<u>On-Line Appendix for:</u>

Is It Harder for Older Workers to Find Jobs? New and Improved Evidence from a Field Experiment*

David Neumark

Ian Burn

Patrick Button

October 2017

Past AC Studies of Age Discrimination

AC methods have been applied to age discrimination; the main studies are Bendick et al. (1997, 1999), Lahey (2008b), and Riach and Rich (2006, 2010).[1] In general, applications of these methods to age discrimination follow the paradigm used in studies of discrimination against other groups, such as blacks or women. Specifically, applicants are made identical (up to random variation) in all respects except age. There is an issue in applying this paradigm to age discrimination, because of age-related differences in experience, which is discussed in the paper.

These studies – summarized in Table A.1 – almost uniformly find evidence of age discrimination in hiring. For example, Bendick et al.'s correspondence study (1997) looks at 32 and 57 year-old applicants. Among applications in which at least one of the two applicants received a positive response, in 43% of cases only younger applicant received the positive response, versus 16.5% of cases in which the older applicant was favored, for a statistically significant difference of 26.5%. This difference is often referred to as "net discrimination," and ignores tests where both applicants have the same outcome.[2] Similar results are reported in the other studies covered in Table A.1, although there are some differences in results reported, and, in one case, in the conclusion.[3] Note that the Riach and Rich and Bendick et al. papers are based on quite small numbers of applications, for correspondence studies.

[1] See also Albert et al. (2011), although their study only covers ages 24, 28, and 38, and hence does not speak to discrimination against older workers, in contrast to the other studies in which older workers are in their 50s or 60s. Similarly, in a recent study Baert et al. (2015) study 38, 44, and 50 year-olds; this paper also discusses a couple of other age discrimination studies.

[2] The analyses reported in our paper simply focus on differences in callback rates in the sample as a whole, as has become standard.

[3] Lahey (2008b) reports rounded estimates suggesting only a marginally significant result, but estimates provided by the author indicate that the difference is significant at the five-percent level. She reports the percentage of applications resulting in interviews, but not the percentage of tests with one or more positive responses (or equivalently, the distribution of responses based on whether only the older or only the young applicant received a callback). Because of this, we can only calculate a range of net discrimination estimates. At one extreme, using Massachusetts as an example, assume that the results were generated by cases with both older and younger applicants offered interviews, or only younger applicants offered interviews. In that case, 5.3% of applications resulted in one or more positive responses, with 0% of the tests with positive responses favoring older applicants, and 28.3% (1.5/5.3) favoring younger applicants, for a 28.3% net discrimination estimate. At the other extreme, if there was no overlap of positive responses, then 9.1% of applications (5.3+3.8) resulted in at least one positive response, and the net discrimination rate is 16.5% (1.5/9.1). Similar calculations for Florida yield a range of 18.1 to 30.6%.

Bendick et al. (1999) report results that capture more than just whether the callback was positive. In particular, they report the percentages of cases in which one paired tester received a more favorable response than the other paired tester. "Favorable responses" are defined to include: an interview, an opportunity to demonstrate skills, a job offer, or a job offer with higher compensation. In general, this echoes other features of his study that try to capture more of the richness of the hiring/recruiting process, which is more feasible in an audit study than a correspondence study. Measured this way, the percentage of tests with a more favorable response for younger applicants (age 32) was 42.2% for age 32, versus 1% for older applicants (age 57), for a statistically significant difference of 41.2%.

Finally, the only contrary evidence comes from one of three cases in Riach and Rich's (2010) correspondence study in England. Specifically, for female applicants for jobs as retail managers, there was statistically significant net discrimination against younger applicants (age 27 versus age 47) of 29.6% for retail manager jobs. Still the other two estimates in this paper provide statistically significant evidence of discrimination against older workers.[4]

[4] Another recent age correspondence study, done concurrently with ours, is Baert et al. (2015), who also considers the commensurate experience issue. Looking at 38, 44, and 50 year-olds, they give all applicants a job in the field to which they are applying for the same number of years prior to the application and immediately after graduating from school. But they otherwise construct three different resume types: one with inactivity in the "extra" years of older applicants, one with work in a different field, and one with work in the same field. Their evidence points to lower callback rates for older workers only in the first two cases of out-of-field employment or inactivity, consistent with bias towards finding age discrimination when older resumes do not show greater continuous experience in the field. However, the narrow age range used in this study (38-50) calls into question whether its results should even be compared to the age discrimination literature. In addition, the study is based on a small number of tests (192 for each type of resume). Moreover, their evidence by age (ignoring the issue of the difference in post-education years) points to lower callback rates for 44 versus 38 year-olds and 50 versus 44 year-olds, but not 50 versus 38 year-olds. Thus, even the overarching age patterns in this study are unusual relative to the literature – although the age range is small and the upper age limit not very old.

Table A.1: Evidence from Past Audit/Correspondence Studies of Age Discrimination

Study	Type	Occupation	Ages	Total number of tests	Tests with ≥ 1 positive response	Older applicant favored, cases with at least one positive outcome (%/no.)	Younger applicant favored, cases with at least one positive outcome (%/no.)	Net discrimination
Bendick et al. (1997)	Correspondence	Management information systems (men only); executive secretary (women only); writer/editor	57 vs. 32	775	79	16.5% (13)	43% (34)	26.5%*
Riach and Rich (2006)	Correspondence (France)	Waitstaff (men only)	47 vs. 27	345	31	19.4% (6)	77.4% (24)	58.1%*
Lahey (2008b)	Correspondence	Entry-level jobs (women only)	50/55/62 vs. 35/45	3,996	Not reported	MA: 3.8% FL: 4.3% (Note: overall interview rates)	MA: 5.3%* FL: 6.2% (Note: overall interview rates)	MA: 16.5 to 28.3% FL: 18.1 to 30.6%
Bendick et al. (1999)	Audit	Entry-level sales or management	57 vs. 32	102	Not reported	1% (Note: from set of 4 possible positive responses)	42.2% (Note: from set of 4 possible positive responses)	41.2%*
				102	Not reported	36.3% (Note: overall interview rate)	41.2% (Note: overall interview rate)	6.3 to 11.9%
Riach and Rich (2010)	Correspondence (England)	New graduates (women only)	39 vs. 21	420	47	4.3% (2)	63.8% (30)	59.6%*
		Waitstaff (men only)	47 vs. 27	470	80	28.8% (23)	57.5% (46)	28.8%*
		Retail managers (women only)	47 vs. 27	300	27	59.3% (16)	29.6% (8)	−29.6%*

Notes: "Net discrimination" is the difference between the percentage of cases in which the older applicant was favored relative to the younger applicant, and the percentage in which the younger applicant was favored relative to the older applicant. * indicates that the estimate is statistically significant at the 5% level or better, as reported in the study. "Total number of tests" refers to the number of jobs for which pairs of applications were submitted. See text for additional explanation.

Estimated Costs of Enforcing Hiring Provisions of the Age Discrimination in Employment Act (ADEA)

Many have raised concerns that the costs of employment discrimination law are high (e.g., Epstein, 1992, Olson, 1997). The exact costs are difficult to estimate, but some investigation allows for a range of estimates of many of the costs. We estimate the costs of age discrimination laws following the framework of Donohue (1992), who provides a careful consideration of different types of costs for employment discrimination law more broadly. We focus on hiring costs only, so our estimates cover only a fraction – and likely a very small fraction – of the total costs associated with the ADEA.

We consider several factors that are relevant to determine the costs of age discrimination law: the likelihood of facing ADEA charges; litigation costs; EEOC administrative budgets; compliance costs; and potential productivity losses. For the costs that we can reasonably quantify, we estimate that the costs of hiring cases under the ADEA are $3.29 billion per year, which is about $5,300 per firm covered by the ADEA, or about $35 per employee at covered firms. The components of this cost estimate are discussed later in this section, but include, for the purposes of this calculation, monetary damages of EEOC cases ($4.6 million, or $7.42 per covered firm per year), the greater of litigation costs or settlement costs paid by the firms (litigation is greater, so $9.67 million to $44.48 million per year, or $15.62 to $71.76 per covered employer per year), EEOC administrative costs ($5.0 million, or $8.06 per covered firm per year), and compliance costs ($3.24 billion, or $5,226 per covered firm per year). Using the upper estimate for the litigation costs, this leads to total costs of $3.29 billion, or $5,315 per covered firm and $34.64 per covered employee. This does not include costs such as time spent by executives and management as part of the case, damages for cases handled at the state level rather than the EEOC, administrative costs for state agencies that enforce state laws, and productivity losses or gains associated with induced changes in employers' hiring behavior.[5]

[5] The firm and employee counts used in these calculations come from https://www.sba.gov/sites/default/files/advocacy/static_us_14.xls (viewed October 10, 2017). Note that the ADEA covers firms with at least 20 employees. Using 2014 estimates, there were 619,818 employers with a firm size of 20 or greater (10.6% of all employers). These firms employ 95,101,641 employees total (78.55% of all employees).

Likelihood of ADEA charges[6]

While employment discrimination cases can be quite costly, the likelihood that an employer faces one, especially for hiring, is extremely rare. From fiscal year 1997 to 2016, there were 387,579 charges filed under the ADEA, or 19,379 per year on average.[7] Given that there are 619,818 firms covered by the ADEA (see footnote 5), this implies that no more than 3.1% of employers face an ADEA charge in any year.[8]

However, most charges do not lead to large costs for the firm. Over this time period, on average, 62.1% of cases were determined by the EEOC to have "no reasonable cause." Plaintiffs could then still exercise their right to bring private court action, but this does not occur often as the chances of success, given this EEOC determination, are low; 20.1% of charges end with administrative closure, one reason for which is related to the futility of the case.[9] Some charges do lead to significant costs for the employer, which are those that lead to a merit resolution (16.4% of all charges), which includes settlements (7.7% of all charges), withdrawal with benefits (4.9%), and determinations of "reasonable cause" (3.8%). If we only consider charges with merit resolution, this decreases the total charges above to 63,543 over the 20-year period (3,177 per year), implying that no more than 0.5% covered firms would expect an ADEA charge with merit resolution in any one year.

We can narrow even further to a smaller subset of charges with merit resolution suits and resolutions handled by the EEOC, which have been filed and resolved in federal district courts.[10] Over

---

[6] While plaintiffs can file age discrimination charges separately under state law, there is not readily available information on how often this occurs. Thus, this section references charges under the federal ADEA, where most charges are filed.

[7] See https://www.eeoc.gov/eeoc/statistics/enforcement/adea.cfm (viewed October 10, 2017) for the charge data referenced in this section.

[8] This follows the same argument in Donohue (1992), assuming that each firm only gets one charge per year, which gives this minimum.

[9] From the EEOC's definition of terms, administrative closure is: "Charge closed for administrative reasons, which include: failure to locate charging party, charging party failed to respond to EEOC communications, charging party refused to accept full relief, closed due to the outcome of related litigation which establishes a precedent that makes further processing of the charge futile, charging party requests withdrawal of a charge without receiving benefits or having resolved the issue, no statutory jurisdiction." (See https://www.eeoc.gov/eeoc/statistics/enforcement/definitions.cfm, viewed October 10, 2017.)

[10] For these statistics, see https://www.eeoc.gov/eeoc/statistics/enforcement/litigation.cfm (viewed October 10, 2017).

this same 20-year period, there were 610 suits and 658 resolutions for suits with ADEA claims, or on average 30.5 suits and 32.9 resolutions per year. This further suggests that employers do not face litigation costs from the ADEA very often.

The preceding estimates apply to all discrimination claims under the ADEA (hiring, firing, promotions, etc.). Hiring discrimination cases are only 5.6% of all cases, or about 319 cases per year.[11] This further suggests that the likelihood of facing a hiring discrimination charge, especially one that leads to a costly merit resolution, is very low.[12]

Litigation and settlement costs

While facing a case under the ADEA, especially for hiring, and especially one with merit resolution, is rare, the costs of such cases could be large. Over the 20-year period 1997-2016, the 387,579 charges filed under the ADEA entailed monetary benefits of $1.6 billion in 2017 dollars.[13] This is $82.11 million on average per year, or $132.47 in any given year for a covered firm, on average. Since hiring cases are only about 5.6% of the total number of cases, this is reduced to $4.60 million on average per year, or $7.42 per covered firm, although this is assuming that damages are the same for hiring cases as for other cases, such as terminations, which is highly unlikely as damages for hiring cases would be lower. Thus, this estimate is an upper bound. On the other hand, these estimates do not include monetary benefits for cases that are not handled by the EEOC. However, including cases not handled by the EEOC would not change the qualitative conclusion that the cost per case is high, but average cost per firm is low given the very low probability of facing a case.

Monetary benefits paid in discrimination cases are transfers between two parties and do not necessarily represent a cost to society as a whole. However, there are direct costs of the process that

---

[11] This was calculated using EEOC data from https://www.eeoc.gov/eeoc/statistics/enforcement/statutes_by_issue.cfm (accessed October 10, 2017). This estimate is calculated as an average for the available fiscal years of 2010 to 2016. For some comparison, discharge cases are 29.5% of all cases, or 11,718 on average per year.

[12] Using these estimates, in any given year no more than 0.03% of covered firms will face a hiring discrimination charge under the ADEA that has a merit resolution.

[13] See https://www.eeoc.gov/eeoc/statistics/enforcement/adea.cfm (viewed October 10, 2017).

generates these transfers, such as attorney fees. Some sources provide estimates of these costs, including Donohue (1992) ($30,000, or $54,342 in 2017 dollars), Olson (1997) ("at least $100,000" if it goes to trial – $152,515 in 2017 dollars), and Rosen (2016) ($50,000 to $250,000, excluding disbursements, deposition fees, and expert fees). Given the earlier estimate of 3,177 cases with merit resolution per year, this gives an estimated cost range of $172.7 million (Donohue) to $794.3 million (upper bound of Rosen's range) for all cases in any one year, or $279 to $1,282 per covered firm per year. Again, these costs estimates are lower when applied to hiring cases only. Based on these cases being 5.6% of the total, the costs ranges fall to $9.67 million to $44.48 million per year, or $15.62 to $71.76 per covered employer per year (which may still be upper bounds if litigation costs for hiring discrimination cases are lower than for other cases, as might be expected if damages are lower).

Cases can be costly even if they do not go to trial. Often, it is more economical for employers to settle cases. In 2007, $66.8 million ($78.9 million in 2017 dollars) was collected for all types of discrimination cases that were resolved through settlement and conciliation, or $4,140 on average for every claim filed ($4,888 in 2017 dollars) (Cavico et al., 2012). This amounts to about $127 per year per covered firm. Applied to the 5.6% of cases that are hiring cases brings this figure to $4.42 million in 2017 dollars, or $7.32 per covered firm.[14]

EEOC enforcement costs

The EEOC's total budget for enforcing non-discrimination statutes in 2016 was $380 million, the largest expense being pay and compensation for the Commission's approximately 2,200 employees (72%), and rent to local, state, and federal governments (16%).[15] The total budget of the EEOC covers all of its activities, while age discrimination complaints are 23% of the total received.[16] Allocating costs proportionally, the EEOC spent $87.4 million in fiscal year 2016 enforcing the ADEA, although, again,

[14] There are additional litigation costs that are hard to quantify, namely the time of executives or managers who may be involved in the case. They may be distracted by the case or may be required to provide paperwork or inputs to the case. It seems unlikely that these costs are large relative to the other costs we estimate.
[15] See https://www.eeoc.gov/eeoc/plan/upload/2016par.pdf (viewed October 10, 2017).
[16] See https://www.eeoc.gov/eeoc/statistics/enforcement/charges.cfm (viewed October 10, 2017).

hiring cases are only 5.6% of all cases (so $5.0 million, or $8.06 per covered firm in 2017 dollars). This is a direct cost to society, entirely funded through government appropriations, and does not include similar costs for state agencies, as these costs are hard to estimate.

Compliance costs

The complexity of the ADEA and employment discrimination law certainly imposes costs on employers through paperwork, human resources and legal training, and procedural changes. As Donohue (1992) argues, it is hard to estimate these costs except to an order of magnitude. Donohue suggested a total cost of complying with discrimination laws of $6.4 billion for all private-sector firms ($11.17 billion in 2017 dollars), based on estimated costs using a sample of 48 firms that represented 5% of the private-sector workforce (from Arthur Andersen & Co., 1979). This represents $18,021 in 2017 dollars per covered firm, or $117.48 in 2017 dollars per employee. However, these latter estimates may be upper bounds since they include a broader set of costs not restricted to the ADEA, including sex discrimination guidelines, ADA-specific regulations on accommodations, and Title VII. It may be more realistic to split these compliance costs equally across all these statutes in a way that is proportionate to the number of ADEA cases, as was done for the EEOC costs above. Since ADEA complaints received are only 29% of all complaints,[17] this suggests that costs are $3.24 billion per year or $5,226 per covered firm per year.[18]

Potential productivity costs

The ADEA could have positive or negative effects on productivity. We do not attempt to quantify these. Some possibilities include:

1. Because of the threat of an age discrimination claim against the employer, older protected workers may be costlier to terminate. This can be viewed as a higher cost of hiring, decreasing hiring for protected workers compared to the efficient level of hiring (Bloch, 1994).

[17] While 23% of EEOC cases are for age, this rises to 29% if charges related to disability and genetics are removed, which makes sense since the Americans with Disabilities Act and the Genetic Information Nondiscrimination Act (GINA) were not active at the time of Arthur Andersen & Co. report.

[18] Unlike for "per charge" costs such as those related to, e.g., litigation, it is not clear that removing one basis for age discrimination from the ADEA would reduce compliance costs much. Thus, we do not adjust these estimated down based on the share of hiring claims.

2. Taste discrimination could lead to firms hiring less-productive younger workers rather than more-productive older workers, which could lower overall output if, in the aggregate, employment of more-productive older workers is reduced. If age discrimination laws make hiring based on taste discrimination costlier, they can increase productivity.
3. By reducing statistical discrimination based on age, employers may rely more on productivity-related factors. This should lead to better job matches, but at increased search costs. The gains may not outweigh the costs if the statistical discrimination is based on correct averages (stereotypes), but stereotypes can be self-fulfilling (Coate and Loury, 1993).

Names

Applicant names were selected randomly from a set of the most common first names and last names for the relevant cohorts. This information was taken from the Social Security Administration list of most popular baby names.[19] We chose first and last names that were most likely to signal that the applicant was Caucasian, by excluding names where fewer than 60% of individuals with the name were Caucasian.[20] All applicants, regardless of age or gender, had last names randomly assigned from the same selected set of last names. For first names, we created six separate sets of first names to draw from randomly for each age group (64 to 66, 49 to 51, and 29 to 31) and sex, using the most common first names for those groups.[21] We chose the 20 most common names for babies born in each corresponding birth year, dropping names that were gender ambiguous unless using the full name made this clear (e.g., Patrick instead of Pat).[22] The composition of names for the middle and older categories were very similar so we combined these categories before choosing our most common names for applicants in each age group. Table A.2 lists the names used. As the table shows, these names are very common, and seem unlikely to signal SES (unlike the black sounding names in Bertrand and Mullainathan, 2004).

[19] See http://www.ssa.gov/OACT/babynames/ (viewed August 11, 2014). We use data from a 100% sample of Social Security card applications for U.S. births. In each year the Social Security Administration (SSA) records the number of males and females born with a name and reports frequency counts of those names by sex, as long as the name is at least two characters long with a frequency of at least five. We match using first name to the SSA data in an individual's birth year.

[20] We use U.S. Census records on most common last names in the 2000 Census for last names. The 2010 data were not available when we chose the names. However, there were only minor changes from 1990 to 2000, so using the 2000 list is not problematic. (See http://www.census.gov/genealogy/www/data/2000surnames/surnames.pdf and http://www.census.gov/genealogy/www/data/1990surnames/index.html, both viewed August 11, 2014.)

[21] We draw randomly from these age ranges, and then assign year of high school graduation to resumes, assuming people graduated at age 18 and are currently older by the number of years between the year of high school graduation and when job applications went out (2015). Since not everyone graduates at age 18, and since some who did graduate at age 18 could have been a year younger than the bottom of each age range if their birthday was between the month and day of high school graduation and the month and day the application went out, employers could have assumed slight deviations from our intended age ranges.

[22] If a name applies to both males and females, we assign the majority gender as long as at least 90% of children born with that name have the same gender.

Table A.2: Names for Resumes

First names						
Men			Women			Last names
Old	Middle aged	Young	Old	Middle aged	Young	
Brian	Brian	Alexander	Amanda	Angela	Abigail	Adams
Charles	Charles	Andrew	Amy	Barbara	Alexis	Allen
Christopher	Christopher	Anthony	Angela	Brenda	Alyssa	Anderson
Daniel	Daniel	Austin	Barbara	Cheryl	Amanda	Baker
David	David	Brandon	Betty	Cynthia	Amber	Campbell
Dennis	Donald	Brian	Brenda	Deborah	Amy	Clark
Donald	James	Christopher	Carol	Debra	Ashley	Evans
Edward	Jeffrey	Daniel	Carolyn	Donna	Ava	Hall
Eric	John	David	Cheryl	Elizabeth	Brianna	King
Frank	Joseph	Ethan	Christina	Jennifer	Brittany	Martin
Gary	Kenneth	Jacob	Christine	Julie	Chloe	Miller
George	Kevin	James	Cynthia	Karen	Christina	Moore
James	Mark	Jason	Dawn	Kimberly	Courtney	Nelson
Jason	Michael	John	Deborah	Laura	Danielle	Phillips
Jeffrey	Paul	Jonathan	Debra	Linda	Elizabeth	Roberts
Jerry	Richard	Joseph	Diane	Lisa	Emily	Smith
John	Robert	Joshua	Donna	Lori	Emma	Thompson
Joseph	Scott	Justin	Dorothy	Mary	Grace	Wilson
Kenneth	Steven	Kyle	Elizabeth	Michelle	Hannah	Wright
Kevin	Thomas	Matthew	Heather	Nancy	Heather	Young
Larry	Timothy	Michael	Helen	Pamela	Isabella	
Mark	William	Nathan	Janet	Patricia	Jennifer	
Matthew		Nicholas	Jennifer	Sandra	Jessica	
Michael		Robert	Jessica	Sharon	Kayla	
Paul		Ryan	Joan	Susan	Kimberly	
Richard		Tyler	Joyce	Tammy	Laura	
Robert		William	Judith	Teresa	Lauren	
Ronald		Zachary	Judy		Madison	
Scott			Julie		Megan	
Stephen			Karen		Melissa	
Steven			Kathleen		Mia	
Thomas			Kelly		Natalie	
Timothy			Kimberly		Nicole	
William			Laura		Olivia	
			Linda		Rachel	
			Lisa		Samantha	
			Lori		Sarah	
			Margaret		Sophia	
			Mary		Stephanie	
			Melissa		Victoria	
			Michelle			
			Nancy			
			Nicole			
			Pamela			
			Patricia			
			Rebecca			
			Sandra			
			Sharon			
			Shirley			
			Stephanie			
			Susan			
			Tammy			
			Teresa			
			Tracy			

Notes: Table shows the names used by age cohorts of applicants, based on Social Security Administration records. Names were drawn from the top 20 most popular baby names by gender from 1948 to 1954 for old and middle-aged workers and 1982 to 1988 for the young workers.

Occupations/Jobs

To get information on "new hires," we used data from the 2008 and 2012 Current Population Survey (CPS) tenure supplements to identify workers with fewer than five years of tenure.[23] We computed, separately for men and women, the shares of new hires in the age ranges 28-32 and 62-70,[24] relative to all new hires in each occupation. Tables A.3 and A.4 present, for the 100 largest occupations (by employment), the proportion of the young and old age groups indicated as a share of all new hires in the occupation, for men and women. We have highlighted in boldface the occupations we use for this study. Lower-tenure older men are quite common for retail salespersons, cashiers, janitors and building cleaners, and security guards. These occupations also have sizable, but somewhat smaller, shares of low-tenure younger men, implying that it would not be odd for an employer looking to fill these jobs to receive applications from both older and younger men. Also, these four occupations typically do not require a significant amount of skills, training, or experience, and are likely also accessible for older workers as partial retirement or bridge jobs. As shown in Table A.4, for women we choose some occupations that overlap those for men (retail salespersons and cashiers), and some that are different (secretaries and administrative assistants, office clerks, receptionists and information clerks, and file clerks).

Employer job advertisements are not categorized the same way as the Census Bureau classifies occupations, as employers often lump sets of these occupations together (like administrative assistant and secretary). We grouped the highlighted occupations from Tables A.3 and A.4 into four larger groupings of jobs, for which we used common resumes: retail sales (corresponding to retail salespersons and cashiers in the Census occupational classification); administrative assistant (secretaries and administrative assistants, receptionists and information clerks, office clerks (general), and file clerks); janitors; and

---

[23] These are the Current Population Survey Displaced Worker, Employee Tenure, and Occupational Mobility Supplement Files (see http://www.nber.org/cps/cpsjan12.pdf, viewed August 18, 2014). We avoided using the 2009 and 2010 CPS tenure supplements because of the Great Recession. The supplements are not available for 2011 or 2013.

[24] These ranges are somewhat larger than the younger and older age ranges for our resumes (29-31, 64-66), to increase the sample size.

security guards (security guards and gaming surveillance officers). These groupings were based on three criteria: how different jobs related to these occupations were in the resumes posted on the web that we studied; how different they were when employers looked to hire, based on job ads; and how many job postings there were for these occupations. While the separate occupations may require slightly different skills and experience, the core requirements and skills within these jobs are the same, allowing one resume to be used to apply to a larger number of occupations. This has the added benefit of allowing us to avoid having to parse job advertisements that are typically not written to fit into a Census occupation code niche, but rather fit broader jobs that entail similar skills.

Our choices of jobs often overlap with past AC studies of age discrimination. One advantage of using similar jobs is that differences in results are more likely to be due to methods than to differences in the jobs studied. Lahey's (2008b) study of women focuses on female-dominated jobs (like cashiers, secretaries, and home health care). Riach and Rich (2010) studied waiters/waitresses and retail jobs.[25]

Figure A.1 reports histograms, for all occupations with non-empty cells, for the share of hiring in each age group relative to hires in the occupation (by sex). The figures also show the value of this share for the occupations we use. For men, all of the occupations we use are fairly central in the distribution, although security guards tend to have more older hires, and janitors more younger hires. For women the shares are also in the mid-range of the distribution, although our occupations exhibit relatively more hiring of older women and less hiring of younger women, suggesting that it is possible our results for women could be biased against finding evidence of age discrimination.[26] Finally, we note that these are fairly low wage jobs, paying about 15-20% less than the median wage across all occupations, with the exception of administrative jobs, which pay a bit above the median; see Table A.5.

[25] The Bendick et al. studies (1997, 1999) use a wider variety of jobs.
[26] Yet our strongest evidence points to age discrimination against older women.

Table A.3: Shares of Recent Male Hires (< 5 Years of Tenure) in Age Group Relative to All Male Hires in Occupation, 100 Largest Occupations for Men, 2008 and 2012 CPS Tenure Supplements

	Age-specific recent hires/all recent hired in occupation			Age-specific recent hires/all recent hired in occupation	
Occupation	**Age 62 to 70**	**Age 28 to 32**	**Occupation**	**Age 62 to 70**	**Age 28 to 32**
Average across all occupations	10.79%	9.11%	Average across all occupations	10.79%	9.11%
Managers, all other	9.23%	5.82%	Machinists	11.60%	2.40%
Driver/sales workers and truck drivers	9.99%	4.52%	Education administrators	22.31%	3.69%
First-line supervisors/managers of retail sales workers	9.46%	6.83%	Computer programmers	5.25%	6.92%
Chief executives	14.77%	2.19%	Civil engineers	9.78%	5.47%
Carpenters	6.71%	8.37%	**Security guards and gaming surveillance officers**	16.32%	8.57%
First-line supervisors/managers of non-retail sales workers	12.81%	5.62%	Bus and truck mechanics and diesel engine specialists	11.39%	6.75%
Construction managers	8.53%	7.52%	First-line supervisors/managers of mechanics, installers, and repairers	8.26%	5.72%
Janitors and building cleaners	11.91%	2.64%	Property, real estate, and community association managers	15.49%	4.00%
Sales representatives, wholesale and manufacturing	10.40%	5.75%	Postal service mail carriers	6.89%	0.28%
First-line supervisors/managers of production and operating workers	6.15%	4.99%	Insurance sales agents	15.76%	5.74%
First-line supervisors/managers of construction trades and extraction workers	6.68%	8.54%	Real estate brokers and sales agents	19.76%	1.85%
Farmers and ranchers	16.61%	5.15%	Engineers, all other	7.37%	3.00%
Retail salespersons	11.31%	7.55%	Customer service representatives	9.41%	9.95%
Laborers and freight, stock, and material movers, hand	6.94%	7.04%	Bailiffs, correctional officers, and jailers	3.59%	4.83%
Lawyers, judges, magistrates, and other judicial workers	14.78%	1.68%	Bus drivers	23.01%	3.52%
General and operations managers	6.85%	9.60%	Heating, air conditioning, and refrigeration mechanics and installers	3.82%	9.71%
Electricians	7.78%	10.46%	Miscellaneous agricultural workers	12.86%	6.73%
Police and sheriff's patrol officers	1.07%	15.45%	Mechanical engineers	5.04%	2.82%
Secondary school teachers	5.06%	7.77%	Shipping, receiving, and traffic clerks	5.97%	4.90%
Farmers, ranchers, and other agricultural managers	11.81%	5.42%	Transportation, storage, and distribution managers	9.43%	3.19%
Automotive service technicians and mechanics	6.56%	7.60%	First-line supervisors/managers of landscaping, lawn service, and groundskeeping	4.15%	7.05%
Accountants and auditors	13.90%	6.84%	Sales representatives, services, all other	13.48%	6.58%
Construction laborers	6.46%	10.21%	**Cashiers**	12.62%	11.33%
Software developers, applications and systems software	2.76%	13.07%	Personal financial advisors	18.07%	5.27%
Production workers, all other	3.16%	7.29%	Human resources, training, and labor relations specialists	7.16%	3.50%
Postsecondary teachers	24.85%	0.51%	Metalworkers and plastic workers, all other	3.06%	2.84%
Physicians and surgeons	18.68%	2.26%	Radio and telecommunications equipment installers and repairers	4.47%	7.42%
Grounds maintenance workers	9.56%	7.08%	Heavy vehicle and mobile equipment service technicians and mechanics	5.30%	7.60%
Elementary and middle school teachers	5.22%	9.53%	Other teachers and instructors	16.29%	3.68%
Computer scientists and systems analysts	7.43%	8.41%	Printing press operators	13.63%	4.63%
First-line supervisors/managers of office and administrative support workers	4.62%	10.06%	Computer, automated teller, and office machine repairers	8.74%	1.48%

Occupation	Age-specific recent hires/all recent hired in occupation: Age 62 to 70	Age 28 to 32	Occupation	Age-specific recent hires/all recent hired in occupation: Age 62 to 70	Age 28 to 32
Computer and information systems managers	3.37%	3.37%	Industrial production managers	5.98%	2.52%
Industrial and refractory machinery mechanics	7.78%	2.91%	Computer support specialists	6.08%	10.47%
Food service managers	6.84%	10.02%	Registered nurses	9.31%	9.28%
Marketing and sales managers	3.79%	7.07%	Securities, commodities, and financial services sales agents	18.93%	4.07%
Miscellaneous assemblers and fabricators	10.05%	5.13%	Taxi drivers and chauffeurs	11.21%	4.29%
Stock clerks and order fillers	6.12%	8.87%	Butchers and other meat, poultry, and fish processing workers	13.29%	6.51%
Pipelayers, plumbers, pipefitters, and steamfitters	6.16%	7.06%	Telecommunications line installers and repairers	1.71%	9.91%
Financial managers	6.79%	11.98%	Dentists	10.95%	3.74%
Cooks	3.59%	12.61%	First-line supervisors/managers of police and detectives	6.02%	5.30%
Maintenance and repair workers, general	13.06%	4.66%	Carpet, floor, and tile installers and finishers	6.24%	4.06%
Welding, soldering, and brazing workers	6.70%	8.61%	Medical and health services managers	5.26%	8.05%
Engineering technicians, except drafters	7.71%	2.01%	First-line supervisors/managers of housekeeping and janitorial workers	5.39%	3.49%
Electrical and electronic engineers	13.16%	3.50%	First-line supervisors/managers of food preparation and serving workers	5.63%	5.03%
Clergy	18.58%	2.97%	Supervisors, transportation and material moving workers	2.24%	13.95%
Industrial truck and tractor operators	4.64%	11.40%	Counselors	13.53%	6.65%
Painters, construction and maintenance	7.67%	5.33%	Aircraft pilots and flight engineers	6.48%	2.46%
Management analysts	18.17%	4.29%	Industrial engineers, including health and safety	13.15%	7.27%
Inspectors, testers, sorters, samplers, and weighers	7.16%	9.01%	Aircraft mechanics and service technicians	7.92%	5.45%
Operating engineers and other construction equipment operators	7.29%	10.16%	Other installation, maintenance, and repair workers	4.71%	4.20%

Notes: The table shows the 100 largest Census occupations for men, ranked by occupation size. Some occupations had empty cells for one or both age groups not in the top 100, and hence are not shown in this table. Occupations that would have been in the top 100 but had an empty cell include firefighters, designers, detectives and criminal investigators, and waiters and waitresses. Occupations in boldface are used in study.

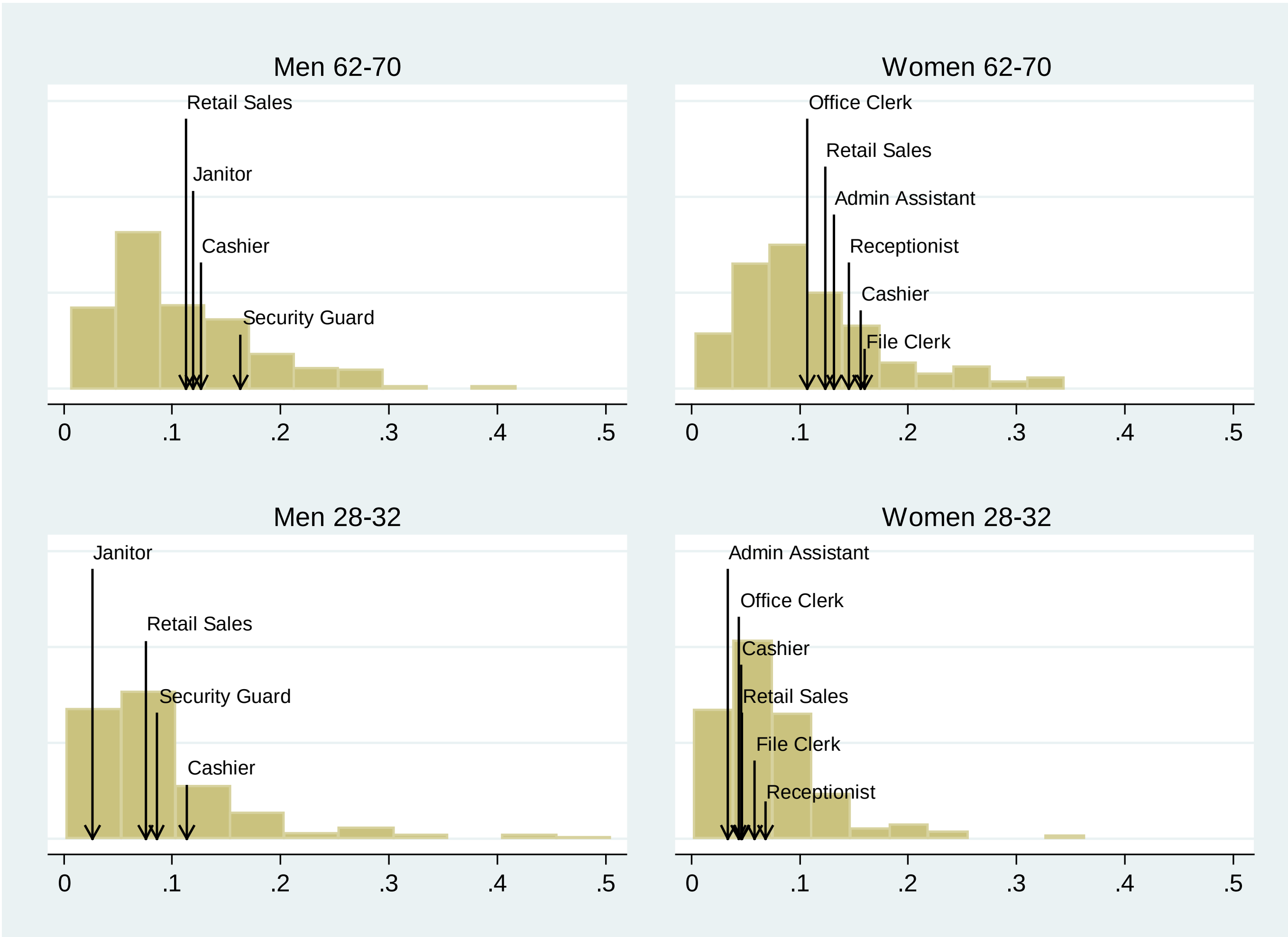
Table A.4: Shares of Recent Female Hires (< 5 Years of Tenure) in Age Group Relative to All Female Hires in Occupation, 100 Largest Occupations, 2008 and 2012 CPS Tenure Supplements

	Age-specific recent hires/all recent hires in occupation			Age-specific recent hires/all recent hires in occupation	
Occupation	**Age 62-70**	**Age 28-32**	**Occupation**	**Age 62-70**	**Age 28-32**
Average across all occupations	10.98%	7.48%	Average across all occupations	10.98%	7.48%
Secretaries and administrative assistants	13.18%	3.39%	First-line supervisors/managers of non-retail sales workers	8.20%	3.65%
Elementary and middle school teachers	6.29%	7.33%	Paralegals and legal assistants	3.52%	6.39%
Registered nurses	7.97%	6.80%	**File clerks**	16.00%	5.86%
Bookkeeping, accounting, and auditing clerks	14.17%	3.36%	Inspectors, testers, sorters, samplers, and weighers	6.84%	3.42%
First-line supervisors/managers of retail sales workers	9.27%	10.11%	Computer scientists and systems analysts	5.59%	6.12%
First-line supervisors/managers of office and administrative support workers	9.91%	5.90%	First-line supervisors/managers of food preparation and serving workers	7.65%	3.20%
Managers, all other	7.87%	3.64%	Management analysts	3.04%	6.19%
Accountants and auditors	8.40%	7.54%	Farmers and ranchers	26.19%	3.25%
Nursing, psychiatric, and home health aides	12.68%	5.37%	Data entry keyers	8.20%	10.44%
Secondary school teachers	9.01%	7.63%	Insurance claims and policy processing clerks	4.51%	7.11%
Maids and housekeeping cleaners	13.01%	2.28%	Production workers, all other	6.30%	7.79%
Teacher assistants	9.29%	4.99%	Loan counselors and officers	3.48%	20.97%
Customer service representatives	3.90%	7.16%	Sales representatives, wholesale and manufacturing	5.32%	7.13%
Office clerks, general	10.70%	4.34%	Clinical laboratory technologists and technicians	9.65%	4.79%
Retail salespersons	12.35%	4.65%	Diagnostic related technologists and technicians	5.07%	2.65%
Receptionists and information clerks	14.55%	6.83%	Laborers and freight, stock, and material movers, hand	11.40%	3.60%
Cashiers	15.60%	4.59%	Librarians	16.38%	2.76%
Financial managers	6.45%	10.40%	Dental assistants	8.33%	7.19%
Education administrators	8.72%	4.42%	Purchasing agents, except wholesale, retail, and farm products	3.87%	2.90%
Child care workers	8.22%	3.03%	Insurance sales agents	12.17%	6.84%
Hairdressers, hairstylists, and cosmetologists	12.67%	8.34%	Social and community service managers	9.27%	5.21%
Chief executives	12.70%	1.57%	Dental hygienists	6.85%	6.76%
Postsecondary teachers	17.16%	2.32%	Software developers, applications and systems software	5.70%	3.78%
Preschool and kindergarten teachers	6.15%	7.67%	Miscellaneous community and social service specialists	5.92%	3.31%
Cooks	15.96%	5.48%	First-line supervisors/managers of production and operating workers	11.33%	2.04%
Office and administrative support workers, all other	9.51%	4.86%	Miscellaneous legal support workers	6.33%	9.92%
Medical assistants and other healthcare support occupations	7.97%	9.70%	Tellers	9.52%	16.12%
Social workers	8.58%	5.87%	Claims adjusters, appraisers, examiners, and investigators	9.12%	6.95%
Human resources, training, and labor relations specialists	6.53%	9.33%	Sewing machine operators	16.06%	3.82%
Janitors and building cleaners	14.50%	2.94%	Business operations specialists, all other	5.87%	12.76%
Medical and health services managers	11.83%	5.13%	Food preparation workers	21.67%	3.28%
Personal and home care aides	13.33%	7.14%	Human resources managers	0.37%	4.99%

Occupation	Age-specific recent hires/all recent hires in occupation Age 62-70	Age 28-32	Occupation	Age-specific recent hires/all recent hires in occupation Age 62-70	Age 28-32
Counselors	5.94%	8.38%	Postal service mail carriers	13.36%	3.68%
Real estate brokers and sales agents	24.60%	3.51%	Payroll and timekeeping clerks	2.42%	5.89%
Other teachers and instructors	10.86%	5.99%	Packers and packagers, hand	6.63%	3.59%
Billing and posting clerks and machine operators	8.55%	5.52%	Recreation and fitness workers	13.37%	13.38%
Licensed practical and licensed vocational nurses	7.38%	2.98%	Sales representatives, services, all other	3.06%	7.76%
Food service managers	5.06%	6.25%	Psychologists	21.46%	3.87%
Bus drivers	10.97%	1.88%	Production, planning, and expediting clerks	7.63%	4.06%
Special education teachers	1.99%	5.22%	Shipping, receiving, and traffic clerks	6.16%	6.95%
Lawyers, judges, magistrates, and other judicial workers	10.50%	7.78%	Transportation attendants	17.76%	18.31%
Waiters and waitresses	9.77%	12.58%	Driver/sales workers and truck drivers	3.88%	14.27%
Farmers, ranchers, and other agricultural managers	19.79%	0.25%	Dispatchers	14.50%	7.66%
Marketing and sales managers	4.82%	12.81%	Computer support specialists	13.09%	10.76%
Designers	15.54%	5.41%	Supervisors, transportation and material moving workers	5.92%	0.75%
Property, real estate, and community association managers	16.21%	3.06%	Computer programmers	3.51%	3.15%
Health diagnosing and treating practitioner support technicians	5.13%	9.46%	Construction managers	11.25%	7.24%
General and operations managers	7.73%	7.81%	First-line supervisors/managers of housekeeping and janitorial workers	28.49%	11.68%
Miscellaneous assemblers and fabricators	9.06%	9.72%	Artists and related workers	7.72%	6.09%
Stock clerks and order fillers	11.06%	6.39%	Computer and information systems managers	1.12%	4.65%

Notes: The table shows the 100 largest Census occupations for women, ranked by occupation size. Some occupations not in the top 100, and hence not shown in this table, had empty cells for one or both age groups. Occupations that would have been in the top 100 but had an empty cell include first-line supervisors/managers of personal service workers, pharmacists, physicians and surgeons, and postal service clerks. Occupations in boldface are used in study.

Figure A.1: Histograms of Shares of Recent Hires (< 5 Years of Tenure) in Age Group Relative to All Hires of Same Sex in Occupation, Chosen Occupations and All Occupations for Men, 2008 and 2012 CPS Tenure Supplements



Notes: Histograms are created for all occupations with non-empty cells for both age groups. There are 203 for men and 150 for women.

Table A.5: Median Hourly Wages for Low-Tenure (< 5 Years) Workers in Targeted Jobs, 2008 and 2012 CPS Tenure Supplements

	Men			Women		
Occupation	**Age 28-32**	**Age 48-52**	**Age 62-70**	**Age 28-32**	**Age 48-52**	**Age 62-70**
Retail salespersons and cashiers	12 [29]	10.1 [17]	9.62 [13]	9 [44]	8.87 [25]	9 [18]
Janitors and building cleaners	9 [11]	16.4 [11]	8.5 [6]	…	…	…
Security guards and gaming surveillance officers	9.5 [6]	10 [3]	10.75 [4]	…	…	…
Secretaries and administrative assistants; office clerks, general; receptionists and information clerks; and file clerks	…	…	…	14 [49]	13 [53]	12.5 [23]
Over all occupations, including those not shown	15 [828]	18 [444]	13.46 [142]	13.78 [805]	14.1 [520]	12 [163]

Notes: Cell sizes are shown in square brackets.

Job Search Methods

As additional evidence that job search methods do not differ sharply between older and younger job searchers, we examined data from the monthly CPS files for 2014 on job search methods among the unemployed. As reported in Table A.6, the distributions of job-search methods are fairly similar across these age groups, although the CPS data do not explicitly capture applying for jobs on-line.

Table A.6: Job Search Methods of the Unemployed, 2014 CPS Monthly Files

	Age 28-32		**Age 48-52**		**Age 62-70**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Contacted employer directly/interview	52.7%	50.8%	53.8%	49.3%	45.6%	44.0%
Contacted public employment agency	21.1%	20.9%	25.0%	21.0%	15.1%	15.7%
Contacted private employment agency	10.2%	9.4%	12.5%	10.1%	11.9%	7.9%
Contacted friends or relatives	31.7%	25.6%	33.6%	30.7%	32.5%	29.5%
Contacted school/university employment center	4.2%	3.9%	3.5%	3.7%	3.9%	4.6%
Sent out resumes/filled out applications	55.5%	61.4%	53.1%	58.9%	46.3%	48.9%
Checked union/professional registers	4.2%	2.9%	6.6%	3.5%	7.0%	2.8%
Placed or answered ads	19.3%	15.2%	17.7%	19.3%	19.0%	18.1%
Other active	8.1%	6.7%	8.8%	9.6%	11.9%	12.1%
Looked at ads	31.8%	31.5%	32.0%	34.0%	30.0%	33.6%
Attended job training programs/courses	1.2%	2.4%	1.8%	2.0%	1.2%	2.0%
Other passive	3.0%	2.9%	3.5%	4.4%	5.9%	8.9%
Nothing	5.0%	3.3%	4.3%	4.8%	4.9%	4.6%
N	2,172	2,098	1,683	1,565	1,143	921

Notes: These estimates are derived from the Current Population Survey (basic monthly) for the year 2014. The sample includes all individuals who were unemployed and thus were asked about their job search methods. Population weights are used to generate estimates that are population representative. The proportions do not sum to one because respondents could list up to six job search methods.

Job History Creation

In using the resume database to build job histories, we searched in the specific cities targeted (and of course for the jobs we chose to target). It was easy to select large numbers of resumes of younger applicants. To select a large number of resumes of older applicants, we selected those whose high school or college graduation dates would likely imply that they were age 50 or older. (Resumes typically do not list age, but rather graduation dates.) Finally, we selected resumes with more than five years of work experience, to focus on resumes of older applicants who were not new labor market entrants.[27] While this search may not yield a representative sample of the universe of resumes of older applicants in the jobs and cities we target, it does yield a large number of resumes in these cities and for these jobs. We downloaded resumes, and then input relevant resume information into a database, including work experience, work-related skills, education, approximate age, gender, and information on the pattern of work experience reported on the resume; note that this resume selection process was different from the more random sample we describe in the paper, which was used to characterize resumes along a number of dimensions.[28]

In constructing the first pass of job histories from the actual jobs pulled from the resumes, we use the resume characteristic randomizer from Lahey and Beasley (2009). The program runs backward from the most current job to the beginning of the potential job history (1970). 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 resumes we downloaded, in terms of number of jobs held and average tenure on a job; this iterative process led us to choose a 15% annual probability that the program will end the current job and move on to the next randomly assigned job.

We used the resume randomizer to produce a large number of job histories, and then selected a smaller set that looked the most realistic based on the resumes found on the job-hunting website. In

---

[27] The website also permits a restriction to resumes with more than 10 years of experience, but for the smaller cities and occupations, the weaker restriction was useful to obtain more resumes.
[28] Prior to creating any data based on the resumes we strip out the personal identifiers to protect the confidentiality of the job applicants who posted the resumes.

particular, we dropped those that had very high levels of turnover, unusual sequences of jobs (such as repeatedly switching between manager and cashier), or long strings of employment in other occupations (e.g., spent 20 of the 40 years as a real estate agent).

Some resumes list months only for very recent jobs, and some list them going further back. We use months in the job histories to better match the majority of the resumes, varying across resumes whether or not months are shown for much earlier jobs.[29] To mimic the actual monthly pattern of job changes for different types of jobs, we randomly draw 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 general monthly distribution of separations for janitor and security resumes, the distribution specific to "Retail Trade" for sales resumes, and the distribution specific to "Business Services" for the administrative assistant resumes. After a separation, with a 0.25 probability the next job starts in the same month or one, two, or three months later.

To reduce the number of job histories, we do not change the job history based on small variations in age within our three-year age ranges; we only change age via the high school graduation year. This should have no bearing on our results for differences across the three broad age groups, which is our focus. Also, it likely to be undetected because most resumes do not go quite all the way back to the likely school leaving age.

[29] And when months are shown, job transitions vary randomly as to whether they occurred in the same month, one month later, two months later, or three months later.

Resumes with Bridge Jobs

To approximate these job profiles over time, we used jobs from our bank of actual resumes. We coded jobs according to their level of responsibility. Entry level, low-skill jobs were coded at 1, while the most high-skill, high-level jobs were coded as a 5. The coding of jobs can be seen in Table A.7. In retail sales, the lowest responsibility job is a cashier or sales associate. Individuals work their way through various levels of store management before peaking as a store manager. In security, workers start out as entry-level security guards, and peak at directors of security; note that for security we do not really see mid-level jobs and therefore the career profiles go from jobs coded 1-2 to jobs coded as 5. For administrative assistants, workers start as a receptionist before working their way to a peak job as an office manager. Janitor resumes did not exhibit the same pattern of peaking and bridging that was found in other occupations, so we did not create bridge resumes for janitors.

To create a bridge resume, we arranged jobs so that each job history exhibited the desired peaking behavior. All jobs held by these workers were within the same occupation. Each new job was the same level or higher. After peaking at the highest available job, workers would continue at jobs at that level until they downshifted to a bridge job. There were two types of bridge resumes: either with this downshift occurring 8-10 years prior (for older applicants only), or currently in progress with the bridge job being the job for which the person is applying. These bridge jobs are the same types of jobs that are used for the entire job history in the non-bridge resumes (O_{HNB} and O_L).

On the real resumes tenure in these high-responsibility jobs is longer than tenure on low-skill jobs. To adjust for this we used a lower annual transition probability (7.5%) to generate longer job tenures, so that on average these workers will stay at these jobs twice as long as they do at the low-skill jobs.[30] The tenure at each job was created using the randomizer code described earlier and then added to the resumes. After the worker downshifted to a low-skill bridge job, they had the same transition

[30] With a constant hazard, the distribution of tenure is exponential, with mean equal to the inverse of the hazard. We also use this lower transition probability for the earlier, lower-responsibility jobs for the bridge resumes, to distinguish those more likely to progress to a higher-responsibility job at the same employer.

probability as other workers in our fictitious sample for every job subsequently held. This was done so bridge jobs appear identical to the jobs on the other resumes. The result is that all O_{HB}^{E} resumes will have very similar job histories to the O_{HNB} and O_{L} resumes for their last 8-10 years.

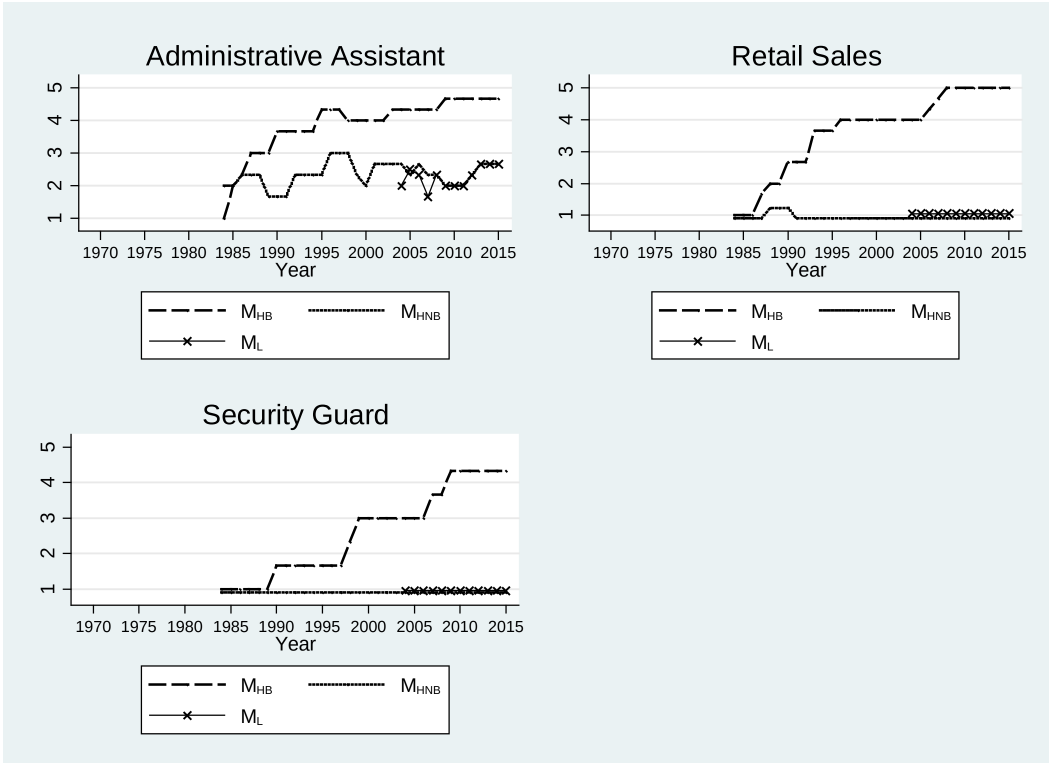
Figures A.2 and A.3 provide a visual representation of the "profiles" of these codes for the different resumes we created. These figures show how the level of responsibility evolves differently in the bridge and non-bridge resumes we use.

Table A.7: Coding of Jobs for Construction of Bridge Resumes

	Retail sales	**Administrative assistant**	**Security guard**
1	Sales associate, cashier, customer service	Receptionist, front desk secretary, secretary	Security guard, security patrol
2	Customer service team leader		
3	Department team leader, shift supervisor	Administrative assistant	Security shift supervisor
4	Assistant manager, department manager		
5	Store manager	Office manager, executive assistant	Director of security

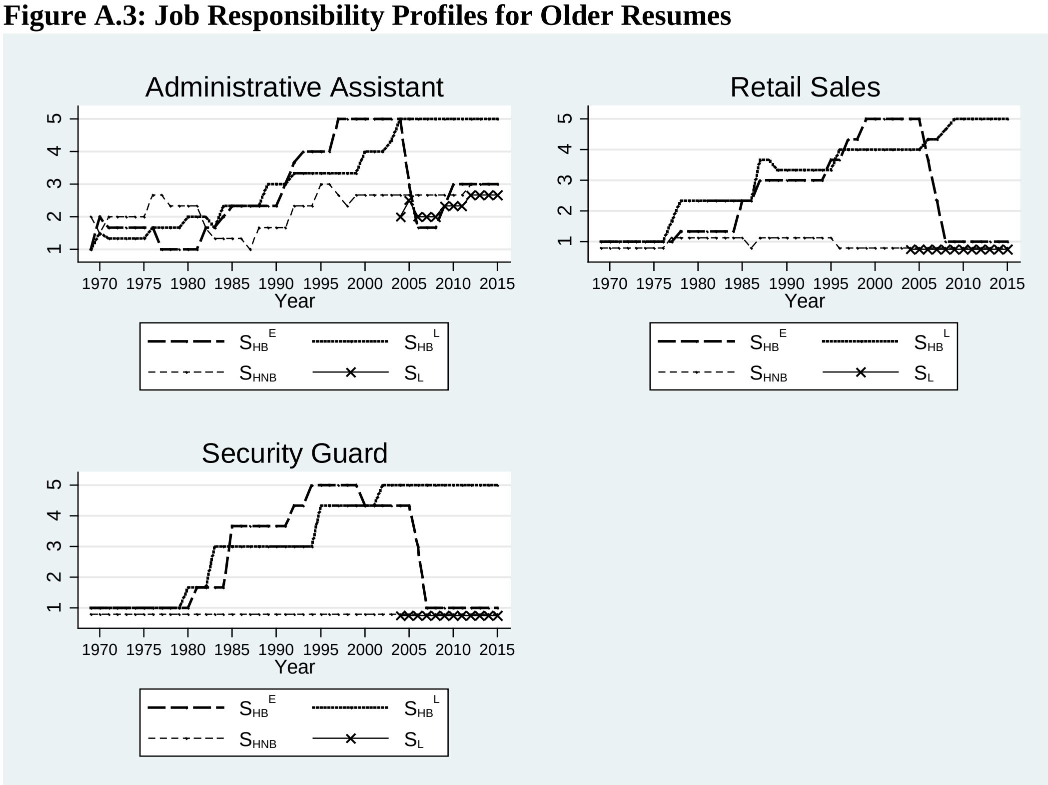
Notes: Each job used in the creation of the resumes was coded using this numeric scale. Using the codes, every resume was coded to create a level of responsibility over time. The three job histories (A, B, and C) for each type of resume were averaged together to create the average responsibility profile over time for the resume type. There was one type of young resume (Y), three types of middle-aged resumes (M_L, M_{HB}, and M_{HNB}), and four types of old resumes (three middle-aged resumes (with B and NB denoting bridge and non-bridge), and {O_L, O_{HB}^E, O_{HB}^L, and O_{HNB}). Figures A.2 and A.3 illustrate the responsibility profiles over time for the different middle-aged and older resumes.

Figure A.2: Job Responsibility Profiles for Middle-Age Resumes



Notes: These are computed as averages by calendar year from the work histories in the resumes we downloaded. See explanation in notes to Table A.7.

Figure A.3: Job Responsibility Profiles for Older Resumes



Notes: See notes to Figure A.2.

Skills

We phrase the skill descriptions to match what we observed in our sample of resumes. We used the same sample of resumes to provide tabulations of skills on actual resumes, based on our scraping of these resumes for descriptions of skills. These are reported in Table A.8, which shows the prevalence of the skills we use on all resumes in all of our occupations (e.g., Spanish), and also the greater prevalence of particular skills for specific occupations (e.g., Microsoft Office for administrative and sales resumes, CPR and first aid for security resumes, and cleaning and related skills and certification for janitor resumes).

The typographical errors (the absence of which represent a possible skill we add) merit a bit more explanation. All low-skill resumes, and the high-skill resumes 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 resumes than spelling errors.

Table A.8: Skills on Resumes, by Occupation

	Searched for	Admin	Janitor	Sales	Security	Total
All	Bilingual, fluent	19%	12%	17%	13%	17%
All	Spanish	18%	10%	15%	10%	15%
Admin, Sales	Microsoft Office (Word, Excel, PowerPoint)	75%	33%	56%	47%	59%
Admin, Sales	QuickBooks	9%	0%	2%	1%	3%
Admin, Sales	POS software, inventory management	2%	2%	3%	1%	2%
Admin, Sales	Quick Learner	3%	3%	4%	3%	4%
Admin	Typing, WPM	29%	6%	15%	12%	18%
	Email, internet	13%	5%	9%	10%	10%
Sales	Communication	25%	18%	28%	23%	26%
Sales	Customer service	31%	22%	37%	26%	33%
Sales	Interpersonal	9%	6%	8%	9%	8%
	Other buzzwords	31%	29%	34%	28%	32%
Security	Security license, guard card	0%	2%	1%	10%	2%
Security	CPR, first aid	7%	4%	6%	13%	8%
Janitor	Certificate in/of Custodial Maintenance	0%	2%	0%	1%	0%
	Cleaning	1%	16%	3%	4%	3%
	Technical cleaning skills	0%	4%	1%	2%	1%
N		4,425	663	8,467	2,938	16,493

Notes: “Other buzzwords” includes: dependable, reliable, flexible, hardworking, attitude, team player, attention to detail, independent, and/or time management. “Cleaning” includes: cleaning, mopping, sweeping, trash, sanitizing, and/or housekeeping. “Technical cleaning skills” includes: plumbing, pest management, hazardous waste management, and/or knowledge in green cleaning/products. “Certificate in/of Custodial Maintenance” is defined as a certificate in janitorial or custodial work, or in any of the above technical cleaning skills.

Additional Resume Elements

Residential addresses

We first chose zip codes that were not too far from the central business district(s) in the metro areas (or the center of the sub-markets used on the job-posting website, as explained in more detail below),[31] so that an employer would not be less likely to offer a job to those perceived as having an excessive commute.[32] We also chose zip codes that were not sparsely populated, and did not have high or low unemployment, family income, share black, or shares of old or young residents.

We began with all zip codes entirely contained within the Core Based Statistical Area (CBSA), Census-defined metropolitan areas that capture a labor market within which people commute.[33] We used data at the zip code level from the American Community Survey (ACS) to exclude any zip codes for which the characteristics listed above were unusual. To avoid sparsely populated areas, we exclude zip codes in the bottom quintile of the total population distribution across zip codes in the CBSA. We first exclude zip codes in the bottom quintile of the proportion of the population aged 25 to 34, 60 to 64, or 65 to 74. We then also exclude any zip codes that have an age distribution that suggests far younger residents than older residents, or vice versa, based on the ratio of those aged 60 to 74 to those 25 to 34.[34] In addition, we drop zip codes in the top or bottom quintiles of the distributions of the unemployment rate or median family income, or if the share black is in the top quintile of the distribution (areas with a low share black are not problematic, as there are many of them). We also exclude military bases and similar areas.

Among the zip codes that remain after imposing these restrictions, we drop zip codes that are

[31] Sub-markets are regions within a city's market.
[32] Data from the 2009 American Community Survey indicate that over 50% of (one-way) commute times to work are 24 minutes or less in length, and only fewer than 15% are 45 minutes or longer (U.S. Census Bureau, 2011).
[33] See http://www.census.gov/geo/reference/gtc/gtc_cbsa.html (viewed August 11, 2014).
[34] We do not simply use percentiles of the distribution, because in some cities that have particularly old populations, the ratio of old to young residents can be quite high even at the bottom of the distribution, for example. We thus base our exclusion rules for the ratio of young to old on a hybrid of relative and absolute criteria, dropping zip codes with the ratio of older to younger residents below the minimum of 0.5 and the 20th percentile, and above the maximum of 2 and the 80th percentile.

more than 25 miles from the central location of the corresponding job market for the job posting locations we use to identify jobs. For central areas, we use the central business district, excluding zip codes more than 25 miles from the center of the zip code to city hall. For sub-markets on the job-posting website, we use distance from the zip code to the center of the sub-market, using city hall if the sub-market included it, and otherwise approximating by visual inspection of maps. Distances are measured using Google Maps, assuming travel by car; Google maps calculates these based on geographic centers of zip codes, except for downtown areas where it uses the city hall. Table A.9 shows, as an example, the zip codes selected for the New York City CBSA and the associated sub-markets. We present summary statistics for the entire CBSA, and then for each zip code we selected. Table A.10 shows all of the zip codes used.

We then assign street addresses for the zip code, using *Zillow* to select streets and addresses so that house prices at the address are about average for the metro area (having already selected zip codes with intermediate values of median family income). For each zip code selected, we search on *Zillow* for all houses for sale or rent, and pick a street where prices were near the averages for the city. We then utilized the "street view" function to select streets that were primarily residential, rather than a mix of residential and business, and to determine if the majority of buildings on the street were apartment buildings or detached houses. Once a suitable street was found, we picked a house to get the exact address (123 Main Street for example) and then used that to create a range of numbers around the house to draw from for our addresses based on 100s (so 100-200, in this example). For streets with mostly apartments, we assigned apartment numbers, choosing randomly from two to nine.

Within each triplet of applications sent in response to an ad, all applications were from different zip codes and different addresses. These were randomly assigned so that applicants with certain characteristics do not have tendencies to be from different kinds of neighborhoods (or homes). Using zip codes and addresses that are not outliers ensures that within triplets, applicants are similar on these dimensions.

Phone numbers and email addresses[35]

We purchased “online” phone numbers for our applicants using *Vumber*. These do not appear any different than regular phone numbers to the employer, but have the benefit that the calls and voicemails are recorded in an online account and no physical phones are required.

We selected phone number area codes for all applicants that were located centrally in each metro area whenever possible. From the set of centrally-located area codes, we tried to avoid picking those that were too old, as these may be difficult to get or are considered “posh” (e.g., 212 in Manhattan), or too young, such that it might be far more likely that the area code would belong to someone younger (e.g., 929 in New York, which was only created in 2010). Table A.11 presents the area codes we used for each metro area, along with information on their coverage areas and dates of creation. Four of the area codes we use were ones that were the first to be assigned to the area, in 1947, in some cases because other area codes that covered a similar geographic area were overlaid too recently. In Birmingham, there is only area code (205). In Phoenix, there were not enough 602 area code numbers available from our provider that were unique enough from each other, so we assigned each of the three applicants to a different area code in the greater Phoenix area (602, 480, and 623).

When employers respond by phone, they may not always leave a message that provides enough information to match them to an exact applicant (let alone job ad). Assigning a unique phone number to every job applicant and job ad would solve this problem, but is prohibitively expensive and complicated.[36] We purchased enough phone numbers to assign unique numbers to each group of job applicants defined by occupation (administrative assistant, janitor, sales, and security), city, sex (for sales, where applicants are either male or female), and type of triplet that the resume is a part of (triplet with two resumes of age 64-66, two resumes of age 49-51, or one of each, along with a young applicant). This results in 360 unique phone numbers. With all of these numbers, it is very unlikely that we would not be able to assign a response to an applicant, although assigning it to a unique job ad requires more

[35] We give credit for some of the ideas in this subsection to an earlier correspondence study by Figinski (2017).
[36] The phone numbers cost $1.25 per number per month.

information (discussed below).

We also needed email addresses for our respondents. Because some of the main email providers do not permit the creation of email addresses for fictitious persons, and because we wanted complete control of the email addresses, we purchased our own domain names and used them to create our own addresses. We purchased three domain names so that we could use different domain names for the applications in each triplet we sent out. With our own domains, we could create unlimited email addresses, so the email addresses we use are almost unique to each applicant. We do this by making each of the following attributes of the email address different for each applicant in a triplet: the domain name; using either the full first and last name (janedoe), the first initial and full last name (jdoe), or the full first name and last initial (janed); using a randomly selected middle initial (using all letters except l, y, z, q, u, and x), a period, an underline, or none of the above between the first and last name or initial, although in the randomization more than one applicant is allowed to have none of the above; appending either a 1, 2, or no number at the end of the email address, with more than one applicant allowed to have no number. This procedure for assigning email addresses also allows us almost perfectly to associate a response with an applicant, if the response is through email and does not otherwise provide sufficient information to assign the response to an applicant.

We created unique websites for our three domains in case employers decided to investigate the domain for legitimacy. The websites look like typical email services and include branding elements such as a logo created by a graphic designer. To add realism, the home pages even include buttons for signing in and creating an account, as well as account access and “contact,” although these are not fully functional. Clicking on any of the latter three generates an email to an email account associated with the domain. These emails, in addition to the number of hits to our website, provide a useful way to gauge if employers are viewing our websites, and ultimately, if there is evidence they are finding the domain names questionable, which could affect response rates. The emails and website hits suggest very limited engagement with our websites.[37]

It is possible that the use of unusual domain names might signal something about tech savvy. Our suspicion is that use of an unusual domain would signal greater, rather than less, savvy (as opposed, say, to using *AOL*). If so, and if employers are more skeptical of tech skills of older workers, then this approach could have overstated the relative tech skills of older applicants, creating a bias against finding age discrimination.[38]

[37] Averaged over the months of February 2015 to May 2015 (four months where we applied for jobs the entire month), and averaged over all three domains, we had 84 unique visits per website per month. We looked at visits data for our websites before we started applying for jobs, and we looked at country of origin of our visitors, and this information roughly suggests that about half of these visits could be attributable to employers and that at least the other half is noise. About 93% of our visits are shorter than 30 seconds, suggesting limited engagement with our websites entailing simply taking a glance at an uncommon domain name for email. We also received 10 emails to these websites (that were not explicitly spam).

[38] The domain name hits are, unfortunately, not informative about the relative evaluation of, or skepticism about, older versus younger resumes.

Table A.9: Examples of Zip Codes Selected for New York City CBSA and Associated Sub-Markets

Sub-market	Zip code	City	State	Population	% aged 25 - 34	% aged 60 to 64	% aged 65 to 74	Ratio 60-74 to 25-34	% black	Unemployment rate	Median family income
CBSA 20th percentile	All			6,497	7.6	4.4	5.6	0.65	1.5	5.5	62,576
CBSA median	All			17,505	12	5.5	7.1	1.09	4.5	7.4	98,046
CBSA 80th percentile	All			40,680	16.4	6.8	9.1	1.97	20.1	10.2	130,535
General, Manhattan, Queens, the Bronx	11358	Flushing	NY	39,143	14.5	5.8	7.6	0.92	2.5	9.1	80,428
	11364	Bayside	NY	35,106	13.5	6.2	8.1	1.06	2.5	7.1	81,657
	11379	Flushing	NY	35,680	11.9	7.1	8.8	1.34	1.7	6.4	84,139
Brooklyn	11209	Brooklyn	NY	72,434	17.2	5.3	6.9	0.71	2.7	8.4	72,535
	11228	Brooklyn	NY	43,396	14	6.3	9.3	1.11	1.9	9	70,667
	11379	Flushing	NY	35,680	11.9	7.1	8.8	1.34	1.7	6.4	84,139
Staten Island	10306	Staten Island	NY	55,692	11.8	6.2	8.3	1.23	3.7	7.3	92,114
	10307	Staten Island	NY	14,418	10.8	4.8	7	1.09	1.1	6.2	101,442
	10314	Staten Island	NY	87,921	11.8	6.7	8.1	1.25	4.2	6.2	91,470
New Jersey	07605	Leonia	NJ	8,998	7.8	6.2	8.1	1.83	4.3	5.5	98,629
	07070	Rutherford	NJ	18,084	12.7	5.7	5.8	0.91	5	7.8	100,278
	07110	Nutley	NJ	28,311	13.1	6.7	7.9	1.11	3.7	8.8	102,049

Notes: Source is the American Community Survey Demographic and Housing Estimates (2012, 5-year estimates), at the zip code level.

Table A.10: Zip Codes Used for Each City and Sub-Market

	ZIP	City	State		ZIP	City	State
Birmingham:				Miami:			
	35023	Hueytown	AL	General, Miami, Dade County	33134	Coral Gables	FL
	35094	Leeds	AL		33145	Miami	FL
	35118	Sylvan Springs	AL		33166	Miami Springs	FL
Boston:				Broward County	33014	Miami Lakes	FL
General, Boston, Cambridge, Brookline	02152	Winthrop	MA		33016	Hialeah	FL
	02170	Quincy	MA		33055	Miami Gardens	FL
	02171	Quincy	MA	New York:			
South Shore	02132	Boston	MA	General, Manhattan, Queens, the Bronx	11358	Flushing	NY
	02170	Quincy	MA		11364	Bayside	NY
	02171	Quincy	MA		11379	Flushing	NY
North Shore, Northwest Suburbs	02152	Winthrop	MA	Brooklyn	11209	Brooklyn	NY
	01906	Saugus	MA		11228	Brooklyn	NY
	01906	Saugus	MA		11379	Flushing	NY
Western Suburbs	02132	Boston	MA	Staten Island	10306	Staten Island	NY
	02152	Winthrop	MA		10307	Staten Island	NY
	02026	Dedham	MA		10310	Staten Island	NY
Charlotte:				New Jersey	07605	Leonia	NJ
	28105	Matthews	NC		07070	Rutherford	NJ
	28120	Mount Holly	NC		07110	Nutley	NJ
	28210	Charlotte	NC	Phoenix:			
Chicago:				General, Central Phoenix, South Phoenix	85283	Tempe	AZ
General, Chicago, Northern Suburbs	60631	Chicago	IL		85013	Phoenix	AZ
	60656	Chicago	IL		85044	Phoenix	AZ
	60706	Norridge	IL	East Valley	85283	Tempe	AZ
Southern Suburbs	60452	Oak Forest	IL		85206	Mesa	AZ
	60453	Oak Lawn	IL		85202	Mesa	AZ
	60655	Chicago	IL	West Valley	85323	Avondale	AZ
Western Suburbs	60513	Brookfield	IL		85338	Goodyear	AZ
	60516	Downers Grove	IL		85345	Peoria	AZ
	60148	Lombard	IL	North Phoenix	85032	Phoenix	AZ
Houston:					85023	Phoenix	AZ
	77009	Houston	TX		85053	Phoenix	AZ
	77018	Houston	TX	Pittsburgh:			
	77055	Houston	TX		15209	Pittsburgh	PA
Los Angeles:					15223	Pittsburgh	PA
General, Central Los Angeles	90027	Los Angeles	CA		15234	Pittsburgh	PA
	90039	Los Angeles	CA	Salt Lake City:			
	91202	Glendale	CA		84106	Salt Lake City	UT
Westside, South Bay	90501	Torrance	CA		84107	Murray	UT
	90504	Torrance	CA		84117	Salt Lake City	UT
	90066	Los Angeles	CA	Sarasota:			
San Fernando Valley	91505	Burbank	CA		34231	Sarasota	FL
	91324	Northridge	CA		34232	Sarasota	FL
	91356	Los Angeles	CA		34239	Sarasota	FL
San Gabriel Valley	90041	Los Angeles	CA				
	91016	Monrovia	CA				
	91754	Monterey Park	CA				
Long Beach, Area Code 562	90241	Downey	CA				
	90242	Downey	CA				
	90650	Norwalk	CA				

Notes: For six of the 12 cities (Boston, Chicago, Los Angeles, Miami, New York, and Phoenix), the job posting website contained “Sub-Markets” that covered different parts of the metropolitan area. When applying to jobs in each sub-market, we use addresses located within these markets. For job ads where it is unclear in which sub-market the job is located, the set of addresses for “General” are used. For Boston: North Shore, Northwest Suburbs, we use the same zip code twice (but still different street addresses) because there were not good alternatives after applying our filters.

Table A.11: Selected Phone Area Codes

Metro area	Area code	Year created	Geographical area
Birmingham, AL	205	1947	Birmingham and portions of northwestern Alabama
Boston, MA	857	2001	Greater Boston (approximately the area within I-95)
Charlotte, NC	980	2001	Charlotte and all or part of the 12 surrounding counties in North Carolina
Chicago, IL	773	1996	Chicago excluding the downtown core
Houston, TX	832	1999	Greater Houston area
Los Angeles, CA	323	1998	Central Los Angeles, excluding Downtown, Koreatown, Echo Park, and Chinatown
Miami, FL	786	1998	Miami-Dade and Monroe Counties
New York, NY	347	1999	The Bronx, Queens, Brooklyn, Staten Island, Marble Hill (Manhattan)
Phoenix, AZ	602	1947	Most of Phoenix
	480	1999	East Valley
	623	1999	West Valley
Pittsburgh, PA	412	1947	Greater Pittsburgh Area
Salt Lake City, UT	801	1947	Davis, Morgan, Salt Lake, Utah, and Weber counties
Sarasota, FL	941	1996	Manatee, Sarasota, and Charlotte counties

Resumes and Examples

We designed the resumes to be randomized across occupations and across cities. There were three types of workers. For middle-aged and older-aged resumes, we created multiple job histories. Middle-aged resumes were assigned one of three different job histories, and older resumes had four different histories. In each occupation, we used three distinct visual styles to make the triplets received by employers different. The result was 24 resumes templates per occupation and city, for a total of 1,152 resume templates.

For each day of the month (1-31), we created a triplet of resumes to be used for each city-occupation pair. Every triplet contained a young resume, with the remaining two containing either a middle-aged or older resume – either middle-old, middle-middle, or old-old, each with probability one-third. The job histories of middle-aged and older resumes were randomly selected, so employers could receive two of the same type (e.g., two M_L resumes, or two different types).

Below, we present four examples of resumes to show how the resumes vary by occupation, skill level, major resume type, and resume style. Resumes 1 and 3 present style A, resume 2 presents style B, and resume 4 presents style C. Table A.12 shows the numbers of each type of resume sent.[39]

Each occupation has different work experience related to the occupation for which the applicant is applying, and some different skills. Resume 1 shows an administrative assistant resume with the possible administrative assistant skills. Resume 2 presents a janitor resume; resume 3 presents a retail sales resume; and resume 4 presents a security resume. Resumes 2-4 do not list skills but the skills would follow the same format as in resume 1, except two of the skills in the skill section are occupation-specific, as discussed in the main paper.

[39] Table A.12 shows that 40,223 resumes were sent out as part of the study. These 40,223 resumes were sent out to 13,371 unique jobs. The total number of jobs applied for is less than one-third of the total resumes sent because in some cases research assistants (RAs) applied to the same job multiple times. RAs applied to the same job in some cases because it was very common for ads to be reposted or refreshed to the top of the search results by companies. When this occurred, RAs were instructed to not apply for that job for a month, but that if the ad appeared again after a month it was acceptable to apply again. In addition, there were a small number of cases where not all three resumes were sent to a job ad because of RA errors or mistakes. The order that resumes were sent to the employer was randomized, so RA errors and mistakes would not be correlated with the age of the applicant.

Resume 1 presents how the skills are placed on the resume, for the "high-skill" resumes. These high-skill resumes get a random selection of five of the following seven skills:

1. Correction of two typos in job descriptions: a missing period and a missing space after a comma.
2. A post-secondary degree (Associate of Arts for Janitor, otherwise Bachelor of Arts).
3. An employee-of-the-month award for the most recent job.
4. Volunteer experience (randomly selected from animal shelter, homeless shelter, or food bank).
5. Fluency in Spanish as a second language
6. Occupation-specific skill 1.
7. Occupation-specific skill 2.

Skills 2 to 7 are shown in italics on Resume 1 for administrative applications (although only five would actually appear). The lack of Skill 1 is highlighted on Resume 2.

Resume 1 presents the three major resume types of Y, M_L, and S_L, where experience is set to be the same as that of the young person and age is varied by filling in the graduation year(s). Resume 2 presents M_{HNB}, where the individual is middle-aged but has experience commensurate with age. The most recent job history would be similar on resumes types Y, M_L, and S_L, but the job history goes further back. The jobs that are added to this resume, relative to what would be on Y, M_L, or S_L is indicated in the box (the two janitor jobs, for this resume). The S_{HNB} resume follows this same format, but additional jobs are added to reflect longer work experience, again at the same level. Resume 3 presents M_{HB}, where the applicant is middle aged and is looking to "bridge" in this application. These resumes have a work history where the prestige and demands of the jobs rise, with the current job being a management position. The $S_{HB}{}^{L}$ resume is similar to this one, but with a longer work history of a similar trajectory. Resume 4 presents the final major resume type, $S_{HB}{}^{E}$, which is for an older applicant who has already bridged. The previous bridging is evident as the most recent work experience is at a responsibility and prestige level that is the same as the jobs on Y, M_L, and S_L resumes, but earlier work experience shows the rising responsibility and prestige of the other bridge resumes.

All resume information that was not added manually was assigned to resumes using Visual Basic for Applications (VBA) programs that we created. Creating our own code allowed us to randomly add and track several resume characteristics. Our VBA programs also grouped our completed resumes into triplets for us, created application scripts, saved our resumes with file names reflecting the names on the resumes, and organized all these files an intuitive folder structure.

Table A.12: Numbers of Resumes Sent

	Template			
Resume type	A	B	C	Total
M_{HB}	1,725	1,363	1,324	4,412
M_{HNB}	1,247	1,456	1,412	4,115
M_L	1,483	1,525	1,196	4,204
S_{HB}^E	937	1,328	1,523	3,788
S_{HB}^L	1,400	1,023	1,274	3,697
S_{HNB}	1,171	792	1,269	3,232
S_L	1,031	1,430	913	3,374
Y	4,401	4,534	4,466	13,401
Total	13,395	13,451	13,377	40,223

Note: The resumes were randomized within a triplet. A triplet always contained a young resume, with the number of middle-aged and old-aged resumes in a triplet randomly assigned. The same resume type could be sent to an employer, but no triplet had the same type-template combinations. So no employer ever got two M_L resumes in template style A.

Example Resume 1: Administrative Assistant, Y, M_L, and S_L, Showing Added Skills

*First Name *Last Name
*Street Address
*City, *State *ZIP
*Phone
*Email

Objective To secure an administrative assistant position.

Experience

<u>Receptionist</u>
HCR Manor Care
Sarasota, FL
May 2011 - Present

I answered phones, screened calls, and transferred calls to the proper parties. I also greeted visitors and handled deliveries while overseeing the front desk. *I was awarded employee of month by my supervisor.*

<u>Administrative Assistant</u>
Hoveround Corporation
Sarasota, FL
Mar. 2009- May 2011

I managed the office calendar, planned travel, processed invoices, tracked and reconciled expenses. I was responsible for overseeing new hire setups and coordinating space planning and office moves.

<u>Administrative Assistant</u>
World Precision Instruments, Inc.
Sarasota, FL
Aug. 2007- Mar. 2009

I met and greeted all visitors. I created and modified documents and forms. I was responsible for general clerical duties.

<u>Library Assistant</u>
US Army
Bradenton, FL
May 2004- July 2007

I helped oversee the library facilities. I answered the phones, handled the mail, and all other responsibilities at the front desk.

Education

High School Diploma — *School Name, *City, *State
*Graduation Year

Bachelor of Arts — **School Name, *City, *State*
**Graduation Year + 4*

Skills

I am fluent in English and Spanish.

Good with computers, able to use Microsoft Office programs at an advanced level. Have a working knowledge of a number of inventory management software.

Excellent typist able to consistently type over 40 words per minute.

Volunteer *I volunteer at the local animal shelter, helping take care of animals and organizing other volunteers.*

References References available if needed.

Example Resume 2: Janitor, M_{HNB} (also similar to $S_{HB}{}^{L}$), Showing Included Typos

***First Name *Last Name**
***Street Address**
***City, *State *ZIP**
***Phone**
***Email**

Objective To obtain a position as a janitor.

Experience

Custodian
Franklin Middle School, Tampa Bay, FL
Nov. 2013 - Feb. 2015
Cleaning, vacuuming and shampoo carpets,stripping and waxing floors, removing trash, and washing floors.

Facilities Manager
Mr. Spiffy's Cleaning, Anna Maria, FL
Jan. 2007 - Aug. 2013
In charge of managing custodial staff. Worked to control costs and find more cost efficient ways to clean and maintain the building.

Custodian
Keller Meyer Building Services, Sarasota, FL
Feb. 2005 - Nov. 2006
Cleaning, vacuuming and shampoo carpet, stripping and waxing floors, removing trash, and washing floors

Janitor
Beckwith Electric, Largo, FL
Feb. 1991 - Nov. 2004
Swept, mopped, vacuumed emptied trash cans. Picked up litter from around building and other areas. Kept an inventory of job related supplies such as toiletries. Maintained an adequate amount of supplies.

Janitor
Yolanda Borsella's Cleaning and Janitorial Services, Bradenton, FL
Nov. 1984 - Nov. 1990
Swept, mopped, vacuumed emptied trash cans. Picked up litter from around building and other areas.

Education

High School Diploma
North Port High School, North Port, FL
1983

References I have references available if needed.

Example Resume 3: Retail Sales, M_{HB} (also similar to S_{HNB})

*First Name *Last Name
*Street Address
*City, *State *ZIP
*Phone
*Email

Objective To secure a position as a retail sales associate.

Experience

Store Manager Goodwill Industries, Bradenton, FL *Dec. 2005 - Present*	Managed the day-to-day operations of the store. Oversaw staff,product orders, cash deposits, and opening and closing of the store. Hired new staff and provided basic training of store protocols Worked to increase sales and customer satisfaction.
Department Manager Men's Wearhouse, Sarasota, FL *1994 – 2005*	Led department staff to provide consistently positive customer service. Disciplined staff and recommended for promotions or raises when deserved.
Department Head Macy's, Sarasota, FL *1989 – 1994*	Led department staff to provide consistently positive customer service. Disciplined staff and recommended for promotions or raises when deserved.
Team Leader Walgreens, Sarasota, FL *1987 – 1989*	Led staff to provide consistently positive customer service. Answered customer questions and trained team members on how to best meet customer needs. Organized the sales floor and displays. Restocked and checked for damaged merchandise.
Sales Associate Sears, Sarasota, FL *1986 - 1987*	Rang customers up at the cash register Handled product exchanges and refunds according to established company policies.

Education

High School Diploma — Sarasota High School, Sarasota, FL
1982

References References available if needed.

Example Resume 4: Security, S_{HB}^{E}

***First Name *Last Name**
***Street Address**
***City, *State *ZIP**
***Phone**
***Email**

<u>Experience</u>

Security Guard
OSA Global Security, Sarasota, FL
Apr. 2008 - Feb. 2015
Maintain the safety and security of visitor and staff. Keep track of all security incidences and call law enforcement or emergency services when needed.

Security Officer
Allegiance Security, Tampa Bay, FL
Oct. 2006 - Apr. 2008
Temporary position with agency that would send me to different company's premises ranging from: pharmacies, large offices, call centers, and hospitals.

Security Team Supervisor
Ringling Shopping Center, Sarasota, FL
Dec. 1999 - Sept. 2006
Led a team of 8 security guards. Responsible for hiring, firing, and all human resource aspects of the security team. Set schedules and approved vacation time to make sure that the department operated efficiently.

Head of Security
Sarasota-Bradenton International Airport, Sarasota, FL
June 1991 - Oct. 1999
Head of security with a team of 12 security guards. Organized schedules for guards. Kept detailed reports of all activities. Compiled reports from shift supervisors to present to management.

Team Leader
Pinkerton, Sarasota, FL
Sept. 1984 - Apr. 1991
Investigated security incidences and filed reports. Responded to alarms and complaints. In charge of the security guards during shifts.

Shift Supervisor
Allied Burton, Mesa, AZ
Feb. 1980 - July 1984
Patrol sites and report incidents, accidents, or occurrences. Scheduled patrols for security team.

Guard
Ringling Museum of Art, Sarasota, FL
June 1971 – Jan. 1980
Patrol sites and report incidents, accidents, or occurrences.

Education, skills, etc, would follow as normal from here on.

Applying for Jobs

The protocol for selecting job ads eligible for the study and applying to them is described briefly in the paper. Here, we provide more details and some elaboration.

With regard to on-line job application websites, which are excluded, large companies often contract out with external human resources firms to recruit. Retail stores such as H&M, Express, and the Gap utilize the services of Workforce1 Recruiting. Workforce1 requires applicants to go to an external page and submit their application using their own system. Other firms such as Walmart, Target, and Best Buy do not advertise online, but will only accept applications on their websites. In addition, there were some ads for Taskrabbit-type employers that were essentially getting people to sign up and be listed as an on-demand employee.

Among the types of skills that might have been required that would have led to exclusion of an ad were speaking a language other than Spanish, or requiring (rather than treating as optional or preferred) a skill that was part of the vector of randomized skills assigned to a resume (or other features that our resumes might not have, like more than 10 years of experience). Job ads were also excluded if the advertisement was for temporary or seasonal work, or if the job ad seemed like a scam collecting emails and other information.

Some of the skill-related exclusion criteria were occupation-specific. In particular, administrative assistant ads were excluded if the job advertised was for a personal assistant, bookkeeping, data entry, appointment setters, or if the job required different technical skills (e.g., assisting with IT). Ads were also excluded if they required the applicant to type at certain speeds, requested more than 10 years of experience, required a Bachelor's degree, or required knowledge of Quickbooks or Outlook. Retail sales ads were excluded if they were for sales jobs that were not in a retail environment, or were for a merchandiser. Sales ads were also excluded if they requested a Bachelor's degree, experience using POS software, or more than 10 years of experience in sales. Security guard ads that requested a Bachelor's degree or certification in CPR and first aid were excluded.[40]

[40] For security guards, requiring a state license was not one of the reasons used to restrict the job ads, because each

Research assistants were directed to avoid all ads that seemed to be spam when they applied to jobs, but in some cases they could not identify the ads as such. When a research assistant applied to a spam ad, the response generally came to the spam folders of our email clients. These responses often asked for credit card or bank information, contained egregious spelling and grammar errors, and were obviously not from legitimate companies (e.g., Canadian sculptors looking for personal assistants in Birmingham, AL). We saved the ads before the email client deleted the responses. At the end of the study, we attempted to identify the spam ads to which we had applied to get a sense of what share of negative/non-responses they constituted, and what cities and occupations generated them. We erred on the side of caution and only flagged the responses and associated job ids where we were very confident of the match. We identified 3,674 spam emails, 2,775 of which could be matched to 1,220 job ads that generated them (suggesting that in most cases spam responses went to all three applicants to the job ad). Spam responses were concentrated in the administrative assistant ads. The majority of spam responses came from cities where it is free to post a job ad, but they did appear in other cities as well. Of the ones that we could match, 93% were for administrative assistants and 78% were in Birmingham, Salt Lake City, and Sarasota. We did not delete these observations from our main analysis for two reasons. First, there may have been other spam responses we did not identify. And second, from the point of view of a job applicant a spam response is an unproductive response to a job application. However, in the paper we report key results for administrative jobs, excluding the spam ads.

In the event of the same ad being posted twice, we endeavored to respond to the job at most once every 30 days. Companies with many openings at the same location received a response for one of the openings listed, but not all of them. When an ad listed openings across multiple locations, resumes were sent without indicating preference for one location.

Search methods for each occupation were standardized so that each research assistant performed

state has different licensing requirements, with additional differences between armed and unarmed security guard jobs. To be consistent across states, we applied to any job that required a license for two reasons: the fact that our resumes claim to be currently employed implies that they possess a security guard license; and jobs that do not ask for the license would presumably have the same requirement but are not stating it explicitly in the posting. However, if the ad required providing a copy of the license, we did not apply.

their search the same way in each city, to ensure that applications were sent to similar jobs in each city and occupation, or at least that the selection rules were similar. With 16 research assistants applying for jobs, we set up numerous procedures to continually monitor and enforce similar job search decisions in each city and occupation. These included direct supervision of research assistants, a Facebook page where research assistants would post questions as they came up that were then answered (with answers conveyed to all research assistants), and periodic meetings of the entire research team to discuss procedures and clarify questions that could lead to research assistants using different procedures. To check that research assistants were following the guidelines, for a four-week period all ads that were read to determine eligibility were saved. Every time a research assistant opened an ad, it was saved as either a rejected ad or an ad to which a research assistant applied. Research assistants also tabulated the reasons that these ads were rejected, for the reasons that arose most frequently. Table A.13 provides information from these tabulations.

In sending out the resume triplets, normally the three resumes would go out on consecutive days. However, if the ad had been up for more than a day (i.e., posted on Saturday and we found it Monday), then the second resume would go out one day later in the morning, and the third resume that evening (at least 12 hours apart). The scheduling of ad submission was done using the "send later" add-on to Mozilla Thunderbird. We created Word and PDF versions, but sent out PDFs unless otherwise specified, since since this format is the easiest for employers to open.[41]

To distinguish further the resumes in each triplet, we named the computer files slightly differently. One resume in the triplet was named "FirstLastResume," where First and Last were replaced with the applicant's first and last names, another resume was named "ResumeFirstLast," while the final resume was named "FirstLast." This naming convention is randomly assigned. Each ad that was applied

[41] We used .doc instead of .docx since job search experts suggest that .doc is easier for employers to use. (See http://jobsearch.about.com/b/2014/02/21/resume-file-format.htm, viewed November 8, 2014.) We removed author and edit history data from our Microsoft Word format resumes so that employers could not potentially see that one of this study's authors or research personnel created or edited the document. We tried to accommodate the requests of the employer (e.g., pasting the resume in the email), as long as the request did not require any changes to the document.

to was saved for later research.

In our email responses to the posting, each application within a triplet uses a different subject line, opening, body, closing, and signature order.[42] Some of these scripts are based on examples and advice articles by job search experts.[43] We assumed that the text of our email responses would satisfy employers' requests to include a cover letter. Differentiating our email scripts further ensures that applicants from the same triplet are not perceived as related by the employer.

With such a complicated protocol, based in part on subjective decisions, it would not be surprising if some errors were made regarding which application went to which job. In the early going of applying for jobs, this process was monitored closely, to reduce errors, and after the first month or so, applications were spot-checked. We tabulated errors that were detected (either by this monitoring, or self-reported by the research assistants in checking their work); these are reported in Table A.14. The rates of occurrence of these errors declined sharply once early errors were pointed out to research assistants and they were better trained. Moreover, the errors that occur in a non-negligible share of cases ("Sent resumes at wrong time" and "Sent resumes in the wrong order") do not invalidate the data. Moreover, these were random with respect to the age of the applicant, as we verified by estimating probit models of these types of errors on the age dummy variables, finding estimated coefficients very close to zero and statistically insignificant. The other errors that could conceivably lead to an invalid observation (e.g., "Sent resume from the wrong occupation") occurred with such low incidence that we chose to retain the observations and avoid subjective decisions about which observations to drop. To assess the sensitivity of the results, however, we re-estimated all of our models dropping cases with errors in the protocol. The results were very robust.

[42] Note that there are only two openings and signature orders used. Our perusal of job application websites generally found only these two openings, so we randomly assigned the two versions to the three resumes. Based on the websites, we used "Dear Hiring Manager" as the opening in two out of three, and made the indicated choice for the signatures.

[43] See http://jobsearch.about.com/od/jobapplications/u/job-applications.htm (viewed August 7, 2014)

Table A.13: Reasons Applications Not Submitted in Response to Job Ads

Reason for dropping	**Admin.**	**Sales**	**Security**	**Janitor**	**All**
College requirement	8%	5%	1%	0%	5%
Already applied	6%	8%	10%	6%	7%
Spam	5%	4%	0%	0%	4%
Same company posting different jobs	3%	5%	4%	0%	4%
CPR (security)	2%	3%	4%	0%	2%
Outlook, QuickBooks, POS program, or given tying speed required	11%	5%	1%	0%	7%
Bilingual requirement	9%	6%	4%	2%	7%
Salary history/requirements, answer questions, submit references, security license number	9%	7%	6%	5%	8%
Need photo	4%	4%	3%	0%	4%
Apply in person, online, or phone call	11%	12%	30%	43%	16%
Temporary, seasonal, or internship	6%	6%	3%	1%	5%
Doesn't fit in job description (e.g., truck driver listed in sales)	11%	12%	16%	6%	11%
Duplicate posting	5%	7%	8%	27%	8%
Wrong market	4%	4%	2%	5%	4%
Managerial/supervisor	6%	10%	6%	3%	7%
Other	1%	2%	0%	0%	1%

Notes: Research assistants did not apply for a job if it did not fit the description of the occupation, was not low skilled, asked for skills that were randomized onto the resumes, or if they required documents that we had not prepared. A job could be dropped for one or more reasons. The numbers reported in this table represent the share of total reasons for dropping, not the percentage of ads that were dropped for that reason. The "spam" ads noted here were identified by research assistants when reading the ads. Many more spam ads were identified after applying; see the text for discussion.

Table A.14: Errors in Applying to Job Ads

Error	**Occurrences**	**Callbacks**
Sent resumes at wrong time	205	26
Sent only some resumes	12	2
Sent from the wrong part of the city	14	6
Applied using the wrong triplet	81	17
Sent resumes in the wrong order	730	148
Sent email with error in the script	4	1
Sent the wrong resume*	10	4
Sent resume from the wrong city*	8	0
Sent resume using the wrong email	6	0
Sent resume from the wrong occupation*	2	0
Sent email when should have applied in person*	6	0
Applied to the same job less than a month apart	29	2
Applied when the job required a skill*	6	2
Applied with men when it asked for only women*	3	0
Sent multiple applications to same job	9	3
Applied to a job that required a salary history*	3	0
Applied to an internship*	3	0
Applied when they required extra information*	3	0

Notes: These errors were reported by research assistants or detected by monitoring. * indicates cases where the error violates the protocol in a way that could invalidate the data. Note that many, but not all, of these cases generate no callbacks.

Other Outcomes

Our data collection allowed us to determine how long it had taken for a response to be received, what order the responses come in, and who else in a triplet received a response. These kinds of characteristics of responses have been used in past studies, and we also look at them, briefly, in addition to the simple callback/no-callback response.[44] Table A.15 presents raw data on whether there were multiple callbacks for the same job ad. The multiple callback rate was highest for young applicants, and falls monotonically with the age of applicants. Although the multiple callback rates are very low (1.3 to 2.4%), the differences by age are statistically significant. Thus, the analysis of multiple callbacks gives similar qualitative evidence of discrimination against older job applicants. However, given the very low incidence of multiple callbacks, we do not analyze this outcome further.

[44] These analyses use only positive response observations that can be matched to specific job ads (Table 3).

Table A.15: Multiple Callback Rates by Age

		Young (29-31)	**Middle (49-51)**	**Old (64-66)**
Callback (%)	No callback or single callback	97.61	98.10	98.69
	Multiple callbacks	2.39	1.90	1.31
Tests of independence (p-value)	Young vs. middle vs. old (0.00)	Young vs. middle (0.01)	Young vs. old (0.00)	Middle vs. old (0.00)

Notes: The p-values reported for the tests of independence are from Fisher's exact test (two-sided). This table includes 39,361 observations. This sample size is smaller than that reported for the full analysis in the paper, because it is not possible to measure multiple callbacks for responses that could not be matched to a specific job, but only to a resume.

Differences in the Effects of Computer Skills for Older Applicants

Employers may in part statistically discriminate against older applicants by assuming that they are less likely to have computer skills than younger applicants. Recall that half of the resumes have a skill vector added to them. This was done to correct for the bias from differences in the variances of unobservables. Table 7 in the paper shows that, for administrative jobs, and for sales jobs to which men applied, the point estimate of the interaction between "old" and computer skills is positive, implying that computer skills reduce the gap in callbacks between older and younger applicants. We took this analysis a bit further, in two directions.

First, for the basic probit analysis, we estimated separate models for the subset of skilled resumes, depending on whether the skill vector included computer skills. (In these models we do not control for the other skills, since otherwise the resumes without computer skills would have more skills.) These results show, as Table 7 would suggest, lower age gaps for the resumes with computer skills. (See Table A.16.) For sales, in fact, the evidence of age discrimination against the older workers appears only for the skilled resumes that do not include computer skills. However, we know (from the paper) that the results for male sales applicants are very sensitive to the unobservables correction (and, in general, the results for males are not robust.) Thus, Table A.17 reports the results incorporating this issue of different effects of computer skills for older workers into the analysis. Note that if the computer skills do more to shift callbacks for older than younger applicants, then we would not want to rely on the assumption of equal effects of all skills in implementing the correction for bias from different variances of the unobservables (to address the Heckman critique). Therefore, we re-estimated the heteroskedastic probit models leaving the "old"-computer skills interaction in the model, relying only on the equality of the other skill effects to identify the model. This virtually no impact on the results. For male sales applicants, we still find no evidence of age discrimination for older workers either with or without computer skills. For administrative applicants, we find evidence of age discrimination for both groups, although the point estimate is larger for those without computer skills.

Table A.16: Probit Estimates for Callbacks by Age with Computer Skills Interactions, Marginal Effects, Skilled Resumes Only

	Administrative		**Sales-Males**	
	(1)	(2)	(3)	(4)
	Computer skills	No computer skills	Computer skills	No computer skills
Callback estimates				
Middle (49-51)	-0.045*** (0.011)	-0.047*** (0.017)	-0.038* (0.022)	0.012 (0.042)
Old (64-66)	-0.061*** (0.010)	-0.088*** (0.015)	-0.019 (0.020)	-0.055* (0.033)
Controls				
City, order, unemployed	X	X	X	X
Callback rate for young (29-31)	15.45	17.31	20.56	23.01
N	8,346	3,880	1,596	686
Clusters	366	173	180	85

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 computed based on clustering at the resume level. Significantly different from zero at 1-percent level (***), 5-percent level (**) or 10-percent level (*).

Table A.17: Heteroscedastic Probit Estimates for Callbacks by Age with Computer Skills Interactions, Old vs. Young Only (Corrects for Potential Biases from Difference in Variance of Unobservables)

	Administrative	**Sales-males**
	(2)	(3)
	All skills	All skills
A. Probit estimates		
Old (marginal)	-0.075*** (0.007)	-0.059*** (0.016)
Old x computer skills (marginal)	0.021* (0.011)	0.047* (0.025)
B. Heteroscedastic probit estimates		
Old (marginal)	-0.075*** (0.007)	-0.062*** (0.016)
Old x computer skills (marginal)	0.020* (0.012)	0.045* (0.025)
Overidentification test: ratios of coefficients on skills for old relative to young are equal (p-value, Wald test)	0.97	0.89
Standard deviation of unobservables, old/young	0.98	0.86
Test: standard vs. heteroscedastic probit (p-value, log-likelihood test)	0.89	0.33
Old-level (marginal)	-0.071** (0.028)	-0.025 (0.040)
(Old + {old x computer skills}-level + (marginal)	-0.055*** (0.010)	0.020 (0.039)
Old-variance (marginal)	-0.004 (0.029)	-0.038 (0.039)
N	16,449	3,570

Notes: Marginal effects are reported, computed as the change in the probability associated with the dummy variable, using the continuous approximation, evaluating other variables at their means. Significantly different from zero at 1-percent level (***), 5-percent level (**) or 10-percent level (*). Control variables correspond to first specification for each occupation in Table 5 (odd-numbered columns), except that skill vector is as noted. Callback rates for young and old applicants are as in Table 4.

Sensitivity of Standard Errors to Clustering at the Job-Ad Level

As noted in the main text, the estimates reported use standard errors clustered at the resume level. There may also be random influences at the level of the job ad, so it is of interest to ask how the standard errors (and hence our inferences) are affected by clustering at the job ad level as well. This requires multi-way clustering (Cameron et al., 2011), given that the same resume could be sent to different job ads.

In this section of the appendix we report key results for the subsample of observations for which we can match at the resume level and at the job-ad level, and using multi-way clustering. As the tables below show, standard errors with the multi-way clustering are quite similar and if anything tend to be smaller in the multi-way clustering,[45] so that our inferences are negligibly affected by clustering only at the resume level, and if anything the conclusions regarding evidence of age discrimination are slightly conservative in rejecting the null hypothesis of no discrimination. Most importantly, for this sample, the alternative clustering never changes the result of a statistical test that otherwise rejects the null hypothesis of no discrimination.

[45] This is not surprising because we would expect negative "serial" correlation among applicants to the same job ad; if one person gets a callback, another is less likely to, so that accounting for non-independence can lead to smaller standard errors.

Table A.18: Probit Estimates for Callbacks by Age, Marginal Effects, Alternative Clustering

	Combined	**Administrative**	**Sales-Males**	**Sales-Females**	**Security**	**Janitor**
	(1)	(2)	(3)	(4)	(5)	(6)
Middle (49-51)						
Marginal effect	-0.0257	-0.0239	-0.0130	-0.0525	-0.0253	-0.0197
Standard error clustered at resume level	(0.0043)	(0.0041)	(0.0135)	(0.0180)	(0.0168)	(0.0291)
Standard error clustered at resume and job ad level (multi-way)	(0.0038)	(0.0038)	(0.0117)	(0.0156)	(0.0137)	(0.0185)
Old (64-66)	-0.0517	-0.0483	-0.0478	-0.0871	-0.0247	-0.0598
Standard error clustered at resume level	(0.0042)	(0.0041)	(0.0129)	(0.0176)	(0.0167)	(0.0285)
Standard error clustered at resume and job ad level (multi-way)	(0.0038)	(0.0038)	(0.0113)	(0.0149)	(0.0139)	(0.0215)
N	39,361	23,777	5,272	4,638	4,032	1,642

Notes: Specifications correspond to Table 5 in the main text. Estimates are shown for the specifications including all controls.

Table A.19: Heteroscedastic Probit Estimates for Callbacks by Age, Old vs. Young Only (Corrects for Potential Biases from Difference in Variance of Unobservables)

	Combined	**Administrative**	**Sales-males**	**Sales-females**	**Security**	**Janitor**
	(1)	(2)	(3)	(4)	(5)	(6)
	5 common skills	All skills	All skills	All skills	All skills	All skills
Heteroscedastic probit estimates						
Old (marginal)	-0.0504	-0.0544	-0.0488	-0.0685	-0.0168	-0.0573
Standard error clustered at resume level	(0.0056)	(0.0050)	(0.0115)	(0.0158)	(0.0190)	(0.0288)
Standard error clustered at resume and job ad level (multi-way)	(0.0051)	(0.0045)	(0.0092)	(0.0144)	(0.0161)	(0.0213)
Old-level (marginal)	-0.0753	-0.0284	-0.0125	-0.1625	-0.0487	-0.1356
Standard error clustered at resume level	(0.0228)	(0.0258)	(0.0366)	(0.0344)	(0.0324)	(0.0801)
Standard error clustered at resume and job ad level (multi-way)	(0.0214)	(0.0254)	(0.0326)	(0.0347)	(0.0286)	(0.0846)
Old-variance (marginal)	0.0249	-0.0259	-0.0363	0.0940	0.0319	0.0783
Standard error clustered at resume level	(0.0242)	(0.0270)	(0.0377)	(0.0416)	(0.0383)	(0.0874)
Standard error clustered at resume and job ad level (multi-way)	(0.0227)	(0.0265)	(0.0332)	(0.0426)	(0.0339)	(0.0917)
N	26,894	16,036	3,518	3,566	2,679	1,095

Notes: Specifications correspond to Table 8 in the main text.

References Not Included in Paper

Albert, Rocío, Lorenzo Escot, and José Andrés Fernández-Cornejo. 2011. "A Field Experiment to Study Sex and Age Discrimination in the Madrid Labour Market." *International Journal of Human Resource Management*, Vol. 22, pp. 351-75.

Arrow, Kenneth J. 1972. "Models of Job Discrimination." and "Some Mathematical Models of Race Discrimination in the Labor Market." In A.H. Pascal, ed. Racial Discrimination in Economic Life (Lexington, MA: D.C. Heath), pp. 89-129.

Arthur Andersen & Co. 1979. Cost of Government Regulation Study for the Business Roundtable. Chicago, IL.

Baert, Stijn, Jennifer Norga, Yannick Thuy, and Marieke Van Hecke. 2016. "Getting Grey Hairs in the Labour Market: An Alternative Experiment on Age Discrimination." *Journal of Economic Psychology*, Vol. 57, pp. 86-101.

Bloch, Farrell. 1994. Antidiscrimination Law and Minority Employment: Recruitment Practices and Regulatory Constraints. Chicago, IL: University of Chicago Press.

Cameron, A. Colin, Jonah G. Gelbach, and Douglas L. Miller. 2011. "Robust Inference with Multi-Way Clustering." *Journal of Business and Economic Statistics*, Vol. 29, pp. 238-49.

Cavico, Frank J., and Bahaudin G. Mujtaba. 2012. "Discrimination and the aging American workforce: legal analysis and management strategies." *Journal of Legal Issues and Cases in Business*, Vol. 1, pp. 1-41.

Coate, Stephen, and Glenn C. Loury. 2003. "Will Affirmative-Action Policies Eliminate Negative Stereotypes?" *American Economic Review*, Vol. 83, pp. 1220-40.

Donohue, John J. III. 1992. "Advocacy Versus Analysis in Assessing Employment Discrimination Law." *Stanford Law Review*, Vol. 44, pp. 1583-614.

Epstein, Richard A. 1992. Forbidden Grounds: The Case against Employment Discrimination Laws. Cambridge, MA: Harvard University Press.

Figinski, Theodore F. 2017. "The Employment Effect of Potential Activations on Military Reservists: Evidence from a Field Experiment." *Industrial and Labor Relations Review*, Vol. 70, p. 1037-56.

Lahey, Joanna N., and Ryan A. Beasley. 2009. "Computerizing Audit Studies." *Journal of Economic Behavior & Organization*, Vol. 70, pp. 508-14.

Olson, Walter. 1997. The Excuse Factory: How Employment Law is Paralyzing the American Workplace. New York, NY: The Free Press.

Rosen, Robert M. 2016. "How to Screen for Success in Employment Law Cases." *Touro Law Review*, Vol. 16, pp. 1319-401.

U.S. Census Bureau, 2011. *Commuting in the United States: 2009.* Available at https://www.census.gov/prod/2011pubs/acs-15.pdf (viewed September 16, 2015).