1991).

² Under the ADA and similar state laws, plaintiffs need to prove that they have a condition that “…substantially limits one or more major life activities…” (42 U.S. Code §12102 (1)) This has proved difficult, leading plaintiffs to lose the vast majority of cases (Colker, 1999). Even with the definition of disability being broader now after the ADA Amendments Act of 2008 (ADAAA), proving coverage is not easy for many conditions, unlike coverage under the ADEA which is obvious.
discrimination laws fail to reduce hiring discrimination, but make it harder to terminate older workers, these laws could actually deter hiring of older workers (Bloch, 1994; Lahey, 2008a; Posner, 1995).

To garner evidence on whether stronger age and disability discrimination laws increase hiring of older workers, we conduct a large-scale résumé correspondence study covering all 50 states, to fully capture variation in state age and disability discrimination laws.³ The evidence from the résumé correspondence study provides direct measures of discrimination in hiring. We utilize information on state age discrimination laws that extend beyond the federal ADEA, and state disability discrimination laws that extend beyond the ADA, to study the relationships between these state laws and the direct measures of age discrimination in hiring from the field experiment.⁴ Our focus is on discrimination against job applicants aged 64 to 66, who are at or near the age of retirement, making this age range particularly important for thinking about whether age discrimination hinders policy reforms to lengthen work lives.

One important caveat is that the variation in age discrimination that we measure is cross-sectional, not longitudinal. This limitation is dictated by the collection of data in our experiment, which occurs over a short period.⁵ Even if we could collect data over a longer period, the ability to study the effects of current variations in state antidiscrimination laws is severely limited, because there are very few changes in these laws in recent decades (Neumark and Song, 2013; Neumark et al., 2017; Button, Armour, and Hollands, 2017a). Thus, our evidence potentially reflects other factors correlated with both

³ This is a substantial expansion from the 12 cities in 11 states studied in Neumark et al. (2015), although we limit the analysis to retail jobs – whereas the previous study sent out résumés for four other types of jobs.

⁴ There is nonexperimental evidence that these state laws affect labor market outcomes for older or disabled workers. Neumark and Song (2013) find that the effects of increases in the Social Security Full Retirement Age on work and later retirement were larger in states with age discrimination laws that are stronger than the federal ADEA. Other analyses of state age and disability discrimination laws (a nonexhaustive list) include Neumark et al. (2017), Jolls and Prescott (2004), Lahey (2008a), Stock and Beegle (2004), and Button (forthcoming). We do not review this evidence here; the reader is referred to those papers. We are aware of only two other papers that look at variation in experimental evidence on discrimination across jurisdictions with different antidiscrimination laws – Tilesik’s (2011) study of discrimination against gay men, and Ameri et al.’s (2015) study of discrimination against individuals with disabilities.

⁵ For an interesting example of correspondence study evidence collected before and after a policy change (in the context of hiring differences of those with and without criminal backgrounds), see Agan and Starr (2016).
employer decisions about callbacks for older workers vs. younger workers, and antidiscrimination laws. However, callback outcomes are responses to very similar résumés in a single industry, and do not reflect, for example, decisions of older workers to apply for jobs, or population differences between older and younger workers. Thus, candidate explanations for a spurious relationship between the discrimination laws and the hiring discrimination we measure are not obvious.

**Correspondence study evidence on age discrimination**

Experimental audit or correspondence (AC) studies of hiring are generally viewed as the most reliable means of inferring labor market discrimination (e.g., Fix and Struyk, 1993). While observational studies try to control for productivity differences between groups, AC studies create artificial job applicants in which there are intended to be no average differences by group, so that differences in outcomes likely reflect discrimination. Audit studies use actual applicants coached to act alike, and capture job offers, whereas correspondence studies create fake applicants (on paper, or electronically) and capture “callbacks” for job interviews. Correspondence studies can collect far larger samples of job applications and outcomes, especially using the internet; because of the time costs of interviews, even large-scale, expensive audit studies typically have sample sizes only in the hundreds. Correspondence studies also avoid “experimenter effects” that can influence the behavior of the actual applicants used in audit studies (Heckman and Siegelman, 1993). For these reasons, we use a correspondence study in this paper.

Past studies on age discrimination in hiring using correspondence study methods point to substantial age discrimination in hiring for both men and women (Bendick, Jackson, and Romero, 1997; Bendick, Brown, and Wall, 1999; Riach and Rich, 2010; Lahey, 2008b; Farber, Silverman, and von Wachter, 2015; Baert et al., 2016). The recent Neumark et al. (2015) study was the first to focus on

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6 For discussions of why, see, for example, Bertrand and Mullainathan (2004) and Neumark (forthcoming). For critiques of this evidence, see Heckman and Siegelman (1993) and Heckman (1998).
workers at or above the age of eligibility for Social Security benefits. Moreover, it addressed sources of bias in the estimates from these past studies that could be in either direction.

First, one potential problem in correspondence studies of age discrimination is the practice of giving older and younger applicants similar labor market experience, consistent with the standard paradigm in these studies. (One cannot, of course, match on the high experience of older applicants.) The absence of relevant experience commensurate with an older applicant’s age may be a negative signal, and on real-world résumés, older applicants tend to report experience commensurate with their age. Neumark et al. (2015) addressed this question by using a variety of résumé types for older workers, including some with experience commensurate with age, which we argued was more consistent with the central policy and legal questions regarding discrimination — and some with low experience matched to that of younger applicants, which hews more closely to the classic correspondence study paradigm. For one occupation (janitors), matching on low experience generated spurious evidence of discrimination against older male workers. However, for the retail sales occupations on which we focus in this paper, there was no such evidence.

Second, Heckman and Siegelman (1993) and Heckman (1998) have demonstrated that if the groups studied have different variances of unobservables, experimental estimates of discrimination can be biased in either direction (formally, it is unidentified) — the “Heckman critique.” This problem may be especially salient with respect to age, as the human capital model predicts greater dispersion in unobserved investments among older workers (Mincer, 1974; Heckman, Lochner, and Todd, 2006). If

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7 Researchers are aware of this problem. Bendick et al. (1997) had both older and younger applicants report 10 years of similar experience on their résumés. However, they had the résumés for older applicants indicate that they had been out of the labor force raising children (for the female executive secretary applications), or working as a high school teacher (for the male or mixed applications). Lahey (2008b) studies women, for whom she argues that time out of the labor force is less likely to be a negative signal. She then includes only 10-year job history for all applicants (in part based on conversations with three human resources professionals she cites who said 10-year histories were the “gold standard”). However, the older résumés in either study could convey a negative signal. Baert et al. (2016) create older applicants with either experience commensurate with age (either in the occupation or out of the occupation) or with a gap in the résumé that is explained to be “at-home-caring tasks.”
the average résumé quality in the study is low compared to the distribution of résumés employers actually observe,\(^8\) then the high variance group is more likely to exceed the threshold for hiring (or a callback), creating a bias in favor of hiring older workers, and hence a bias against finding evidence of age discrimination. This problem was addressed by using a method developed in Neumark (2012), which is explained in more detail later in the paper. Neumark et al. (2015) found that the results for the sales occupations we study in the present paper are sensitive to correcting for this source of bias, although they also noted that the evidence for these occupations might not be robust. Hence, we build the same bias correction into the present study.

Correspondence studies do not directly distinguish between taste discrimination and statistical discrimination. However, both are illegal under U.S. law.\(^9,10\) Nonetheless, economists are interested in which model might explain discriminatory behavior, and the policy response may differ. Moreover, in applying these methods to older workers, there are many plausible channels of statistical discrimination. First, employers might expect older workers to have health problems, which could raise absenteeism, lower productivity, or pose accommodation costs. Second, employers might expect that older workers (our highest age range is 64-66) would be near retirement, and hence be less likely to want to invest in them. Third, an older applicant with experience commensurate to their age applying for the same job as a younger applicant might be viewed as less qualified or having less potential, because he or she has been at that job level for longer — i.e., has a slower “speed of success” (Tinkham, 2010). Finally, employers may make assumptions about skill differences across cohorts – perhaps most important that older applicants have fewer computer skills.

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\(^8\) As one example in a different context, Bertrand and Mullainathan (2004, p. 995) claim that they tried to avoid over-qualified applicants who employers might not bother trying to hire.

\(^9\) EEOC regulations state: “An employer may not base hiring decisions on stereotypes and assumptions about a person’s race, color, religion, sex (including pregnancy), national origin, age (40 or older), disability, or genetic information” (http://www1.eeoc.gov//laws/practices/index.cfm?renderforprint=1, viewed September 27, 2015).

\(^10\) Customer discrimination is also illegal. For a number of cases showing failure of defenses based on customer preference, see https://www1.eeoc.gov//eeoc/initiatives/e-race/caselist.cfm?renderforprint=1#customer (viewed September 26, 2016).
We cannot definitively rule out a role for these explanations of the evidence — and as we noted above, it does not matter from a legal perspective. Nonetheless, Neumark et al. (2015) present a number of types of evidence suggesting that these potential sources of statistical discrimination do not play much of a role. Some of these are based on evidence external to the field experiment. For example, with respect to separations, younger workers are also likely to leave a job; although this is for other jobs rather than retirement, the reason for turnover is irrelevant to the employer. In 2015:Q1 data from the Quarterly Workforce Indicators, the separation rate (relative to beginning-of-quarter employment) was 9.9 percent for workers aged 55-64, and 18.7 percent for workers aged 25-34 (our youngest age range is 29-31). Other evidence comes from the study. For example, the study also used résumés with different kinds of “bridging” or partial retirement behavior, which we know is sometimes associated with declining health (Johnson, Kawachi, and Lewis, 2009; Johnson, 2014). Since employers should know this from past experience, if declining health is an issue, older applicants with “bridge résumés” should experience lower callback rates than other older applicants; but they do not.

The experimental design

The present study builds on the approach and findings from the prior study. The extension to all 50 states is critical for studying the effects of antidiscrimination laws. At the same time, the extensive resources required to extend to all 50 states necessitated omitting some of the occupations included in the previous study. In particular, we omit administrative assistant, security, and janitorial jobs, and focus only on jobs in retail sales. A clear implication of this limitation is that the evidence must be regarded as a case study, which may not generalize to other low-skill jobs. On the other hand, of the

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11 See http://qwiexplorer.ces.census.gov/#x=0&g=0 (viewed August 11, 2016).
12 The reader is referred to Neumark et al. (2015) for discussion of additional evidence on statistical discrimination, as well as other potential challenges to the validity of interpreted differences in outcomes by age as discrimination.
13 These kinds of studies typically use a very limited number of jobs. For example, Farber et al. (2015) focuses only on age discrimination against women in administrative assistant jobs.
jobs included in Neumark et al. (2015), retail sales is the one for which both male and female applicants were submitted, so in the present study we obtain evidence on whether there are difference in the results for men and women. In addition, given the evidence from Neumark et al. (2015) that in retail sales there was no difference in measured age discrimination whether high-experience or low-experience résumés were used for older applicants, in this paper we use low-experience résumés that match those of younger applicants. This simplified the résumé creation because a long work history did not have to be developed for the older applicants.

**Basic analysis framework**

The core analysis uses probit models for callbacks (C) as a function of dummy variables for age (S for older/senior) and observables (from the résumés) X. The latent variable model (for C*) is

\[ C_i^* = \alpha + \gamma S_i + \delta X_i + \epsilon_i. \]

In this basic model, the null hypothesis of no discrimination implies that \( \gamma = 0 \) (for older workers). We always estimate the model for men and women separately.

Here we outline the solution proposed in Neumark (2012) to address the Heckman critique; the original paper provides details. To see the intuition behind the solution, recall that in a probit model, all that is identified is the ratio of the coefficient in the latent variable model to the standard deviation of the unobservable. If we are willing to assume that \( \delta \) in equation (1) is the same for younger and older applicants, then we can identify the ratio or the standard deviation of the unobservables, denoted \( \sigma_S / \sigma_Y \), from the ratios of probit coefficients older (senior) and younger applicants. Thus, information from a correspondence study on how variation in observable qualifications is related to callback outcomes can be informative about the relative variance of the unobservables, and this, in turn, identifies an unbiased estimate of the effect of discrimination.

The parameters are estimated using a heteroskedastic probit model with variance differing between younger and older applicants, and requires that at least one element of \( \delta \) is equal for younger
and older workers.\textsuperscript{14} With data on multiple productivity-related characteristics in $X$, there is an over-identifying restriction that the younger/older ratios of coefficients on any element of this vector are equal (to the same $\sigma^I_\text{S}/\sigma^I_\text{Y}$). The method also requires that at some of the applicant characteristics in $X$ affect the callback probability (since if all the effects are zero we cannot learn about $\sigma^I_\text{S}/\sigma^I_\text{Y}$ from these coefficient estimates). AC studies typically do not try to include variables that shift the callback probability, but instead create one “type” of applicant for which there is only random variation in characteristics that are not intended to affect outcomes. However, we build this information into the study design, through assignment to some résumés of random elements of a vector of skills and other characteristics that should increase the callback probability.

\textit{Résumé creation}\textsuperscript{15}

The core of a correspondence study is the bank of résumés created for the artificial job applicants, since these résumés constitute the study data. Our over-arching strategy was to use empirical evidence whenever possible in making decisions about creating the résumés, to minimize decisions that might limit the external or “comparison” validity of the results. In many cases, this empirical evidence came from a large sample of publicly available résumés we downloaded from a popular national job-hunting website. We downloaded a sample of over 25,000 résumés, which we then scraped for a variety of types of information that we use in our résumé design decisions. In addition, we used public-use data to inform other issues in designing the résumés.

\textsuperscript{14} Thus, we could have begun by writing equation (1) with different coefficients on $X$ for young and old workers.

\textsuperscript{15} Many additional details are provided in the on-line appendix to Neumark et al. (2015), although with some differences because that paper presents a more complex study with additional occupations, additional résumé types, etc. We do not do anything in the current paper that extends beyond what was done in Neumark et al. (2015), but in some cases what we do is more limited.
Basic parameters

Past studies have tended to use workers near age 30 as the young group, and workers near age 50 as the older group. We include a similar age range for young workers (29-31), but compare results to older workers near the retirement age (64-66), who are the focus of policy efforts to respond to population aging. We convey age, on the résumés, via high school graduation year, which is common on the actual résumés we examined. Given these age ranges, we chose common names (by sex) for the corresponding cohorts based on data from the Social Security Administration. To focus on age, we chose first and last names that were most likely to signal that the applicant was Caucasian. In response to each job ad, we send out a quadruplet of résumés consisting of a young and old male applicant and a young and old female applicant.

Neumark et al. (2015) used the résumé database to document that there are older applicants in retail sales, which is consistent with data from the Current Population Survey (CPS) Tenure Supplement showing a sizable representation of low-tenure older workers in the occupations that make up retail sales (retail salespersons and cashiers in the Census occupational classification). Furthermore, the presence of older résumés on the résumé posting website suggests that older workers do use on-line resources such as we use in this study to apply for jobs. That paper also showed that retail sales capture appreciable shares of new hiring of older workers (and, of course, higher shares for the types of low-skill jobs that could plausibly be candidates for the study), and are in the upper tier in terms of the proportions of older people hired.16

As noted above, we use cities in all 50 states to maximize external validity and to include variation in antidiscrimination laws across all states. This contrasts quite sharply with most of the past studies, which use at most a handful of cities (e.g., Lahey, 2008b; Bendick et al., 1999). Because low-

16 As additional evidence, Rutledge, Sass, and Ramos-Mercado (2016) compute the ratio of older (50-64) to prime age (30-49) hires in detailed occupations. Retail sales is in the top 10, based on 1996-2012 CPS data. They also report that the jobs into which older workers tend to be hired are much narrower for less-educated workers. Thus, although the study was never meant to provide representative evidence on all older job seekers, it seems to point to a significant part of the labor market, especially for less-skilled older workers.
skill workers have low geographic mobility (Molloy, Smith, and Wozniak, 2011), we also target the résumés to retail jobs in specific cities (one per state, see Table 2), with the job and education history on each résumé matching the city from which the job ad to which we apply originates. This customization of résumés was a factor underlying our decision to limit the analysis in this paper to retail sales jobs.

Job histories

We relied on the actual job histories from the résumé database, as well as other data sources, to create realistic job histories on our résumés. Examination of our scraped résumés indicted that even in the low-skilled retail sales jobs we study, résumés are tailored to the jobs. To construct the job histories, we first pool job titles and descriptions from the actual résumés to create a set of entries in the retail field, with only minor changes such as phrasing or grammar for consistency. We combined these job descriptions using the résumé characteristic randomizer program created by Lahey and Beasley (2009). The program randomized the combination of job titles and descriptions, and job tenures. The program runs backward from the most current job to the beginning of the potential job history. We had to build in a probability of a job ending, and experimented with the randomizer to choose a probability that appeared to create job histories similar to the résumés we downloaded in terms of number of jobs held and average tenure on a job. This iterative process led us to choose a 15 percent annual probability that the program will end the current job and move on to the next randomly assigned job.

We used the résumé randomizer to produce a large number of job histories, and then selected a smaller set that looked the most realistic based on the résumés found on the job-hunting website. In particular, we dropped those that had very high levels of turnover. From this sample of acceptable histories, we created four job histories for each city (and for each style of résumés we create). We added employer names and addresses randomly to each job in our final job histories. We identified 15 possible employers for each city and assigned each employer to a job description such that no employer is used more than once on the same résumé, or more than once across résumés in the quadruplet of résumés that
are sent to each employer. We ensured that the job title and description was realistic for the employer. In addition, we used employers that were active at the time and in the region listed, relying mainly on national chains that had stores in many cities.

To mimic the seasonal pattern of job changes, we randomly drew the separation month for each job, except the most recently held job, from the distribution of job separation dates from the Job Openings and Labor Turnover Survey (JOLTS). We use the distribution specific to “Retail Trade.” We distinguish résumés based on whether applicants are currently unemployed. We assign all applicants within each quadruplet as either employed (the most recent job end date listed as “Present”), or unemployed, with 50 percent probability for each. When applicants are unemployed, the résumés indicate that their last job ended in the month prior to the job application. During the course of the field experiment, every month we moved the ending date of the most recent job forward one month, so that unemployment durations did not lengthen during the time the experiment was in the field.

Skills

To address the Heckman critique, we designate half the résumé quadruplets to be high-skilled and half to be low-skilled. For each type of high-skill résumé, there are seven possible skills, five of which are chosen randomly so that they are not perfectly collinear within a job. Included in the skill vector are five general skills: a Bachelor of Arts degree; fluency in Spanish as a second language; an “employee of the month” award on the most recent job; one of three volunteer activities (food bank, homeless shelter, or animal shelter); and an absence of typographical errors. Two skills of the seven

17 We did not want random assignment of unemployed or employed résumés within a quadruplet to dominate the effect of age.
18 Like for unemployment, we make the set of résumés sent to each employer uniformly high-skill or low-skill because skill and age define different treatment groups.
19 Thus, all low-skill résumés and the high-skill résumés not assigned this skill include two typos. We use a missing space and a missing period, with one of these appearing for the most recent job, which employers are most likely to read. These kinds of errors were more common on actual résumés than spelling errors.
are specific to retail sales, including Microsoft Office and programs used to monitor inventory (VendPOS, AmberPOS, and Lightspeed).

Additional résumé elements

Residential addresses were selected to be realistic for both older and younger applicants to the jobs for which we were applying, with regard to socioeconomic status, demographic characteristics, and distance to jobs. We also chose addresses to avoid signaling a race other than white and to avoid sending an unusual signal (positive or negative) about the applicant. The addresses were randomly assigned with respect to age, so there is no association between socioeconomic status of the neighborhood and age of applicant.

We randomly assign high schools, and colleges and universities for the high-skilled résumés, for each city, to each applicant in our quadruplet. We use local schools, colleges, and universities that were in operation since 1960 so that there is no possibility that an applicant attended a school that was not operational at the time. We also restrict our schools to significant share of its student population be white. For smaller cities, this often limits the number of high schools or colleges that were available. In six cities, we were only able to find two high schools that fit our criteria. For the rest, we selected three different high schools.\(^\text{20}\) We avoided top-tier/flagship universities whenever possible. We also restricted our schools to not include historically black colleges. In two states (Wyoming and Delaware), there was only one university that fit our criteria.

Résumé quadruplets

Each of the four résumés in the quadruplet was randomly assigned a different résumé template, which ensured that all four résumés looked different. Most other characteristics were randomly and uniquely assigned to each résumé in each quadruplet to further ensure that the applicants were

\(^{20}\) There were many cities for which we could not identify four high schools. In such cases, employers should not be surprised to get two résumés listing the same high school.
distinguished from each other, and that any résumé characteristics that inadvertently were more or less appealing to employers were distributed randomly with respect to the four applicants in each quadruplet. These characteristics included first and last names, school names, addresses, phone numbers, email address formats and domains, cover letter style, and the language describing jobs and skills.\textsuperscript{21}

\textit{Applying for jobs}

We identify jobs to apply for using a common job-posting website. Research assistants read the posts regularly to select jobs for the study, using a well-specified set of criteria. Jobs had to be entry level (e.g., not managers or supervisors), and the ads could not require in-person applications or inquiries by phone were discarded, or require applicants to use an external website. The ads could not require additional documents we had not prepared (e.g., a salary history, etc.), or skills that our résumés did not have.

Research assistants saved the list of jobs to apply for in a shared folder. We wrote Python code to automate the application process from the jobs put in this shared folder. This substantially reduced labor costs, removed human error such as attaching the wrong résumé, and ensured that jobs applications used a uniform procedure. The code matched the job ad data to the applicant based on city and date. Each day was randomly assigned a different quadruplet of résumés in terms of skill levels, and employed or unemployed. Within each quadruplet the order of résumés was randomized. The code ran every other day and added seven- to eight-hour delays between applications to the same jobs.\textsuperscript{22}

\textit{Sample size}

In an experiment, it is important not to continue to collect data until the estimated differences become statistically significant. We had an explicit data collection plan that covered two academic

\textsuperscript{21} The on-line appendix from Neumark et al. (2015) provides examples of résumé types exhibiting these and other variations.

\textsuperscript{22} See Chehras (2017) for details, including instructions and access to the code.
quarters, in which we collected as much data as the available job ads would allow. No data were analyzed until the data collection was complete. During that time period, we sent 14,428 applications to 3,607 jobs.

Collecting responses

Responses to job applications could be received by email or phone. All responses were forwarded to a central email account, with voicemails arriving as attachments. We then read each email and listened to each voicemail to record the response. We often used additional information to match a response to a specific job ad, using information on the job ads recorded during the job application process, like company name.

If the email was sent as a reply to the job-listing website submission, then the email also contained a unique id number for the job ad. Sometimes firms responded directly to the individual, in which case we had to use other information to match to the specific job. Phone call responses conveyed less information. Every voicemail contained the phone number of the firm calling and the phone number on the résumé they were trying to contact. The automated voicemail message instructed firms to include their name and their number in their message. Identifying information that was extracted from a voicemail included, when possible, the firm name, applicant name, the job title, and any information that could be used to narrow down the list of possible job ads (e.g., how long ago they received the résumé). The information extracted from the voicemail was used to match each voicemail to a job ad. Table 1 reports the distribution of responses by phone or email (or both).

Each response was coded as an unambiguous positive response (e.g. “Please call to set up an interview”), an ambiguous response (e.g. “Please return our call, we have a few additional questions”), or an unambiguous negative response (e.g. “Thank you for your interest, but the job has been filled”).
To avoid having to classify subjectively the ambiguous responses, they were treated as callbacks;\textsuperscript{23} the negative responses were treated the same as no callbacks.

**Coding of antidiscrimination laws**

Our coding of age discrimination laws and disability discrimination laws was developed, and is fully described in Neumark and Song (2013) and Neumark et al. (2017); these papers also report some analyses of the effects of these laws, albeit using only nonexperimental data. The compilation of information on these laws entailed extensive background research on state statutes and their histories, culled from legal databases including Lexis-Nexis, Westlaw, and Hein Online, as well as many other sources (e.g., case law, secondary sources, law journal articles, state offices, unpassed bills, jury instructions). This is discussed in-depth in our legal appendix.

The current laws are reported in Table 2.\textsuperscript{24} We focus on the two aspects of age discrimination laws that the past research suggested were important. The first is the minimum firm-size cutoff for the law to apply.\textsuperscript{25} We use a firm-size cutoff of fewer than 10 workers to capture state laws that extend to substantially smaller firms (the minimum for the ADEA to apply is 20). The smaller firm-size cutoff may be important because older workers are more likely to be employed at smaller firms (Neumark and Song, 2013). The second is whether compensatory or punitive damages are allowed, which they are not under federal law.\textsuperscript{26}

\textsuperscript{23} The ambiguous responses are 7.8\% of all cases coded as positive callbacks.

\textsuperscript{24} Table 2 reveals that the distribution of stronger protections across states does not reflect the usual pattern related to generosity of social programs, minimum wages, etc. For example, some southern states have among the strongest antidiscrimination protections.

\textsuperscript{25} For example, in Florida a worker who works at a firm that employs fewer than 15 employees is not covered under the Florida state law. On the contrary, all employees in Colorado are covered by state law because it is applicable to all firms with at least one employee.

\textsuperscript{26} See United States Equal Employment Opportunity Commission (2002). Some states require proof of intent to discriminate in order for compensatory or punitive damages to be awarded, whereas others require “willful” violation. Because the federal law allows additional liquidated, non-punitive damages (double back pay and benefits) when there is “willful” violation, the question of whether the state requires intent or willful violation may seem to be potentially relevant in deciding whether a state law offers greater protection. However, willful violation is a much stricter standard than intent (Moberly, 1994). Moreover, compensatory or punitive damages are almost certainly greater than liquidated damages, and they can be much greater. As a consequence, a state law
State disability discrimination laws are sometimes stronger than the federal ADA in three principal ways, all captured as well in Table 2. Like with age laws, there is a minimum firm size to which disability discrimination laws apply. The minimum firm size for the ADA to apply is 15; in our analysis we distinguish states with a firm size minimum lower than 10, the same as for age discrimination laws. There is also variation in damages, through higher or uncapped compensatory and punitive damages, relative to the capped damages available under the ADA. We distinguish states with larger damages than the ADA; we base this classification on punitive rather than compensatory damages, since punitive damages are likely to drive large judgments.

Finally, state laws vary in terms of the definition of disability. Most states adopt the ADA definition, either explicitly or via case law. Some states use a laxer definition, changing a key part of the definition of disability from “substantially limits one or more major life activities” to either “materially limits” (Minnesota) or just “limits” (California) (Button, forthcoming). Other states vary the definition of disability by requiring that the disability be “medically diagnosed” without regard to whether the impairment limits major life activities (Long, 2004); the disability definition in these states is the broadest. The table includes information on both dimensions of the definition of disability, and we use both in our analysis.

Results

Basic callback rates

Figures 1-3 display information on callback rates by age and by sex. Figure 1 plots the callback rates for young and older male applicants, and Figure 2 plots them for young and older female applicants. In our view, the evidence across all the states in our sample is remarkably consistent, as the callback rate is higher for young applicants in nearly every state, and usually notably so. This is
particularly true for women, where there is only one state (Maine) for which the callback rate for older applicants is higher. For men, there are eight states. However, most are states with very small number of observations; the exceptions are Florida and North Carolina, for which the numbers of observations are higher but the estimated differences in callback rates are very small. Figure 3 provides a contrast between the results by age for men versus women. The bars to the left of zero indicate how much lower the callback rate is for older applicants, and the comparison shows that the difference is much more often larger for female applicants.

Table 3 aggregates the data, reporting raw differences in callback rates by age and statistical tests of whether callback rates are independent of age. In Panel A, for males, we find strong overall evidence of age discrimination, with callback rates statistically significantly lower by 7.6 percentage points for older workers compared to younger workers, or 30.4 percent lower. The evidence in Panel B, for females, similarly points to age discrimination. The absolute difference is a bit larger (8.5 percent), although it is more similar in relative terms because the callback rate is about 3.5 percentage points higher for women than for men. These results are similar to those in Neumark et al. (2015), although there the callback differential was larger for women (about 10 percent versus 6 percent for men).  

In correspondence studies, there is a question of what evidence on callbacks tells us about hiring. For example, if employers believe there is age discrimination, then they may expect older applicants to be more likely to respond positively to a callback. Nondiscriminatory employers might then direct more callbacks to older workers, which would generate a bias against finding evidence of age discrimination (although employers might do the opposite if they have a target share of older worker hires). However, there is evidence that differences in callback rates accurately reflect hiring discrimination. The Bendick

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27 Across all the job ads, 3.6 percent of the observations come from Florida, and 2.4 percent from North Carolina. For the other six states, these percentages range from 0.08 percent to 1.2 percent.
28 This test treats the observations as independent. In the regression (probit) analyses that follow, the standard errors are clustered appropriately.
29 Note that the callback rates at all ages are higher for women than for men. Similarly, Neumark et al. (2015) and Bertrand and Mullainathan (2004) did not find discrimination against women in retail.
et al. (1999) audit study that captured differences in outcomes at different stages of the application process, and found that three-quarters of the overall discriminatory difference in treatment occurred at the pre-interview stage. Thus, there is good justification for assuming that our results for callbacks would carry over to job offers, although of course the magnitudes could differ.

Multivariate estimates

Table 4 reports results of probit estimates for callbacks (equation (1)), showing marginal effects. In each case, we first report results with controls for the state, the order in which applications were submitted, current employment/unemployment, and skills. We then add controls for an extensive set of résumé features listed in the table notes. The random assignment of age to résumés in AC implies that the controls should not affect the estimated differences associated with age. That is reflected here, as the estimates in Table 4 are very similar to those in Table 3, with an estimated percentage point shortfall in callbacks of 7.5-7.7 percentage points for men, and 8.6-8.9 percentage points for women.

In this and subsequent tables the estimates are clustered at the age-by-state level. We do this because the policy variation we study when we estimate the effects of state antidiscrimination laws on callbacks varies by state and by age (since we include age-by-state interactions).

Given that the additional résumé feature controls make essentially no difference to the estimates, nor should they, going forward we use the more parsimonious specifications in columns (1) and (3). These specifications retain the skill variables we added to address the Heckman critique (as well as the unemployment and order of application variables, which may also function like the skill variables).

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30 An employer is more likely to discriminate at the pre-interview (callback) stage than at the interview stage. Because company personnel systems often create data records for those interviewed, discrimination in offering jobs to applicants may be much easier to detect than discrimination in deciding who to call back for an interview.

31 Absent this consideration, one might want to cluster at the level of the résumé or the job ad. In Neumark et al. (2015) we verified that the two alternatives have virtually no effect on the standard errors.
Adding state antidiscrimination laws

We next turn to the main contribution of this paper – the estimation of the effects of state antidiscrimination laws protecting older workers on callback rates for older relative to younger workers. We do this by modifying equation (1) to include interactions of dummy variables for these state laws (in some cases a vector) with the dummy variable for older applicants. Because we include state dummy variables, we do not include the main effects of the state antidiscrimination laws. Excluding the state dummy variables, and including the main effects of the laws, would be a less saturated model, whereas the models we estimate allow more flexibly for differences in callback rates for younger workers across states than only variation correlated with the state antidiscrimination laws. Of course, we have to assume that state-by-age interactions are excluded from the model to estimate the interactive effects of interest. Adding to equation (1) an ‘s’ subscript to denote states, and defining $A_s$ as the dummy variable (or vector of dummy variables) capturing state antidiscrimination laws, we augment the model to be

$$C_{is}^* = \alpha + \gamma S_{is} + S_{is} A_s \gamma' + X_{is} \delta + \varepsilon_{is},$$

where, recall, $X$ includes the state dummy variables. Our interest centers, of course, on whether stronger state antidiscrimination laws are associated with differences in the relative callback rate of older workers, captured in $\gamma'$.

In columns (1) and (2), Table 5, we add, separately, the two features of age discrimination laws on which we focus – a smaller firm-size cutoff, and larger damages. In column (3) we add these simultaneously, which has no bearing on the estimates. The main effects of “Old” refer to states where the federal law binds, and the interaction with the feature of the law considered captures the differential in the relative callback rate where there is a stronger state law. For a lower firm-size cutoff, the estimated interaction for men is negative but insignificant, while the estimate for women is positive and statistically significant. The estimates for women imply that in the states where the federal law binds, the callback differential by age is quite a bit larger than for men (around 10 versus six percentage points lower). It is not clear, a priori, why the estimated effect of the lower firm-size cutoff would be different
for women than for men. In the actual labor market, it is possible that older women on average apply to work at smaller firms. But in the correspondence study that should not play a role, since all job ads receive two male and two female applicants. On the other hand, the estimates suggest more baseline age discrimination against female applicants. The estimated interactions with the dummy variable for larger damages are small and insignificant (and negative) for both men and women.

Table 6 turns to state disability discrimination laws. This table is more complicated because there is a third feature of the laws that we study – the definition of disability – and because there are two different classifications of this definition. Looking first at the results for the lower firm-size cutoff, we find small and insignificant effects in every case. For larger damages, we find a positive and statistically significant effect (at the 10-percent level) for older women in the specifications adding one law at a time (column (8)), and in one of the two cases where we add all laws simultaneously (with one of the two types of broader definitions of disability, in column (11)); the estimate is slightly smaller in column (12). The finding of reductions in age discrimination for older women associated with larger damages contrasts with the evidence for age discrimination laws, where we found a positive and significant effect of a lower firm-size cutoff for women. But both results are similar in the sense that for women, but not for men, we find a positive and significant effect of some feature of state antidiscrimination laws that strengthens the law relative to the federal law.

Columns (3), (4), (9), and (10) report estimates of the effects of a broader definition of disability on the relative callback rate for older workers. Here, all the estimates are negative, but only one (for men, and for the medical only definition) is statistically significant. The effect of a broader definition can, of course, cut two ways. On the one hand it can extend protections and increase hiring. But on the other hand, it could make employers warier of hiring an older worker who might suffer a health decline and become subject to state disability discrimination protections – in this case, more easily because of the broader disability definition.
Note that the statistically significant evidence that a broader definition of disability reduces callbacks for older workers arises when using the medical only definition, which is the broadest one (in columns (3) and (5)). This evidence weakens when adding in the two states (California and Minnesota) with “intermediate” definitions based on a weaker definition of “limits” than the ADA. Since one of these two states is California (with the data in the study coming from Los Angeles), it makes sense that the effect of a broader definition of disability might weaken noticeably when these two states are added.

The previous two tables may not estimate the independent effects of each of the variations in state antidiscrimination protections, because the presence or absence of different features of state laws are correlated across states, as Table 2 indeed suggests. Thus, in Table 7 we add the law interactions for both age discrimination laws and disability discrimination laws simultaneously. In this table, however, we combine the firm-size cutoffs, defining a single variable for whether the firm-size cutoff under either state age or disability discrimination laws (or both) is less than one. We do this because there are very few states, and they are small ones with not much data, for which there is independent variation in the two types of firm-size cutoffs. This restriction results in there being no evidence that a lower firm-size cutoff increases callbacks for older female applicants – which we found for age discrimination laws in Table 5. However, we still find evidence that the medical-only broader definition of disability reduces callbacks for older male applicants. And the point estimates for larger damages under disability discrimination laws for older women are similar to those in Table 6, although not statistically significant at the 10-percent level.

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32 For example, New Jersey has a lower firm-size cutoff and larger damages for both age discrimination and disability discrimination, and a broader medical definition, Rhode Island has the first four but not a broader disability definition, and Nebraska has no stronger protections for either type of discrimination.

33 This leads to highly variable estimates, which we view as unreliable. The estimates including both type of firm-size cutoffs as separate variables are reported in Appendix Table A1, which shows that the estimated effects of the two different types of firm-size cutoffs vary in explicable ways between men and women. The other estimates, however, are robust.

34 However, in Appendix Table A1 there is stronger evidence that a lower firm-size cutoff under age discrimination law boosts callbacks for older women, and stronger evidence that larger damages under disability discrimination laws also boost callbacks for older women. However, we are warier of the estimates in this table.
Overall, the examination of the effects of stronger state age and disability discrimination protections on hiring of older workers provides a somewhat mixed message. For men, the evidence of effects that we find points to a negative effect — in particular, in states where the definition of disability that extends to medical issues. For women, there is, although it is statistically weaker, that larger damages for disability discrimination may increase hiring. From this, we draw two key conclusions: (1) there clearly is not unambiguous evidence that stronger age and disability discrimination protections boost hiring of older workers; and (2) there is some evidence — for men — that these laws may be more likely to reduce hiring of older workers.

City weights and representativeness

We next briefly explore the sensitivity of the results to weighting. The estimates reported thus far are based on unweighted data, and hence the estimates are representative of the distribution of job ads we identified in the course of the study. As it turns out, we obtained quite different numbers of observations by city relative to what would be expected based on the number of retail jobs in the city. This is attributable to two reasons. First, for some cities the website from which we took the job ads define the market as the whole city, whereas for others, when there are multiple markets (which occurs for very large cities), we used a single market because of the resource constraints imposed by collecting data for cities in all 50 states. Second, for a couple of very large cities where there was a huge number of ads, the research assistants did not apply to every job, whereas for other cities they applied to all of them. Figure 4 displays this information. What we see, for example, is a very large number of jobs in Seattle (WA) in the experimental data (black bar), relative to the share of retail jobs computed from the Quarterly Workforce Indicators data for retail, in the ranges covering the age groups we study (gray because of the large changes in estimates relative to the earlier tables, the large magnitudes, and their dependence on a small number of states (which likely explains these findings and renders them unreliable).
bar). In contrast, New York City (NY) has a large number of retail jobs, as does Los Angeles (CA), but fewer observations in the experimental data.

We thus report estimates where we reweight the data by the ratio of the percent of employment in the QWI data to the percent of observations in the experimental sample in the city. This will make the estimates representative of the distribution of retail jobs by city in the QWI data. As shown in Table 8, which should be compared with Table 7, this has little impact on the estimates. The estimates are similar as are most of the qualitative conclusions.

The one difference is that the evidence for the shift in callback rates associated with the broader disability definition (medical only) is now more similar for older men and older women, although the t-statistic for women is only 1.5. If anything, this slightly reinforces the conclusion that this kind of broader definition of disability protection may reduce hiring of older workers.

**Correcting for Bias from Differences in the Variances of Unobservables**

We next turn to the estimates that are intended to eliminate the bias identified by the Heckman critique. To briefly explain the procedure, we first estimate a probit model with the controls and their interactions with “Old” included. We then test the over-identifying restriction for the controls, to see whether the data are consistent with the effects for young and old differing in a way that is driven only by the difference in variance of the unobservables (that is, the ratios of effects for young and old

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35 These data are for NAICS codes 44-45, for the MSA-level data, for ages 25-34, 55-64, and 65-99. The percentages reported by the gray bars are the sum across age ranges and sexes for the MSA, divided by the total for the MSAs used in the states covered by the graph. We use only the portion of the MSA in the state in question. The QWI data are for 2015Q1-Q3. Given the lag in the release of QWI data, this is the closest we could get to the period in which the experimental data were collected (February-July, 2016); note we try to overlap quarters to capture the same seasonal pattern. And for two states (Michigan and Wyoming) we have to use data from 2014Q1-Q3, since the 2015 data were not yet available.

36 For example, the Seattle data are weighted by 0.27, reflecting the overrepresentation of Seattle observations by a factor of about four in the experimental data (Figure 4). And the New York City data are weighted by 4.58, consistent with the underrepresentation of New York City observations in the experimental data (Figure 4).

37 We do not report these results here. It turns out that the skill variables have stronger effects on callback probabilities than we obtained in Neumark et al. (2015) using the same variables, in our job applications for sales jobs. That could be because of the smaller number of cities (12, in 11 states) to which we sent applications, especially given that New York and Los Angeles provided very large numbers of observations.
workers are equal). It turns out that the over-identifying restrictions using all of the controls are not rejected by the data, so we do not have to narrow down the set of variables used to identify the relative variance. We then estimate a heteroskedastic probit model that imposes equal coefficients of the controls in the latent variable model, with the variance of the residual differing between young and old workers. The estimates of this model are used to estimate marginal effects, and to decompose the marginal effects to isolate the effects of the variables on the level of the latent variable, which are the unbiased estimates of discrimination. (The decomposition also identifies the effect of “Old” via the variance, which, as explained in Neumark (2012), is artifact of the study design using a very narrow range of résumé quality.)

The results are reported in Table 9. The upper rows of the table report the marginal effects corrected for bias. The specifications are otherwise the same as those in Table 7, using all the laws simultaneously, and hence can be compared directly. One result is that the estimates for the main effects of “Old,” which measure age discrimination in the states where the federal laws bind, becomes a larger for both men and women. Thus, for these states the evidence of age discrimination strengthens, while remaining stronger for women.

The third panel of the table reports the ratio of the standard deviation of the unobservable for old relative to young workers. For men, this ratio exceeds 1.1 in column (1), is not large, and in the other columns it is relatively close to 1 (always higher). The larger standard deviations for older workers, coupled with the larger estimates of discrimination, are consistent with the résumés on average being of lower quality. However, the estimated interactions between “Old” and the features of state antidiscrimination laws do not change much from correcting for the bias from different variances of the 

38 To identify the effect of the old-state law interactions, we have to assume equal coefficients for the state dummy variables, so this restriction is simply imposed. The over-identification test we use pertains to all of the other controls.

39 This decomposition is unique when using the calculation of marginal effects that treats the variables as continuous, which is not standard but has virtually no effect on the estimated marginal effects. The standard calculation of the marginal effect for discrete variables does not yield a unique decomposition.
unobservables, consistent with the relative standard deviations of the unobservables being relatively close to 1.\textsuperscript{40}

**Conclusions and discussion**

In this study, we provide evidence from a field experiment – a correspondence study – on age discrimination in hiring for retail sales jobs. The unique contribution of this paper is to collect experimental data in all 50 states, and then to relate the measure of age discrimination – the difference in callback rates between old and young applicants – to variation across states in antidiscrimination laws offering protections to older workers that are stronger than the federal laws. We study both age discrimination and disability discrimination laws. While age discrimination laws explicitly target discrimination against older workers, we argue that it is natural to expect disability discrimination laws to do far more to protect older workers than younger workers.

The experimental evidence provides direct estimates of discrimination in hiring – which is the goal of the correspondence study methods we use in this paper. The findings on age discrimination point consistently to evidence of hiring discrimination against older men and more so against older women.

The key new evidence in this paper, however, concerns the relationship between hiring discrimination against older workers and state variation in age and disability discrimination laws. On this question, we find some evidence consistent with stronger state age discrimination laws reducing discrimination against older women, although this evidence is not very robust. We find stronger

\textsuperscript{40} We found more evidence of bias in Neumark et al. (2015) – which only estimated the effects of age – with the bias correction strengthening the evidence of discrimination for women, and weakening it substantially for men. Those estimates may have been less robust because of using many fewer states (cities), as well as because the skill variables had weak predictive power for callbacks in sales. In addition, it is possible there was more bias because with fewer states, the résumés we sent out may have more uniformly been on one side of the distribution of résumé quality that employers observe. In both studies, our résumés used for different states were of uniform quality. But if applicant quality differs across the states/cities, then by using more of them we may have reduced the bias.
evidence that state disability discrimination laws that broaden the definition of disability may reduce hiring of older men.

Clearly this evidence does not support a general conclusion that stronger antidiscrimination protections reduce measured hiring discrimination against older workers. Indeed, some evidence points to stronger protections under state laws increasing measured discrimination. This latter effect is possible, because protections that might make it more difficult to terminate an older worker, or – in the case of disability — raise future accommodation costs for employers, can deter hiring of the protected group, especially if the antidiscrimination laws are relatively ineffective at reducing discrimination in hiring (while being more effective with regard to terminations).

Finally, this evidence does not mean that these antidiscrimination laws do not boost employment of older workers. Past nonexperimental work indicates that adoption of age discrimination laws boosted employment of older workers (Adams, 2004, Neumark and Stock, 1999). Age discrimination laws may increase employment of older workers — perhaps by reducing terminations and encouraging them to look for new jobs — without necessarily reducing discrimination as measured by correspondence study methods. Given the problem of population aging, higher employment of older workers is still a potentially valuable consequence of stronger age discrimination laws.

The nonexperimental evidence on disability discrimination laws is less clear (e.g., Stock and Beegle, 2004; Kruse and Schur, 2003; Button, Armour, and Hollands, 2017b). The more ambiguous evidence on the effects of disability discrimination laws — including both the experimental evidence in this study pointing to potentially adverse effects, and the ambiguous nonexperimental evidence on employment effects — makes it harder to say whether disability discrimination laws are helpful in keeping older workers employed. Of course, these laws may still have a strong rationalization in terms of fairness to individuals with disabilities.
References


Table 1: Level of Matching of Callbacks

<table>
<thead>
<tr>
<th></th>
<th>Matched positive responses</th>
<th>No responses</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voicemail</td>
<td>1,614</td>
<td>N.A.</td>
<td>1,614</td>
</tr>
<tr>
<td>Email</td>
<td>1,218</td>
<td>N.A.</td>
<td>1,218</td>
</tr>
<tr>
<td>Both</td>
<td>438</td>
<td>N.A.</td>
<td>438</td>
</tr>
<tr>
<td>All</td>
<td>3,270</td>
<td>11,158</td>
<td>14,428</td>
</tr>
</tbody>
</table>

Notes: There are 3,270 matched responses to 14,428 résumés that were sent out. For responses received from employers, we tried to match each response to a unique job identifier. We received three voicemails that we were unable to match to either a unique job identifier or to the résumé that was sent.
Table 2: State Disability and Age Discrimination Laws, 2016

<table>
<thead>
<tr>
<th>State (City)</th>
<th>Minimum firm size</th>
<th>Larger damages than ADEA</th>
<th>Minimum firm size</th>
<th>Larger damages than ADA</th>
<th>Broader (medical) definition of disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama (Birmingham)</td>
<td>20</td>
<td>No</td>
<td>No law</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Alaska (Anchorage)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Arizona (Phoenix)</td>
<td>15</td>
<td>No</td>
<td>15</td>
<td>No (no punitive damages)</td>
<td>No</td>
</tr>
<tr>
<td>Arkansas (Little Rock)</td>
<td>No law</td>
<td>No law</td>
<td>9</td>
<td>No (same as ADA)</td>
<td>No</td>
</tr>
<tr>
<td>California (Los Angeles)</td>
<td>5</td>
<td>Yes</td>
<td>5</td>
<td>Yes (uncapped)</td>
<td>Yes (“limits” only)</td>
</tr>
<tr>
<td>Colorado (Denver)</td>
<td>1</td>
<td>No</td>
<td>1</td>
<td>No (same as ADA)</td>
<td>No</td>
</tr>
<tr>
<td>Connecticut (Hartford)</td>
<td>3</td>
<td>No</td>
<td>3</td>
<td>Yes*</td>
<td>No</td>
</tr>
<tr>
<td>Delaware (Wilmington)</td>
<td>4</td>
<td>Yes</td>
<td>4</td>
<td>No (same as ADA)</td>
<td>No</td>
</tr>
<tr>
<td>Florida (Miami)</td>
<td>15</td>
<td>Yes</td>
<td>15</td>
<td>No (punitive capped at $100k)</td>
<td>No</td>
</tr>
<tr>
<td>Georgia (Atlanta)</td>
<td>1</td>
<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Hawaii (Honolulu)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Idaho (Boise)</td>
<td>5</td>
<td>Yes</td>
<td>5</td>
<td>No (punitive capped at $10k)</td>
<td>No</td>
</tr>
<tr>
<td>Illinois (Chicago)</td>
<td>15</td>
<td>Yes</td>
<td>1</td>
<td>No (no punitive)</td>
<td>Yes</td>
</tr>
<tr>
<td>Indiana (Indianapolis)</td>
<td>1</td>
<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Iowa (Des Moines)</td>
<td>4</td>
<td>Yes</td>
<td>4</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Kansas (Wichita)</td>
<td>4</td>
<td>Yes</td>
<td>4</td>
<td>No (no punitive damages, damages capped at $2k)</td>
<td>No</td>
</tr>
<tr>
<td>Kentucky (Louisville)</td>
<td>8</td>
<td>Yes</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Louisiana (New Orleans)</td>
<td>20</td>
<td>Yes</td>
<td>20</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Maine (Portland)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Maryland (Baltimore)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>No (same as ADA, no punitive damages in Baltimore County for employers &lt; 15)</td>
<td>No</td>
</tr>
<tr>
<td>Massachusetts (Boston)</td>
<td>6</td>
<td>Yes</td>
<td>6</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Michigan (Detroit)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Minnesota (Minneapolis)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>No (punitive capped at $25k)</td>
<td>Yes (“materially limits” only)</td>
</tr>
<tr>
<td>Mississippi (Jackson)</td>
<td>No law</td>
<td>No law</td>
<td>No law</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Missouri (Kansas City)</td>
<td>6</td>
<td>Yes</td>
<td>6</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Montana (Billings)</td>
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<td>Yes</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Nebraska (Lincoln)</td>
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<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
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<td>Nevada (Las Vegas)</td>
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<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>New Hampshire (Manchester)</td>
<td>6</td>
<td>Yes</td>
<td>6</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>New Jersey (Trenton)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>Yes (uncapped)</td>
<td>Yes</td>
</tr>
<tr>
<td>New Mexico (Albuquerque)</td>
<td>4</td>
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<td>4</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>New York (New York)</td>
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<td>Yes</td>
<td>4</td>
<td>No (no punitive)</td>
<td>Yes</td>
</tr>
<tr>
<td>North Carolina (Charlotte)</td>
<td>15</td>
<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>North Dakota (Bismarck)</td>
<td>1</td>
<td>No</td>
<td>1</td>
<td>No (no damages)</td>
<td>No</td>
</tr>
<tr>
<td>Ohio (Columbus)</td>
<td>4</td>
<td>Yes</td>
<td>4</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Oklahoma (Oklahoma)</td>
<td>1</td>
<td>No</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>State (City)</td>
<td>Age discrimination laws</td>
<td>Disability discrimination laws</td>
<td>Notes: State laws are as of 2016. Age discrimination laws are from Neumark and Song (2013) and disability discrimination laws are from Neumark et al. (2017), but are updated. For Maryland, under Minimum firm size, we list the value 1. This is the case for Baltimore County, from which our data come; the minimum is 15 for the rest of the state. For the states listed as “Yes” under Larger Damages than ADA, but not uncapped, details are as follows: Alaska – uncapped compensatory damages, punitive damages capped above ADA levels; Maine – exceeds ADA cap for firms of 201+ employees. As discussed more in-depth in our legal appendix, the evidence favors punitive damages not being available, and compensatory damages were definitely not available.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------------</td>
<td>-------------------------</td>
<td>-----------------------------</td>
<td>---</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Minimum firm size</td>
<td>Larger damages than ADEA</td>
<td>Minimum firm size</td>
<td>Larger damages than ADA</td>
<td>Broader (medical) definition of disability</td>
</tr>
<tr>
<td>Oregon (Portland)</td>
<td>1</td>
<td>Yes</td>
<td>6</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Pennsylvania (Pittsburgh)</td>
<td>4</td>
<td>No</td>
<td>4</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Rhode Island (Providence)</td>
<td>4</td>
<td>Yes</td>
<td>4</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>South Carolina (Columbia)</td>
<td>15</td>
<td>No</td>
<td>15</td>
<td>No (same as ADA)</td>
<td>No</td>
</tr>
<tr>
<td>South Dakota (Sioux Falls)</td>
<td>No law</td>
<td>No law</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Tennessee (Memphis)</td>
<td>8</td>
<td>Yes</td>
<td>8</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Texas (Houston)</td>
<td>15</td>
<td>Yes</td>
<td>15</td>
<td>No (same as ADA)</td>
<td>No</td>
</tr>
<tr>
<td>Utah (Salt Lake City)</td>
<td>15</td>
<td>No</td>
<td>15</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Vermont (Burlington)</td>
<td>1</td>
<td>Yes</td>
<td>1</td>
<td>Yes (uncapped)</td>
<td>No</td>
</tr>
<tr>
<td>Virginia (Virginia Beach)</td>
<td>1</td>
<td>No</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Washington (Seattle)</td>
<td>8</td>
<td>Yes</td>
<td>8</td>
<td>No (no punitive)</td>
<td>Yes</td>
</tr>
<tr>
<td>West Virginia (Charleston)</td>
<td>12</td>
<td>No</td>
<td>12</td>
<td>Yes (uncapped)</td>
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<tr>
<td>Wisconsin (Milwaukee)</td>
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<td>No</td>
<td>1</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
<tr>
<td>Wyoming (Cheyenne)</td>
<td>2</td>
<td>No</td>
<td>2</td>
<td>No (no punitive)</td>
<td>No</td>
</tr>
</tbody>
</table>
Table 3: Callback Rates by Age

<table>
<thead>
<tr>
<th></th>
<th>Young (29-31)</th>
<th>Old (64-66)</th>
<th>Absolute (percentage point) difference in callback rate for old</th>
<th>Percent difference in callback rate for old</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Males (N=7,212)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Callback (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>75.01</td>
<td>82.61</td>
<td>-7.60</td>
<td>-30.42%</td>
</tr>
<tr>
<td>Yes</td>
<td>24.99</td>
<td>17.39</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Tests of independence (p-value), young vs. old</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>B. Females (N=7,212)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Callback (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>71.58</td>
<td>80.12</td>
<td>-8.54</td>
<td>-30.05%</td>
</tr>
<tr>
<td>Yes</td>
<td>28.42</td>
<td>19.88</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Tests of independence (p-value), young vs. old</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The p-values reported for the tests of independence are from Fisher’s exact test (two-sided). There were no positive responses for West Virginia, so it drops out of the probit analysis in subsequent tables. We therefore also drop West Virginia from this table to have results for the same sample; this has virtually no impact on the estimates in this table.
Table 4: Probit Estimates for Callbacks by Age, Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.077***</td>
<td>-0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State, order, unemployed, skills</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Résumé features</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td><strong>Callback rate for young (29-31)</strong></td>
<td>24.99%</td>
<td>28.42%</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>7,212</td>
<td>7,212</td>
</tr>
<tr>
<td><strong>Clusters</strong></td>
<td>3,607</td>
<td>3,607</td>
</tr>
</tbody>
</table>

Notes: Marginal effects are reported, computed as the discrete change in the probability associated with the dummy variable, evaluating other variables at their means. Standard errors are clustered at the age-by-state level. Significantly different from zero at 1-percent level (***), 5-percent level (**) or 10-percent level (*). Résumé features include: template; email script; email format; script subject, opening, body, and signature; and file name format. See notes to Table 3.

Table 5: Probit Estimates for Callbacks by Age, with Effects of State Age, Antidiscrimination Laws Added, Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.063***</td>
<td>-0.067***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Old (64-66) x Firm-size cutoff &lt; 10</td>
<td>-0.020</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Old (64-66) x Larger damages</td>
<td>-0.014</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State, order, unemployed, skills</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Callback rate for young (29-31)</strong></td>
<td>24.99%</td>
<td>28.42%</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>7,212</td>
<td>7,212</td>
</tr>
</tbody>
</table>

Notes: See notes to Tables 3 and 4.
<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) (12)</td>
<td></td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.070*** (0.011)</td>
<td>-0.076*** (0.009)</td>
</tr>
<tr>
<td></td>
<td>-0.070*** (0.007)</td>
<td>-0.072*** (0.011)</td>
</tr>
<tr>
<td></td>
<td>-0.067*** (0.011)</td>
<td>-0.068*** (0.010)</td>
</tr>
<tr>
<td></td>
<td>-0.084*** (0.007)</td>
<td>-0.092*** (0.006)</td>
</tr>
<tr>
<td></td>
<td>-0.083*** (0.006)</td>
<td>-0.081*** (0.011)</td>
</tr>
<tr>
<td></td>
<td>-0.088*** (0.011)</td>
<td>-0.088*** (0.011)</td>
</tr>
<tr>
<td>Old (64-66) x Firm-size cutoff &lt; 10</td>
<td>-0.010 (0.014)</td>
<td>0.003 (0.015)</td>
</tr>
<tr>
<td></td>
<td>-0.002 (0.016)</td>
<td>-0.003 (0.012)</td>
</tr>
<tr>
<td></td>
<td>-0.005 (0.013)</td>
<td>-0.000 (0.013)</td>
</tr>
<tr>
<td>Old (64-66) x Larger damages</td>
<td>-0.004 (0.015)</td>
<td>-0.014 (0.014)</td>
</tr>
<tr>
<td></td>
<td>-0.007 (0.016)</td>
<td>0.022* (0.013)</td>
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<tr>
<td></td>
<td>0.022* (0.013)</td>
<td>0.020 (0.012)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical only)</td>
<td>-0.034** (0.015)</td>
<td>-0.039 (0.015)</td>
</tr>
<tr>
<td></td>
<td>-0.012 (0.015)</td>
<td>-0.003 (0.016)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical or limits)</td>
<td>-0.017 (0.016)</td>
<td>-0.018 (0.017)</td>
</tr>
<tr>
<td></td>
<td>-0.017 (0.014)</td>
<td>-0.012 (0.014)</td>
</tr>
<tr>
<td></td>
<td>-0.012 (0.014)</td>
<td></td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State, order, unemployed, skills</td>
<td>X X X X X X X X X X X</td>
<td></td>
</tr>
<tr>
<td><strong>Callback rate for young (29-31)</strong></td>
<td>24.99%</td>
<td>28.42%</td>
</tr>
<tr>
<td>N</td>
<td>7,212</td>
<td>7,212</td>
</tr>
</tbody>
</table>

Notes: See notes to Tables 3 and 4.
Table 7: Probit Estimates for Callbacks by Age, with Effects of State Age and Disability Antidiscrimination Laws Added Together, with Minimum Firm-Size Cutoff Variable Defined for Age and/or Disability Laws, Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th></th>
<th>Female</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.061***</td>
<td>-0.061***</td>
<td>-0.088***</td>
<td>-0.088***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.012)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Old (64-66) x Age and/or disability firm-size cutoff &lt; 10</td>
<td>-0.005</td>
<td>-0.008</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.018)</td>
<td>(0.013)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Old (64-66) x Larger damages</td>
<td>-0.001</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Old (64-66) x Disability larger damages</td>
<td>-0.012</td>
<td>-0.005</td>
<td>0.022</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.014)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical only)</td>
<td>-0.036**</td>
<td>-0.003</td>
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<tr>
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<td>(0.016)</td>
<td>(0.017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical or limits)</td>
<td></td>
<td></td>
<td>-0.013</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td><strong>Controls</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State, order, unemployed, skills</td>
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<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Callback rate for young (29-31)</strong></td>
<td>24.99%</td>
<td></td>
<td>28.42%</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>7,212</td>
<td></td>
<td>7,212</td>
<td></td>
</tr>
</tbody>
</table>

Notes: See notes to Tables 3 and 4.
Table 8: Probit Estimates for Callbacks by Age, with Effects of State Age and Disability Antidiscrimination Laws Added Together, with Minimum Firm-Size Cutoff Variable Defined for Age and/or Disability Laws, Marginal Effects, Reweighted based on QWI Retail Employment

<table>
<thead>
<tr>
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<th>Males</th>
<th>Female</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.053***</td>
<td>-0.052***</td>
<td>-0.092***</td>
<td>-0.093***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Old (64-66) x Age and/or</td>
<td>-0.015</td>
<td>-0.019</td>
<td>0.011</td>
<td>0.012</td>
</tr>
<tr>
<td>disability firm-size cutoff &lt; 10</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Old (64-66) x Larger damages</td>
<td>0.013</td>
<td>0.008</td>
<td>0.005</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Old (64-66) x Disability</td>
<td>-0.000</td>
<td>0.011</td>
<td>0.016</td>
<td>0.022</td>
</tr>
<tr>
<td>larger damages</td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical only)</td>
<td>-0.037*</td>
<td>-0.024</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical or limits)</td>
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<td>-0.008</td>
<td></td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
<td>(0.015)</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State, order, unemployed,</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>skills</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Callback rate for young</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(29-31)</td>
<td>23.02%</td>
<td></td>
<td>25.67%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7,212</td>
<td></td>
<td>7,212</td>
<td></td>
</tr>
</tbody>
</table>

Notes: See notes to Tables 3 and 4. The observations are reweighted by the percent of employment in the QWI in the city (for ages 25-34, 55-64, and 65-99) divided by the percent of observations in the experimental sample in the city.
Table 9: Probit Estimates for Callbacks by Age, with Effects of State Age and Disability Antidiscrimination Laws Added Together, Marginal Effects, with Correction for Bias from Different Variances of Unobservables for Young and Old Applicants

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(heteroskedastic probit, marginal effect via level)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.088**</td>
<td>-0.071**</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Old (64-66) x Age and/or disability firm-size cutoff &lt; 10</td>
<td>0.001</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Old (64-66) x Age larger damages</td>
<td>-0.005</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Old (64-66) x Disability larger damages</td>
<td>-0.014</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical only)</td>
<td>-0.048**</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical or limits)</td>
<td>-0.016</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td><strong>Callback estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(heteroskedastic probit, marginal effect via variance)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>0.031</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Overidentification test: ratios of coefficients on skills for old relative to young are equal (p-value, Wald test)</td>
<td>0.793</td>
<td>0.796</td>
</tr>
<tr>
<td>Standard deviation of unobservables, old/young</td>
<td>1.141</td>
<td>1.047</td>
</tr>
<tr>
<td>Test: standard vs. heteroscedastic probit (p-value, log-likelihood test)</td>
<td>0.431</td>
<td>0.773</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>State, order, unemployed, skills</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Callback rate for young (29-31)</td>
<td>24.99%</td>
<td>28.42%</td>
</tr>
<tr>
<td>N</td>
<td>7,212</td>
<td>7,212</td>
</tr>
</tbody>
</table>

Notes: In this table marginal effects are computed as the change in the probability associated with the dummy variable, using the continuous approximation, evaluating other variables at their means; we use the continuous version of the partial derivative, because this version gives an unambiguous decomposition of the estimates from the heteroscedastic probit model (Neumark, 2012). The overidentification test is based on interactions of the skill variables, order of application, and unemployment, with the dummy variable for old. See notes to Tables 3 and 4.
Figure 1: Callback Rates by State, Male Applicants
Figure 2: Callback Rates by State, Female Applicants
Figure 3: Relative Callback Rates for Old vs. Young, Male and Female Applicants

![Relative Callback Rates Diagram](image-url)
Figure 4: Percent Observations by State (City) in Experiment, and in QWI Data for Retail
Appendix Table A1: Probit Estimates for Callbacks by Age, with Effects of State Age and Disability Antidiscrimination Laws Added Together, with and without Separate Minimum Firm-Size Cutoffs for Age and Disability Discrimination Laws, Marginal Effects

<table>
<thead>
<tr>
<th>Callback estimates</th>
<th>Males</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Callback estimates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Old (64-66)</td>
<td>-0.061*** (0.016)</td>
<td>-0.057*** (0.014)</td>
</tr>
<tr>
<td>Old (64-66) x Age and/or disability firm-size cutoff &lt; 10</td>
<td>-0.005 (0.017)</td>
<td>-0.008 (0.018)</td>
</tr>
<tr>
<td>Old (64-66) x Age firm-size cutoff &lt; 10</td>
<td>-0.047*** (0.011)</td>
<td>-0.035*** (0.012)</td>
</tr>
<tr>
<td>Old (64-66) x Disability firm-size cutoff &lt; 10</td>
<td>0.044*** (0.015)</td>
<td>0.029* (0.016)</td>
</tr>
<tr>
<td>Old (64-66) x Age larger damages</td>
<td>-0.001 (0.014)</td>
<td>-0.003 (0.014)</td>
</tr>
<tr>
<td>Old (64-66) x Disability larger damages</td>
<td>-0.012 (0.014)</td>
<td>-0.014 (0.014)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical only)</td>
<td>-0.036** (0.016)</td>
<td>-0.049*** (0.012)</td>
</tr>
<tr>
<td>Old (64-66) x Broader disability definition (medical or limits)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Callback rate for young (29-31)</td>
<td>24.99%</td>
<td>28.42%</td>
</tr>
<tr>
<td>N</td>
<td>7,212</td>
<td>7,212</td>
</tr>
</tbody>
</table>

Notes: See notes to Tables 3 and 4. Estimates in odd-numbered columns repeat estimates from Table 7.
Legal appendix

Coding of state laws

To study the effects of disability discrimination laws, we first needed to code up these laws. To do this, we followed the procedure developed in Neumark and Song (2013) to code state age discrimination laws. This required extensive background research on state statutes and their histories, culled from legal databases including Lexis-Nexis, Westlaw, and Hein Online, as well as many other sources. The first step in assembling information on state disability discrimination laws was to identify the appropriate state statute, which can be complicated because the disability discrimination law can be listed under various sections of state law (e.g., a fair employment act, a separate disability discrimination act). After the appropriate statute was identified, we traced the history of the statute using the legal databases to look for changes over time. In some cases, we had to look beyond the statutes to information from state agencies, case law, or other sources.

Because it is complicated to read and interpret the law correctly based solely on statutes, we cross-checked our understanding of the statute with other legal references or treatises and additional sources of information on state laws.\textsuperscript{41} The other sources were also useful because of a further challenge in reading statutes. In particular, one section may define what a discriminatory act is, while other provisions may be delegated to the Civil Rights Commission, or the remedies may be listed under a different section of the statute.

To minimize inaccuracies, once all the necessary information was obtained from these sources, we attempted to compare and validate it using other sources. If information obtained from different sources matched, we were confident that the information was correct. In cases of what should be

unambiguous information – in particular the minimum firm size for laws to apply – we use the information from the statute regardless. However, in cases of information that can be more easily misinterpreted from the statute, when we found discrepancies we turned to state agencies or other sources for corroborating information. We also examined case law, using the legal databases, to see if rulings established fixed features of the state laws that were not specified in the statute, such as damages allowed.

As a result of these efforts, we were able to fill in all the information on these laws for our sample period. The only possible exception is for damages. In particular, if our information on damages came not from statutes (since the statutes did not mention damages) but rather from case law or other sources, then we did not necessarily have an explicit “reading” on these damages in every year. But since our other sources cover many years, the only variation we could miss was some short-term change between the level of damages we get from other sources. We assume, though, that there is little or no such variation.

As noted in the main text, there are three major ways in which state disability discrimination laws can be stronger than the federal ADA. Here we provide some general discussion of these differences, and then we provide state-specific details.

The minimum firm size for the ADA to apply is 15. We create an indicator variable equal to one if the firm size minimum is lower than 10 (i.e., substantially lower than the ADA minimum), and zero otherwise. When the firm size minimum is lower, more workers (and employers) are covered.

Defining disability is of course more complicated than defining other protected groups, like age, race, and sex, and the definition of disability differs across states. Most states adopt the same definition as the ADA, either explicitly or via case law. The ADA provides three routes for an individual to be considered disabled:

“The term “disability” means, with respect to an individual-
A. a physical or mental impairment that substantially limits one or more major life activities of such individual; 
B. a record of such an impairment; or 
C. being regarded as having such an impairment” (42 U.S. Code §12102 (1)).

Given that the definition of physical and mental impairment is quite broad, the “substantially limits” requirement can probably be thought of as the main criterion defining disability under the ADA and similar state laws. Moreover, the “substantially limits” phrase has been interpreted by the courts as quite restrictive⁴². The U.S. Supreme Court, in the “Sutton Trilogy” of cases (Sutton v. United Airlines (119 S. Ct. 2139 (1999)), Murphy v. United Parcel Service, Inc. (119 S. Ct. 2133 (1999)), and Albertson's, Inc. v. Kirkingburg (119 S. Ct. 2162 (1999))), deemed individuals to be not disabled if mitigating measures, such as glasses or medication, made the limiting features of the disability dormant. A U.S. Court of Appeals, 4th Circuit, decision also restricted episodic conditions, such as epilepsy, from being considered a disability in EEOC v. Sara Lee Corp., 237 F.3d 349 (4th Cir., 2001).⁴³

Some states use a weaker criterion in this regard than the “substantially limits” requirement of the ADA under the first criterion above. In two states this is done by the statutes substituting “materially limits” (MN) or just “limits” (CA) for “substantially limits,” with legal interpretations or statutes being explicit that this is a less stringent standard. Several states (CT, IL, NJ, NY, and WA) adopt an even laxer definition, considering an individual to be disabled if their impairment is medically diagnosed, regardless of whether the impairment substantially limits one or more major life activities. Long (2004) argues, as seems quite reasonable, that these medical definitions broaden coverage relative

⁴² For example, Burgdorff (1997, p. 536-538) cites numerous cases stemming from numerous cases stemming from Forrisi v. Bowen, 794 F.2d 931, 934 (4th Cir. 1986), which interpreted the ADA to only cover the “truly disabled” and not those with more minor impairments.

⁴³ These decisions were reversed by the ADA Amendments Act (ADAAA), effective in 2009, which is beyond our sample period. Under the ADAAA, states where the ADA’s definition of disability prevailed became more like those states using a medical impairment definition, discussed next. In principle we could use data pre- and post-2009 for identifying information on this dimension of variation in disability discrimination laws, but the confounding effects of the Great Recession make this unlikely to be informative.
to the ADA. To capture this variation, we create a dichotomous variable called “broader definition” which equals one for states with the medical definition of disability, and zero otherwise.\footnote{We also considered including the other states with laxer definitions (California and Minnesota) in the broader definition category, but decided not to because the definition in these states seems much closer to the ADA definition. Nonetheless, we verified that results with this alternative classification were similar.}

Damages are likely to play a major role in the strength of discrimination laws, based in part on evidence from age discrimination laws (Neumark and Song, 2013). The ADA caps the sum of compensatory and punitive damages per claimant based on firm size, as follows:

1. 15-100 employees: $50,000
2. 101-200 employees: $100,000
3. 201-500 employees: $200,000
4. 500 plus employees: $300,000.

Few states follow this exact schedule (AR, CO, DE, MD, SC, and TX). 12 states allow larger potential damages, either through higher caps (AK and ME) or, more commonly, through allowing compensatory damages and uncapped punitive damages (CA, HI, MA, MO, NJ, OH, OR, RI, VT, and WV). We create a dichotomous variable called “larger damages,” which equals one for the 12 states where potential damages exceed those under the ADA, and zero otherwise. Three states (FL, ID, and MN) have lower damage caps than the ADA, and two states (AL and MS) have no law (in which case we code the state as not having the stronger provision). There are 26 states with no punitive damages. We do not include these states in the larger damages category because compensatory damages require documentation and in many cases seem unlikely to be as large; an example might be medical bills if an employee was terminated unjustly, and dropped from a health insurance plan. Thus, punitive damages are likely more the driver of large judgments.\footnote{For reasons explained below, some of our analyses incorporate information on two features of state age discrimination laws – larger damages, and the firm-size cut-off – in some of our analyses. This information (from Neumark and Song, 2013) is listed in the last two columns of Table 2. As the table shows, firm-size minimums are similar for disability and age discrimination laws, but there are 11 states that have a different minimum (AL, AR, GA, IL, IN, KY, LA, NE, OR, SD, and VA). With regard to damages, we focus on whether compensatory or}
Definition of disability

Some state laws bypass the requirement that a mental or physical impairment “substantially limits” one or more major life activities. This occurs either by replacing “substantially limits” with either just “limits” (California) or “materially limits” (Minnesota), or by defining disability as a medical diagnosis (Connecticut, Illinois, New Jersey, New York, Washington effective May 4, 2007). These state laws are discussed in more detail below.

California

California’s disability discrimination law is discussed in further detail by Button (forthcoming) but we provide a summary here. California adopts a similar definition of disability to the ADA, but specifies in statute that the impairment must “limit” instead of “substantially limit” a major life activity. Although dropping the word “substantially” may seem trivial, this did in fact make establishing that a disability exists less burdensome, but not initially. The Prudence Kay Poppink Act took effect in California in 2001, and this act made it explicit that the “limits” requirement in California was less burdensome than the federal ADA. Before this act passed however, the “limits” requirement was interpreted in the same way as the federal ADA (Long, 2004). For example, in Colmenares v. Braemer Country Club, Inc., 63 P.3d 220, 223 (Cal. 2003), the plaintiff was deemed not disabled because his case

punitive damages are allowed, which they are not under federal age discrimination law (the ADEA). Some states require proof of intent to discriminate in order for compensatory or punitive damages to be awarded, whereas others require “willful” violation. Because the federal law allows additional liquidated, non-punitive damages (double back pay and benefits) when there is “willful” violation, the question of whether the state requires intent or willful violation may seem to be potentially relevant in deciding whether a state law offers greater protection. However, willful violation is a much stricter standard than intent (Moberly, 1994). Moreover, compensatory or punitive damages are almost certainly greater than liquidated damages, and they can be much greater. As a consequence, a state law that provides compensatory or punitive damages, whether or not this requires proof of intent or willful violation, clearly entails stronger remedies than the federal law, so our classification captures whether either is allowed.

In principle one might classify states with combinations of the three dimensions of laws tabulated in Table 2 as having the strongest laws. However, this would provide virtually no difference in variation, and hence almost no additional variation. As Table 2 shows, the set of states with the broader definition is quite small, and only one state (New Jersey) overlaps this dimension of state laws with larger damages. Similarly, for the overlap between broader definition and smaller firm size, no states differ. And finally, if we look at the overlap between larger damages and smaller firm size, only one state with larger damages leaves its firm size cutoff at 10 or greater (West Virginia); the independent variation in firm size cutoffs comes from the states that do not have larger damages.
preceded the Poppink Act, when California’s “limits” was interpreted the same as the ADA’s “substantially limits.”

**Connecticut**

In Connecticut, a diagnosis of a physical or mental impairment makes the individual disabled under law, bypassing the “substantially limits” requirement. CONN. GEN. STAT. § 46a-51(15) states that “‘Physically disabled’ refers to any individual who has any chronic physical handicap, infirmity or impairment, whether congenital or resulting from bodily injury, organic processes or changes or from illness, including, but not limited to, epilepsy, deafness or hearing impairment or reliance on a wheelchair or other remedial appliance or device.”

Connecticut is even more explicit in its definition of mental disability (Long, 2004), as CONN. GEN. STAT. § 46a-51(20) states that “‘Mental disability’ refers to an individual who has a record of, or is regarded as having one or more mental disorders, as defined in the most recent edition of the American Psychiatric Association's ‘Diagnostic and Statistical Manual of Mental Disorders’.”

**Illinois**

775 ILL. COMP. STAT. 5/1-103(I) defines a disability as “…a determinable physical or mental characteristic of a person, including, but not limited to, a determinable physical characteristic which necessitates the person's use of a guide, hearing or support dog, the history of such characteristic, or the perception of such characteristic by the person complained against, which may result from disease, injury, congenital condition of birth or functional disorder…”

**Minnesota**

Similar to California, MINN. STAT. § 363.01(12) defines disability as “…any condition or characteristic that renders a person a disabled person. A disabled person is any person who (1) has a physical, sensory, or mental impairment which materially limits one or more major life activities; (2) has
a record of such an impairment; or (3) is regarded as having such an impairment.” While the distinction between materially and substantially may seem trivial, Long (2004) notes that the Minnesota Supreme Court, in Sigurdson v. Carl Bolander & Sons, Co., 532 N.W.2d 225, 228 n.3 (Minn. 1995), stated that the Minnesota definition is less stringent.

New Jersey

N.J. STAT. ANN. § 10:5-5(q) defines disability as a “…physical disability, infirmity, malformation or disfigurement which is caused by bodily injury, birth defect or illness including epilepsy and other seizure disorders, and which shall include, but not be limited to, any degree of paralysis, amputation, lack of physical coordination, blindness or visual impediment, deafness or hearing impediment, muteness or speech impediment or physical reliance on a service or guide dog, wheelchair, or other remedial appliance or device, or any mental, psychological or developmental disability, including autism spectrum disorders, resulting from anatomical, psychological, physiological or neurological conditions which prevents the normal exercise of any bodily or mental functions or is demonstrable, medically or psychologically, by accepted clinical or laboratory diagnostic techniques. Disability shall also mean AIDS or HIV infection.”

New York

New York's Executive Law § 292(21)(a) defines a disability as “a physical, mental or medical impairment resulting from anatomical, physiological, genetic or neurological conditions which prevents the exercise of a normal bodily function or is demonstrable by medically accepted clinical or laboratory diagnostic techniques.” The requirement that the impairment be “demonstrable by medically accepted clinical or laboratory diagnostic techniques” bypasses the “substantially limits” requirement and makes New York disability discrimination law more broadly applicable (Long, 2004).
Washington

Washington’s definition of disability was rather vague before an amendment, effective May 4, 2007, changed Washington’s definition to follow a medical diagnosis definition like Connecticut, Illinois, New Jersey, and New York. Prior to this amendment, WASH. REV. CODE § 49.60.180 prohibited discrimination on the basis of physical disability, but the term was not defined. Noting this, Long (2004) could not categorize Washington’s laws and instead put them in a “miscellaneous” category. It appears that Washington’s lack of definition caused courts to rely on the federal definition of disability, which included the “substantially limits” requirement.47 After the 2007 amendment, Washington law states that “‘Disability’ means the presence of a sensory, mental, or physical impairment that:

(i) Is medically cognizable or diagnosable; or

(ii) Exists as a record or history; or

(iii) Is perceived to exist whether or not it exists in fact” (Wash. Rev. Code § 49.60.040 (7)(a)).

Compensatory and punitive damages

As discussed in the main text, we classify 12 states as having damages that exceed those provided by the ADA. Of these 12 larger damages states, two states (AK and ME) have caps on either compensatory or on punitive damages, but these caps exceed those of the ADA caps on the sum of compensatory and punitive damages. The remaining ten states (CA, HI, MA, MO, NJ, OH, OR, RI, VT, and WV) allow compensatory damages and allow punitive damages that are uncapped. Of the 38 states that we classify as not having damages that exceed the ADA, six states (AR, CO, DE, MD, SC, and TX) have the exact same damage caps as the ADA, three (FL, ID, MN) have lower damage caps, 26 do not allow punitive damages (AZ, GA, IA, IL, IN, KS, KY, LA, MI, MT, NC, ND, NE, NH, NM, NV, NY, OK, PA, SD, TN, UT, VA, WA, WI, and WY), two (AL, MS) do not have an employment

nondiscrimination law for disability, and CT had an ambiguous law at the time of data collection, such that we code it is not having larger damages since this category is a much better fit.

**States with Compensatory Damages and Uncapped Punitive Damages**

Ten states (CA, HI, MA, MO, NJ, OH, OR, RI, VT, and WV) offer both compensatory damages and uncapped punitive damages. Determining that these damages were in fact uncapped was difficult. For all these states, statutes did not mention explicit caps on damages, nor was there explicit mention that damages were uncapped. While it seemed likely that these states allowed uncapped damages, we confirmed this conjecture with various sources.

**California**

California’s employment non-discrimination law is vague as to what damages are available, and this had to be clarified in case law. The Fair Employment and Housing Act (Cal. Govt. Code §§12900–12996) provides no mention of statutory caps on civil damages. The case Commodore Home Sys., Inc. v. Superior Court, 32 Cal. 3d 211, 221 (1982) concluded that allowable damages fell under Cal. Civ. Code, § 3294, which provides no caps.48 The National Conference of State Legislatures (2015) (henceforth NCSL) also indicates that punitive damages are available.

**Hawaii**

Hawaii’s employment non-discrimination law states that compensatory and punitive damages are available, but no caps, or lack thereof, are explicitly mentioned (HI ST § 378-5, HI ST § 368-17). DRI (2011, p. 97) and NCSL (2015) confirm that there are in fact no caps. Jury instructions mention punitive damages but do not mention caps49. Punitive damages are discussed in-depth by Antolini (2004) who notes that punitive damages are not capped (p. 159).

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Massachusetts

Massachusetts’ employment non-discrimination law states that compensatory and punitive damages are available, but no caps, or lack thereof, are explicitly mentioned (MA ST 151B). These damages can only be obtained from trial court and not through the Massachusetts Commission Against Discrimination (DRI, 2011, p. 191; Sperino, 2010). NCSL (2015) and Guide to Employment Law & Regulation (2016) (henceforth GELR) also indicates that punitive damages are available.

Missouri

Missouri’s employment non-discrimination law states that compensatory and punitive damages are available, but no caps, or lack thereof, are explicitly mentioned (MO ST 213). According to case law mentioned by DRI (2011, p. 223) “…the Missouri Courts of Appeals have indicated that, in most situations, the courts should not allow punitive damages in excess of a single digit ratio to actual damages. State ex rel. Bass Pro Outdoor World, LLC v. Schneider, 302 S.W.3d 103 (Mo. App. 2009). At least one court has held, however, that in appropriate circumstances a punitive damage award could significantly exceed a single digit ratio. Lynn v. TNT Logistics North America, Inc., 275 S.W.3d 304 (Mo. App. 2008)” Sperino (2010, p. 709), NCSL (2015), and GELR (2016) also indicate that punitive damages are uncapped.

New Jersey

New Jersey’s employment non-discrimination law states that “All remedies available in common law tort actions shall be available to prevailing plaintiffs” (N.J.S.A. 10:5-13). This includes compensatory and punitive damages (DRI, 2011, p. 254) but there is no explicit mention of caps, or lack thereof. Case law, such as Baker v. National State Bank, 801 A.2d 1158 (N.J. App. Div. 2002) indicates that these damages are uncapped (DRI, 2011, p. 253). NCSL (2015) and GELR (2016) also indicate that punitive damages are available.
Ohio

Ohio law allows for “…damages, injunctive relief, or any other appropriate relief.” (OH ST. § 4112.99). According to DRI (2011, p. 311), this includes uncapped compensatory and punitive damages for civil actions but these damages are capped if the case is handled by the Ohio Civil Rights Commission. NCSL (2015) also indicates that punitive damages are available.

Oregon

Oregon’s employment non-discrimination law states: “The court may award, in addition to the relief authorized under subsection (1) of this section, compensatory damages or $200, whichever is greater, and punitive damages…” (OR ST § 659A.885(3)(a)). DRI (2011, p. 326) confirms that damages are uncapped, noting that there are caps only if the action is against a government entity. NCSL (2015) and GELR (2016) also indicate that punitive damages are available.

Rhode Island

Rhode Island’s employment non-discrimination law states that: “Any person with a disability who is the victim of discrimination prohibited by this chapter may bring an action in the Superior Court against the person or entity causing the discrimination for equitable relief, compensatory and/or punitive damages or for any other relief that the court deems appropriate” (RI ST § 42-87-4). NCSL (2015) and GELR (2016) confirm that punitive damages are available for a private action. DRI (2011, p. 352) confirms that there are no caps, but notes that judges may intervene in cases when juries wish to award punitive damages that are deemed excessive, as in Mazzaroppi v. Tocco, 533 A.2d 203 (R.I. 1987).

Vermont

Vermont’s employment non-discrimination law states that: “Any person aggrieved by a violation of the provisions of this subchapter may bring an action in superior court seeking compensatory and punitive damages or equitable relief, including restraint of prohibited acts, restitution of wages or other
benefits, reinstatement, costs, reasonable attorney's fees and other appropriate relief” (21 V.S.A. §495b). DRI (2011, p. 399) interprets this to mean that both compensatory and punitive damages are uncapped. NCSL (2015) similarly confirms that punitive damages are available. The language “compensatory and punitive damages” was added by 1999, No. 19, § 5. Before this, the statute just said “damages” and it was left ambiguous as to if punitive damages were covered. This ambiguity prior to the 1999 amendment was settled in Fernot v. Crafts Inn, Inc., 895 F. Supp. 668, 682 (D. Vt. 1995), where it was deemed that punitive damages were not allowed.

**West Virginia**

West Virginia’s employment non-discrimination law does not directly state that compensatory and punitive damages are available. It states that remedies include: “…reinstatement or hiring of employees, granting of back pay or any other legal or equitable relief as the court deems appropriate. In actions brought under this section, the court in its discretion may award all or a portion of the costs of litigation, including reasonable attorney fees and witness fees, to the complainant” (W. Va. Code §5-11-13). DRI (2011, p. 428) deems punitive damages to be available, citing Haynes v. Rhone-Poulenc, Inc., 521 S.E.2d 331 (W. Va. 1999) as an example. The question of if compensatory damages were available was settled in State Human Rights Commission v. Pauley, 212 S.E.2d 77 (W. Va. 1975), where the West Virginia Supreme Court deemed compensatory damages to be available. NCSL (2015) lists both compensatory and punitive damages.

*States with caps that exceed the ADA*

**Alaska**

Alaska’s damages, as described in AS § 09.17.020(h), exceed those of the ADA for all firm sizes:
“(h) Notwithstanding any other provision of law, in an action against an employer to recover damages for an unlawful employment practice prohibited by AS 18.80.220, the amount of punitive damages awarded by the court or jury may not exceed

(1) $200,000 if the employer has less than 100 employees in this state;

(2) $300,000 if the employer has 100 or more but less than 200 employees in this state;

(3) $400,000 if the employer has 200 or more but less than 500 employees in this state;

and

(4) $500,000 if the employer has 500 or more employees in this state.”

These caps are just caps on punitive damages, and these caps are even above the ADA caps which are caps on the sum of compensatory and punitive damages. NCSL (2015) lists that compensatory and punitive damages are available.

Maine

Maine’s compensatory damages, as described in 5 M.R.S.A. §4613(2)(B)(8)(e), exceed those of the combined damages allowed under the ADA for firms with 201 or more employees, and are equal for all other firm sizes.

“(e) The sum of compensatory damages awarded under this subparagraph for future pecuniary losses, emotional pain, suffering, inconvenience, mental anguish, loss of enjoyment of life, other nonpecuniary losses and the amount of punitive damages awarded under this section may not exceed for each complaining party:

(i) In the case of a respondent who has more than 14 and fewer than 101 employees in each of 20 or more calendar weeks in the current or preceding calendar year, $50,000;

(ii) In the case of a respondent who has more than 100 and fewer than 201 employees in each of 20 or more calendar weeks in the current or preceding calendar year, $100,000;
(iii) In the case of a respondent who has more than 200 and fewer than 501 employees in each of 20 or more calendar weeks in the current or preceding calendar year, $300,000; and

(iv) In the case of a respondent who has more than 500 employees in each of 20 or more calendar weeks in the current or preceding calendar year, $500,000.”

The statute also allows for punitive damages “A complaining party may recover punitive damages under this subparagraph against a respondent if the complaining party demonstrates that the respondent engaged in a discriminatory practice or discriminatory practices with malice or with reckless indifference to the rights of an aggrieved individual protected by this Act.” (5 M.R.S.A. §4613(2)(B)(8)(c)) This is confirmed both by DRI (2011, p. 170) and NCSL (2015).

States with the same damage caps as the ADA

Arkansas

The Arkansas Civil Rights Act (Ark. Code Ann. §§16-123-101 et seq.) specifies the same damage caps as the ADA (§§16-123-107(c)(2)(A)). However, since firms of size nine to 14 are also covered under this law, the damage cap for this group is set at $15,000.

Colorado

The Colorado Anti-Discrimination Act (C.R.S. §§24-34-301 et seq.) allows both compensatory and punitive damages, but explicitly mentions that they are capped at ADA levels (see 42 U.S.C. sec. 1981a(b)(3)). Since the firm size minimum is one, damage caps are $10,000 for one to four employees, and $25,000 for five to 14 employees (C.R.S. §§24-34-405(d)).
Delaware

The Delaware Discrimination in Employment Act (19 Del. C. §711 et seq.) specifies that damages are capped at the same level as Title VII of the Civil Rights Act of 1964, which are the same damage caps that apply to the ADA.

Maryland

The Maryland Fair Employment Practices Act (Md. Code Ann., State Gov’t §20–601 et seq.) provides for the same damage caps as the ADA (Md. Code Ann., State Gov’t §20–1009(3)). Prior to the passage of Acts 2007, c. 176, however, the Maryland Fair Employment Practices Act did not allow punitive damages. The statute allows for a minimum employer size of one for the law to apply in Baltimore County, but punitive damages are not allowed in Baltimore County in cases with employers of size one to 14 employees.

South Carolina

The South Carolina Human Affairs Law (S.C. Code §§1-13-10 et seq.) does not explicitly mention compensatory or punitive damages. DRI (2011, p. 363) argues that the damages are identical to those under Title VII / ADA cases, noting case law which states: “Thus, Title VII cases which interpret provisions or procedures essentially identical to those of the Human Affairs Law are certainly persuasive if not controlling in construing the Human Affairs Laws (Orr v. Clyburn, 290 S.E.2d 804 (S.C. 1982)).”

Texas

The Texas Commission on Human Rights Act (Tex. Lab. Code §§21.001 et seq.) lists the same damage caps as the ADA.
States with lower damage caps than the ADA

Florida

The Florida Civil Rights Act of 1992 (Fla. Stat. §§760.01 et seq.) allows uncapped compensatory damages, but it caps punitive damages at $100,000 (Fla. Stat. §§760.11(5)).

Idaho

Idaho allows “actual damages,” and the statute does not mention caps, or a lack thereof (Idaho Code §67-5908(c)). Secondary sources were uninformative as to if this meant that actual damages were uncapped (DRI, 2011, p. 105; Green 1992; Buckley and Green 1997, 2002, 2006, 2008, 2009, and 2011). However, punitive damages are capped at $1,000 per willful violation (Idaho Code §67-5908(e)).

Minnesota

The Minnesota Human Rights Act (Minn. Stat. §363A) allows for compensatory damages capped at three times actual damages and punitive damages capped at $25,000 (Minn. Stat. §363A.29 Subd.4(a)).

States that do not allow punitive damages

Arizona

Arizona’s employment nondiscrimination law does not mention compensatory or punitive damages, only mentioning non-monetary remedies, back pay, and that there is available “… any other equitable relief as the court deems appropriate” (A.R.S. §41-1481(G)). The history preamble to H.B. 2319 (Ariz. 45th legislature, 2001), an unpassed bill that attempted to amend this law, states that “Under Arizona law, the Attorney General’s Civil Rights Division may only seek relief on behalf of a victim of discrimination in the name of the aggrieved party. Compensatory and punitive damages are not currently available to an aggrieved party under Arizona employment law, although under Arizona’s
housing law an aggrieved party may be awarded compensatory and punitive damages, and under the Arizonans with Disabilities Act, compensatory damages.” This suggests that compensatory and punitive damages are in fact not available. DRI (2011) and GERL (2015) do not mention punitive damages, with DRI (2011) mentioning that “A successful plaintiff under the ACRA may recover damages similar to those available under Title VII prior to it being amended by the 1991 Civil Rights Act.” (p. 13) Before the 1991 Civil Rights Act, punitive damages were not available.

Georgia

O.C.G.A. §45-19-38(d) states that “Any monetary award ordered pursuant to this article shall be for actual damages only.” This rules out punitive damages, which is echoed by DRI (2011, p. 88) and NCSL (2015). GELR (2016) also does not mention punitive damages.

Illinois

The statute allows for “actual damages, as reasonably determined by the Commission, for injury or loss suffered by the complainant” (775 ILCS 5/8A-104). No punitive damages are mentioned. Smith, O’Callaghan, and White50 and DRI (2011, p. 111) state that in the Illinois Human Rights Act (775 ILCS 5/1-101 et seq.), punitive damages are not allowed but the actual damages allowed are uncapped. Sezer and Epting (2012) also state that punitive damages are not allowed. GELR (2016) also does not list punitive damages. Although this law was amended in 2007 to allow a private right of action, this did not change the available remedies. However, NCSL (2015) lists punitive damages as being available, so there is some contradiction in the secondary sources. Given this, case law could help resolve this uncertainty. Case law confirms the lack of punitive damages, with the Illinois Supreme Court striking a punitive damages award in Crittenden v. Cook County Commission on Human Rights, 2013 IL 114876 on June 20, 2013. While punitive damages may have been unclear before this case, it is clear since then that they are not allowed.

Indiana

The Indiana Civil Rights Law (Ind. Code §22-9-1-1, et seq.) does not mention compensatory or punitive damages. Case law clarified that the Indiana Civil Rights Commission (ICRC) is authorized to award damages to compensate for both economic and emotional distress losses but is not authorized to award punitive damages. See Indiana Civil Rights Com'n v. Alder, 1999, 714 N.E.2d 632 (referenced by Westlaw, 2013b, p. 39 and p. 67). NCSL (2015) also indicates that punitive damages are not available, DRI (2011, p. 121) does not mention punitive damages, and GELR (2016) does not mention damages as being available.

Iowa


Kansas

The Kansas Act Against Discrimination (K.S.A. §44-1001, et seq.) caps damages at $2,000 and does not list punitive damages. DRI (2011, p. 139), citing Labra v. Mid-Plains Constr., Inc., 32 Kan.
App. 2d 821, 823, 90 P.3d 954 (2004), notes that it is unclear if this cap applies only to administrative proceedings or if it also applies to private actions. Neither DRI (2011) nor GELR (2016) nor NCSL (2015) indicate that punitive damages are available.

**Kentucky**


**Louisiana**

Louisiana allows compensatory damages, and the statute mentions no caps (La. R.S. §23:303(A)). DRI (2011, p. 160) also states that there are no caps. Punitive damages are not available, as DRI (2011, p. 160) notes that “… punitive damages are not available under Louisiana law unless expressly authorized by statute. See, e.g., Ross v. Conoco, Inc., 2002-0299 (La. 10/15/02); 828 So. 2d 546, 555.” (This case also cites Richard v. State, 390 So. 2d 882 (La. 1980); Killebrew v. Abbott Labs., 359 So. 2d 1275 (La. 1978) on this point). NCSL (2015) and GELR (2016) also do not mention that punitive damages are available.
Michigan

The Michigan’s Persons with Disabilities Civil Rights Act (M.C.L. §§37.1101 et seq.) is not explicit about compensatory and punitive damages, stating that: “… ‘damages’ means damages for injury or loss caused by each violation of this act, including reasonable attorneys’ fees.” (M.C.L. §§37.1606(3)) DRI (2011, p. 201) states that while compensatory damages are allowed and uncapped, punitive damages (exemplary damages) are not allowed. The lack of punitive damages is confirmed in Dorsey v City of Detroit, 157 F Supp 2d 729 (ED Mich 2001). NCSL (2015) and GELR (2016) also list punitive damages.

Montana

The Montana Human Rights Act does not explicitly mention compensatory damages. DRI (2011, p. 229) and Perry (2011) both state that compensatory damages are allowed and uncapped. However, punitive damages are not allowed for employment discrimination and this is noted explicitly in statute (Mont. Code Ann. §§49-2-506(2)). The lack of punitive damages is also noted by NCSL (2015) and GELR (2016) does not list punitive damages.

Nebraska

The Nebraska Fair Employment Practice Act (Neb. Rev. Stat. §§48-1101 et seq.) does not explicitly indicate if compensatory or punitive damages are available. Gradwohl (1995) provides an in-depth discussion of punitive damages in Nebraska and both Gradwohl (1995) and DRI (2011, p. 235) state that punitive damages are generally unavailable in Nebraska. Other secondary sources suggest the lack of punitive damages in Nebraska for employment discrimination (NCSL, 2015; GELR, 2016)\(^5\).

\(^5\) See also, e.g., http://www.workplacefairness.org/file_NE (accessed January 11, 2017).
Nevada


New Hampshire

According to New Hampshire’s employment non-discrimination law, compensatory damages are available (N.H. R.S.A. 354A-21(d)). Punitive damages are not mentioned in this statute, but a more general statute on punitive damages states: “No punitive damages shall be awarded in any action, unless otherwise provided by statute.” (N.H. R.S.A. 507:16) DRI (2011, p. 247) and NCSL (2015) also state that New Hampshire law does not allow punitive damages, and GELR (2016) lists compensatory damages only. Case law appears to indicate that punitive damages are not available\(^{52}\).

New Mexico

The New Mexico Human Rights Act provides for “actual damages” with no caps mentioned (NMSA §§28-1-11-E). DRI (2011, p. 265) indicates that this mean that there are uncapped compensatory damages.\(^{53}\) Punitive damages, however, are not available: “The NMHRA provides that an employee may recover actual damages and reasonable attorneys’ fees. NMSA 1978, §§28-1-11(E), 28-1-13(D). This has been interpreted to be confined to compensatory damages. See Trujillo, 2001-NMSC-004, ¶30 (“[T]he Human Rights Act does not permit the award of punitive damages.”); Gandy v. Wal-Mart Stores, Inc., 117 N.M. 441, 443, 872 P.2d 859, 861 (1994) (“Punitive damages… are not available”\(^{52}\)."

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\(^{53}\) Also see http://www.lawatbdb.com/employee-rights/file_NM?agree=yes (viewed February 2, 2015).

**New York**

According to New York Executive Law §297(4)(c), punitive damages are not allowed: “(iii) awarding of compensatory damages to the person aggrieved by such practice; (iv) awarding of punitive damages, in cases of housing discrimination only…” DRI (2011, p. 274), GELR (2016), and NCSL (2015) also indicate that punitive damages are not available.

**North Carolina**

Neither compensatory nor punitive damages are mentioned in the “Persons with Disabilities Protection Act” (N.C.G.S.A. §168A-11). Rather this statute states “(b) Any relief granted by the court shall be limited to declaratory and injunctive relief, including orders to hire or reinstate an aggrieved person or admit such person to a labor organization. In a civil action brought to enforce provisions of this Chapter relating to employment, the court may award back pay.” and reasonable attorney’s fees are also available under part (d). NCSL (2015), GELR (2016), and DRI (2011, p. 289) also do not indicate that punitive damages are available.

**North Dakota**

“Neither the department nor an administrative hearing officer may order compensatory or punitive damages under this chapter” (N.D. Cent. Code §14-02.4-20). Neither NCSL (2015) nor DRI (2011, p. 305) nor GELR (2016) indicate that these damages are available.
Oklahoma

Unlike for other protected classes in Oklahoma, aggrieved employees with claims of disability discrimination were previously able to pursue a private action and receive compensatory damages (DRI, 2011, p. 317). However, this was removed effective November 1, 2011, when an amendment (Laws 2011, c. 270, § 21) repealed Okla. Stat. tit. 25, §§1901. NCSL (2015) does not mention punitive damages as being available after this legal change. It appears that punitive damages were never available before this change, as neither the statute nor DRI (2011, p. 317) mention them as having been available. GELR (2016) and NCSL (2015) also do not list punitive damages.

Pennsylvania

There is no mention of punitive damages in the Pennsylvania Human Relations Act (43 P.S. §§ 951 et seq.). DRI (2011, p. 340) argues that they are not available, citing Hoy v. Angelone, 554, Pa. 134, 720 A.2d 745 (1998), which stated: “[i]n sum, we are of the view that the Legislature’s silence on the issue of punitive damages, together with the statutory language, interpreted consistent with the laws of statutory construction and in the context of the nature and purpose of the Act, requires the conclusion that the Legislature did not intend to permit the award of exemplary damages.” NCSL (2015) and GELR (2016) also do not indicate that punitive damages are available.

South Dakota

According to South Dakota’s discrimination law, compensatory damages are available, but punitive damages are not available. More specifically, the statute states that “…In a civil action, if the court or jury finds that an unfair or discriminatory practice has occurred, it may award the charging party compensatory damages. The court may grant as relief any injunctive order, including affirmative action, to effectuate the purpose of this chapter. Punitive damages may be awarded under § 21-3-2 for a violation of §§ 20-13-20 to 20-13-21.2, inclusive, 20-13-23.4, or 20-13-23.7” (SDCL §20-13-35.1). However, these listed sections where punitive damages are allowed do not apply to employment
discrimination based on disability. NCSL (2015) also does not indicate that punitive damages are available.

Tennessee


Utah

The Utah Anti-Discrimination Act states that the following relief is available for those successful in an employment discrimination claim:

“(b) provide relief to the complaining party, including:

(i) reinstatement;

(ii) back pay and benefits;

(iii) attorneys' fees; and

(iv) costs” (U.C.A. §34A-5-107(9)(b)).

Punitive damages are not mentioned. According to DRI (2011, p. 391), NCSL (2015), and the Labor Commission of the State of Utah54, they are not allowed. GELR (2016) also does not list punitive damages.

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Virginia

According to Virginians with Disabilities Act: “Any circuit court having jurisdiction and venue pursuant to Title 8.01, on the petition of any person with a disability, shall have the right to enjoin the abridgement of rights set forth in this chapter and to order such affirmative equitable relief as is appropriate and to award compensatory damages and to award to a prevailing party reasonable attorneys' fees, except that a defendant shall not be entitled to an award of attorneys' fees unless the court finds that the claim was frivolous, unreasonable or groundless, or brought in bad faith. Compensatory damages shall not include damages for pain and suffering. Punitive or exemplary damages shall not be awarded” (Va. Code §51.5-46(A)). DRI (2011, p. 407), GELR (2016), and NCSL (2015) also confirm that punitive damages are not available.

Washington

Washington’s employment non-discrimination law (R.C.W. §49.60.030) states that “actual damages” are available, which has been interpreted to be uncapped compensatory damages (DRI, 2011, p. 491). DRI (2011, p. 491), NCSL (2015), and other sources state that punitive damages are not allowed, and GELR (2016) does not list punitive damages. The lack of punitive damages is confirmed explicitly, with case law citations, in the Washington Civil Jury Instructions:


Punitive damages are contrary to Washington's public policy. E.g., Dailey v. North Coast Life Ins. Co., 129 Wn.2d 572, 574, 919 P.2d 589 (1996). The Supreme Court held that the Legislature, in enacting the state Law Against Discrimination (RCW Chapter 49.60), which allows for “any other

55 See also http://www.workplacefairness.org/file_WA (viewed February 3, 2014).
remedy authorized by … the United States Civil Rights Act of 1964 as amended,” had not
unambiguously manifested an intention to make punitive damages available. Dailey v. North Coast Life
Ins. Co, 129 Wn.2d at 575–77.”

Wisconsin

For most of its history, the Wisconsin Fair Employment Act (Wis. Stats. §§111.31–111.397) did
not mention punitive damages. For a brief period between the passage of 2009 Act 20 (effective June 8,
2009) and the passage of 2011 Act 219 (effective April 20, 2012), the Wisconsin Fair Employment Act
allowed the same damages as the ADA, which could be recovered in circuit court after the completion of
administrative proceedings. But punitive damages were removed by 2011 Act 219. Wisconsin’s
Department of Workforce Development also notes that punitive damages are not currently available
under state law\textsuperscript{57} and GELR (2016) does not mention punitive damages.

Wyoming

compensatory or punitive damages, or a lack thereof. DRI (2011, p. 449) seems to suggest that these
damages are not available. NCSL (2015) and Hickox (1996) also notes that punitive damages are not
available, and GELR (2016) does not mention punitive damages.

States with No Law

Alabama

Alabama only has an employment non-discrimination law that protects older workers, but not
any other groups.

\textsuperscript{57} See https://dwd.wisconsin.gov/er/discrimination_civil_rights/publication_crd_6160_p.htm (accessed January
13, 2017).
Mississippi

Mississippi does not have an employment non-discrimination law.

Unclear Cases

Connecticut

The statute does not mention compensatory or punitive damages: “The court may grant a complainant in an action brought in accordance with section 46a-100 such legal and equitable relief which it deems appropriate including, but not limited to, temporary or permanent injunctive relief, attorney’s fees and court costs. The amount of attorney's fees allowed shall not be contingent upon the amount of damages requested by or awarded to the complainant.” (Conn. Gen. Stat §46a-104)

The failure to mention compensatory and punitive damages made it unclear if these damages really were not allowed. The case Michael Tomick v. United Parcel Service, Inc. clarified if punitive damages were available under this statute. The court originally authorized punitive damages for disability discrimination in this case, but the defendant’s motion to set aside the award of punitive damages was granted on October 28, 2010. The Supreme Court of Connecticut then ruled on December 30, 2016 that punitive damages were not available under Conn. Gen. Stat §46a-104 (Tomick v. United Parcel Service, Inc., SC19505 (Conn. 2017)). NCSL (2015) indicates that punitive damages are available (“litigated in court”) but this is rather vague, providing little information. The confusion on punitive damages up until the final Tomick case at the end of 2016 is discussed thoroughly by Michael D. Colonese and Cassie N. Jameson in an article in the Connecticut Law Tribune58. This ambiguity in case law was also mentioned by the Williams Institute, who referenced difference cases59.

As for compensatory damages, there were not allowed in employment cases since a 1995 Supreme Court of Connecticut ruling that the Connecticut Commission on Human Rights and Opportunities does not have the statutory authority to provide for these damages (Bridgeport Hospital v. Commission on Human Rights and Opportunities 232 Conn. 91). See also Commission on Human Rights & Opportunities v. Truelove & Maclean, Inc., 238 Conn. 337, 350, 680 A.2d 1261 (1996).

NCSL (2015) indicates that neither compensatory or punitive damages are expressly provided for in the statute and further notes that the Connecticut Supreme Court did not provide for compensatory damages in 1995 (referencing the above case).

In this case, we code Connecticut as not having larger damages than the federal ADA on the grounds that compensatory damages are not available, and it was not sufficiently likely that punitive damages were either, especially after the reversal of the punitive damages in the Tomick case in 2010.

A brief note on age discrimination laws

As Table 2 in the paper shows, firm-size minimums are similar for disability and age discrimination laws, but there are 12 states that have a different minimum (AL, AR, DE, GA, KY, IL, IN, LA, NE, OR, SD, VA). With regard to damages, we focus on whether compensatory or punitive damages are allowed, which they are not under federal age discrimination law (the ADEA). Some states require proof of intent to discriminate in order for compensatory or punitive damages to be awarded, whereas others require “willful” violation. Because the federal law allows additional liquidated, non-punitive damages (double back pay and benefits) when there is “willful” violation, the question of whether the state requires intent or willful violation may seem to be potentially relevant in deciding whether a state law offers greater protection. However, willful violation is a much stricter standard than intent (Moberly, 1994). Moreover, compensatory or punitive damages are almost certainly greater than liquidated damages, and they can be much greater. As a consequence, a state law that provides compensatory or punitive damages, whether or not this requires proof of intent or willful violation,
clearly entails stronger remedies than the federal law, so our classification captures whether either is allowed. For more details see Neumark and Song (2013).
Appendix references


