Age, women, and hiring: An experimental study

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Abstract

As the baby boom cohort reaches retirement age, demographic pressures on public programs such as Social Security may cause policy makers to cut benefits and encourage employment at later ages. This prospect raises the question of how much employer demand exists for older workers. This paper reports on a labor market experiment to determine the hiring conditions for older women in entry-level jobs in Boston, MA and St. Petersburg, FL. Differential interviewing by age is found for these jobs. A younger worker is more than 40 percent more likely to be offered an interview than is an older worker. No evidence is found to support taste-based discrimination as a reason for this differential, and some suggestive evidence is found to support statistical discrimination.

1 Introduction

In a 2004 speech to the Federal Reserve Board, Federal Reserve Chairman Alan Greenspan suggested that encouraging older people to work could solve many of the problems that will occur as the large baby boom cohort reaches retirement age.[1] If older workers remained in the labor force, Social Security benefits could be cut without compromising living standards. From a productivity standpoint, workers should be capable of working longer than they have in the past. Not only are people living longer, but several studies suggest that today's 70-year-olds are comparable in health and mental function to 65-year-olds from 30 years ago (Schaie 1996, Baldes et al 1988). Many older Americans also may need to work even if Social Security benefits are not cut. Bernheim (1997) estimates that baby boomers on average are only saving a third of what they need to maintain a pre-retirement standard of living after retirement. This lack of adequate retirement savings is especially acute for older widows, who, on average, suffer a 30 percent drop in living standards upon the death of a husband (Holden and Zick 1998). In fact, the poverty rate for older widows is 15 percent, compared to 4 percent for married women of the same age range (Favreault et al. 2002). Finally, Abraham and Houseman (2004) find that although most older workers plan to continue working at least part-time instead of fully retiring, those who would have to change jobs in order to reduce hours are likely to stop working entirely, suggesting that the costs of job change are high, perhaps due to the difficulty of finding new employment.[2]

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[1] Alan Greenspan was not the first to suggest encouraging older workers to remain in the labor force as a partial solution to the Social Security problem; see, for example, Burtless and Quinn (2001, 2002) and Diamond and Orszag (2002) for more discussion about Social Security and lengthening work-lives.

[2] Obviously not all potential older workers would have their quality of life negatively affected by not being able to find entry-level work should Social Security age be raised—some are getting more utility from leisure than they would from additional work. However, as discussed in this paragraph, a substantial

Will older American women be able to find work? Economists generally assume that labor force non-participation is voluntary for those in good health, so only supply-side factors come into play in policy discussions, such as those regarding Social Security. This labor market experiment evaluates potential demand-side barriers to older women's finding employment by exploring the hiring behavior, specifically the interviewing behavior, of firms that are seeking entry-level or close to entry-level employees. Although a number of sociology and psychology studies have directly examined age discrimination, these studies typically present a human resources manager (or worse, a group of undergraduate psychology students) with two résumés, one of an older worker and one of a younger worker, and ask which the manager would be more likely to hire (e.g., Nelson 2002). In contrast, this experiment analyzes real rather than hypothetical choices by businesses that do not know they are being studied.

My study examines the entry-level or close-to-entry-level labor market options for women ages 35 to 62 in Boston, MA and St. Petersburg, FL. I send pairs of résumés to employers in these two cities and measure the response rates by age, as indicated on each resume by date of high school graduation. I find evidence of differential interviewing by age in these two labor markets. A younger worker is 42 percent more likely than an older worker to be offered an interview in Massachusetts and 46 percent more likely to be offered an interview in Florida. Because of the limited number of positions available, these differences in offer rates imply welfare losses for older job seekers.

In addition, I explore reasons for differential responses to résumés by age in several ways. First, I explore statistical discrimination, which is defined as an employer

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minority, especially elderly widows, are close enough to the poverty line that their utility from income is much higher than from leisure.

judging a job applicant based on the average characteristics of her age group rather than on her own individual characteristics. To study this type of discrimination, I look at the effect of resume elements that could signal that the older worker does not fit a stereotype/group characteristic of older workers. Second, I look at employer taste-based discrimination by examining the effect of a firm having a human resources department, because these departments are likely to have had training in discrimination law. Third, I examine employee taste-based discrimination by looking at the age breakdown of workers in each firm's geographic area. Finally, I examine consumer taste-based discrimination by looking at the residential demographics of each firm's geographic area. I find suggestive evidence that statistical discrimination may be responsible for this differential treatment of older applicants. This study finds little to no evidence for taste-based discriminatory behavior, whether from employers, co-workers or consumers, although the tests used are not perfect and more research is needed.

Previous economic research has established that older workers experience worse hiring outcomes than do younger, but this correlation is difficult to interpret causally. Although displaced older workers take longer to find employment than do younger,[3] it is not known whether this delay is due to discrimination, higher reservation wages, or clustering in dying industries (Diamond and Hausman 1984, Hirsch et. al 2000, Hutchens 1988, Johnson and Neumark 1997, Miller 1966, Shapiro and Sandell 1985). Experimental labor market studies such as this one have the advantage of directly observing differential treatment, or in shorthand terminology, "discrimination," as it

[3] The 2000 CPS Displaced Worker Survey finds that the average search time, 12 weeks, for workers age 55 to 74 was 3.6 weeks longer than that for workers age 19 to 39. Additionally, 39 percent of displaced older workers in the February 2000 CPS had not found reemployment by the time of the survey, whereas only 19 percent of those between 40 and 54 had not found reemployment (U.S. General Accounting Office 2001).

happens.[4] Such studies have primarily examined discrimination on the basis of gender and race (e.g., Fix and Struyk 1993, Yinger 1998, Neumark et al. 1996; also see Riach and Rich 2002 for a recent literature review). Only one set of these studies (a résumé study combined with a matched pairs audit) has explored age discrimination (Bendick et al. 1996, Bendick 1999) and there is concern that these studies lack comparable controls (Riach and Rich 2002).

In all likelihood, the main reason for this lack of audit studies on age is that it is very difficult to separate age from experience. I try to control for this problem using a number of constraints on the experiment. First, I limit résumés to, at most, ten-year work histories, as is the current standard. Second, I limit to entry-level jobs where in most cases, turnover is high, experience is less important, and on-the-job training is generally brief. Third, I limit to those aged 35 to 62; I am comparing not teenagers, but rather prime-aged workers to older workers. Fourth, I only look at women, who are more likely to take time out of the labor force for family reasons unrelated to work ability. Indeed, age of labor market re-entry may be a noisy signal of worker quality for women, as those forced to work earlier because of divorce or husband's low earnings may actually be lower quality than those who choose to work later in life.[5] Finally, I only study the

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[4] When discussing the term "discrimination," I use a value-free definition of the word, such as in Lundberg and Startz (1983) that includes forms of differential behavior such as statistical discrimination, where it is possible for the same average productivity to receive the same average compensation. It does not imply that there is necessarily any animus-based discrimination, simply differential behavior.

[5] It is sometimes assumed that older job seekers are of lower quality than younger, both because workers may experience declines in productivity as they age and because high quality older workers should have already found stable employment matches. However, it is not a priori clear that younger workers will be preferred to older in all labor markets. For example, as the AARP often argues, older workers may exhibit greater loyalty, responsibility, or adherence to work norms (Towers Perrin 2005). In addition, older female cohorts seeking entry-level jobs may be higher quality than younger because more recent female cohorts have had more opportunities for advancement and have historically had stronger labor force attachment than older cohorts (Hayghe 1997, Jacobsen and Levin 1995, Omori and Smith 2006). Thus employers might expect that the cross-section of older female entry-level applicants would be of higher inherent quality than that of younger.

interview stage by sending résumés and do not send matched actors. While none of these factors alone would guarantee a clean experiment, together they mitigate potential confounds.[6]

This paper is structured as follows: Section 2 gives some background information on discrimination laws, ways of testing for discrimination and types of discrimination. Section 3 gives details of the experimental design Section 4 describes the empirical framework for identifying both differential interviewing by age and possible reasons for that differential interviewing. Section 5 provides results and Section 6 discusses implications. Section 7 concludes. Further information on the specifics of the experimental design can be found in the data appendix at the end of the paper.

2 Background

The Age Discrimination in Employment Act, implemented in 1968 and enforced in 1978, covers workers age 40 and up in firms with 20 or more employees, with a few exceptions.[7] This law prohibits discrimination based on age against older workers through hiring, firing, and failure-to-promote mechanisms. Since it is more difficult for workers to determine why they failed to receive an interview than it is for workers to determine why they have been fired, firms that wish to retain only a certain type of

[6] The resumes I send look like typical résumés sent to entry-level positions. Those who have not scanned through hundreds of entry-level résumés may be surprised at how bad many of them are. Work histories, especially among women applicants of all ages, are often spotty and include absences from the labor force. Very few applicants have worked at one job for more than a few years, and this mobility is reflected in my fictional résumés. Additionally, these résumés sometimes contain personal information and more often than not contain typographical errors. Most entry-level job seekers do not appear to have read any of the top-selling books on résumé crafting.

[7] Firms are exempt if they can prove a bona-fide occupational qualification (BFOQ) that is directly related to age (for example, an acting position), or if the position is a high-salaried policymaking position. Note that although the ADEA covers people over the age of 40, the majority of people who utilize the law are over the age of 50. Psychology studies suggest that firms most value workers in their 30s (Nelson 2002); if the law covered only workers age 50 and over, firms could conceivably choose to do mass firing of 49-year-olds and still be within the law. Firing 39-year-olds in order to avoid lawsuits from 40-year-olds may seem less attractive.

worker without being sued would prefer to discriminate in the hiring stage rather than at any other point of the employment process.

Labor market studies such as this one that test for discrimination in the hiring process by sending résumés are called "résumé audits" in the United States and "correspondence tests" in the United Kingdom. These studies directly test for discrimination with a minimum of omitted variables bias. Other audit studies send two trained "auditors," matched in all respects except the variable of interest, usually race, to rent an apartment, buy a house, or interview for a job. In practice, however, it is difficult to match people exactly;[8] one cannot rule out systematic differences observable to the employer between the two groups being studied. Experiments such as this one, using computer-randomized résumés, potentially bypass the matching problem. This type of experiment also has the benefit of being able to explore the different reasons that employers might discriminate against older workers.

Economic theory generally distinguishes between two major types of discrimination: statistical discrimination and taste-based discrimination. Statistical discrimination occurs when an individual is judged based on group characteristics. This form of discrimination is generally thought to be efficient for employers in cases of imperfect information (Arrow 1972).[9] For example, if, in general, it is true that older workers take longer to learn unfamiliar tasks, then an employer may be reluctant to hire an older worker, because testing each older applicant for ability to learn is costly. Taste-based discrimination occurs when an employer, a set of employees, or a customer base gets disutility from working with individuals from a specific group. This form of

[8] Other problems with this method are elucidated by Heckman and Siegelman (1993) and Heckman (1998).
[9] Though, of course, it is not in the best interest of high achieving individuals in the discriminated against group and may have negative welfare implications overall.

discrimination is generally thought to be inefficient in terms of overall social welfare, although it provides utility to the discriminator (Becker 1971).

3 Experimental Design

I sent résumés to 3996 firms in the greater Boston, Massachusetts and greater St. Petersburg, Florida areas over a full year from February 2002 to February 2003. Boston was chosen for convenience and St. Petersburg was chosen because it has a similar demographic mix to what the U.S. Census projects the entire United States to have in the 2020s, that is, it has a large concentration of elderly. Each Sunday, 40 want-ads were randomly drawn from the Sunday *Boston Globe* and 40 from the online version of the Sunday *St. Petersburg Times*.[10] Monday through Wednesday of each week, company names and numbers were randomly selected from the Verizon superpages for Boston and for St. Petersburg and 10 firms were chosen in each city as "call-ins." A computer program mixed and matched work histories and other résumé parts from actual entry-level applicants to randomly create new résumés for specified positions. Genuine résumés for many different job categories were taken off of online sites such as www.americasjobbank.com. These résumés were sorted by occupation and age and had items such as previous work experience, licensure, awards, hobbies, and volunteer work collected together and entered into a computer program. Summary statistics for the resumes can be found in the Appendix Tables 1a and 1b. Employers could reply to the job seekers via a voicemail box obtained from www.mynycoffice.com and an e-mail address from www.hotmail.com. Detailed information on the process of résumé creation

[10] The *St. Petersburg Times* puts all of its want-ads online, whereas the *Boston Globe* charges employers extra to be included in the online listings. For more details about the randomization procedure used, please refer to the Appendix.

and distribution can be found in the Data Appendix.

For the most part, the résumés created for the audit used items from actual résumés (but not in any way that could be connected to the original résumé). Two items included in some of the sent résumés did not appear in actual résumés: the specific places of high school graduation and a declaration of health insurance status. Two schools from small college towns from the Midwest were chosen so that employers could not use perceived high school quality (from 17 to 44 years ago) as a signal for worker quality. Some résumés in the experiment included a statement that the applicant did not need health insurance benefits. First names chosen for the job candidates were the first and second most popular female names in the United States for the year of birth of that candidate (Mary and Linda), and the last names chosen were the first and second most popular last names in the United States (Smith and Jones), according to Social Security administration data.[11] The addresses chosen were from middle class neighborhoods which, according to the census, had a wide variation in income and other demographic characteristics (for example, Somerville, MA).

Unlike race or gender, age is a continuous variable. Because I use multiple ages in my study instead of only two ages (as in, e.g., Bendick et al. 1999), I can better understand how age interacts with hiring decisions. I chose age 62, the early retirement age, rather than 65, the full retirement age, as the later endpoint for the survey because 65 is the age Medicare benefits generally begin and thus could signal lower health care costs to potential employers. I did not use ages earlier than 35 for two reasons. First, I had to

[11] http://www.ssa.gov/OACT/NOTES/note139/original_note139.html. Recent literature has included concerns that particular names may cause employer responses other than those intended to be measured (Fryer & Levitt 2004); I avoid these concerns by choosing these highly representative names. Regressions on name choice find no difference between them.

limit the total number of ages I used in order to be able to collect a sample size large enough to preserve power and because my focus is on the older ages, 35 seemed more natural than, for example, 25, as a cutoff. Second, because the current résumé standard is to display a ten-year job history, I wanted a potential employer to assume that each applicant was doing the same thing during that ten-year history if there were gaps in the résumé (in particular, taking care of her family rather than going to school).

Word of mouth, not formal advertisement, accounts for most job matches, according to Holzer (1996). However, formal methods are still important, especially for those lacking informal employment networks. To get a more representative sample of job openings than can be found through the want-ads alone, I added 10 entries per city per week that were generated by calling companies randomly chosen from the Verizon yellow pages.[12] The response rate for call-ins was about half that for want-ads. However, the ratio of younger *positive*/*interview* responses to older was very similar whether the ad had been generated via want-ad or via call-in,[13] thus providing some evidence that the degree of differential interviewing does not vary much with method used, at least if the method still has some degree of formality. For more information on how these "call-ins" were generated, see the Data Appendix.[14]

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[12] The marginal additional call-in was much more time intensive to collect than the marginal additional want-ad.

[13] *Positive* or "callback" responses are those where the applicant was called back and given a "positive" sounding response but not specifically offered an interview. The exact ratios of younger *positive* responses to older (keeping in mind older contains more observations than younger) for Massachusetts are: .778 *positive* if want-ad, .770 if call-in; .920 interview if want-ad, 1.00 if call-in. For Florida these ratios are: *Positive*: .763 if want-ad, .741 if call-in; Interview: .906 if want-ad and 1.14 if call-in. The ratios of negative/null responses follow a similar pattern.

[14] Online resume clearinghouses were also tried, but, since the economy had cooled by the time the experiment started, the responses they generated were representative of what one finds in one's spam filter.

Résumés were sent in pairs via fax.[15] A coin was flipped each time a pair of résumés was sent to determine which would be sent first. Via the randomness of the computer program used to create résumés, employer bias was randomized across each high school graduation date. Employers who left at least two messages for the prospective candidate were informed in a timely fashion that the candidate had already accepted a job elsewhere so as not to inconvenience area firms. Overall I had a "*positive*" response rate of 8 percent in Massachusetts and 10 percent in Florida and an "*interview*" rate of 4 percent in Massachusetts and 5 percent in Florida.

To distinguish between age discrimination and discrimination based on differences in human capital or perceived gaps in work history, I employed a number of design measures. First, I only sent résumés for women, because an employer is more likely to assume that a woman entering or re-entering the labor market has been taking care of her family, rather than returning from prison or a long spell of unemployment, as would be the case for a man.[16] In addition, many entry-level or close to entry-level jobs, such as cashier positions, secretarial work, or home health care, tend to be female-dominated jobs, and thus it would not seem unusual for a woman to apply for these positions, whereas a man applying to these positions might be considered suspect. Second, I limited work histories to up to 10 years, because conversations with human resource professionals and an examination of actual résumés suggested that this length is

[15] Only two résumés were sent to each employer because an employer would be likely to get suspicious should he or she receive four virtually identical résumés in a short time period, whereas two résumés are much more likely to be thought of as a coincidence if noticed at all.
[16] Intermittent labor force participation is common for women in the cohorts included in the study. For example, in the NLSY only 16 percent of women between the ages of 34 and 41 worked continuously in 1985. These intermittent workers also on average had 13 years of education under their belts, and thus are quite comparable to the fictional women included in this study (Sorensen 1993).

common practice.[17] Third, I indicated that the applicant was currently employed at an entry-level job so that all applicants had current experience at some form of work (thus diminishing fears that older workers had a longer time for human capital to deteriorate). Finally, I limited my study to entry-level jobs, in which entry-level is defined as anything that requires at most one year of education plus experience. For these jobs, job-specific human capital should be less of a concern, thus further allowing me to determine that I am measuring age rather than experience discrimination.

Although with these restrictions my experiment can only definitively speak about a particular segment of the labor market, the benefit of these restrictions is that my controls are comparable enough that the results for this segment are reliable. Additionally, this particular segment is an important part of the labor force; the population of older women is larger than that of men, and older women are more likely to be living in poverty than are older men (Favreault et al. 2002).

4 Empirical Framework

4.1 Differential Interviewing by Age

To test for differential interviewing by age, I sent paired résumés matched on all

[17] I spoke to human resource professionals from three places—first, several professionals from the hiring department at a large university, second, someone who had worked as a human resources professional for a business firm, but had recently had a career transition to a post where she helped other people determine career transitions, and third, two representatives from a non-profit temporary agency/career placement firm. They all said that ten-year histories are the current gold standard for resumes, although they get many resumes that do not look like the standard. The placement agency said that a big part of their job was to get applicants to make their resumes look like the current standard and the university hiring department said that using an outdated resume style was often an indication that the applicant was older. The university HR department told me that while one was not supposed to put dates of education on resumes, most people did, and it was generally in an applicant's best interest to put down dates of education if it was recent. The hundreds of actual resumes reviewed from online and from actual jobs reflect these statements, with by far the majority showing less than 10 years of experience and almost all giving dates of education.

characteristics except age,[18] as indicated by date of high school graduation, to prospective employers in the entry-level labor market. Then I measured the rate of *positive* responses and *interview* responses by age. *Positive* or "callback" responses are those where the applicant was called back and given a "positive" sounding response but not specifically offered an interview. Examples included asking the applicant to call back or saying that the caller has questions. They did not include responses that are obviously negative, such as information that the position has been filled. *Interview* responses are those in which the caller specifically asked the applicant to call back to set up an interview or to meet in person.

The main equation of interest looks at the effect of age on *positive* and *interview* responses:

$$\mathrm{pr}[Response_i = 1] = \Phi[B_1(Controls)_i + B_2 A_i] \qquad (1)$$

in which Φ represents the normal CDF. The tables report the marginal effects, ∂ prob $(Response_i = 1)/\ \partial X_i$, where X_i is the vector of explanatory variables. *Response* is either a *positive* response or an *interview* response; *i* refers to the individual. *Controls* include the number of years of work history out of 10, typos, college experience, relevant computer experience, volunteer work, sport, other hobby, insurance, flexibility, attendance award, and a set of occupation dummies. Since the explanatory variables are dummy variables, this marginal probit reports the discrete change in the probability of *interview* for each

[18] Résumés were not identical, but they were functionally identical in terms of experience and additional items on the résumé. It is of note that I did not need to match the résumés on characteristics because I use standard differential probit (and OLS) methods to analyze the data, much like modern field experiments (see List 2004), rather than the audit methodology of a "paired difference of means" test. Since I targeted a large number of firms, the résumés were sent randomly, and I clustered on firm, I should get the same results with the regressions I run even had I not matched the résumés. Indeed, since there are five possible ages, it is not even clear what the proper "paired difference of means" test should be. Other possible problems with the "paired difference of means" technology (that a standard large sample OLS methodology avoids) are discussed extensively in Heckman (1998) and Yinger (1998) and in Fix and Struyk (1993). More specifics of résumé creation can be found in the Appendix.

variable.[19] Because each firm received two somewhat similar résumés, I cluster standard errors at the firm level.

There are many ways to measure age, A_i, given my setup. The results should be similar, but different age configurations give varying amounts of power. First, I measure age using graduation cohort dummies that include indicators for graduating in 1959, 1966, 1971, 1976, and 1986. A second way to test for discrimination is to treat age indicated on the résumé as a continuous variable. Then the marginal effect $\partial \mathrm{pr}(Response_i = 1)/ \partial X_i$ represents the discrete change in the probability of a *positive* response or *interview* for each of the controls, and the infinitesimal change in the probability of *interview* for age. Finally, employers may mentally group workers into "older" and "younger" categories. I break up high school graduation dates into two groups, one for workers age 50 and older and one for workers under age 50. The marginal effect $\partial \mathrm{pr}(Response_i = 1)/\partial X_i$ then represents the discrete change in the probability of *interview* for each variable. I also compare older and younger groups, controlling for résumé and industry characteristics. I run equation *(1)* as an OLS regression and retrieve the predicted probability for the response. Then I compare these predicted probabilities for each group using a t-test.

4.2 Reasons for Differential Interviewing by Age

4.2.1 Statistical Discrimination

My experimental setup enables me to explore different possible reasons for this differential treatment, or discrimination.[20] The first type of discrimination I look at is

[19] The Stata command used for the marginal probit is margfx. Results are similar using dprobit.
[20] I do not differentiate between stereotypes that are true (and thus fit in standard models of statistical discrimination, such as Phelps (1972)) and stereotypes that are false, but employers believe to be true. One

statistical discrimination, which, in its most basic definition, is judging an individual on group characteristics rather than individual characteristics. More formally, I utilize the model by Phelps (1972) as outlined in Aigner and Cain (1977), which assumes that employers measure expected skill through an indicator y based on the observed true skill level q and a measurement error u, thus $y = q + u$. I assume that the variance of u is equal for the two groups and the variance of q is greater for older workers than for younger.[21] Within this model, positive information about ability, that is, a higher y, helps older workers more than it helps younger workers (the y-E(q) graph will have a steeper slope for older workers than for younger). For example, an indication that an older worker has taken a computer class will cause a greater marginal increment to expected productivity for the older than for the younger worker, that is, it will help an older worker more than it will help a younger worker.[22]

I tested for statistical discrimination by randomly including items on résumés that signaled that the worker did not fit into a standard stereotype.[23] For example, to test whether employers think older workers are inflexible and unchanging, I include a

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can make the argument that because workers who are hired young often age into the firm, firms that employ larger numbers of workers may have some experience with older workers and are less likely to believe false stereotypes. Additionally, the notion of feedback effects (as in Lundberg and Startz 1983) into educational choices is less of an issue because even though older workers may choose training, the majority of education decisions have already been made. There may still be feedback effects in terms of decisions whether or not to remain in the labor market, however.

[21] In this model, average true ability for the two groups is assumed to be either equal or lower for older workers than for younger. Recall that even though the Aigner and Cain (1977) model focuses on wage differentials, in fixed wage (e.g. minimum wage or salary scale) jobs like the majority of those in this experiment, the hiring margin will adjust when the wage margin cannot.

[22] Different assumptions provide a model where the test is less reliable for older workers and thus a positive ability signal would help younger workers more than older. However, there is no reason to assume that either younger workers have larger variance in, for example, computer ability or that they would get more out of a basic computer skills course than older workers, unlike the case where many black high schools are assumed to be of more variable or worse quality than many white high schools.

[23] Stereotypes examined came from a list of the top 10 reasons for discrimination against older workers according to a 1984 survey of 363 companies in which hiring managers were asked for reasons that other companies might discriminate against older workers (Rhine 1984). Not all top 10 reasons could be explored using this experimental design; those will be explored separately in future research.

statement that the applicant was flexible or "willing to embrace change." To test for the effect of these variables on the probability of getting a callback or interview, I interact each of these variables with *older:*

$$\mathrm{pr}[Response_i = 1] = \Phi[\mathrm{B}_1(Controls)_i + \mathrm{B}_2(Q_i) + \mathrm{B}_3(Older_i) + \mathrm{B}_4(Older_i * Q_i)] \qquad (2)$$

in which Q is the reason for statistical discrimination that is being tested and *Controls* include the number of years of work history out of 10, typos, college experience, relevant computer experience, volunteer work, sport, other hobby, insurance, flexibility, attendance award, and a set of occupation dummies, except when the reason tested is one of those controls.

Because an interaction term is measuring the difference between the slopes of the Q term when *Older* = 0 and when *Older* = 1, I can measure the results for a fully interacted "*Older*" model by running the regressions separately for each group. I also run regressions on just the controls and variables of interest (not including an age-related variable) separately for older and younger groups and compare the estimated coefficients for each group. This format is identical to running a full age interaction but has the benefit of efficiently showing multiple interactions at the same time.

Another method to differentiate between statistical discrimination and employer taste-based discrimination, by using the presence of a human resources department, is described in the next section.

4.2.2 Taste-Based Discrimination

Employer

Human resource professionals may be less likely to engage in taste-based discrimination because they have training in and knowledge of discrimination laws. On the other hand, they might be more likely to practice statistical discrimination because they have learned more about average group characteristics.[24] Thus, I study employer discrimination by interacting a dummy indicating whether a company has a human resources department with the age variable. The equation used is the same as equation *(2)* with $Q = 1$ if the firm has a separate human resource department.

Employee

My tests for employee taste-based discrimination and customer taste-based discrimination rely on the assumption that people are less likely to discriminate against those in their own group.[25] To study employee discrimination, I interact age with the percentage of people employed in the area where the business is located over the age of 50. Again the equation is identical to *(2)* where Q is a continuous variable indicating the percentage of people over the age of 50 who work in the firm's place of work PUMA (public use metropolitan area), as indicated by the 2000 Census.

Customer

My test for customer taste-based discrimination is similar to that for employee taste-based discrimination, except that instead of looking at the percentage of people employed in an area, I look at the percentage of people who reside in the area where the business is located. Here, using *(2)*, Q is a continuous variable indicating the percentage of people over the age of 50 who live in the firm's zip code, as indicated by the 2000 Census. Because people who work in services and sales are more likely to interact with

[24] Unlike the usual case for race or gender, one's age status does change while employed. Thus an employer can end up observing the productivity of a group of older workers even if it never hired older workers.

[25] To my knowledge, the only economics paper differentiating between taste-based and statistical discrimination that does not use this or a similar assumption for race or gender, is John List's "The Nature and Extent of Discrimination in the Marketplace: Evidence from the Field" 2004 *QJE* paper. Unfortunately, the setup he uses in that paper is not applicable to this type of audit experiment.

consumers than are people in other positions, I also run this specification with only service and sales occupations in the universe.

5 Results

5.1 Differential Interviewing by Age

Figures 1a and 1b show an upward trend for the *positive* response based on date of high school graduation, as in equation (*1*). This trend is much more marked using *interview* as the dependent variable. Although no two adjacent years are statistically significantly different at the 5 percent level, the results are suggestive. In Massachusetts, the *interview* results show a statistically significant difference at the 5 percent level between the oldest, *hsgrad59*, and youngest *hsgrad86*. *Interview* results may be stronger than *positive* for two reasons. First, not all "*positive*" responses may actually be positive — some asking for more information could be preludes to rejection, thus producing measurement error. Secondly, more subtle forms of discrimination, such as calling one person back more enthusiastically than another, are less likely to be discovered than overtly failing to call back the older candidate. In fact, the caller may not even realize that he or she has treated the candidates differently.

The most significant results are found breaking up age categories into "older/younger" groups where older is defined to be age 50, 55, and 62 and younger is defined to be ages 35 and 45.[26] Table 1 describes t-test results comparing the mean response rates for these two age categories with and without controls. For callbacks, there is a difference of 1.5 percentage points, or 19 percent, in Massachusetts and 1.7 percentage points, or 18 percent, in Florida. For interviews, these differences are 1.6

[26] I also tried breaking up older and younger categories by placing 50 in the younger category (older2 and younger2) and leaving 50 out altogether (older3 and younger3). Results were similar across categories but defining 50 as older produced the strongest results.

percentage points, or 42 percent, for Massachusetts and 2.0 percentage points, or 46 percent, for Florida.[27] The mean younger job seeker in Massachusetts needs to file, on average, 11 ads to get one callback, while an older job seeker needs to file 13. A younger seeker needs to file 19 ads for one *interview* request and an older job seeker 27. In Florida, a younger worker needs to file 9 and an older worker 11 ads to get a *positive* response. These numbers are 16 and 23 respectively for an *interview* response. A marginal probit including *older* as an age dummy, as in equation (*4*), results in a negative and significant coefficient for *older* for interviews in Massachusetts and Florida and for callbacks in Massachusetts, as shown in Table 2, columns 3, 6, 9, and 12.

A final way of looking at the effect on age is to actually regress on age as if it were a continuous variable. This method provides more power than using age dummies. Columns 2 and 9 in Table 2 show that the coefficient on age given by the marginal effect of the probit is negative and significant at the 5 percent level for *positive* responses in Massachusetts but negative and not significant in Florida. That is, for each additional year of age, a worker is .08 percent less likely to be called back in Massachusetts and between .04 percent and .075 percent less likely to be called back in Florida.[28] This effect is both negative and significant at the 5 percent level for the *interview* response, with each additional year of age causing a worker to be .08 percent less likely to be called back for an interview in Massachusetts and between .075 percent and 0.09 percent less

[27] If I take the lowest point in the confidence interval for younger workers and divide that by the highest point in the confidence interval for older workers, and then do the same with the highest point for younger workers and lowest point for older workers, I get a range of a younger worker being -.05 to 113 percent more likely to get an interview in Massachusetts and -.02 to 117 percent more likely to get an interview in Florida.

[28] Depending on whether or not controls are included. Since employers may treat certain characteristics differently depending on age, in a non-linear probit model the coefficient of age can change based on whether or not they are included, even if the characteristics are randomized across résumés. In an ordinary least squares model the coefficient would not (and does not) change. Additionally, although age is uncorrelated with the controls by design, in a finite sample there may still be correlation induced by chance.

likely to be called for an interview in Florida. Thus there is differential interviewing by age. Specifically, assuming linearity,[29] in Massachusetts, the mean applicant would have to answer 1.3 additional ads to receive a callback for each additional 10 years of age, and 5 additional ads to receive an interview request. In Florida, each additional 10 years of age would require .4 more ads to produce a callback and 3.5 more ads to produce an interview.

Companies could also discriminate in more subtle ways than by failing to call back or to ask for an interview. Other possible outcomes are calling back the younger applicant sooner than the older applicant, or calling back the younger applicant multiple times but only calling the older applicant once. Although there are examples in which either of these outcomes is the case, on average there is not statistically significant discrimination for either of these possibilities (results not shown). I also examined actual negative responses, but not only were there very few of these, but I have reason to believe that when negative responses are sent out, many of them are sent via postal mail.[30] Because I do not have information on postal responses for the majority of applications, it is not feasible to use negative responses as an outcome.

5.2 Reasons for Differential Interviewing by Age

Economists recognize two main categories of discrimination: statistical discrimination and taste-based discrimination. Statistical discrimination can occur based

[29] An age squared term came up insignificant in probit regressions. However, I cannot reject a cubic age specification for the interview response in the Florida set. The cubic age specification is not significant in the Massachusetts set.

[30] In the Massachusetts part of the sample, I was able to collect mail at one of the two addresses that were randomly assigned to résumés. Through this collection, I did not find any *positive* or interview responses, but did receive some negative responses. The majority of written responses were postcards stating receipt of the application. There were a few requesting more information, but these also requested more information via phone or e-mail as well.

on observables, such as work history or typographical errors, or unobservables, such as energy or ability to learn. In my experimental setup, observables other than age are functionally identical for each résumé pair sent within firm and are randomized across firms and thus cannot be responsible for the differential interviewing. To look at the effect of unobservables, I included items on the résumés to signal that the applicant did not fit a number of stereotypes cited by managers as reasons firms might be reluctant to hire older workers (Rhine 1984). The effects of these variables are discussed in more detail below and are detailed in Table 3 which gives results separately by older status.

5.2.1 Statistical Discrimination

Employers may discriminate statistically because they fear that older workers will "cost" more in terms of absences and benefits.[31] To test whether companies discriminate statistically against older workers because they assume older workers will have more absences, I introduced an item on the résumé saying that the applicant has won an attendance award. This variable is positive but not significant at the 5 percent level. If anything, attendance awards help younger workers more than older in terms of magnitude. To see whether higher health insurance costs are a reason older workers are not hired, I put in the statement that a worker does not need insurance coverage.[32] Although having insurance seems to help in getting a callback overall in Massachusetts,

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[31] As mentioned in the previous section, unless otherwise noted, this list of statistical discrimination items came from a survey by Rhine (1984), with the exception of transportation costs, which was suggested by a seminar participant. Rhine (1984) surveyed hiring managers in firms and asked them why they thought that other hiring managers might be less likely to hire older workers.

[32] Although, according to Blue Cross/Blue Shield of Massachusetts (personal communication) and Sheiner (1999), health insurance costs vary less with age for women than for men (the possibility of pregnancy goes down as a woman ages), there is some doubt that human resource managers are aware of the fact. Additionally, insurance costs may not follow the same pattern in all cases. Scott et al. (1995) find that older age hiring is lower in firms that offer health insurance and in firms where health insurance is more expensive. However, firms that offer benefits such as health insurance are different than firms that do not. For example, they tend to be larger and have steeper earnings profiles as well (Idson and Oi 1999). Firms with different healthcare costs may also differ in ways not exogenous to employee age.

nothing can be said by age at the 5 percent level. Already having insurance increases the likelihood of getting a callback or interview in Massachusetts, but helps only younger workers and may hurt older workers in Florida, although, again, these results are not statistically significant. Employers could also fear that older workers may be less likely to have reliable transportation, and thus may be tardy or absent from work for this reason. There is no evidence that commute time, matched by zipcode to place of work PUMA affects older or younger workers differently (results not shown).

Employers may also worry that older workers will not be as productive as younger. First, they may believe that older workers' knowledge and skills are obsolete. For this reason, I added a variable indicating that the worker had gotten a computer certificate in 1986 (which would be outdated), 1996, or 2002/2003, when such skills would be relevant and recent. Although not significant, relevant computer experience helps younger workers to get interviews in Florida more than older workers. However, in Massachusetts, it helps older workers more than younger, although the interaction term is not significant.[33] Vocational training[34] helps younger workers more than older workers to get both callbacks and interviews. An interaction between vocational training and older (not shown) is significant at the 5 percent level for Florida, but not for Massachusetts. Second, employers may be worried that older workers lack energy. To test this reason, I introduced an item on the résumé saying the applicant plays sports. For the most part, this variable is not significant. It is significant at the 10 percent level and negative for the *callback* response for younger workers in Massachusetts and significant

[33] Interaction results have also been done using the Norton adjustment, and the results still hold (Norton et al. 2002). Some magnitudes may change, but signs and 5 percent significance do not.

[34] Note that occupation and vocational training are related mechanically in this experiment because vocational training was only included in résumés for which it was required (such as dental assisting or nursing).

and positive at the 5 percent level for the *interview* response for younger workers and workers overall in Florida. Although an interaction term suggests that putting sports on the résumé hurts older workers less than younger workers, this finding is only significant for *positive* responses at the 20 percent level in Massachusetts.

Third, previous research has suggested that older women use volunteer work as a "stepping stone" to labor market work (Stephen 1991), and, indeed, I find that having volunteer work listed helps older women more than younger.[35] Fourth, Bendick (1996) finds that the biggest help to an older worker's résumé is to signal that he or she is flexible or "willing to embrace change." Although the interaction term is only significant for Massachusetts, I found that having this statement on a résumé hurts an older worker, but does not hurt a younger worker.[36] This difference in findings may be because the AARP has been recommending that older workers put such statements on their résumés since the time of Bendick's study and thus this statement now signals that the worker is old.

Finally, experience may interact with age as a form of statistical discrimination. Employers may assume that older workers have more experience, or they may be prejudiced against an older worker if she does not have more experience than a younger worker. I looked at this issue in two different ways. First, I looked to see what effect having experience in the same occupation for which the worker was applying had for the different age groups. Although no interactions of same-occupation experience with age are significant at the 5 percent level (not shown), having occupational experience listed

[35] The interaction of older and volunteer is positive and significant at the 20 percent for *positive* outcomes and 30 percent level for interview outcomes in Florida, but only at the 40 percent level for interview in Massachusetts.

[36] The interaction of older and flexible is significant at the 5 percent level for the interview variable in Massachusetts and at the 60 percent level for Florida.

on the résumé similar to the occupation being applied for helps younger workers more than older workers as shown in Table 4, columns 1-6. However, a different effect is found for implied experience — that is, when the want-ad requires experience;[37] older workers were hurt less than were younger workers, as shown in Table 4, columns 7 through 12, although again, this interaction is not significant at the 5 percent level. Thus there is slight evidence that employers are more likely to give older workers the benefit of the doubt in terms of experience, but only when neither applicant lists the required experience on the résumé. Otherwise, having the required experience may help younger workers more than older. This possibility suggests that the entry-level labor market may be different in terms of age discrimination from markets requiring more experience.

5.2.2 Taste-Based Discrimination

Employer

One form of taste-based discrimination is employer discrimination, in which employers (or those doing the hiring) prefer one group over another based on their own tastes. Human resource professionals may have less taste-based discrimination because of training and knowledge of discrimination laws, although they might be more likely to practice statistical discrimination based on learning from past hires. Bendick (1994) assumes that firm size is a proxy for having a human resources department and finds that there is no link between race discrimination and firm size. I found no link between having a human resources department and being more or less discriminatory.[38] In my study, firms with human resources departments may be more likely to interview younger

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[37] Admissible want-ads could include requirements of up to a year of experience, whether the applicant had it on the résumé or not.
[38] I also have a rough variable for firm size (fewer than 15 employees, 15 to 19 employees, 20 or more employees). I find no relationship between firm size and hiring practices.

workers, which would support the case of statistical rather than taste-based discrimination, but this finding is not significant.[39] The controlled coefficient on the interaction term between *Older* and *HR* for Florida for the *interview* outcome is -0.025 with a standard error of 0.026 and this coefficient for Massachusetts is -0.030 with a standard error of 0.0214.[40]

Employee

Another form of taste-based discrimination occurs when employees prefer to work with members of a certain group. Younger employees might prefer to not to work with older employees, especially when the older employee is in a subordinate position. To test for this type of discrimination, I match zip codes from my dataset to place of work PUMA information on worker age from the Census and look at the effect of percentage of workers over 40, over 50, and over 61 employed in the PUMA.[41] I find no effect of the age of a company's workforce on the differential interviewing by age, thus providing no support for employee taste-based discrimination (results not shown).[42] However, this measure may be too crude, as it matches zip code to place of work PUMA information rather than using the percentage of workers by age in a firm.

Customer

A final source of taste-based discrimination comes from the consumer base.

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[39] Another possible way of measuring employer taste-based discrimination is to examine the interviewing interaction between the ages of employers or human resources professionals and applicants. However, I have been unable to collect information on employer age. Additionally, just because an employer is a member of a group does not mean that he or she will not discriminate against other members. For example, Dick Clark, age 76, has been sued for age discrimination *http://www.cnn.com/2004/LAW/03/02/dick.clark.sued.ap/*.

[40] A Norton correction does not change the sign or significance of these effects.

[41] This effect of older workers in a company influencing the age of new hires is not mechanical because older employees may have been hired young and aged with the company.

[42] For the percentage over age 50 interaction with older, the FL coefficient is .00139 with a standard error of .00286 and the MA coefficient is -.660 with a standard error of .478.

Consumers may prefer to buy from or interact with employees who are like them. To test for this type of discrimination, I used the census to get age profiles of zip codes in Florida and Massachusetts and matched them to the zip codes of the companies applied to in the study. Taste-based discrimination should be even higher in occupations where there is interaction with the public, such as in sales and service. There is no evidence of consumer taste-based discrimination; areas with higher percentages of population over the age of 50 are more likely to call back or to interview in general and these results are stronger for younger workers than for older. The results are similar when only service and sales positions are looked at (results not shown). Thus there is no evidence that younger consumer bases prefer workers in the same age group.

6 Implications

These differential responses have real implications for older potential workers. One may wonder, "So older workers have to send in a few more applications to get an interview, so what?" Aside from the psychological implications of implied rejection, there are economic consequences to this sort of differential that are more severe for some occupations than others. First, there are a limited number of positions open and advertised each week. The number of positions available also varies by occupation. For example, on a randomly chosen Sunday in Florida, there were 34 LPN (licensed practical nurse) jobs being offered but only 8 pre-school teacher positions. For some professions, such as jewelry appraiser (which requires 6 months to a year of training), it is possible to call almost every jewelry store in the area over the course of a year and only net one interview. Second, the number of applications sent to receive an interview varies by occupation. Using general occupation categories, the number of applications needed for an interview ranges from a low of 5.5 for younger workers and 10 for older workers in healthcare positions in Florida to a high of 32 ads for younger workers and 72 ads for older workers seeking clerical positions in Massachusetts.[43] Finally, given that the wages in many of these occupations are not very high (often minimum wage), it is likely that persons seeking these jobs also do not have a large amount of wealth to finance an extended job search, especially if they are ineligible for unemployment benefits.

What does this mean for older versus younger workers? Conditional on getting an *interview* response, it takes, on average, 8 days to be offered an interview. I have not been able to find information on the number of interviews it takes to get an entry-level job, but one online firm[44] finds that it takes 7 to 10 interviews on average for a college graduate to obtain a job offer. Using a back of the envelope calculation for one of the professions most likely to be hired, a new licensed practical nurse[45] sending out 30 applications a week can expect 3 interviews a week as an older worker and 6 interviews a week as a younger worker. Assuming it takes 7 to 10 interviews to land a job, the average younger worker could expect an employment offer in a little over a week, and an average older worker 3 weeks. But this is the best case scenario. An older worker attempting to find clerical work could file close to 100 applications per week and expect to be given an offer 7 to 10 weeks later (a younger worker would get an offer in half that time), using the same back of the envelope calculation, and that is only assuming that

[43] With "low" and "high," I am only including general occupation categories that have at least 200 résumés sent. There are some occupational categories with low sample sizes, such as professional/technical non-healthcare (mostly pre-school teachers) in Florida that received no responses for older workers, and thus would, by the metric used, require an infinite number of resumes to receive an interview. However, only 51 résumés were sent to p/t non-healthcare positions in Florida. There were 558 healthcare résumés sent in Florida and 1057 clerical résumés sent in Massachusetts.

[44] www.onestop.com

[45] A profession that takes 1 year of training and had a median salary of $31,440 in 2002 according to the BLS *Occupational Outlook Handbook.* http://bls.gov/oco/ocos102.htm

there are 100 unique new clerical ads each week, which, as a large number of ads are run at least two weeks in a row, is unlikely. For someone who needs to work because of a lack of savings, several months without income could be critical.

7 Concluding Comments

This study clearly shows differential interviewing by age for entry-level positions in contemporary labor markets. I find that younger applicants are 44 percent more likely than are older applicants to be offered an interview in Massachusetts and 43 percent more likely in Florida. The extent of discrimination against older workers is similar to that of discrimination against women or blacks.[46] I found no evidence of taste-based discrimination. I found some suggestive evidence for statistical discrimination against workers along a few dimensions, such as skills obsolescence, as signaled by adding relevant computer experience to a resume (but only in Massachusetts). Many resume items helped younger workers but either hurt or did not affect older workers. Pinpointing the reasons for differential treatment by age is an area fertile for future research.

In the current labor market, older workers face greater difficulty obtaining interviews for entry-level positions than do younger workers. The demand for older workers is a function of taste-based and statistical discrimination, as discussed above, but also possibly employer misinformation and market conditions. These forces may change over time as the labor force ages. Employers may be willing to hire more older workers

[46] Neumark et. al (1996) find evidence of 47 percent differential interview requests against female wait staff in high-price restaurants and 40 percent toward female wait staff in lower-price restaurants. Bertrand and Mullainathan (2004) find that applicants with white sounding names are 50 percent more likely to be called for an interview than applicants with black sounding names. It is somewhat difficult to compare the extent of the magnitude of age discrimination to race or gender discrimination, since age is not a binary variable and breaking into older and younger categories can be done arbitrarily. I might have found more had I been comparing, for example, 32-year-olds to 90-year-olds only.

as younger workers become relatively scarce. However, as younger workers become scarce, the relative demand for them should rise, assuming older and younger workers are imperfect substitutes. Current evidence suggests that older workers will still face employment difficulties in the near future. Triest et al. (2006), looking at cohort crowding, predict that wages of older workers will continue to be depressed even as the boomer cohort retires. I chose St. Petersburg, FL, as a microcosm for the future, with its top-heavy age structure, and found that older workers in this area have very similar labor market outcomes to Boston, MA in terms of both relative demand and time out of work in my back of the envelope calculation. However, my study of St. Petersburg is only a snapshot of a specific labor market at a specific point in time. Perception of what ages constitute "older" may also change with increases in longevity and cognitive ability and as institutional bounds such as the "Normal Retirement Age" for Social Security are increased. Finally, demand for all workers may change as the national economy grows or shrinks. Future policy implementation will have to take these possible changes into account.

Future research needs to be done both exploring other labor markets, such as the non-entry-level market, and pinpointing additional reasons for statistical discrimination. In non-entry-level positions, there may be taste-based discrimination against younger workers supervising older workers, which would suggest that there would be less age discrimination against older workers in these markets. For example, managerial positions in Florida (but not Massachusetts) tended to prefer older workers, interviewing 4 percent of older applicants and 1 percent of younger workers. I also found differences in differential interviewing between occupations; Blue-collar and male-dominated occupations in the sample tend to prefer older workers to younger. Because these occupations in my sample tend to be clustered in dying industries, there may be a bias towards hiring workers with shorter expected future work-lives. (Sample sizes are not large enough to present these results in detail.)

Another reason for discrimination against older workers that could not be tested in this setup is that older workers cost more because they can sue employers under the Age Discrimination in Employment Act. Lahey (2006) looks at the effect of age discrimination laws on older workers. Although that study finds that these laws have a significant and negative effect on employment outcomes for older white men, it does not find a similar effect for older women. Because the current cohort of older women is unlikely to sue, employers may not take possible litigation into consideration in the hiring process.

This study provides evidence supporting the idea that the demand for labor from older workers is smaller than that for younger workers. Simply encouraging older workers to reenter the labor force may not guarantee that they will be able to find jobs in a timely manner, if at all. This study also has important implications for women who are most likely to need additional work — those with little work experience who need to enter the labor market unexpectedly, such as widows, those whose husbands have lost jobs and cannot find employment, or divorcees. Although there are more older women than older men, the majority of economic surveys on aging and work focus on a random sample of men and, if they include women at all, only include spouses. Any policy that depends on older people finding work to maintain their quality of living, such as changing Social Security benefits, needs to consider this demand side.

8 Data Appendix

The use of a computer program to randomly generate items in order to create many different possible résumés is a large improvement over earlier studies. First, unlike studies in which a limited number of résumés are used, it lessens (and can test for) the possibility that an employer is reacting to something specific in the particular résumé sent out. Additionally, because there is no human interaction with the résumé during its creation, the possibility of injecting subjectivity into the process of matching résumés with job openings is completely eliminated. Résumés and résumé items (other than the objective) are truly randomly assigned to job openings, eliminating many possibilities for bias.

The computer program used to prepare and match résumés is best explained through example. Say that a job vacancy for a receptionist has been found. The researcher will open the computer program specifying jobs for a receptionist position. The computer program will first randomly choose two of the possible women to apply to the job, for example, Linda Jones (age 45) and Mary E. Smith (age 62). It will then pick an objective statement for Linda ("To obtain a position as a receptionist") and a matching one for Mary ("To secure a position as receptionist"). Similarly it will match work histories and high school. Next it will decide whether to test for one or more of the possible reasons for discrimination through adding items to the résumé. As an example, to see if lack of energy is a reason employers discriminate against older people, the computer will put under hobbies that Linda Jones is a tennis player, then designate Mary E. Smith as a racquetball player. Regressions found no significant difference between response rates for tennis and racquetball players, or any of the other possible paired choices.

Variations on the résumés ranged as follows. Candidates were named Mary E. Smith or Linda Jones.[47] The objectives included sales positions, office positions, entry-level nursing positions, wait staff positions, and other entry-level or close to entry-level positions that require only a year of combined post-high school education and experience to obtain. All résumés had the applicant currently working at a job. Dates of high school graduation included 1959, 1966, 1971, 1976 and 1986. High schools chosen were Ames High School in Ames City, IA and DeKalb High School in DeKalb, IL. Some résumés had experience in computer classes, either from 1986, which makes such experience obsolete, 1996, when the experience is useful but not recent, or 2002/2003, when the experience is both useful and recent. Current employment varied as well and ranged from cashier work to secretarial work with a couple of "unusual" jobs possible, such as those giving fork-lift experience. Volunteer work included work at homeless shelters or food banks. Hobbies included some combination of tennis, racquetball, gardening, and crafting. An attendance award could also be listed. All résumés had e-mail addresses listed.[48] Appendix Tables 1a and 1b show how resume characteristics were distributed across high school graduation dates.

Typos were introduced to the study in two different ways: First, purposeful

[47] Mary gets a middle initial because in my experience, and the experience of those with whom I have spoken, anyone over the age of 30 whose first name is Mary always adds her middle name or middle initial, especially if her last name is also common (unless there's a "Peter, Paul, and…" in front of the Mary). I have not had the same experience with Linda as a first name, although when asked, Linda's middle initial is M.

[48] The census finds that 47 percent of householders aged 45 to 64 have Internet access at home (http://www.census.gov/prod/2001pubs/p23-207.pdf). Additionally, places that help people find work, such as Project Able, strongly encourage applicants to get e-mail addresses and many job finding sites actually take seekers through the steps of signing up for a free Hotmail account. Finally, adding an e-mail address to an older résumé is likely to work in the older resume's favor, and thus I should find even lower acceptance rates for older workers without adding e-mail addresses.

typographical errors were programmed into the résumé machine during the first half of the study when there was more interviewing in general. These typos were representative of those found in actual résumés — they included things like missing punctuation marks, large words that had been misspelled, and inconsistent indentation. The second kind of error was introduced inadvertently when applying for a job that did not fit one of the major job categories in the résumé program. These errors included things like putting an "a" where an "an" should be or other similar mistakes that native English speakers do not often make. There are many fewer of these errors and they tend to be most prevalent in Florida and when there was a research assistant regime change.

Forty want-ads were drawn without replacement per week per city from the Sunday *Boston Globe* and the online version of the *St. Petersburg Times*. For the *Boston Globe*, the number of pages of non-professional want-ads were counted. Then this number was entered into a random number generator to pick a random page. On this page, the number of want-ads on the page were counted. This new number was entered into a random number generator. That number ad was circled and checked to see if it: 1.) advertised an entry-level job, 2.) provided a fax or phone, or e-mail address, and 3.) had not been applied to in a previous week. If it did not fit those criteria, another ad from the same page was chosen. If it did fit those criteria, it was copied to a word document for résumé creation purposes later and a new page was picked randomly. For the *St. Petersburg Times*, a fixed number of want-ads appeared on each online page, otherwise the procedure was the same as for Boston. After 40 new ads were collected, résumé creation and sending could begin. This procedure biases toward ads that ran multiple weeks or that, in Boston, had larger ads or shared pages with larger ads. Real job applicants may also share these biases.

Call-ins were performed because many entry-level jobs are never advertised via want-ad. I could not use walk-ins because a pilot study showed that, not only were walk-ins time consuming, but many of them generated actual paper job applications with questions whose answers were difficult to control, but hurt an application if left blank, for example, "Describe your ideal job situation." Additionally, there was a worry that a manager would connect the person picking up or turning in an application with the job applicant, rather than looking at the résumé characteristics alone. To generate a call-in, a young woman randomly generated an entry in the telephone book. Since large firms tend to have more entries in the telephone book than do small firms, and certain industries, such as law offices, tend to have multiple entries, call-ins tend to have a slight bias towards generating these firms. However, they do a better job of generating small firms than do want-ads. The company was then called and asked, "Hello, my name is Elizabeth Williams, I was wondering, do you have any entry-level jobs available?" If the person on the phone did not understand, the caller followed with, "Are you hiring for any entry-level positions?" If the person on the phone said no, the caller moved on to another phone book entry. If the person on the phone said yes, the caller tried to elicit a fax number or e-mail address and later generated a résumé and sent it. If there was no fax or e-mail available, the caller first checked to see if there was an online application, and if there was, she sent a resume via that method. Otherwise, the caller coded the company as "no fax/email available" and generated another telephone book entry.

Response rates differ somewhat by method of application as shown in Appendix Table 2a. Want-ads are more likely to get both *positive* and *interview* responses than

Call-ins, faxes slightly more likely than e-mails. There are some occupational differences in response rates between Massachusetts and Florida. For example, professional/technical non healthcare positions, which are mostly preschool teaching positions, were 1.5 times as likely to hire younger workers in Massachusetts, but there was a much smaller number of positions advertised in Florida, so the sample size could not be compared. There was no difference in age for interviewing healthcare workers, mostly licensed nurse practitioners and certified nurse assistants, in Massachusetts, but Florida healthcare agencies were twice as likely to hire younger workers (results not shown). The composition of jobs available differs as well, as can be seen under "firm characteristics" in Appendix Tables 1a and 1b. A quarter of the jobs available in both metropolitan areas were clerical work, but the Boston area was much more likely to hire sales workers, at 24.5 percent of openings compared to 19.5 percent in the St. Petersburg-Tampa area. Entry-level professional, education, and managerial jobs were also more likely to be advertised in Massachusetts whereas craftsman, operative, service, and laborer jobs were more likely to be advertised in Florida. The order in which the résumé were sent did not matter.

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Figure 1: **Response Rates in Massachusetts**

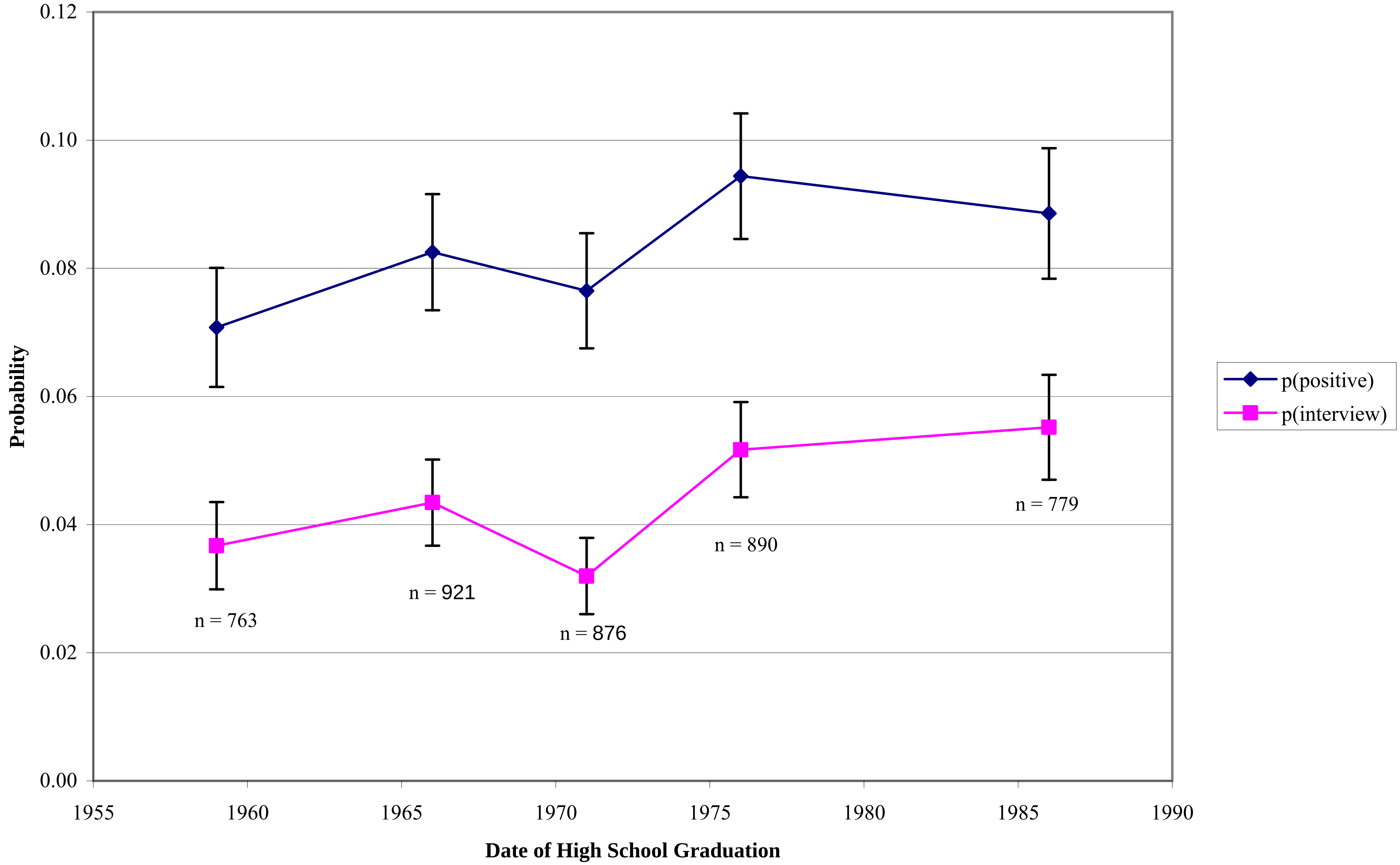

Figure 2: **Response Rates in Florida**

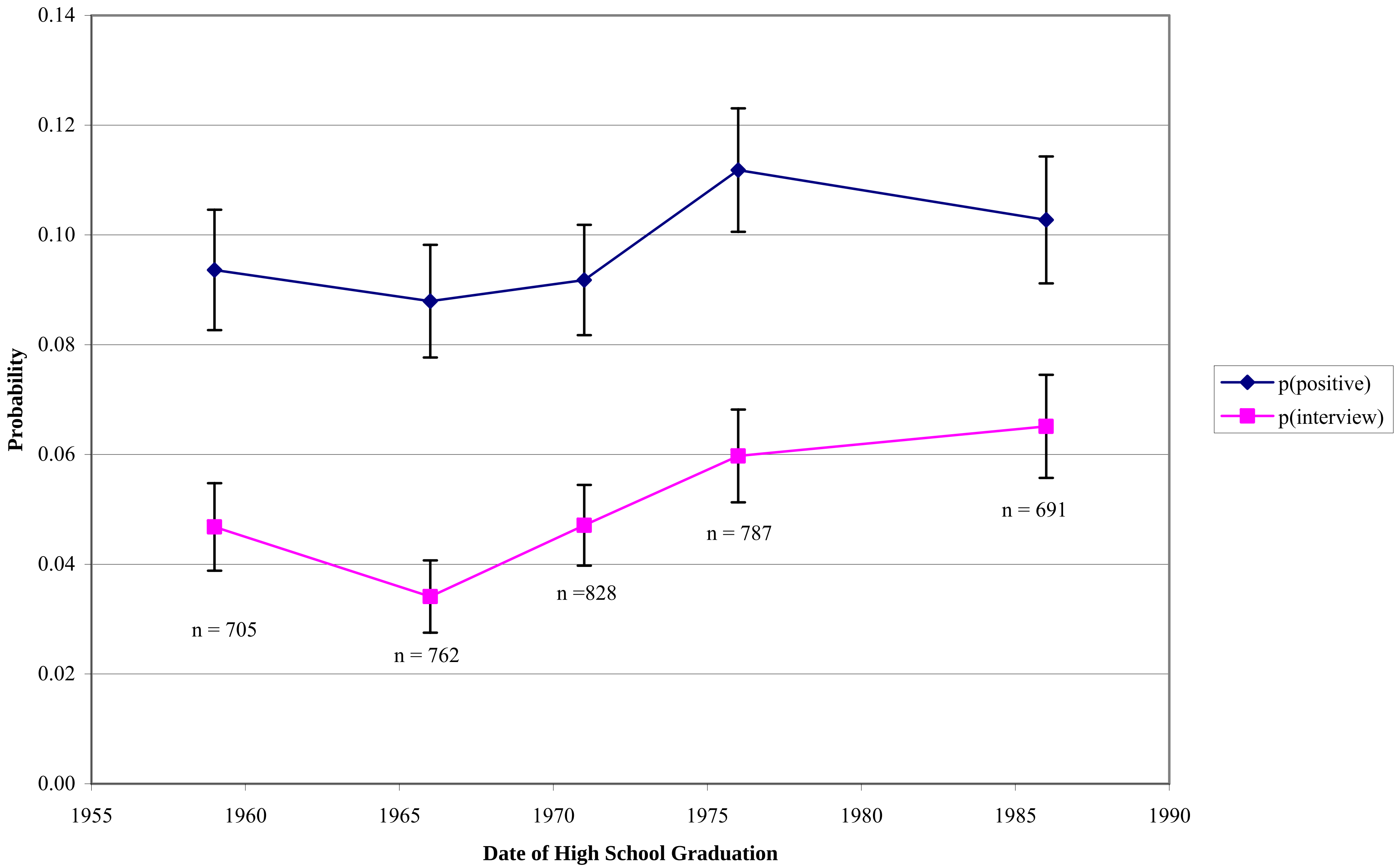

Table 1
Mean Response Rates by Age

	Older		Younger		Difference		# ads needed for one response			
							Older		Younger	
	Positive	Interview	Positive	Interview	Positive	Interview	Positive	Interview	Positive	Interview
MA										
	0.077	0.038	0.092	0.053	0.015	0.016	12.99	26.67	10.91	18.75
	[2560]	[2560]	[1669]	[1669]	(0.09)	(0.01)				
FL										
	0.091	0.043	0.108	0.062	0.017	0.020	10.98	23.42	9.30	16.07
	[2295]	[2295]	[1478]	[1478]	(0.10)	(0.01)				

Notes: Cell number is reported in brackets. P-values are reported in parentheses and refer to two-tailed t-tests.

Table 2

Marginal Effect of Age on Likelihood of a Response

	Massachusetts						Florida					
	Positive			Interview			Positive			Interview		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
age		-0.00083			-0.00080			-0.00043			-0.00075	
		(0.00041)*			(0.00032)*			(0.00046)			(0.00035)*	
older=50+			-0.016			-0.017			-0.015			-0.018
			(0.007)*			(0.006)**			(0.008)+			(0.007)*
hs59	-0.022			-0.018			-0.002			-0.010		
	(0.011)*			(0.007)*			(0.014)			(0.009)		
hs66	-0.008			-0.012			-0.012			-0.026		
	(0.012)			(0.008)			(0.013)			(0.008)**		
hs71	-0.016			-0.023			-0.003			-0.010		
	(0.010)			(0.007)**			(0.013)			(0.008)		
hs76	0.002			-0.005			0.017			0.001		
	(0.012)			(0.008)			(0.014)			(0.009)		
Observations	4229	4229	4229	4229	4229	4229	3773	3773	3773	3755	3755	3755
Ho†	7.13	4.01	4.83	15.02	6.23	9.40	5.60	0.86	3.10	13.92	4.58	6.48
Ho: p-value	(0.129)	(0.045)	(0.028)	(0.005)	(0.013)	(0.002)	(0.231)	(0.353)	(0.078)	(0.008)	(0.032)	(0.011)

Notes: Results reported are marginal effects from a probit equation using the margfx command in Stata. Robust standard errors in parentheses. The dummy hs86 is omitted. Controls include years out of 10 in the labor force, years out of 10 in the labor force squared, workgap, college, computer classes. since 1996, volunteering, sports, already has insurance, flexible, attendance award, typos, and the following occupational dummies: professional, education, health, manager, sales, craftsman, operative, service, and laborer. For the interview outcome, education and laborer predict failure perfectly and 18 and 133 observations are dropped respectively. Results are clustered on firm.

+ significant at 10%; * significant at 5%; ** significant at 1% Ho†: Age effects are all zero

Table 3

Marginal Effect of Resume Characteristics on Likelihood of Response

	Massachusetts						Florida					
	Positive			Interview			Positive			Interview		
	All	Older	Younger	All	Older	Younger	All	Older	Younger	All	Older	Younger
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
work gap	-0.014	-0.006	-0.026	-0.006	0.001	-0.015	-0.002	0.009	-0.020	0.002	0.001	0.007
	(0.011)	(0.012)	(0.014)+	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)	(0.016)	(0.009)	(0.009)	(0.013)
vocational train.	0.079	0.065	0.102	0.037	0.016	0.083	0.128	0.125	0.140	0.050	0.038	0.074
	(0.025)**	(0.026)*	(0.035)**	(0.019)*	(0.015)	(0.034)*	(0.028)**	(0.032)**	(0.037)**	(0.019)**	(0.018)*	(0.029)*
computer	0.007	0.007	0.008	0.011	0.012	0.009	0.014	0.010	0.019	0.020	0.015	0.028
	(0.011)	(0.012)	(0.016)	(0.009)	(0.009)	(0.012)	(0.013)	(0.015)	(0.017)	(0.010)*	(0.010)	(0.014)+
volunteer	0.032	0.029	0.038	0.015	0.017	0.010	-0.001	0.008	-0.016	-0.012	-0.005	-0.023
	(0.011)**	(0.012)*	(0.015)**	(0.008)+	(0.008)*	(0.012)	(0.012)	(0.014)	(0.016)	(0.009)	(0.010)	(0.013)+
sports	-0.014	-0.004	-0.027	-0.006	-0.004	-0.008	0.009	0.009	0.009	0.019	0.013	0.029
	(0.011)	(0.012)	(0.015)+	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)	(0.016)	(0.009)*	(0.010)	(0.013)*
insurance	0.017	0.016	0.020	0.010	0.008	0.014	-0.002	-0.005	0.001	-0.008	-0.012	-0.003
	(0.011)	(0.012)	(0.015)	(0.008)	(0.008)	(0.012)	(0.012)	(0.014)	(0.016)	(0.009)	(0.010)	(0.013)
flexible	-0.011	-0.018	0.000	-0.002	-0.009	0.009	-0.013	-0.009	-0.020	-0.008	-0.010	-0.004
	(0.011)	(0.012)	(0.015)	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)	(0.016)	(0.009)	(0.010)	(0.013)
attendance	0.009	0.005	0.017	0.005	0.004	0.008	0.017	0.016	0.019	0.002	0.001	0.003
	(0.011)	(0.012)	(0.014)	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)	(0.016)	(0.009)	(0.010)	(0.013)
typo	0.012	0.017	0.005	-0.004	0.003	-0.011	0.011	0.003	0.023	0.005	0.005	0.007
	(0.016)	(0.017)	(0.021)	(0.011)	(0.011)	(0.014)	(0.014)	(0.016)	(0.019)	(0.010)	(0.011)	(0.015)
Observations	4229	2560	1669	4229	2560	1669	3773	2279	1478	3755	2267	1427
Ho†	25.53	17.47	25.93	12.55	10.09	13.53	25.21	18.7	22.25	19.10	10.01	21.13
p-value	(0.0013)	(0.0256)	(0.0011)	(0.1283)	(0.2584)	(0.0950)	(0.0014)	(0.0166)	(0.0045)	(0.0143)	(0.2640)	(0.0068)
standard dev.‡	0.064	0.067	0.067	0.032	0.037	0.038	0.066	0.057	0.090	0.036	0.027	0.054

Notes: Results reported are marginal effects from a probit equation using the margfx command in Stata. Additional controls not shown are occupational controls for professional, education, healthcare, manager, sales, craftsman, operative, service, laborer and clerical. For the Florida interview outcome, education predicts failure perfectly in (10) professional and education in (11), and education and laborer in (12). Results are clustered on firm.

+ significant at 10%; * significant at 5%; ** significant at 1%; †Ho: Resume characteristics effects are all zero; ‡ Standard deviation of predicted callback.

Table 4

The Effect of Experience on Interview Requests

	Massachusetts			Florida			Massachusetts			Florida		
	All	Older	Younger	All	Older	Younger	All	Older	Younger	All	Older	Younger
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
same	0.018	0.013	0.024	0.016	0.004	0.037						
experience	(0.011)	(0.012)	(0.016)	(0.012)	(0.012)	(0.019)						
experience							-0.023	-0.019	-0.028	-0.031	-0.029	-0.036
required							(0.008)**	(0.008)*	(0.011)**	(0.009)**	(0.009)**	(0.013)**
Observations	3651	2207	1444	3266	1980	1168	4228	2560	1668	3755	2267	1427

Notes: Results reported are marginal effects from a probit equation using the margfx command in Stata. Standard errors are reported in parentheses. Controls include years out of 10 in labor force, (years out of 10 in labor force squared), workgap, college, computer classes since 1996, volunteering, sports, already has insurance, flexible, attendance award, typos, and the following occupational dummies: professional, education, health, manager, sales, craftsman, operative, service and laborer. Results are clustered on firm.

* significant at 5%; ** significant at 1%.

Appendix Table 1a

Summary Statistics: Massachusetts

Variables	All	older	younger	1959	1966	1971	1976	1986
resume characteristics:								
hsgrad	1971.561	1965.625	1980.667	1959.000	1966.000	1971.000	1976.000	1986.000
yrs of 10 in LF	5.590	5.567	5.624	5.468	5.692	5.522	5.697	5.542
typo	0.163	0.171	0.151	0.118	0.198	0.188	0.181	0.117
college	0.196	0.195	0.197	0.204	0.203	0.177	0.212	0.180
computer	0.520	0.523	0.515	0.512	0.533	0.522	0.509	0.521
volunteer	0.504	0.498	0.513	0.509	0.481	0.508	0.520	0.506
sport	0.487	0.483	0.494	0.481	0.493	0.474	0.494	0.493
other hobby	0.196	0.192	0.202	0.210	0.186	0.183	0.199	0.205
insurance	0.503	0.508	0.496	0.528	0.506	0.493	0.487	0.506
flexible	0.517	0.523	0.508	0.533	0.511	0.525	0.515	0.501
attendance	0.493	0.500	0.482	0.499	0.489	0.513	0.480	0.485
recent computer	0.152	0.151	0.154	0.168	0.145	0.142	0.139	0.171
relevant computer	0.378	0.377	0.379	0.377	0.381	0.373	0.376	0.383
age	49.439	55.375	40.333	62	55	50	45	35
method of sending:								
fax	0.786	0.780	0.795	0.790	0.771	0.780	0.816	0.772
email	0.179	0.186	0.170	0.176	0.191	0.188	0.157	0.185
online	0.034	0.034	0.034	0.033	0.037	0.032	0.027	0.041
firm characteristics:								
EOE/AA	0.124	0.127	0.119	0.127	0.135	0.120	0.110	0.130
professional	0.040	0.039	0.040	0.045	0.043	0.031	0.042	0.039
education	0.025	0.028	0.020	0.022	0.033	0.027	0.020	0.021
health	0.140	0.146	0.132	0.144	0.147	0.146	0.145	0.118
manager	0.066	0.062	0.070	0.072	0.054	0.062	0.064	0.076
clerical	0.250	0.252	0.247	0.249	0.256	0.250	0.230	0.266
sales	0.245	0.245	0.244	0.241	0.254	0.240	0.240	0.248
craftsman	0.022	0.021	0.024	0.024	0.017	0.023	0.022	0.026
operative	0.044	0.043	0.046	0.045	0.048	0.037	0.049	0.041
service	0.145	0.140	0.154	0.135	0.126	0.159	0.162	0.145
laborer	0.018	0.019	0.017	0.017	0.015	0.025	0.018	0.017
# obeservations	4229	2560	1669	763	921	876	890	779

Notes:

	hs grad	age		hs grad	age
Older includes:	hs1959	62	Younger includes:	hs1976	45
	hs1966	55		hs1986	35
	hs1971	50			

Appendix Table 1b

Summary Statistics: Florida

Variables	All	older	younger	1959	1966	1971	1976	1986
resume characteristics:								
hsgrad	1971.538	1965.654	1980.675	1959	1966	1971	1976	1986
yrs of 10 in LF	5.694	5.674	5.726	5.684	5.672	5.667	5.752	5.696
typo	0.259	0.264	0.252	0.206	0.282	0.296	0.288	0.211
college	0.186	0.190	0.179	0.183	0.207	0.180	0.159	0.201
computer	0.511	0.506	0.518	0.506	0.501	0.510	0.522	0.514
volunteer	0.494	0.494	0.493	0.523	0.478	0.484	0.484	0.502
sport	0.499	0.493	0.508	0.495	0.508	0.478	0.513	0.502
other hobby	0.183	0.179	0.188	0.189	0.177	0.173	0.188	0.188
insurance	0.500	0.505	0.493	0.536	0.484	0.496	0.484	0.502
flexible	0.510	0.515	0.502	0.513	0.495	0.536	0.511	0.492
attendance	0.500	0.496	0.505	0.508	0.499	0.483	0.526	0.482
recent computer	0.156	0.152	0.163	0.150	0.151	0.153	0.159	0.168
relevant computer	0.380	0.371	0.393	0.360	0.378	0.373	0.402	0.384
age	49.462	55.346	40.325	62	55	50	45	35
method of sending:								
fax	0.837	0.839	0.834	0.831	0.839	0.847	0.830	0.838
email	0.134	0.136	0.129	0.145	0.134	0.132	0.137	0.120
online	0.029	0.024	0.037	0.024	0.028	0.022	0.033	0.042
firm characteristics:								
EOE/AA	0.149	0.144	0.158	0.152	0.146	0.135	0.146	0.172
professional	0.008	0.007	0.009	0.007	0.005	0.008	0.008	0.010
education	0.005	0.005	0.004	0.004	0.005	0.006	0.005	0.003
health	0.148	0.150	0.144	0.142	0.165	0.144	0.140	0.149
manager	0.048	0.044	0.053	0.051	0.035	0.047	0.058	0.048
clerical	0.262	0.264	0.260	0.247	0.280	0.263	0.263	0.258
sales	0.195	0.189	0.205	0.204	0.180	0.185	0.187	0.226
craftsman	0.042	0.042	0.041	0.043	0.038	0.046	0.044	0.038
operative	0.081	0.081	0.079	0.078	0.085	0.081	0.097	0.059
service	0.173	0.176	0.169	0.180	0.161	0.185	0.165	0.174
laborer	0.035	0.038	0.030	0.044	0.041	0.031	0.029	0.032
# observations	3773	2295	1478	705	762	828	787	691

Notes:

Appendix Table 2a

Response Percentage by Method of Delivery

	Massachusetts			Florida		
	Positive	Interview	# observations	Positive	Interview	# observations
Fax						
Want-Ad	0.09	0.05	2687	0.11	0.06	2508
Call-in	0.06	0.02	636	0.05	0.03	650
All	0.09	0.05	3323	0.10	0.05	3158
Email						
Want-Ad	0.08	0.04	614	0.11	0.05	364
Call-in	0.01	0.01	145	0.06	0.04	140
All	0.07	0.03	759	0.10	0.05	504
Online						
Want-Ad	0.18	0.11	28	0.13	0.13	16
Call-in	0.08	0.03	115	0.04	0.02	95
All	0.10	0.05	143	0.05	0.04	111
All						
Want-Ad	0.09	0.05	3333	0.11	0.06	2888
Call-in	0.05	0.02	896	0.05	0.03	885
All	0.08	0.04	4229	0.10	0.05	3773

Notes:

Appendix Table 2b

Marginal Effect of EOE on Response Rate for Massachusetts

	All Occupations		Non-health Occupations	
Variables	Positive	Interview	Positive	Interview
EOE/AA	0.025	0.016	-0.001	-0.002
	(0.022)	(0.016)	(0.021)	(0.014)
Older	-0.015	-0.018	-0.015	-0.017
	(0.010)	(0.007)*	(0.009)	(0.007)*
EOE/AA*Older	0.000	0.012	-0.009	0.004
	(0.025)	(0.020)	(0.025)	(0.021)
Observations	4229	4229	3635	3635

Notes: Standard errors in parentheses.

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