AGE, WOMEN, AND HIRING:
AN EXPERIMENTAL STUDY

Joanna Lahey

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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 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% more likely to be offered an interview than 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.

Joanna Lahey
Post-Doctoral Fellow
National Bureau of Economic Research
1050 Massachusetts Avenue
Cambridge, MA 02138-5398
jlahey@nber.org

1 Introduction

In a 2004 speech to the Federal Reserve Board, 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 had 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, Baltes et al 1988). Many older Americans also 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% (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 there is something preventing them from finding a new job.

Will older American women be able to find work? Economists generally assume that staying out of the labor force is a choice for women, so only supply-side factors come into play in policy discussions, such as those regarding social security. This study explores the demand-side of policies that rely on older women finding jobs at the normal

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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, Diamond and Orszag (2002).

age of retirement by running a labor market experiment to explore the hiring behavior of firms 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 resumes, 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 hiring 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 resumes to employers in these two cities and measure the response rates by age, as indicated on each resume by date of high school graduation. In addition, I explore reasons for differential responses by age to resumes in several ways. First, I explore statistical discrimination, which is defined as an employer judging a job applicant based on her age-group status 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, since these departments would be likely to have had training in discrimination law. Third, I examine employee taste-based discrimination by looking at the age break-down 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 evidence of differential hiring by age in these two labor markets. A

younger worker is 42% more likely than an older worker to be offered an interview in Massachusetts and 46% more likely to be offered an interview in Florida. Statistical discrimination is the most likely explanation for this differential hiring behavior. 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.

Age discrimination is comparatively understudied by economists.[2] 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. Experimental labor market studies such as this one have the advantage of directly observing discrimination as it happens. 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). Only one set of these studies (a resume study combined with a matched pairs audit) has explored age discrimination (Bendick et al. 1996, Bendick 1999) and there is concern that this study lacks comparable controls (Riach and Rich 2002).

This paper is structured as follows: Section II gives some background information on discrimination laws, testing for discrimination and types of discrimination. Section III gives an overview of the experimental design. Section IV describes the empirical framework for both differential hiring by age and reasons for differential hiring by age. Section V provides results and Section VI discusses

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[2] 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.
[3] The 2000 CPS Displaced Worker Survey finds that the average 12 weeks search time for workers age 55 to 74 was 3.6 weeks longer than that for workers age 19 to 39. Additionally, 39% of displaced older workers in the February 2000 CPS had not found reemployment by the time of the survey, whereas only 19% of those between 40 and 54 had not found reemployment (US General Accounting Office 2001).

implications. Section VII 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.[4] This law prohibits discrimination 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 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 hiring by sending resumes are called "resume 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[5]; one cannot rule out systematic differences observable to the employer between the two groups being studied. Experiments such as this one, using randomized resumes, 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

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[4] Firms are exempt if they can prove a bona-fide occupational requirement (BFOQ) that is directly related to age (for example, an acting position), or if the position is a high salaried policy making position.
[5] Other problems with this method are elucidated by Heckman and Siegelman(1993) and Heckman (1998).

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[6] (Arrow 1972). 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 discrimination is generally thought to be inefficient from an overall welfare point of view, although it provides utility to the discriminator (Becker 1971).

3 Experimental Design

I sent resumes to 3996 firms in the greater Boston, Massachusetts and greater St. Petersburg, Florida areas. Boston was chosen for convenience and St. Petersburg was chosen because it both has a similar demographic mix to what the US Census projects the entire United States to have in the 2020s, that is, it has a large concentration of elderly, and because the St. Petersburg/Tampa Bay MSA is approximately equal in magnitude to the Boston PMSA.[7] Each Sunday, 40 want-ads were culled from the Sunday Boston

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[6] 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.

[7] The Boston PMSA had a population of 3,285,387 in 1998, Tampa/St. Petersburg had a population of 2,254,405 in 1998.

Globe and 40 from the online version of the Sunday St. Petersburg Times.[8] 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 resume parts from actual entry-level applicants to randomly create new resumes for

specified positions. Genuine resumes for many different job categories were taken off of

online sites such as www.americasjobbank.com. These resumes 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 email address from www.hotmail.com. Detailed

information on the process of resume creation and distribution can be found in the Data

Appendix.

For the most part, the resumes created for the audit used items from actual

resumes (but not in any way that could be connected to the original resume). Two items

included in some of the sent resumes did not appear in actual resumes: 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 resumes 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

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[8] 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.

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 US (Smith and Jones), according to social security administration data.[9] 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 (e.g. as in 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 limit the total number of ages I used in order to be able to collect a sample size large enough to preserve power and since my focus is on the older ages, 35 seemed more natural than, for example, 25, as a cutoff.[10] Second, because the current resume standard is to display a 10 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 resume (e.g. taking care of her family and not 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 social 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 generated

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[9] http://www.ssa.gov/OACT/NOTES/note139/original_note139.html
[10] Initially I had chosen 45 as my "start" age, but after I obtained additional funding, I was able to add 35 before the start of the actual study.

from calling companies randomly chosen from the Verizon yellow pages.[11] The response rate for call-ins was about half that for want-ads. However, the ratio of older positive/interview responses to younger was very similar whether the ad had been generated via want-ad or via call-in[12], thus providing some evidence that the degree of differential hiring 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.[13]

Resumes were sent in pairs via fax.[14] A coin was flipped each time a pair of resumes was sent to determine which would be sent first. Via the randomness of the computer program used to create resumes, 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% in Massachusetts and 10% in Florida and an "interview" rate of 4% in Massachusetts and 5% in Florida.

To distinguish between age discrimination and discrimination based on differences in human capital or based on perceived gaps in work history, I employed a number of design measures. First, I only sent resumes for women because an employer is

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[11] I did not add more because the marginal additional call-in was much more time intensive to collect than the marginal additional want-ad.

[12] The exact ratios of younger positive responses to older (keeping in mind older contains more dates of high school graduation than younger) for Massachusetts are: .778 positive if want-ad, .770 if call-in; .92 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.

[13] 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.

[14] Only two resumes were sent to each employer because an employer would be likely to get suspicious should he or she receive four virtually identical resumes in a short time period, whereas two resumes are much more likely to be thought of as a coincidence if noticed at all.

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. Second, I limited work histories to 10 years, since conversations with human resource professionals and an examination of actual resumes suggested that this length is common practice.[15] 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, where entry-level is defined as anything which requires at most one year of education plus experience combined. For these jobs, job-specific human capital should be less of a concern.

Although these limitations can only say something about a specific segment of the labor market, my controls are comparable enough that my results can be trusted. Additionally, I study an important segment 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 men (Favreault et al. 2002). Finally, 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

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[15] I spoke to human resource professionals from three places—first, several professionals from the hiring department from 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.

positions, whereas a man applying to these positions might be considered suspect.

4 Empirical Framework

4.1 Differential Hiring by Age

To test for differential hiring by age, I sent paired resumes matched on all characteristics except age[16], 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 specifically asked the applicant to call back to set up an interview or to meet in person.

There are many ways to measure age given my setup. I looked at high school graduation cohort dummies, age as a continuous variable, and a dummy which broke high school graduation cohorts into two groups: older and younger. The results should be similar, but different age configurations give varying amounts of power.

First I ran differential probits on positive response and interview responses using high school graduation dummies as the independent variables of interest:

$$\text{pr}[Response_i = 1] = \text{pr}[B_1(Controls)_i + B_2(Graduation\ Cohort)_i + \varepsilon_i] \qquad (1)$$

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[16] It is of note that I did not need to match the resumes on characteristics since I use standard differential probit methods to analyze the data rather than the audit methodology of a "paired difference of means" test. Since I targeted a large number of firms, and the resumes were sent randomly, I should get the same results with the regressions I run even had I not matched the resumes. Indeed, since there are five possible ages, it is not even clear what the proper "paired difference of means" test should be.

$$= \Phi[B_1(Controls)_i + B_2(Graduation\ Cohort)_i]$$

where 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. Here, *Response* is either a positive response or an interview response, *i* refers to the individual, and the set of graduation cohort dummies include indicators for graduating in 1959, 1966, 1971, 1976 and 1986. *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. Each firm in the sample received two resumes, so results were clustered on firm. Since the explanatory variables are dummy variables, this differential probit reports the discrete change in the probability of interview for each variable.

A second way to test for discrimination is to treat age indicated on resume as a continuous variable using a probit:

$$pr[Response_i =1] = \Phi[B_1(Controls)_i + B_2(Age)_i] \tag{2}$$

Then the marginal effect ∂ prob $(Response_i =1)/\ \partial X_i$ represents the discrete change in the probability of a positive response or interview for each of controls, and the infinitesimal change in the probability of interview for age. *Controls* are as reported before.

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, and run a t-test comparing the probability

of being called back or interviewed for each group. To compare older and younger groups, controlling for resume and industry characteristics, I run an OLS regression for each group:

$$Response_i = \text{B}_1(Controls)_i + \text{B}_2(Older)_i + \varepsilon_t \qquad (3)$$

and retrieve the predicted probability for the response. Then I run a t-test comparing these predicted probabilities for each group. Alternatively, another test for these two groups, again using the probit, is:

$$\text{pr}[Response_i = 1] = \Phi[\text{B}_1(Controls)_i + \text{B}_2(Older)_i] \qquad (4)$$

Where *Older* is a dummy indicating that the worker is age 50 or older. The marginal effect $\partial\text{pr}(Response_i = 1)/ \partial X_i$ represents the discrete change in the probability of interview for each variable.

4.2 Reasons for Differential Hiring by Age

4.2.1 Statistical Discrimination

My experimental setup enables me to explore different possible reasons for this differential hiring, or discrimination.[17] The first type of discrimination I look at is

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[17] I do not differentiate between stereotypes which are true (and thus fit in standard models of statistical discrimination, such as Phelps (1972)) and stereotypes which are false, but employers believe to be true. One can make the argument that since workers who are hired young often age into the firm, that firms which 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

statistical discrimination, which in its most basic definition, is judging an individual on group characteristics rather than individual characteristics. More formally, I assume the model by Phelps (1972) as outlined in Aigner and Cain (1977) where I assume 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.[18] This model provides a framework where positive information about the 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 younger worker, that is, it will help an older worker more than it will help a younger worker.[19]

I tested for statistical discrimination by randomly including items on resumes that signaled that the worker did not fit into a standard stereotype.[20] For example, to test whether employers think older workers are inflexible and unchanging, I include a 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:*

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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.

[18] Average true ability for the two groups is assumed either equal or that true ability is lower for older workers than for younger.

[19] 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 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/worse quality than many white high schools.

[20] Stereotypes examined came from a list of the top 10 reasons for discrimination against older workers according to a 1984 survey of 363 companies where 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.

$$\text{pr}[Response_i = 1] = \Phi[B_1(Controls)_i + B_2(SDR_i) + B_3(Older_i) + B_4(Older_i * SDR_i)] \quad (5)$$

Where *SDR* is the reason for statistical discrimination which 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.

Since an interaction term is measuring the difference between the slopes of the *SDR* term when *Older* = 0 and when *Older* = 1, I can measure the same results 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 coefficients. This format is identical to the interaction:

$$\text{pr}[Response_i = 1] = \Phi[B_1(Controls)_i + B_2(SDR_i) + B_3(Older_i) + B_4(Older_i * SDR_i)] \quad (6)$$

Where *SDR* here is a vector of reasons for statistical discrimination and other variables are as described earlier. Showing regressions separately for *Older* = 1 and *Older* = 0 has the benefit of efficiently showing multiple interactions at the same time.

Another method to differentiate between statistical discrimination and employer taste-based discrimination 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 have less taste-based discrimination because of training and knowledge of discrimination laws, although they might be more likely to practice statistical discrimination through learning.[21]   Thus, I study employer discrimination by interacting a dummy indicating whether or not a company has a human resources department, *HR,* with age:

$$\text{pr}[Response_i = 1] = \Phi[B_1(Controls)_i + B_2(HR_i) + B_3(Older_i) + B_4(Older_i * HR_i)] \quad (7)$$

where *HR* is a dummy variable indicating whether or not a company has a human resources department. *Older* and *Controls* are as described before.

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[22]. To study employee discrimination, I interact age with *Over*50*Work,* the percentage of people employed in the area where the business is located over the age of 50:

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[21] 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.

[22] 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 set-up he uses in that paper is not applicable to this type of audit experiment.

$$pr[Response_i=1]$$

$$= \Phi[B_1(Controls)_i + B_2(Over50Work_i) + B_3(Older_i) + B_4(Older_i * Over50Work_i)] \quad (8)$$

Here *Over*50*Work* is a continuous variable indicating the percentage of people over the age of 50 who work in the firm's place of work PUMA, as indicated by the 2000 census. *Controls* and *Older* are defined as above.

Customer

My test for customer taste-based discrimination is similar to that of 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:

$$pr[Response_i=1]$$

$$= \Phi[B_1(Controls)_i + B_2(Over50_i) + B_3(Older_i) + B_4(Older_i * Over50_i)] \quad (9)$$

Here *Over*50 is a continuous variable indicating the percentage of people over the age of 50 who live in the firm's zipcode, as indicated by the 2000 census. Since people who work in services and sales are more likely to interact with consumers, I also run equation *(9)* using only service and sales occupations.

5 Results

5.1 *Differential Hiring 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 from the 0 to 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.[23] Table 1 describes t-test results comparing the mean response rates for these two age categories with controls as calculated in (*3*) and without controls. For callbacks, there is a difference of 1.5 percentage points, or 19%, in Massachusetts and 1.7 percentage points, or 18%, in Florida. For interviews, these differences are 1.6 percentage points, or 42%, for Massachusetts and 2.0 percentage points, or 46%, for Florida.[24] The average younger job seeker in Massachusetts needs to

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[23] 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.

[24] 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% more likely to get an interview in Massachusetts and -.02 to 117% more likely to get an interview in Florida.

file, on average, 11 ads to get one callback whereas an older 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 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 callbacks in Massachusetts, as shown in Table 2.

A final way of looking at the effect on age is to actually regress on age as if it were a continuous variable as in equation (*2*). This method provides more power than using age dummies. Table 2 shows that the marginal effect coefficient on age is negative but and significant at the 5% level for positive responses in Massachusetts but negative and not significant in Florida. That is, for each additional year of age, a worker is .07% less likely to be called back in Massachusetts and between .04% and .06% less likely to be called back in Florida.[25] This effect is both negative and significant at the 5% level for the interview response, with each additional year of age causing a worker to be .07% less likely to be called back for an interview in Massachusetts and between .067 and -0.09 less likely to be called for an interview in Florida. Thus there is differential interviewing by age. Specifically, assuming linearity[26], in Massachusetts, the mean applicant would have to answer 1 additional ad to receive a callback for each additional 10 years of age, and 4.5 additional ads to receive an interview request. In Florida, each additional 10

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[25] 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 resumes. In ordinary least squares model the coefficient would not change. Additionally, although age is uncorrelated with the controls by design, in a finite sample there may still be correlation induced by chance.

[26] 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.

years of age would require 5 more ads to produce a callback and 3.5 more ads to produce an interview (interview responses have a lower base rate, so even though the percentage decrease by age is more interviews, .067% rather than .04%, this decrease translates into a worker having to apply to 10.7 rather than 10.2 ads for each year of age to get a callback and 23.2 rather than 22.9 ads for each year for an interview).

Companies could also discriminate in more subtle ways than 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 where 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 briefly looked at 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.[27] Since 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 Hiring by Age

Economists recognize two main categories of discrimination: statistical discrimination and taste-based discrimination. Statistical discrimination can occur based on observables, such as work history or typographical errors, or unobservables, such as energy or ability to learn. In my experimental setup, observables are identical for each

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

resume pair sent and thus cannot be responsible for the differential hiring. To look at the effect of unobservables, I included items on the resumes 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 from running equation (*5*) separately by older status.

5.2.1 Statistical Discrimination

Employers may statistically discriminate because they fear that older workers will "cost" more in terms of absences and benefits. To test whether or not companies statistically discriminate against older workers because they assume older workers will have more absences, I introduced an item on the resume saying that the applicant has won an attendance award. This variable is positive but not significant at the 5% level. If anything, attendance awards help younger workers more than older in terms of magnitude. To see whether or not 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.[28]   Although having insurance seems to help getting a callback overall in Massachusetts, nothing can be said by age at the 5% 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

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[28] Although, according to Blue Cross/Blue Shield of Massachusetts (personal communication), health insurance costs generally stay the same for women until the age of 65 (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 which 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.

results are not 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 only significant at the 40% level.[29] Vocational training[30] helps younger workers more than older workers to get both callbacks and interviews. An interaction between vocational training and older (not shown) gives this result to be significant at the 5% 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 resume saying the applicant plays sports. For the most part, this variable is not significant. It is significant and negative for the callback response for younger workers in Massachusetts and significant and positive for the interview response for younger workers in Florida. Although an interaction term shows putting sports on the resume to hurt older workers less than younger workers, this finding is only significant for positive responses at the

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[29] Interaction results have also been done using the Norton adjustment, and results still hold (Norton et al. 2002). Magnitudes may change, but signs and 5% significance do not.
[30] Note that occupation and vocational training are mechanically related in this experiment because vocational training was only given to resumes for which it was required (such as dental assisting or nursing).

20% 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.[31] Fourth, Bendick (1996) found that the biggest help to an older worker's resume was to signal that he or she was flexible or "willing to embrace change." Although only significant at the 10% level for Massachusetts, I found that having this statement on a resume hurts an older worker, but does not hurt a younger worker.[32] This difference in findings may be because the AARP has been recommending that older workers put such statements on their resumes 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 experience with age are significant at the 5% level (not shown), having occupational experience listed on the resume similar to occupation being applied to the helps younger workers more than older workers as shown in Table 4. However, a different effect is found for implied experience—that is, when the want-ad requires experience[33]; older workers were hurt less

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[31] The interaction of older and volunteer is positive and significant at the 25% for positive outcomes and 30% level for interview outcomes in Florida, but only at the 46% level for interview in Massachusetts.

[32] The interaction of older and flexible is significant at the 14% level for the interview variable in Massachusetts and at the 70% level for Florida.

[33] Admissible want-ads could include requirements of up to a year of experience, whether the applicant had it on the resume or not.

than younger workers, as shown in Tables 4, although again, this finding is not significant at the 5% 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 resume. 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 the employer him or herself (or those doing the hiring) prefers one group over another based on his or her 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 using equation[34] (7). In my study, firms with human resources departments may be more likely to interview younger workers, which would support the case of statistical rather than taste-based discrimination, but this finding is not

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[34] I also have a rough variable for firm size (fewer than 15 employees, 15-19 employees, 20 or more employees). I find no relationship between firm size and hiring practices.

significant.[35] The controlled coefficient on the interaction term between *Older* and *HR* for Florida for the interview outcome is -0.007with a standard error of 0.018 and this coefficient for Massachusetts is -0.017 with a standard error of 0.0195.[36]

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 zipcodes 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.[37] I found no effect of the age of a company's workforce on the differential hiring by age, thus providing no support for employee taste-based discrimination (results not shown).[38] However, this measure may be too crude, as it matches zipcode 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. Consumers may prefer to buy from or interact with employees who are like them. To test

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[35] Another possible way of measuring employer taste-based discrimination is to examine the hiring 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, was recently sued for age discrimination *http://www.cnn.com/2004/LAW/03/02/dick.clark.sued.ap/.*

[36] A Norton correction does not change the sign or significance of these effects. The main effects for Florida are -0.008 for older and 0.010 for HR. In Massachusetts, these effects are -0.021 for older and 0.018 for HR.

[37] 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.

[38] 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.

for this type of discrimination, I used the census to get age profiles of zipcodes in Florida and Massachusetts and matched them to the zipcodes 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 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, the number of applications sent to receive an interview vary 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.[39] Second, many occupations have a limited number of positions advertised each week. For example, on a

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[39] With "low" and "high," I am only including general occupation categories that have at least 200 resumes 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 resumes were sent to p/t non-healthcare positions in Florida. There were 558 healthcare resumes sent in Florida and 1057 clerical resumes sent in Massachusetts.

randomly chosen Sunday in Florida, there were 34 LPN 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.[40] Finally, given that the wages for 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 cannot receive employment benefits.

What does this mean for older vs. 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[41] finds that it takes 7-10 interviews on average for a college graduate to obtain a job offer. Using a back of the envelope calculation with one of the professions most likely to be hired, a new licensed practical nurse[42] 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 7-10 interviews to land a job, a younger worker could expect an employment offer in a little over a week, and an 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 there are 100 unique new clerical ads each week, which, since a large number of ads are run at least two weeks in a

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[40] Which was the case in Florida.

[41] www.onestop.com

[42] A profession which 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

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 found that younger applicants are 44% more likely to be requested for an interview in Massachusetts and 43% more likely in Florida. The extent of discrimination against older workers is similar to that of discrimination against women or blacks.[43] I found no evidence of taste-based discrimination. I found some 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.

In the current labor market, older workers face greater difficulty obtaining interviews for entry-level positions than do younger workers. The demand for older compared to 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 as younger workers become relatively scare. However, as younger workers become scarce, the relative demand for them should rise, assuming

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[43] Neumark et. al (1996) find evidence of 47% differential interview requests against female waitstaff in high-price restaurants and 40% towards female waitstaff in lower-price restaurants. Bertrand and Mullainathan (2003) 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.

older and younger workers are imperfect substitutes. Demand for all workers may change as the national economy grows or shrinks. 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. 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% of older applicants and 1% of younger workers. I also found differences in differential hiring between occupations; Blue-collar and male-dominated occupations in the sample tend to prefer older workers to younger. Since 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.

Another reason for discrimination against older workers that could not be tested in this set-up is that older workers cost more because they can sue employers under the Age

Discrimination in Employment Act. Lahey (2005), looks at the effect of age discrimination laws on older workers. Although it finds that these laws have a significant and negative effect on older white men, it does not find a similar effect for older women. Since 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 that the demand for labor from older workers is smaller than that for younger workers. Simply encouraging older workers to reenter the labor force will 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 unexpectedly need to enter the labor market, 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 which 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 to create many different possible resumes is a large improvement over earlier studies. First, unlike studies where a limited number of resumes are used, it lessens (and can test for) the possibility that an employer is reacting to something specific in the particular resume sent out. Additionally, because there is no human interaction with the resume during its creation, the possibility of injecting subjectivity into the process of matching resumes

with job openings is completely eliminated. Resumes and resume 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 resumes 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 or not to test for one or more of the possible reasons for discrimination through adding items to the resume. 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 resumes ranged as follows. Candidates were named Mary E. Smith or Linda Jones.[44] 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

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[44] Mary gets a middle initial because in my experience, and the experience of those I've spoken with, 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.

to obtain. All resumes 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, Iowa and DeKalb High School in DeKalb, IL. Some resumes

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 resumes had email addresses

listed.[45] 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, purposefully

coded typographical errors were programmed into the resume machine during the first

half of the study when there was more hiring in general. These typos were representative

of those found in actual resumes—they included things like missing punctuation marks,

large words that had been misspelled and inconsistent indentation. The second kind of

error was inadvertently introduced when applying for a job that did not fit one of the

major job categories in the resume program. These errors included things like putting an

"a" where an "an" should be or other similar mistakes that native English speakers do not

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

normally 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.

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 resume 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 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 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 email address and later generated a resume and sent it. If there was no fax or email 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 2. Want-ads are more likely to get both positive and interview responses than Call-ins, faxes slightly more likely than emails. 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 hiring 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% of openings compared to 19.5% 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.

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Figure 1:   Response Rates in Massachusetts
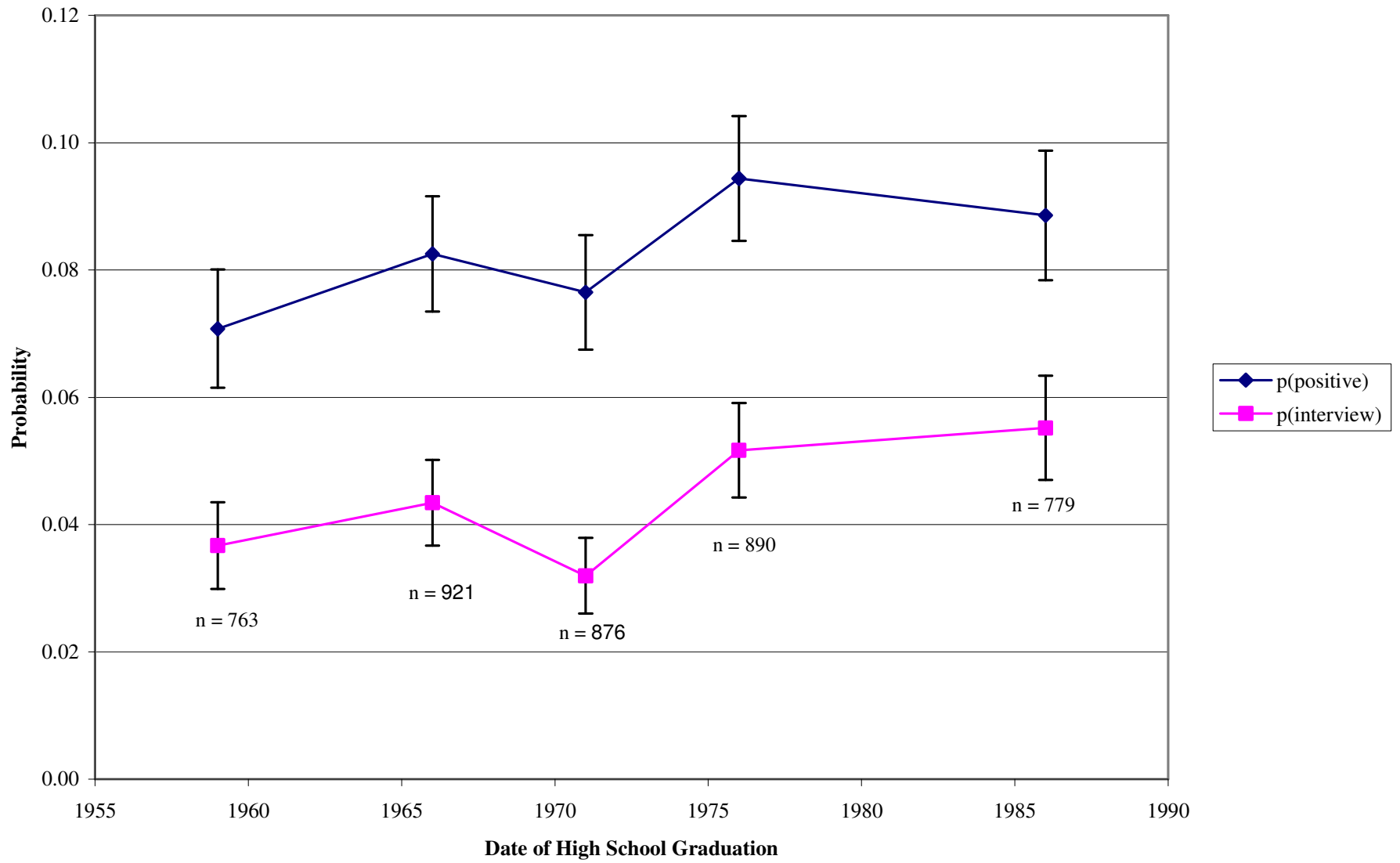
Figure 2:   Response Rates in Florida
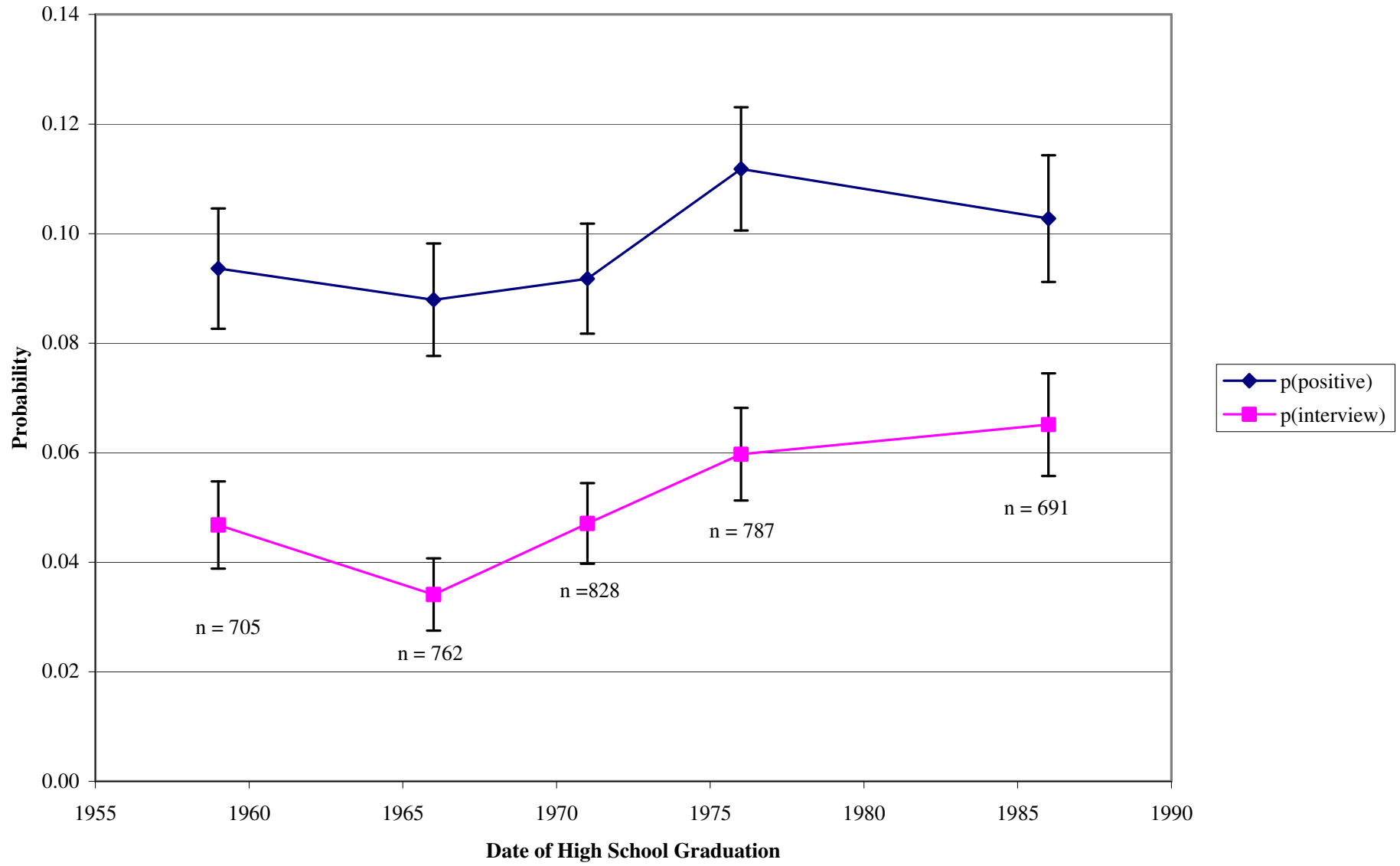
Table 1
Mean Response Rates by Age

	Older		Younger		Difference		# ads needed Older		Younger	
	Positive	Interview	Positive	Interview	Positive	Interview	Positive	Interview	Positive	Interview
MA										
no controls	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)				
with controls	0.076	0.037	0.092	0.053	0.016	0.016	13.08	27.06	10.87	18.79
	[2564]	[2564]	[1673]	[1673]	(0.07)	(0.01)				
FL										
no controls	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)				
with controls	0.091	0.042	0.103	0.060	0.013	0.018	11.05	24.07	9.66	16.74
	[2321]	[2321]	[1510]	[1510]	(0.14)	(0.01)				

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

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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		-0.00077			-0.00071			-0.00042			-0.00073	
		(0.00038)*			(0.00029)*			(0.00045)			(0.00032)*	
older=50+			-0.015			-0.016			-0.014			-0.017
			(0.007)*			(0.005)**			(0.008)+			(0.006)**
hs59	-0.020			-0.016			-0.002			-0.009		
	(0.010)*			(0.006)**			(0.013)			(0.008)		
hs66	-0.007			-0.010			-0.011			-0.025		
	(0.011)			(0.007)			(0.012)			(0.007)**		
hs71	-0.014			-0.020			-0.003			-0.009		
	(0.009)			(0.006)**			(0.012)			(0.008)		
hs76	0.002			-0.004			0.017			0.001		
	(0.011)			(0.007)			(0.014)			(0.008)		
Observations	4229	4229	4229	4229	4229	4229	3769	3769	3769	3618	3618	3618
Ho[†]	6.45	4.02	5.00	12.22	6.30	10.26	5.70	0.88	3.16	12.08	4.82	7.14
Ho: p-value	(0.1680)	(0.0450)	(0.0254)	(0.0158)	(0.0121)	(0.0014)	(0.2226)	(0.3483)	(0.0752)	(0.0168)	(0.0282)	(0.0075)

Notes: Results reported are marginal effects from a probit equation. 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					
	Callback			Interview			Callback			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	-0.013	-0.005	-0.025	-0.005	0.001	-0.014	-0.002	0.009	-0.019	0.002	0.001	0.006
	(0.008)	(0.009)	(0.013)	(0.006)	(0.006)	(0.010)	(0.009)	(0.012)	(0.015)	(0.006)	(0.008)	(0.011)
vocational train.	0.077	0.063	0.100	0.035	0.015	0.081	0.127	0.124	0.138	0.047	0.036	0.070
	(0.019)**	(0.022)**	(0.036)**	(0.014)*	(0.013)	(0.032)*	(0.024)**	(0.031)**	(0.037)**	(0.016)**	(0.020)	(0.028)*
computer	0.007	0.006	0.008	0.010	0.011	0.009	0.013	0.009	0.018	0.018	0.014	0.025
	(0.008)	(0.010)	(0.014)	(0.006)	(0.007)	(0.011)	(0.009)	(0.012)	(0.015)	(0.007)**	(0.008)	(0.012)*
volunteer	0.030	0.027	0.036	0.013	0.015	0.010	-0.001	0.008	-0.015	-0.011	-0.005	-0.020
	(0.008)**	(0.009)**	(0.013)**	(0.006)*	(0.006)*	(0.010)	(0.009)	(0.011)	(0.015)	(0.006)	(0.008)	(0.011)
sports	-0.013	-0.004	-0.026	-0.005	-0.003	-0.007	0.008	0.008	0.008	0.017	0.012	0.026
	(0.008)	(0.009)	(0.013)*	(0.006)	(0.006)	(0.010)	(0.009)	(0.011)	(0.015)	(0.006)**	(0.008)	(0.011)*
insurance	0.016	0.015	0.019	0.009	0.007	0.013	-0.002	-0.005	0.001	-0.007	-0.011	-0.002
	(0.008)*	(0.009)	(0.013)	(0.006)	(0.006)	(0.010)	(0.009)	(0.012)	(0.015)	(0.006)	(0.008)	(0.011)
flexible	-0.010	-0.016	0.000	-0.002	-0.008	0.008	-0.012	-0.009	-0.019	-0.007	-0.009	-0.004
	(0.008)	(0.009)	(0.013)	(0.006)	(0.006)	(0.010)	(0.009)	(0.012)	(0.015)	(0.006)	(0.008)	(0.011)
attendance	0.009	0.004	0.016	0.005	0.003	0.007	0.016	0.016	0.018	0.002	0.001	0.003
	(0.008)	(0.009)	(0.013)	(0.006)	(0.006)	(0.010)	(0.009)	(0.012)	(0.015)	(0.006)	(0.008)	(0.011)
typo	0.011	0.016	0.005	-0.003	0.003	-0.010	0.011	0.003	0.022	0.005	0.004	0.006
	(0.011)	(0.014)	(0.018)	(0.007)	(0.009)	(0.013)	(0.011)	(0.013)	(0.018)	(0.007)	(0.009)	(0.013)
Observations	4229	2560	1669	4229	2560	1669	3773	2279	1478	3755	2267	1427
Ho[†]	49.87	24.70	29.97	21.55	11.92	17.52	52.16	29.82	28.47	32.27	13.56	22.20
p-value	(0.0000)	(0.0017)	(0.0002)	(0.0058)	(0.1548)	(0.0252)	(0.0000)	(0.0002)	(0.0004)	(0.0001)	(0.0941)	(0.0046)
standard dev.[‡]	0.056	0.055	0.064	0.031	0.030	0.039	0.067	0.055	0.094	0.042	0.031	0.064

Notes: Results reported are marginal effects from a probit equation. Additional controls not shown are occupational controls for professional, education, healthcare, manager, sales, craftsman, operative, service, laborer and clerical.

* 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 experience	0.016 (0.008)*	0.012 (0.008)	0.025 (0.013)	0.011 (0.008)	0.002 (0.009)	0.029 (0.015)						
experience required							-0.021 (0.005)**	-0.017 (0.006)**	-0.025 (0.009)**	-0.027 (0.006)**	-0.026 (0.007)**	-0.030 (0.011)**
Observation	3651	2207	1444	3266	1980	1168	4228	2560	1668	3755	2267	1427

Notes: Results reported are marginal effects from a probit equation. 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.

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

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					

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	0.044	0.027	0.018	0.007
	(0.025)	(0.019)	(0.026)	(0.017)
Over 50	-0.015	-0.018	-0.013	-0.016
	(0.010)	(0.007)	(0.009)	(0.007)
EOE/AA*over 50	-0.009	0.004	-0.024	-0.010
	(0.024)	(0.019)	(0.022)	(0.016)

Notes: Standard errors in parentheses