Experimental Age Discrimination Evidence and the Heckman Critique, David Neumark, Ian Burn and Patrick Button

Replication exercise from Justine Nayral

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Abstract

This essay replicates the paper from David Neumark, Ian Burn and Patrick Button, published in 2016 as proceeding in the *American Economic Review.* This paper, using a method developed by Neumark (2012) emphasizes the necessity for accounting for the Heckman Critique and difference in unobservables variances in order to get an accurate measurement of discrimination. After conducting a large correspondence study, they observe more ambiguous effect of age discrimination against men than in past studies.

This replication exercise checks the robustness and discuss the main results. It extends the paper by providing a similar analysis for women applicants, which suggests a differentiated age discrimination according to gender. It also uses the dataset provided by the author to explore the temporality of the hiring process. While the time for responding is quite similar across age groups, a jump in the hazard rate suggests different strategies for hiring from employers.

Keywords: Age Discrimination, Labor Market, Replication

1 Introduction

Population ageing, combined with falling fertility rates, is affecting many developed countries. On average, the proportion of the population aged over 65 has risen from less than 9% in 1960 to more than 17% in 2019 in OECD countries, and according to projections, this trend will continue unabated over the coming decades. In response to this ageing population, reforms have been introduced in the US to extend the retirement age at which full benefits are available from age 65 to age 67, and to reduce Social Security benefits at the early retirement age of 62.

However, despite laws condemning discrimination in the United States such as the Equal Pay Act (1964), Title VII of the Civil Rights Act (1964), the Age Discrimination in Employment Act (ADEA, 1967), and the Americans with Disabilities Act (1991), studies by economists and other social scientists point to the persistence of age discrimination in the labour market. People in their fifties and sixties tend to be unemployed for longer periods (Neumark and Button, 2014). Experimental studies such as Bendick, Jackson and Romero (1997) estimated a "net discrimination" of 26.5%. Young applicants (age 32) received for 43% positive responses versus 16.5% for Older applicants (age 57).

Experimental methods, are based on audit or correspondence studies to measure discrimination. While audit studies use 'real' candidates coached to like alike and measure differences in job offer rates they may not ensure that applicants look identical to employers. Correspondence studies address this problem by using fictitious candidates, either electronically or on paper, and measure 'call-backs' for interviewers. Correspondence studies allow the collection of large samples and avoid the "experimenter effects" that can make the behaviour of candidates different in audit studies (Heckman and Siegelman, 1993). However, Heckman (1998) pointed out that in audit or matching studies, when the variance in unobservable productivity, which cannot be eliminated by the design of the experiment, is different from one group to another, biaises in favor or against the presence of discrimination can be generated.

In this scientific context, Neumark, Burn and Button in their paper Experimental Age Discrimination Evidence and the Heckman critique (2014), used a method developed in Neumark (2012), aiming at measuring age discrimination, while accounting for the Heckman critique. Indeed, the problem raised by Heckman could be important in the measure of age discrimination. As mentioned , in the model of human investment, the range of earnings widens with age, potentially generating greater variance in unobservables between Younger and Older candidates. The variation in investment in human capital is unlikely to be fully conveyed on the resumes.

This paper replicates, analyses and checks the results of, Neumark, Burn and Button (2016) to study age discrimination against Old men in the labor market taking into account the Heckman critique. Section 2 provides a brief summary of the paper and a presentation of the empirical methodology adopted by the authors. Section 3 presents their theoretical framework. Section 4 replicates, checks the robustness and discusses the main finding of the authors. Section 5 extends the analysis by providing original extensions, which consist in running an analog analysis for women and studying if the delay for responses differs among different age groups.

2 Summary

Neumark, Burn and Button (2016) study age discrimination by following the standard procedure for designing a correspondence studies and then run a statistical analysis taking into account the Heckman critique. They first study if there is a significant difference in the callback rates between different age group, which would have suggested a discrimination towards the Oldest applicants. Then, they estimate, using a probit specification, the effect of skills and interaction between skills and age on the probability of receiving a positive response in order to get an intuition on the difference in variances unobservables. Finally, they use an heteroscedastic model and decompose the estimate for age into a part explained by differences in variances of unobservables and a part capturing discrimination. They find ambiguous evidence for age discrimination, suggesting the issue caused by differences in variances of unobservables need to be considered when experiments are designed. Section 3 presents in detail the theoretical framework adopted by the authors to account for the Heckman critique

In order to run such an econometric analysis, they constructed fake resumes and measure how the callback rates differs among groups. They used the Current Population Survey (CPS) Tenure Supplement database to identify jobs with a high representation of Older workers with low tenure (five years or less). They chose "retail sales (retail salespersons and cashiers); administrative assistant (secretaries and administrative assistants, receptionists and information clerks, office clerks, and file clerks); Janitors (Janitors and building cleaners); and security guards (security guards and gaming surveillance officers)" (Neumark, Burn and Button, 2015). They targeted the resumes to jobs in specific cities, with a job and education history matching with each place, as low skill workers have low geographic mobility (Molloy et al., 2011). They constructed job histories based on job titles and description from actual resumes. They created jobs applicants aged 29-31, 49-51 and 64-66. To address the Heckman critique, they designated half of the resume within each age category to be low or high skilled applicants. High skills resumes indicate five among seven possible skills, randomly chosen. There are five common skills (fluency in spanish, college degree, "employee of the month" award in the most recent job, a volunteer activity among three possible, absence of grammar mistakes in the resume) and two occupation-specific skills. Low skill resumes only list a high school diploma and two typos. They assigned applicants to the same employer, either high or low skilled with a 50 probability each. Residential addresses were chosen to be realistic without "signaling a race other than white, or other positive or negative information" and were randomly assigned with age so there was no association between the socioeconomic status of the neighborhood and the age of the applicants (Neumark, Burn and Button, 2015). The authors sent more than 40 000 resumes. They constructed triplet, for each job ad, with one Young applicant and, with one third probability, either two Middle-aged applicants, two Old applicants, or one Old and one Middle applicants. For the Middle-aged and Older applicants the resumes differs if they indicate commensurate experience or by the different types of bridge resumes. Every triplet are differentiated according to sex, city and day of the month resumes are sent to the employer.

In this paper, Neumark, Burn and Button only investigate discrimination for male applicants in Sales, Security and Janitors, analysing almost 7000 applications. Even if the resumes were randomly sent, some occupations received only gender specific resumes. Table A.1 indicates the proportion and absolute number of applicants per gender. In Administration and Security respectively, only women and men resumees were sent. In Janitor, only 2.86 % of resumees concerned women applicants. In Sales however, the proportion of men and women is closed, respectively 53.19% and 46.81%. The authors study discrimination relative to age within each of the three occupations, were men applicants are present: Security, Sales and Janitor.

Summarizing the data for each gender, we get the proportion of each category of individuals by gender. Table A.2.1 and Table A.2.2, respectively indicates the proportion of men and women applicants having a specific skills, within each age group. As mentioned above, in all cases (except Janitor for women) we notice that the proportion of high skilled applicants in each category is closed to 0.5 as expected by the random assignment. Moreover, the proportion of jobs applicants having a common or specific skills does not vary across age groups. It is closed to 30% as expected by the random assignment. However, for women job applicants in Janitor (Table A.2.2), low skills applicants represents 75% of women applicants and the attribution of skills is not balanced accross group. For instance, 0% of Middle age applicants are fluent in spanish while this proportion is 19% and 25% respectively of Young and Old applicants. This is can be due to the low number of applicants (48 and only 16 for each age category). Moreover, while the number of applicants for each age category is quite the same within each occupation for men, there are 2040 Old women applicants in Sales against 1599 and 1098 respectively Young and Middle age. Because the number of observations is relatively high, this is not a major problem.

With a perfect random assignment, the mean of each variable would be the same for each age group. Even if there are some minor differences within each occupation between Middle, Young and Old applicants, skills are almost equally distributed among age groups, except for women applicants in Janitor. Because of the high heterogeneity in skills attribution, it is likely the causal effect from this too small sample would be biased. That's why this group is excluded from the analysis in Section 5.

3 Adressing the Heckman critique: econometric specification

This section presents the theoretical framework adopted by the author to adress the Heckman critique and potential bias in the measure of age discrimination. In this model, productivity depends linearly on two productive characteristics: X^I, included in the resume and observable and X^{II}, unobserved by the firms. S and Y, respectively denote Older and Young applicants. γ is an additional linear additive term which captures taste discrimination, not correlated with productivity. This means that for identical productive characteristics, the employer prefers one group to another. In addition to this taste-based discrimination, can exist statistical discrimination: $E(X_S^{II}) \neq E(X_Y^{II})$. This reflects the employer beliefs, that the unobserved variables are on average different across groups. Both kinds of discrimination are illegal in most of the countries and in the United States in particular.

The Old worker receives a positive response (i.e. $T(X^{I*}, X_S^{II})|(S = 1) = 1$, if the perceived productivity minus the distaste factor γ exceeds a certain threshold c. Similarly, the Young worker receives a positive response if the perceived productivity is above the same threshold c.

$$T(X^{I*}, X_S^{II})|(S = 1) = 1 \quad \text{if} \quad \beta_1 X^{I*} + X_S^{II} + \gamma > c \tag{1}$$

$$T(X^{I*}, X_Y^{II})|(S = 0) = 1 \quad \text{if} \quad \beta_1 X^{I*} + X_Y^{II} > c \tag{2}$$

X_S^{II} and X_Y^{II} are the residuals.

If an assumption is made about the distribution of unobserved characteristics, the probability of the callback rate can be calculated. For instance if X_S^{II} and X_Y^{II} are normally distributed with zero mean and respectively σ_S^{II} and σ_Y^{II}, their standard errors, the callback probability can be estimated using a distribution function Φ.

$$S = 1 : \Phi\left[\frac{\beta_1 X^{I*} + \gamma - c}{\sigma_S^{II}}\right] \tag{3}$$

$$S = 1 : \Phi\left[\frac{\beta_1 X^{I*} - c}{\sigma_Y^{II}}\right] \tag{4}$$

As such the probability of hiring depends on observed characteristics X^I and variance on unobserved characteristics X^{II}, the latter being a source of uncertainty. However, assuming there is no statistical nor taste-based discrimination , a difference in the variance of unobservables can generate bias in either direction.

Suppose X^{I*} described observed characteristics defined by the researcher and is the same among both Young and Old group. It is set low relative to the resumes the employer usually sees. Then if $\sigma_S^{II} > \sigma_Y^{II}$, the Old are more likely to exceed a given productivity threshold. If the resumes are on average low skilled, the Young (low variance group) are less likely to have a high productivity above the thresehold and reversely the Old (high variance group) are more likely to have a high productivity. As such, Old will be favored against Young. We can find $\Phi\left[\frac{\beta_1 X^{I*}+\gamma-c}{\sigma_S^{II}}\right] > \Phi\left[\frac{\beta_1 X^{I*}-c}{\sigma_Y^{II}}\right]$ even if $\gamma = 0$. If $\sigma_S^{II} < \sigma_Y^{II}$ and X^{I*} low, the reverse can happen for the same reasons as described above. Because the researchers does not know X^{I*}, even if he knows if $\sigma_S^{II} > \sigma_Y^{II}$, it is impossible to assess the sign of the bias.

In Neumark (2012), a solution to this problem is proposed. Substracting equation (4) and (5), we get the difference in probability between Old and Young applicants:

$$\Phi\left[\frac{\beta_1 X^{I*}+\gamma-c}{\sigma_S^{II}}\right] - \Phi\left[\frac{\beta_1 X^{I*}-c}{\sigma_Y^{II}}\right]$$

In a standard Probit, only coefficients relative to the standard deviation of the unobservable can be observed. Normalizing $\sigma_Y^{II} = 1$, thus $\frac{\sigma_S^{II}}{\sigma_Y^{II}} = \sigma_{SY}^{II}$, which implies:

$$\Phi\left[\frac{\beta_1 X^{I*}+\gamma-c}{\sigma_{SY}^{II}}\right] - \Phi\left[\beta_1 X^{I*}-c\right]$$

Without knowing, σ_{SY}^{II}, it is not possible to assess if the difference in probabilities differs because of discrimination $\gamma \neq 0$ or because of a difference in the variance of unobservables $\sigma_{SY}^{II} \neq 1$. It is however possible to get an estimate for σ_{SY}^{II} if there is variation in the level of qualifications used as controls X^{I*}. Indeed, it becomes possible to identify β_1, and $\frac{\beta_1}{\sigma_{SY}^{II}}$ and thus get an estimate for σ_{SY}^{II}. Thanks to this estimate for σ_{SY}^{II}, it is possible to identify γ. That is why the authors decided to sent resumes with different skills, for them to identify γ.

Assumption 1:
The underlying coefficients β_1 are the same for all age groups.

The key assumption to make such an identification is that β_1 is the same for Young and Old applicants otherwise it is not possible to identify σ_{SY}^{II}. In reality, it is not likely β_1 is the same among groups. For instance, the Older cohort may not have the same opportunities in terms of schooling mobility and may not have attended the same school. An additional year of schooling may have different effects on productivity. However, in the correspondence study, it is possible to correct from these different by controlling from cities, and schooling district.

The next section presents the empirical results from Neumark, Burn and Button, which point out the importance for accounting for the Heckman critique in order to avoid a biased measurement of age discrimination.

4 Results and Robustness checks

Applying the method developed by Neumark (2012), this section presents the empirical strategy adopted by the authors, replicates the main results of the paper and discuss their robustness.

4.1 Difference in Callback Rates

The authors try to identify discrimination by comparing the callback rates of men applicants by age within each occupation. The callback rates is defined as the proportion of applicants, who received a call after applying to a job offer. Even if the correspondence study only captures the callbacks rate and not the actual jobs offers, some studies found evidence indicating that most of the discrimination occurs at the selection for interview stage. For instance, Riach and Rich (2002) based on studies from the International Labour Organization (ILO), found that 90% of the discrimination in these studies occured at the first stage of the selection. Similar findings are reported in Neumark (1996). As such, the callback rates is an indicator for the presence of discrimination.

Table 4.1 replicates the original table 1 in the paper, adding the callbacks rate for the Middle category and the p-value for each combination. Adding this intermediate category allow to assess the robustsness of the result of the authors. Indeed, it may be possible that there exist only significant differences for Young vs Old applicants. The number of observations is thus higher than in the original paper (it includes Middle category). For Janitor, only resumes for Older and Middle applicants with commensurate experiences are used. Indeed, having the same low experience for Old and Young applicants can generate biased measure of age discrimination. The absence of relevant experience commensurate to the age of Older applicants can be perceived as a negative signal for the employer. It can make the Older applicants less qualified than the other Older applicants the employers use to see. This can lead to an overestimation of age discrimination towards Older applicants. The authors found in their working paper (Neumark, Burn, Button, 2015) that this is particularly true for Janitors, which justify using only the high (commensurate) experience resumes for Older Janitor applicants.

According to Table 4.1, the callback rates decreases with the age of the applicants for any occupation. The authors run a Fisher two-sided exact test to assess the difference in the callbacks rate is significant between the group studied. Under the null hypothesis that the callback rates are independent of age, a low p-value indicates that there is a low probability for the null hypothesis being true. The lowest the p-value, the more likely the presence of discrimination is. For Sales jobs, the callback rate is significantly lower at the 0.01 level for Older applicants (14.70%) than for Young and Middle job applicants, respectively 21.09% and 20.89%. This difference in the callback rate is significant for Young vs Old vs Middle (p-value=0.000) but is not between Midle and Young only. For Security, the callback rate also decreases with age but the different is marginally significant for Young vs Old (p=0.123) and Middle vs Young (p=0.094). For Janitors, the callbackrate and the

p-value differ slightly in Table 4.1 from the table in the original paper. Indeed, while the authors only consider men for their analysis of age discrimination, they have forgotten to exclude the few women in Janitor occupations. Below is the corrected table. Despite this error, the differences in callback rates remain similar as well as the p-value for Young vs Old (0.48 in the original paper against 0.528 in Table 4.1). The callback rate difference for Janitor is quite similar as the one for Security but is not statistically significant.

Thus, Table 4.1 suggests it could exist discrimination against Older applicants. In the rest of their study, the authors only consider potential discrimination of Older applicants compared to the Youngest. Indeed, there are no clear evidence for discrimination of Young vs Middle and for Middle vs Old (except in Sales). Nevertheless, the authors mention that the evidence of age discrimination are less strong than in past studies, which can be due to a difference in unobservables.

Table 4.1: Callback Rates of Men by Age
(Table 1 in original paper)

		Young (29-31)	Middle (49-51)	Old (64-66)
Sales ($N = 5348$)				
Callback (%)	No	79.11	78.91	85.30
	Yes	20.89	21.09	14.70
Test of independence (p-value)	Young vs Old vs Middle	Young vs Old	Middle vs Young	Middle vs Old
	0.000	0.000	0.902	0.000
Security ($N = 4147$)				
Callback (%)	No	75.72	78.45	78.26
	Yes	24.28	21.55	21.74
Test of independence (p-value)	Young vs Old vs Middle	Young vs Old	Middle vs Young	Middle vs Old
	0.163	0.123	0.094	0.926
Janitor ($N = 1090$)				
Callback (%)	No	66.97	67.28	69.20
	Yes	33.03	32.72	30.80
Test of independence (p-value)	Young vs Old vs Middle	Young vs Old	Middle vs Young	Middle vs Old
	0.810	0.528	1.000	0.647

Notes: The p-values are calculated from a Fisher exact test (two sided test). For Janitor, only resume with commensurate experience are used for Older and Middle applicants.

4.2 Probit estimates for Callbacks per Age

Then the author run a probit regression including skills indicator and interactions between the skills and the age indicator, which suggests that there exist variance in unobservables. They run a probit regression corresponding to the following latent model:

$$C_i = \alpha + \gamma S_i + \beta X_{iI}^I + \delta X_{iI}^I S_i + \varepsilon_i \tag{5}$$

With S_i a dummy variable taking value 1 for senior applicants and 0 for Young. Under assumption 1 that the underlying coefficients for the two age groups are the same, differences between the probit coefficients by age are informative about differences in the variances of unobservables. For example, taking the Young applicants as the reference group, if the variance in unobservables is higher for Seniors than for Young applicants, for any skills, the probit coefficient for the skill variable and the probit coefficient for the interaction should be the opposite signs. The interaction terms decreases the overall absolute skill effect for Older applicants . Indeed, the combined effect of the skill for senior applicants should be closed to zero.

Table 4.2 replicates table 2 in the original paper, which provides the probit estimates for callbacks by age for Old versus Young including the marginal effect of skills and interactions of Old with skills. They controlled for city, order of resume submission and employed/unemployed status. As in Table 4.1 the number of observations for Janitor is slightly lower and there are minor differences in the coefficients obtained. Indeed, the authors have forgotten to exclude women in their analysis for Janitors. The authors performs a t-test under the null hypothesis that the coefficient of interest is zero.

For Sales applicants, there are no skills of which coefficient are statistically significant. For some skills, such that employee of the month, the interaction is in the opposite sign, suggesting a higher variances of unobservables for Older applicants while for consumer service, both coefficient are positive, which would lead to the inverse conclusion. As such, the way the estimate would change while accounting for differences in variances of the unobservable is not clear. For Security applicants, spanish and license, the coefficients are significant and positive. These skills may predict hiring. On the contrary, the coefficient for CPR is negative and significant at the 0.1 level. For spanish, the interaction coefficient is also positive, which suggests the overall effect for Old applicants is larger. It may indicate a lower variance in unobservables. However, for license and CPR, the overall effect is closed to zero, the interaction coefficient being in the opposite sign as the skill coefficient. This suggests a higher variance in unobservables for Older applicants. Finally, for Janitors, college and technical skills, coefficients are positive and significant at the 0.05 level while the interactions coefficients are negative, which is consistent with a higher variance in unobservables for Old applicants. However, the coefficient for volunteer is negative and significant at the 0.05 level and the interaction coefficient is also negative, which could predict the contrary.

Table 4.2: Probit estimates for callbacks by age, Old versus Young, effects of skills and interactions of Old with skills, marginal effect (Table 2 in original paper, men)

	Sales	Security	Janitor
Old	-0.062	-0.037	0.061
	(0.085)	(0.057)	(0.232)
Common skills			
Spanish	0.007	0.081*	-0.026
	(0.025)	(0.045)	(0.051)
Spanish x Old	-0.046	0.038	-0.089
	(0.032)	(0.060)	(0.121)
Grammar	-0.017	0.025	-0.002
	(0.020)	(0.034)	(0.049)
Grammar x Old	0.041	-0.019	0.041
	(0.037)	(0.045)	(0.126)
College	0.008	0.023	0.130**
	(0.023)	(0.038)	(0.053)
College x Old	-0.007	0.003	-0.069
	(0.031)	(0.049)	(0.109)
Employee of the month	0.033	-0.071*	-0.061
	(0.028)	(0.036)	(0.047)
Employee of the month x Old	-0.017	0.024	0.167
	(0.034)	(0.053)	(0.120)
Volunteer	-0.027	-0.019	-0.105**
	(0.024)	(0.039)	(0.050)
Volunteer x Old	0.053	-0.034	-0.051
	(0.040)	(0.051)	(0.103)
Occupation	*1: Computer*	*1: CPR*	*1: Technical skills*
specific skills	*2: Customer service*	*2: License*	*2: Certificate*
Skill 1	0.001	-0.064*	0.133*
	(0.024)	(0.034)	(0.067)
Skill 1 x Old	0.034	0.111**	-0.094
	(0.039)	(0.060)	(0.095)
Skill 2	0.012	0.065*	-0.006
	(0.024)	(0.039)	(0.065)
Skill 2 x Old	0.008	-0.052	-0.045
	(0.036)	(0.044)	(0.114)
Observations	3570	2746	818

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

Notes: Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resume level. Other controls include city, order of resume submission, and employment status. All controls are interacted with "Old" so main effect of "Old is not meaningful. This table is for men. For Janitor, only resume with commensurate experience are used.

Some robustness checks are necessary to assess the robustness of the coefficients obtained in Table 4.2.

Additional controls:
Table B.1 provides the probit estimates for callbacks by age for Old versus Young the marginal effect of skills and interactions of Old with skills; with additional controls. Additional controls, compared to Table 4.2, are the resume features such that the email format or the resume format. Indeed, the format of the resume could increase or decrease the callback rates, creating an omitted variable bias. Comparing the two tables, with and without additional controls, the coefficients are similar as well as the level of significance, except for technical skills for Janitor which is no longer significant. For Sales, while the coefficient for volunteer x Old becomes significant, the way the estimate may change while accounting for the Heckman critique remain not clear.

Logit specification:
The specification chosen by the author is the probit model. Table B.2 provides the logit estimates for callbacks by age for Old versus Young including the marginal effect of skills and interactions of Old with skills. Specification (1) used the same control variables as in the original Table 2, city, order of resume submission and employed/unemployed status, while specification (2) added controls for the format of the resume and email. The coefficient obtained are quite similar to the ones with the probit model as well as the level of significance, when is considered the same specification for control variables. The only noticeable difference comes from the coefficient for license which is no longer significant and the coefficient for CPR x Old significant at the 0.1 against 0.05 in the probit model.

As such, the coefficients estimated in table 2 are robust to a change in control variables and model specification.

Finally, Table 4.2 suggests they would exists differences in unobservables, which could lead to a biased measure of age discrimination.

4.3 Heteroscedastic Probit Estimates for Callbacks by Age

While the model presented in Table 4.2 is not necessary to implement a bias correction, it gives some information about the differences the coefficient relative to skills as well as some intuition about the possible sign of the variance of the unobservables. The heteroskedastic probit model implements the bias correction for differences in variance of unobservables.

Table 4.3 replicates Table 3 in the original paper, while the correcting for the presence of women in Janitor. The authors calculate the probit estimates coefficient for age, in the standard and in the heteroscedastic probit model. Even if the coefficients are quite similar for both specifications, only the one for Sales is significant in both specification at the 0.01 level.

However, despite this high significance for this coefficient, while correcting for the Heckman critique, this effect disappears for men applicants in Sales while an effect, weakly significant appears for men in Security.

First of all, the authors perform an overidentification test. In this section, the same latent model as the one defined in section 4.2 is used (equation (5)). With several productive characteristics X^I, in order to identify discrimination γ, the ratio of probit coefficients specific to a skill β_k for Young applicants and $\beta_k + \delta_k$ for Old applicants should be equal to the same ratio of variance of unobservables:

$$\frac{\beta_k}{\beta_k + \sigma_k} = \frac{\sigma_S^{II}}{\sigma_Y^{II}}$$

Under the null that the coefficients on skills for Old relative to Young are equal, high p-values for the overidentification test (based on a Wald test) for the three occupations indicate the overidentifying restrictions cannot be rejected. The table reports also the ratio $\frac{\sigma_S^{II}}{\sigma_Y^{II}}$ and the p-value (based on a Wald test) for the ratio is equal to 1, meaning that the variances in unobservables are equal. For Sales, the ratio is below 1, suggesting that the variance of unobservables for Older applicants would be lower than the one for Young applicants. For Security and Janitor, this ratio is above 1, indicating the contrary conclusion for variance in unobservables. The reported p-values are such that the null hypothesis cannot be rejected, even if it remains quite low for Sales.

Finally, the authors decompose the heteroscedastic probit estimate with an unbiased part measuring age discrimination "Old-level (marginal)" and a part explained by the difference in variance of unobservables, "Old-variance (marginal)". Only the coefficient for Security is significant at the 0.1 level. All remains closed to zero suggesting that most of the effect of age on employment comes from variance in unobservables. While the effect for men in Sales was highly significant in the heteroscedastic probit estimates, this effect disappears while accounting for the Heckman critique. The lowest variance in unobservables for Old applicants would lead to an overestimation of the effect of age , which is what we found without correcting for the critique. On the contrary, the highest variance in unobservables for Security and Janitor, would lead to an underestimation of the effect of age if the average quality of resumes is low.

As such, even if the results from the standard probit model are robust, they can lead to a biased measurement of age discrimination.

Table 4.3: Heteroscedastic probit estimates for callbacks by age, Old versus Young (Table 3 in original paper)

	Sales	Security	Janitor
Panel A: Probit estimates			
Old (64-66, marginal)	-0.044***	-0.028	-0.032
	(0.012)	(0.017)	(0.038)
Panel B: Heteroscedastic probit estimates			
Old (marginal)	-0.049***	-0.022	-0.032
	(0.012)	(0.020)	(0.042)
Overidentification test: ratios of coefficients on skills for old relative to young are equal (p-value)	0.88	0.85	0.99
Standard deviation of unobservables, old/young	0.84	1.16	1.43
Test: ratio of standard deviations = 1 (p-value)	0.23	0.35	0.59
Old-level (marginal)	-0.005	-0.058*	-0.095
	(0.039)	(0.030)	(0.111)
Old-variance (marginal)	-0.043	0.036	0.063
	(0.040)	(0.035)	(0.101)
Observations	3570	2746	818

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

Notes: Marginal effects computed as the change in the probability associated with "Old", using the continuous approximation, evaluating other variables at their means; the continuous approximation yields an unambiguous decomposition of the heteroscedastic probit estimates. p-values are based on Wald tests. This table is for men. For Janitor, only resume with commensurate experience are used.

As a complement to Table 4.3, Table B.3 reports the estimates for the standard probit model with bootstrapped standard errors with 1000 repetitions. Table B.4 reports the heteroscedastic estimates. Coefficients and significance levels are similar in both specification. As in Table 4.2, spanish for Security, college and volunteer for Janitor, may have an impact on the callback rate.

Robustness checks

Standard model with bootstrapped standard errors: Table B.3
After running 1000 repetition and calculating the bootstrapped standard errors, all estimates are robust. The coefficient for Old for the three occupation are the same, at the same significance level. Only the significance level for college and volunteering are lower with bootstrapped standard errors.

Model with additional control
Table B.5 replicates the original Table 3 while adding additional control for the resume format. The results are quite similar to the ones obtained in Table 4.2 except for the coefficients for Security in the standard and heteroscedactic model without corrections. They become significant at the 0.05 for the standard model and the p-value remains low for the heteroscedatic model (p-value=0.115). Moreover the coefficient for Sales in the heteroscedactic model, previously significant at the 0.01 level is no longer significant while including additional controls. However, the conclusion of the authors remain similar: the strongest evidence of age discrimination in the standard model (for retail store) disappears while considering for the Heckman Critique. The coefficient for Security is the only one suggesting a discrimination against Older worker, significant at the 0.05 level.

Finally, even if the estimates from the standard probit model are robust with bootstrapped standard errors, they can lead to a biased measurement of age discrimination without accounting for the Heckman critique.

5 Extensions

This section provides two extensions to the paper from Neumark, Burn and Button (2016). The first one extend the paper by running the same analysis for women, suggesting stronger age discrimination towards Older women. The second extension proposed to analyse if there would exist some age discrimination in the time for getting a positive respond. It may be possible that short-listed Young applicants receive immediately a call while the short-listed Older one do not.

5.1 Women and ageism

As a complement of this analysis of age discrimination, it is interesting to complement the working paper, written one year before the paper replicated.. Using the data from women in Administration and Sales, Table C.1, C.2 and C.3, respectively replicate tables 1, 2 and 3 in the original paper with data for women to assess if a potential age discrimination is stronger for women applicants. As mentioned above, only Administration and Sales are studied. Indeed, the sample for Janitor does not displayed enough observations for women and the distribution of skills is not balanced. The results found correspond, with only minor differences to the one provided in the working paper from Neumark, Burn and Button (2015). The code for women applicants is not provided in the replication packages for the paper published in 2016. They do not exist replication packages for the 2015 version.

According to Table C.1, the difference in the Callback rates is significantly lower for aged women for all age groups compared. The p-values are always below the 0.01 level except for Middle vs Young in Sales, which remains extremely low (p-value=0.113). These results suggest a potential age discrimination against women when they get older.

However, this is not enough to only compare the callback rates to assess if there is a discrimination towards Older women applicants compared to Young applicants. According to the Heckman critique, differences in the variance of unobservables may bias the measure of discrimination. The Table C.2 replicates Table 4.2 by providing the probit estimates for callbacks by age, Old vs Young, with two specifications: the first with the controls used by the authors in the original paper and the second with full controls. Thanks to this table, one can get an intuition on the difference in unobservables. For Sales applicants, there is, as for men, no coefficient significant for skills. These variables are unsuccessful in predicting a positive response. However, all coefficients for skills and the ones for the interaction between Old and skills have opposite signs. This suggests a higher variance in unobservables for Older women. In Administration, grammar, college and words per minute are significant at the 0.05 level in both specification. This suggests that these skills may predict hiring. The coefficient for the interaction are the opposite signs for these qualifications, which suggests an overall effects closer to zero, which is consistent with a larger variance in unobservables for Older women applicants. This is not the case for spanish and employee of the month, for which the interaction suggests a larger effect for Older applicants but these coefficients are not statistically significants.

Finally, the same method as in the paper is used to decompose the heteroscedastic estimate for age in a part explained by differences in variances of unobservables and a part capturing discrimination (Table C.3). In Table C.3, the coefficients for Old are highly significant for Sales and Administration in the standard and heteroscedastic models, pointing for the presence of age discrimination. The p-value for the overidentification test is very high, suggesting we will not reject the null hypothesis (under the null, the ratios of the skill coefficients between Younger and Older workers are equal across all of the skills).

For Sales, the ratio of standard deviations between Old and Young is above 1. The test for the ratio of standard deviations between these groups, indicates a p-value under 0.1, suggesting we can reject the null hypothesis. Thus, there is some statistical evidence, as expected in Table C.3, for the variance of unobservables for Older applicants being higher. The higher variance for Older women, suggests that the standard probit would underestimate discrimination if the resume were on average low quality. Indeed, the Old-level coefficient is -0.161 (significant at the 0.01 level), when we correct for the Heckman critique, whereas it is -0.093 for the standard probit. The Old-variance coefficient is also positive and significant at the 0.05 level.

For Administration, the standard deviation of unobservable is slightly below 1, suggesting the variance in unobservables is lower for Older applicants and the standard probit estimate would overestimate age discrimination in case of low quality resume on average. However, the p-value for the test of the ratio of standard deviations is really high. Thus, the null hypothesis, under which the two standard deviations of unobservables are equal, cannot be rejected. The coefficient, while correcting for bias caused by difference in variance of unobservables is negative and significant at the 0.1 level. It is a bit below the one obtained under the standard probit, as expected.

Finally, the results for women applicants are in line with the results obtained by the authors for men. The measure of discrimination can be under or overestimate when there exists variance in unobservables and if the resume are on average low quality. Moreover, the coefficient obtained for women for Sales is highly significant and above the unique significant (only at the 0.1 level) for men (in Security). The coefficient for women in Administration is also significant after the correction. This suggests differentiated age discrimination according to gender, stronger for women, which would be interesting to study further.

5.2 Exploring further the time to respond

The second extension aims at studying if age discrimination also manifests in the delay to respond for an applicant receiving a call depending of his age. The authors calculated the cumulative frequency of applicants receiving a callback, depending on the number of days to respond. Graph C.4, not shown in the original paper, displays the cumulative frequencies of men and women applicants receiving a callback per days to respond. The curves obtained are similar for the three categories. Its concavity suggests that, when the applicants receive a positive replies, the delay to respond is quite small.

We complete this descriptive analysis by calculating the hazard rate defined as the probability of receiving a call, conditional the number of days the applicants has already waited for a respond C.5. It is calculated as the ratio of the density to the survival rate at tenure k. The cumulated number of days since the sending of the resume is used as measure of tenure. Moreover, even if the data are right censored for tenure above 120 days, it seems not be a major problem as it becomes very unlikely an applicants receive a call after three months. The graphs obtained are noisy, because the number of applicants receiving a call is quite low in the sample. Only tenure below 30 are represented as the number of observations for tenure above is extremely low.

The Hazard rate is decreasing suggesting the probability of receiving a call given the applicants has already waited k days is decreasing. Similar trends are observed for all age groups, suggesting no differences. However, it is interesting to notice a jump around 12 days in the hazard rate, for all categories. This suggests that the probability of receiving a call is higher for the days just after sending the resume and jump after 12 days. It seems reasonable, as the employer may have interest to wait for receiving resumes before doing her first selection based on it. It may have different hiring strategy, which could be interesting to study, depending on, among others, the sector, the legislation, the cost of the application process for the employer.

Finally, while the first extension suggest higher age discrimination for women, the analysis of the temporality of responses for short-listed applicants seem not to depend on age.

6 Conclusion

The paper of Neumark, Burn and Button (2016) emphasizes the necessity for accounting for the Heckman critique. Even if the results from a probit estimates in a correspondence studies are robust, the estimates obtained may be biased by differences in unobservables. Indeed, while the coefficient for Sales was the highest and the more significant in the standard model, the effect disappears after correction for differences in unobservables. On the contrary, the coefficient for Security becomes weakly significant. Thus this paper highlights the importance of this critique when researches design correspondence studies to measure discrimination on the labor market.

This replication paper provides a similar analysis for women, which also emphasize the importance of the correction. It also suggests a differentiated age effect, opening the door for further studies. While the effect of age disappears for men in Sales, it is highly significant for women.

Finally, this replication paper also question some possible differentiated treatment in the recruitment process. Despite, noisy data, it suggests age has no effect in the delay for responding but they may exists a temporality. While the hazard rate is the highest for the days after sending the resume and decreases, it jumps around 12 days. Some employers may wait before calling back an applicants, while other do not. It would be interesting to study if this difference in temporality is sector specific, skill specific, depends on different legislation, by linking it with the cost of the hiring process for employer.

7 References

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A Appendix: Descriptive statistics

Table A.1: Proportion of men and women within each occupation

	Number	Percentage
Administration		
Male	0	0
Female	24350	100
All	24350	100
Janitor		
Male	1632	97.14
Female	48	2.86
All	1680	100
Sales		
Male	5348	53.19
Female	4707	46.81
All	10055	100
Security		
Male	4138	100
Female	0	0
All	4138	100
All		
Male	11118	27.64
Female	29105	72.36
All	40223	100

Notes: For each occupation, the table indicates the proportion of men and women and the absolute number of them.

Table A.2.1: Summary statistics per occupation, for men

	High skill	Spanish	Grammar	College	Employee of the month	Volunteer	Skill 1	Skill 2	Observations
Janitor									
Young	0.515	0.376	0.356	0.369	0.371	0.343	0.386	0.369	544
Middle	0.515	0.441	0.372	0.445	0.372	0.326	0.289	0.346	546
Old	0.513	0.395	0.371	0.401	0.388	0.311	0.353	0.344	544
All	0.514	0.404	0.367	0.405	0.377	0.327	0.343	0.353	1632
Security									
Young	0.441	0.358	0.302	0.300	0.304	0.320	0.304	0.314	1781
Middle	0.452	0.374	0.346	0.302	0.346	0.314	0.300	0.277	1778
Old	0.430	0.343	0.318	0.297	0.310	0.324	0.286	0.270	1789
All	0.441	0.359	0.322	0.300	0.320	0.319	0.298	0.287	5348
Sales									
Young	0.427	0.333	0.312	0.317	0.312	0.309	0.300	0.253	1380
Middle	0.347	0.285	0.241	0.272	0.223	0.224	0.262	0.228	1392
Old	0.505	0.401	0.339	0.401	0.302	0.414	0.333	0.337	1366
All	0.423	0.340	0.297	0.330	0.279	0.316	0.298	0.273	4138

Notes:The eight first columns indicate the proportion of men job applicants for each age category and a specific occupation. For instance, 37.6% of Young men applicants for Janitor job speaks spanish. The last column display the number of observations for each age category and a specific occupation.

Occupation-specific skills:

	Janitor	*Security*	*Sales*
Skill 1	Technical skills	CPR	Computer
Skill 2	Certificate	License	Customer service

Table A.2.2: Summary statistics per occupation, for women

	Highskill	Spanish	Grammar	College	Employee of the month	Volunteer	Skill 1	Skill 2	Observations
Sales									
Young	0.455	0.352	0.364	0.280	0.344	0.350	0.275	0.311	1569
Middle	0.471	0.393	0.358	0.338	0.383	0.290	0.291	0.301	1098
Old	0.447	0.354	0.317	0.294	0.370	0.326	0.279	0.293	2040
All	0.455	0.362	0.342	0.299	0.364	0.325	0.281	0.301	4707
Administration									
Young	0.502	0.388	0.345	0.379	0.328	0.324	0.389	0.356	8113
Middle	0.465	0.397	0.340	0.338	0.353	0.313	0.284	0.301	7901
Old	0.537	0.443	0.395	0.367	0.396	0.347	0.353	0.385	8336
All	0.502	0.409	0.361	0.362	0.359	0.328	0.343	0.348	24350
Janitor									
Young	0.250	0.188	0.250	0.250	0.125	0.125	0.250	0.125	16
Middle	0.250	0.000	0.250	0.125	0.188	0.188	0.250	0.250	16
Old	0.250	0.250	0.188	0.125	0.188	0.125	0.125	0.250	16
All	0.250	0.146	0.229	0.167	0.167	0.146	0.208	0.208	48

Notes: The eight first columns indicate the proportion of women job applicants for each age category and a specific occupation. For instance, 35.2% of Young women applicants for Sales job speaks spanish. The last column display the number of observations for each age category and a specific occupation.

Occupation-specific skills:

	Sales	*Administration*	*Janitor*
Skill 1	Computer	Computer	Technical skills
Skill 2	Customer service	WPM	Certificate

B Appendix: Robustness checks of Tables 1, 2 and 3 in the original paper

Table B.1: Probit estimates for callbacks by age, Old versus Young, effects of skills and interactions of Old with skills, marginal effect with additional control

	Sales	Security	Janitor
Old	-0.080	-0.059	0.120
	(0.082)	(0.059)	(0.235)
Common skills			
Spanish	0.001	0.074*	-0.033
	(0.027)	(0.044)	(0.057)
Spanish x Old	-0.056	0.048	-0.11
	(0.033)	(0.060)	(0.115)
Grammar	-0.017	0.023	0.009
	(0.021)	(0.031)	(0.052)
Grammar x Old	0.044	-0.023	0.023
	(0.038)	(0.043)	(0.126)
College	0.007	0.026	0.123**
	(0.025)	(0.038)	(0.055)
College x Old	-0.011	0.001	-0.076
	(0.033)	(0.048)	(0.105)
Employee of the month	0.029	-0.065*	-0.045
	(0.027)	(0.034)	(0.048)
Employee of the month x Old	-0.017	0.014	0.198*
	(0.034)	(0.050)	(0.124)
Volunteer	-0.029	-0.016	-0.136***
	(0.025)	(0.037)	(0.049)
Volunteer x Old	0.080**	-0.042	-0.039
	(0.044)	(0.049)	(0.103)
Occupation specific skills	*1: Computer 2: Customer service*	*1: CPR 2: License*	*1: Technical skills 2: Certificate*
Skill 1	0.006	-0.063*	0.102
	(0.025)	(0.033)	(0.076)
Skill 1 x Old	0.029	0.116**	-0.072
	(0.041)	(0.060)	(0.103)
Skill 2	0.013	0.074*	0.017
	(0.025)	(0.040)	(0.072)
Skill 2 x Old	0.007	-0.056	-0.026
	(0.040)	(0.043)	(0.119)
Observations	3570	2746	818

C4.2 Add control

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

Notes: Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resume level. Other controls include city, order of resume submission, employment status, email format and resume format. All controls are interacted with "Old" so main effect of "Old is not meaningful. This table is for men. For Janitor, only resume with commensurate experience are used.

Table B.2: Logit estimates for callbacks by age, Old versus Young, effects of skills and interactions of Old with skills, marginal effect, with and without additional controls

	Sales		Security		Janitor	
	(1)	(2)	(1)	(2)	(1)	(2)
Old	-0.064	-0.081	-0.039	-0.062	0.065	0.107
	(0.080)	(0.077)	(0.053)	(0.055)	(0.212)	(0.209)
Common skills						
Spanish	0.007	0.002	0.076*	0.070*	-0.028	-0.035
	(0.025)	(0.027)	(0.041)	(0.040)	(0.048)	(0.054)
Spanish x Old	-0.047	-0.058	0.031	0.039	-0.079	-0.103
	(0.038)	(0.039)	(0.053)	(0.053)	(0.130)	(0.128)
Grammar	-0.017	-0.018	0.023	0.023	-0.001	0.009
	(0.020)	(0.021)	(0.031)	(0.029)	(0.046)	(0.049)
Grammar x Old	0.039	0.042	-0.013	-0.019	0.036	0.021
	(0.034)	(0.034)	(0.044)	(0.043)	(0.120)	(0.120)
College	0.006	0.004	0.020	0.024	0.121**	0.116**
	(0.023)	(0.025)	(0.034)	(0.034)	(0.050)	(0.051)
College x Old	-0.005	-0.009	0.004	-0.0001	-0.065	-0.070
	(0.032)	(0.034)	(0.045)	(0.045)	(0.116)	(0.114)
Employee of the month	0.033	0.030	-0.071*	-0.066*	-0.060	-0.044
	(0.026)	(0.026)	(0.037)	(0.035)	(0.045)	(0.046)
Employee of the month x Old	-0.017	-0.020	0.023	0.012	0.142	0.173
	(0.037)	(0.036)	(0.048)	(0.046)	(0.104)	(0.107)
Volunteer	-0.029	-0.030	-0.018	-0.014	-0.102**	-0.134**
	(0.024)	(0.025)	(0.038)	(0.036)	(0.052)	(0.052)
Volunteer x Old	0.049	0.073**	-0.033	-0.040	-0.054	-0.037
	(0.036)	(0.037)	(0.052)	(0.051)	(0.108)	(0.106)
Occupation specific skills	*1: Computer 2: Customer service*		*1: CPR 2: License*		*1: Technical skills 2: Certificate*	
Skill 1	-0.001	0.004	-0.062*	-0.060*	0.121*	0.089
	(0.023)	(0.024)	(0.035)	(0.033)	(0.062)	(0.071)
Skill 1 x Old	0.033	0.030	0.090*	0.094**	-0.090	-0.067
	(0.036)	(0.038)	(0.047)	(0.046)	(0.106)	(0.108)
Skill 2	0.013	0.015	0.055	0.062*	-0.003	0.019
	(0.023)	(0.024)	(0.035)	(0.035)	(0.062)	(0.067)
Skill 2 x Old	0.006	0.006	-0.048	-0.051	-0.042	-0.024
	(0.035)	(0.039)	(0.047)	(0.047)	(0.117)	(0.115)
Observations	3570	3570	2746	2746	818	818

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

Notes: Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resume level. Other controls include city, order of resume submission, and employment status. All controls are interacted with "Old" so main effect of "Old is not meaningful. This table is for men. For Janitor, only resume with commensurate experience are used.
(1): Controls include city, order of resume submission, and employment status.
(2): Controls include city, order of resume submission, employment status, email format and resume format.

Table B.3: Probit estimates for callbacks by age, Old versus Young, effects of skills, marginal effect with and without bootstrapped standard errors.

	Sales		Security		Janitor	
	(1)	(2)	(1)	(2)	(1)	(2)
Old	-0.044***	-0.044***	-0.027	-0.027	-0.031	-0.031
	(0.012)	(0.013)	(0.017)	(0.017)	(0.037)	(0.040)
Common skills						
Spanish	-0.022	-0.022	0.087***	0.087***	-0.040	-0.040
	(0.018)	(0.019)	(0.027)	(0.029)	(0.047)	(0.052)
Grammar	-0.002	-0.002	0.020	0.020	-0.004	-0.004
	(0.017)	(0.018)	(0.022)	(0.023)	(0.042)	(0.047)
College	0.010	0.010	0.032	0.032	0.094**	0.094*
	(0.015)	(0.017)	(0.023)	(0.025)	(0.045)	(0.050)
Employee of the month	0.018	0.018	-0.066***	-0.066***	-0.029	-0.029
	(0.017)	(0.018)	(0.024)	(0.026)	(0.044)	(0.051)
Volunteer	0.001	0.001	-0.035	-0.035	-0.089**	-0.089*
	(0.017)	(0.019)	(0.026)	(0.027)	(0.045)	(0.051)
Occupation	*1: Computer*		*1: CPR*		*1: Technical skills*	
specific-skills	*2: Customer service*		*2: License*		*2: Certificate*	
Skill 1	0.020	0.020	-0.014	-0.014	0.093*	0.093*
	(0.017)	(0.019)	(0.024)	(0.025)	(0.049)	(0.053)
Skill 2	0.014	0.014	0.025	0.025	-0.016	-0.016
	(0.017)	(0.018)	(0.024)	(0.026)	(0.050)	(0.055)
Observations	3570	3570	2746	2746	818	818

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

Notes: Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resume level. Other controls include city, order of resume submission, employment status. This table is for men. For Janitor, only resume with commensurate experience are used.
(1): clustered standard errors
(2): bootstrapped clustered standard errors

Table B.4: Heteroscedastic probit estimates for callbacks by age, Old versus Young

	Sales	Security	Janitor
Old	-0.049***	-0.022	-0.032
	(0.012)	(0.020)	(0.042)
Common skills Spanish	-0.023	0.089***	-0.036
	(0.018)	(0.028)	(0.045)
Grammar	-0.001	0.020	-0.001
	(0.017)	(0.023)	(0.040)
College	0.011	0.033	0.099**
	(0.015)	(0.025)	(0.044)
Employee of the month	0.019	-0.069***	-0.040
	(0.017)	(0.025)	(0.044)
Volunteer	0.020	-0.033	-0.095**
	(0.017)	(0.027)	(0.045)
Occupation specific skills	*1: Computer* *2: Customer service*	*1: CPR* *2: License*	*1: Technical skills* *2: Certificate*
Skill 1	0.021	-0.017	0.102**
	(0.017)	(0.025)	(0.050)
Skill 2	0.016	0.027	-0.015
	(0.017)	(0.025)	(0.051)
Observations	3570	2746	818

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

Notes: Marginal effects computed as the change in the probability associated with "Old", using the continuous approximation, evaluating other variables at their means; the continuous approximation yields an unambiguous decomposition of the heteroscedastic probit estimates. p-values are based on Wald tests. This table is for men. Other controls include city, order of resume submission, employment status. For Janitor, only resume with commensurate experience are used.

Table B.5: Heteroscedastic probit estimates, corrected from differences in variance of unobservables, for callbacks by age, Old versus Young, with additional controls

	Sales	Security	Janitor
Panel A: Probit estimates			
Old (64-66, marginal)	-0.047***	-.039**	-0.017
	(0.014)	(0.019)	(0.041)
Panel B: Heteroscedastic probit estimates			
Old (marginal)	-0.048	-0.032	-0.022
	(0.181)	(0.020)	(0.050)
Overidentification test: ratios of coefficients on skills for old relative to young are equal (p-value)	0.22	0.77	0.99
Standard deviation of unobservables, Old/Young	0.85	1.28	1.40
Test: ratio of standard deviations = 1 (p-value)	0.39	0.20	0.73
Old-level (marginal)	-0.013	-0.090**	-0.082
	(0.047)	(0.036)	(0.185)
Old-variance (marginal)	-0.038	0.058	0.060
	(0.048)	(0.040)	(0.155)
Observations	3570	2746	818

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

Notes: Marginal effects computed as the change in the probability associated with "Old", using the continuous approximation, evaluating other variables at their means; the continuous approximation yields an unambiguous decomposition of the heteroscedastic probit estimates. p-values are based on Wald tests. Additional controls include city, order of resume submission, employment status, email format and resume format. This table is for men. For Janitor, only resume with commensurate experience are used.

C Appendix: Extensions

Table C.1: Callback Rates of Women by Age

		Young (29-31)	Middle (49-51)	Old (64-66)
Sales ($N = 4707$)				
Callback (%)	No	71.32	74.13	81.57
	Yes	28.68	25.87	18.43
Test of independence (p-value)	Young vs Old vs Middle	Young vs Old	Middle vs Young	Middle vs Old
	0.000	0.000	0.113	0.000
Administration ($N = 24350$)				
Callback (%)	No	85.59	89.70	92.42
	Yes	14.41	10.30	7.58
Test of independence (p-value)	Young vs Old vs Middle	Young vs Old	Middle vs Young	Middle vs Old
	0.000	0.000	0.000	0.000

Notes: The p-values are calculated from a Fisher exact test (two sided test).

Table C.2: Probit estimates for callbacks by age, Old versus Young, effects of skills and interactions of Old with skills, marginal effect (Table 2 in original paper with women data)

	Sales		Administration	
	(1)	(2)	(1)	(2)
Old	-0.102	-0.133*	-0.090***	-0.086***
	(0.077)	(0.080)	(0.020)	(0.022)
Common skills				
Spanish	-0.038	-0.038	0.003	-0.001
	(0.037)	(0.035)	(0.010)	(0.010)
Spanish x Old	0.029	0.019	0.016	0.024
	(0.056)	(0.054)	(0.019)	(0.018)
Grammar	-0.010	-0.020	-0.019**	-0.019**
	(0.033)	(0.031)	(0.009)	(0.009)
Grammar x Old	-0.015	-0.007	0.031**	0.031**
	(0.043)	(0.042)	(0.016)	(0.016)
College	0.016	0.020	0.024**	0.024**
	(0.028)	(0.027)	(0.010)	(0.010)
College x Old	-0.017	-0.024	-0.023*	-0.021
	(0.038)	(0.037)	(0.013)	(0.013)
Employee of the month	-0.018	-0.024	0.003	0.00003
	(0.029)	(0.028)	(0.009)	(0.009)
Employee of the month x Old	0.042	0.057	0.002	0.007
	(0.044)	(0.045)	(0.014)	(0.014)
Volunteer	0.022	0.021	0.016*	0.014
	(0.032)	(0.031)	(0.009)	(0.009)
Volunteer x Old	-0.024	-0.016	-0.014	-0.013
	(0.044)	(0.042)	(0.013)	(0.013)
Occupation specific-skills	*1: Computer 2: Customer service*		*1: Computer 2: Words per minute*	
Skill 1	0.026	0.033	-0.012	-0.012
	(0.028)	(0.028)	(0.010)	(0.010)
Skill 1 x Old	-0.019	-0.031	0.034**	0.035**
	(0.038)	(0.036)	(0.016)	(0.016)
Skill 2	0.008	0.012	0.021**	0.019**
	(0.029)	(0.029)	(0.010)	(0.010)
Skill 2 x Old	-0.039	-0.043	-0.024*	-0.023*
	(0.037)	(0.036)	(0.012)	(0.012)
Observations	3609	3609	16449	16449

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

Notes: Marginal effects computed as the discrete change in the probability associated with the variables, evaluating other variables at their means. Standard errors are computed based on clustering at the resume level. All controls are interacted with "Old" so main effect of "Old is not meaningful.
(1): Controls include city, order of resume submission, and employment status.
(2): Controls include city, order of resume submission, employment status, email format and resume format.

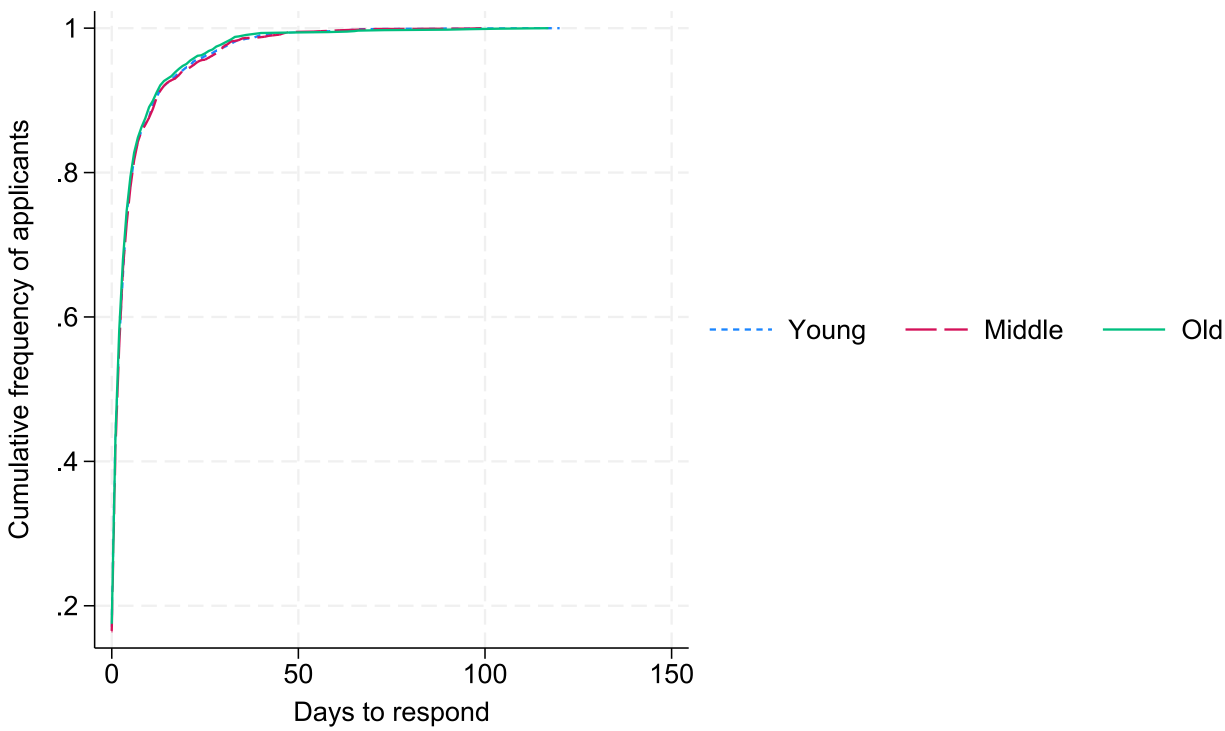
Table C.3: Heteroscedastic probit estimates for callbacks by age, Old versus Young (Replication of table 3 in original paper with women data)

	Sales	Administration
Panel A: Probit estimates		
Old (64-66, marginal)	-0.093***	-0.067***
	(0.014)	(0.005)
Panel B: Heteroscedastic probit estimates		
Old (marginal)	-0.074***	-0.068***
	(0.015)	(0.006)
Overidentification test: ratios of coefficients on skills for old relative to young are equal (p-value)	0.91	0.78
Standard deviation of unobservables, old/young	1.44	0.94
Test: ratio of standard deviations = 1 (p-value)	0.07	0.61
Old-level (marginal)	-0.161***	-0.054*
	(0.034)	(0.028)
Old-variance (marginal)	0.086**	-0.014
	(0.040)	(0.029)
Observations	3609	16449

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

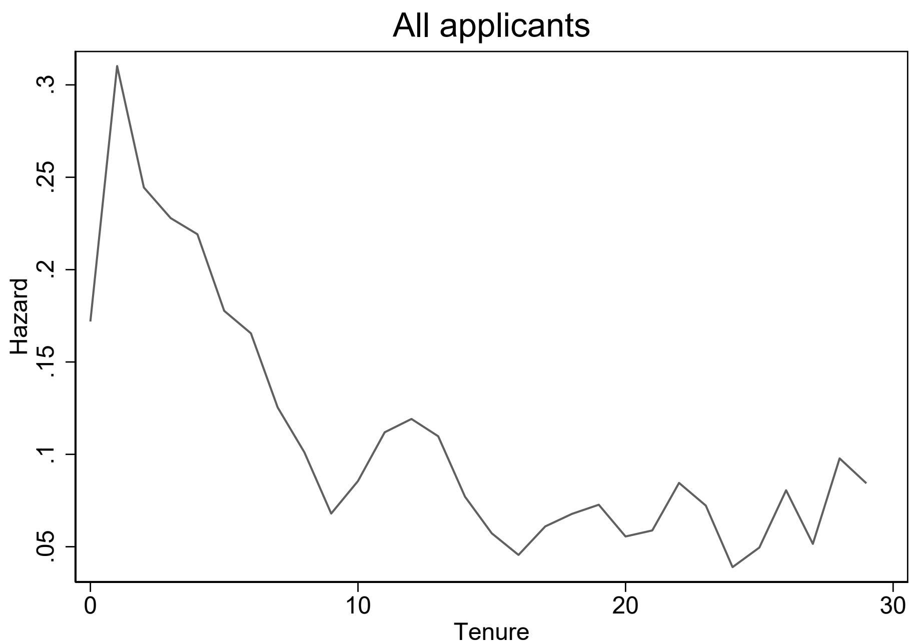
Notes: Marginal effects computed as the change in the probability associated with "Old", using the continuous approximation, evaluating other variables at their means; the continuous approximation yields an unambiguous decomposition of the heteroscedastic probit estimates. p-values are based on Wald tests. This table is for women.

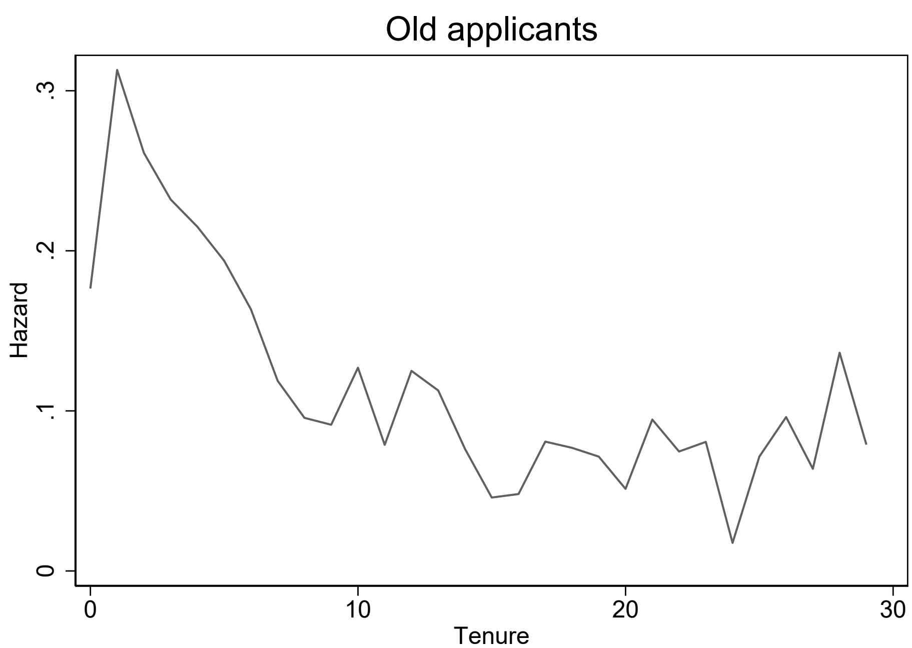
Graph C.4: Cumulative frequencies of applicants receiving a call

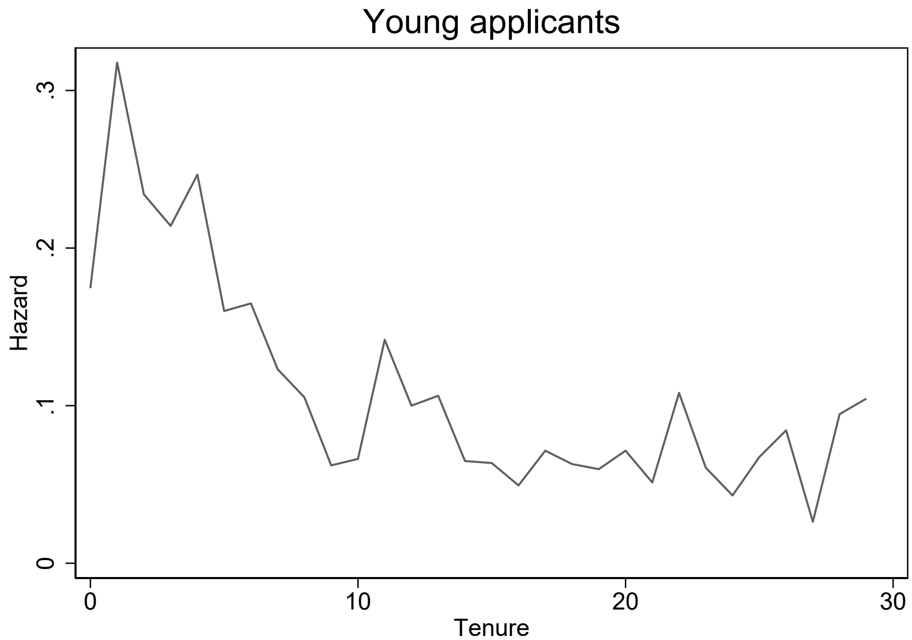


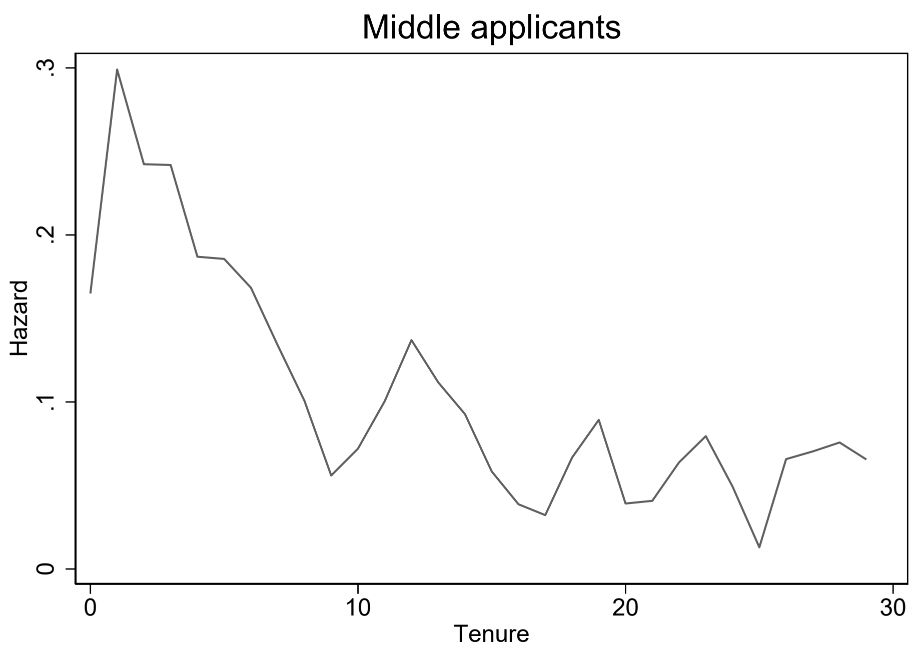
Notes: The cumulative frequency of applicants is calculating among those receiving a callback, including both men and women.

Graphs C.5: Hazard rates









Notes: The hazard rate is is defined as the probability of receiving a call, conditional the number of days the applicants has already waited for a respond. It is calculated as the ratio of the density to the survival rate at tenure k. The cumulated number of days since the sending of the resume is used as measure of tenure. These graphs include both men and women applicants. The total number of applicants is respectively 39419, 13023, 13871 and 12467 for All, Young, Old and Middle aged applicants. The number of applicants receiving a callback is respectively 5320, 2217, 1593 and 1697 for All, Young, Old and Middle aged applicants.

D Appendix: Stata code

The code used in this replication paper is based on the original code. All pieces of code borrowed from Neumark, Button and Burn (2016) are indicated. It is divided into 4 dofiles: master.do, cleandataset.do, descriptivestatistics.do, analytictables.do. The description of each dofile is in the master program.

Master.do

```
/* master.do

*Author:
        -Justine Nayral

*This program:
        -is the master program for the replication paper of Neumark, Burn, Putton (2016)
*/

**#Global
global path "C:\Users\justi\Labour\Age\Workfile" //workfile
global dofile "${path}\dofile" //where dofiles are stored
global datapath "${path}\data" //where data are stored
global output "${path}\output" //where output are stored
global data "${datapath}\mergefinal.dta" //where original dataset is stored
global cleaneddata "${datapath}\mergefinalcleaned.dta" //where final dataset is stored
cd $path

**#Packages
ssc install mehetprob //To compute marginal effects at the mean and their standard errors
ssc install estout //To print results in table

**#Dofiles
do "dofile\cleandataset.do"
*Original code from Neumark, Burn, Putton (2016) to clean the dataset

do "dofile\descriptivestatistics.do"
*In this dofile, I generated tables A.1, A.2.1 and A.2.2 which provide summary statistics.
*I borrowed the initial code from Neumark, Burn, Putton (2016) to generate Table 1.
*I added the middle age group and p-values associated and corrected the original code by excluding women
* in Janitor. I studied women data and generates an equivalent of table 1 for this group.

do "dofile\analytictables"
* I replicated table 2 and 3, borrowing the original code from Neumark, Burn, Putton (2016),
*while correcting the error for Janitor.
*I conducted some robustness checks for these results (tables B).
*Finally, I studied women data and generates an equivalent of tables 2 and 3 for this group
*and generated graphs C.
```

cleandataset.do

```
    /*
cleandataset.do

*Authors:
        -Neumark, Burn, Putton (2016)

*This program :
                -cleans the dataset for further analysis
        Input:
                -dataset "mergefinal.dta" saved into £{datapath}
        Output:
                -cleaned dataset "mergefinalcleaned.dta" saved into £{datapath}

*/

**#Initialisation
clear
clear matrix

set more off

log using "${output}\cleandataset.log", replace
set mem 6000m

use $data

*Description of the data set
summ //summary statistics

desc //description of variables

tab callback if age~=.
tab positive* if age~=. & callback~=.

compress

* Recode to separate email-occ pairs in the few cases of overlaps;

gen emailhold=email
replace email=email+occupation // Still text variable but concatenates

* Convert email to unique number;
codebook email
encode email, generate(emailx)
codebook emailx
drop email
```

```
gen email=emailx


* Positive response

drop callback

gen callback=1 if positiveresponse=="yes"|positiveresponse=="maybe"
replace callback=0 if missing(callback) & type~=""

label define callbackoutcome 0 "no" 1 "yes"
label values callback callbackoutcome
label variable callback "Callback outcome"

* Generate dummy variables:

tabulate order, gen(orderdv)
tabulate highschool, gen(highschooldv)

* Month dummies;

destring month, generate(monthc)

* tabulate monthc, gen(monthdv);
tabulate month, gen(monthdv)

* Dummies to define cities by law and age;

gen oldcity=0
replace oldcity=1 if city=="sarasota" | city=="miami" | city=="pittsburgh"

gen yngcity=0
replace yngcity=1 if city=="houston" | city=="los angeles" | city=="salt lake city"

gen strdamcity=0
replace strdamcity=1 if city=="sarasota" | city=="miami" | city=="new york" | city=="boston"
| city=="chicago" | city=="houston" | city=="los angeles"

gen lowfsccity=0
replace lowfsccity=1 if city=="new york" | city=="boston" | city=="los angeles" | city=="pittsburgh"

tabulate scriptsubject, gen(scriptsubjectdv)
tabulate scriptopening, gen(scriptopeningdv)
tabulate scriptbody, gen(scriptbodydv)
tabulate scriptsignature, gen(scriptsigndv)
tabulate saveformat, gen(saveformatdv)
egen emailformat=group(emailfirstname emaillastname)
tabulate emailformat, gen(emailformatdv)
```

```
tabulate firstname, gen(firstnamedv)
tabulate lastname, gen(lastnamedv)
tabulate raname, gen(ranamedv)

gen admin=1 if occupation=="admin"
replace admin=0 if missing(admin) & occupation~=""

gen janitor=1 if occupation=="janitor"
replace janitor=0 if missing(janitor) & occupation~=""

gen sales=1 if occupation=="sales"
replace sales=0 if missing(sales) & occupation~=""

gen security=1 if occupation=="security"
replace security=0 if missing(security) & occupation~=""

tab occupation
tab admin
tab janitor
tab sales
tab security

gen employed=1 if employment=="Employed"
replace employed=0 if missing(employed) & employment~=""
gen unemployed=1 if employment=="Unemployed"
replace unemployed=0 if missing(unemployed) & employment~=""

tab employment
tab employed
tab unemployed

gen female=1 if gender=="Female"
replace female=0 if missing(female) & gender~=""

gen male=1 if gender=="Male"
replace male=0 if missing(male) & gender~=""

tab gender
tab female
tab male

gen highskill=1 if skill=="High"
replace highskill=0 if missing(highskill) & skill~="";

gen lowskill=1 if skill=="Low"
replace lowskill=0 if missing(lowskill) & skill~=""
```

```
gen oldhighsk=old*highskill
gen middlehighsk=middle*highskill

tab skill
tab highskill
tab lowskill

gen mhbres=1 if type=="MB"
replace mhbres=0 if missing(mhbres) & type~=""

gen mhres=1 if type=="MH"
replace mhres=0 if missing(mhres) & type~=""

gen mlres=1 if type=="ML"
replace mlres=0 if missing(mlres) & type~=""

gen ohberes=1 if type=="OBE"
replace ohberes=0 if missing(ohberes) & type~=""

gen ohblres=1 if type=="OBL"
replace ohblres=0 if missing(ohblres) & type~=""

gen ohres=1 if type=="OH"
replace ohres=0 if missing(ohres) & type~=""

gen olres=1 if type=="OL"
replace olres=0 if missing(olres) & type~=""

gen yres=1 if type=="Y"
replace yres=0 if missing(yres) & type~=""

drop middle old

gen young=1 if (yres==1)
replace young=0 if missing(young) & type~=""
gen middle=1 if (mhbres==1|mhres==1|mlres==1)
replace middle=0 if missing(middle) & type~=""
gen old=1 if (ohberes==1|ohblres==1|ohres==1|olres==1)
replace old=0 if missing(old) & type~=""

* Create interactions for testing bridge vs. comparable non-bridge resumes;
gen midhi=1 if (mhbres==1|mhres==1)
replace midhi=0 if missing(midhi) & type~=""
generate midhib=midhi*mhbres
gen oldhi=1 if (ohberes==1)|(ohblres==1)|(ohres==1)
replace oldhi=0 if missing(oldhi) & type~=""
gen midhibr=midhi*mhbres
gen oldhibr=oldhi*(ohberes==1)|(ohblres==1)
```

```
* Create interactions for testing low vs. high experience differences;
gen middlelowexp=middle*mlres
gen oldlowexp=old*olres

gen resbyage=1*(young==1)+2*(middle==1)+3*(old==1) if type~=""
label define resbyagecat 1 "young" 2 "middle" 3 "old"
label values resbyage resbyagecat
label variable resbyage "Resume type by age"

* Coding skills;

* missingskill1 and missingskill2 are the two skills left off the resume.
*Spanish is a skill in all occupations, and missingskill1/2 are set to 1 if Spanish is the missing skill.
*So if neither is equal to 1, Spanish must be on the resume;

drop spanish grammar college employeemonth volunteer
computer liscense certificate customerservice techskills cpr wpm

gen spanish=1 if (missingskill1 !=1 & missingskill2 !=1)
& skill=="High"
replace spanish=0 if (missingskill1 ==1 |missingskill2 ==1) | skill=="Low"

* Same for grammar, college, employeemonth, and volunteer (coded as 4=7);

gen grammar=1 if (missingskill1 !=4 & missingskill2 !=4)
& skill=="High"
replace grammar=0 if (missingskill1 ==4 |missingskill2 ==4) | skill=="Low"

gen college=1 if (missingskill1 !=5 & missingskill2 !=5)
& skill=="High"
replace college=0 if (missingskill1 ==5 |missingskill2 ==5) | skill=="Low"

gen emplmon=1 if (missingskill1 !=6 & missingskill2 !=6)
& skill=="High"
replace emplmon=0 if (missingskill1 ==6 |missingskill2 ==6) | skill=="Low"

gen vol=1 if (missingskill1 !=7 & missingskill2 !=7)
& skill=="High"
replace vol=0 if (missingskill1 ==7 |missingskill2 ==7) | skill=="Low"

* Skills 2 and 3 are occupation specific.  Set to missing if not application to occupation;

* Skill 2: computer for sales or admin, license for security, and certification for janitor;

gen computer=1 if (missingskill1 !=2 &  missingskill2 !=2) & (occupation=="sales"|occupation=="admin")
& skill=="High"
replace computer=0 if ((missingskill1 ==2 | missingskill2 ==2)
```

```
& (occupation=="sales"|occupation=="admin") & skill=="High")
| ((occupation=="sales"| occupation=="admin") & skill=="Low")

gen license=1 if (missingskill1 !=2 & missingskill2 !=2) & occupation=="security" & skill=="High"
replace license=0 if ((missingskill1 ==2 | missingskill2 ==2)
& occupation=="security" & skill=="High") | (occupation=="security" & skill=="Low")

gen cert=1 if (missingskill1 !=2 & missingskill2 !=2) & occupation=="janitor" & skill=="High"
replace cert=0 if ((missingskill1 ==2 | missingskill2 ==2)
& occupation=="janitor" & skill=="High") | (occupation=="janitor" & skill=="Low")

gen certr=1 if (missingskill1 !=2 & missingskill2 !=2) & occupation=="janitor" & skill=="High"
& (template1==1|template2==1)
replace certr=0 if ((missingskill1==2 | missingskill2==2)
& occupation=="janitor" & skill=="High" & (template1==1|template2==1)) | (occupation=="janitor" & skill=="Low")

replace certr=1 if (missingskill1 !=3 & missingskill2 !=3)
& occupation=="janitor" & skill=="High" & (template3==1)
replace certr=0 if ((missingskill1==3 | missingskill2==3)
& occupation=="janitor" & skill=="High" & (template3==1)) | (occupation=="janitor" & skill=="Low")

tab cert template
tab certr template
tab cert certr

* Skill 3: customer service for sales, cpr for security, techskills for janitor, and wpm for admin;

gen custserv=1 if (missingskill1 !=3 & missingskill2 !=3) & occupation=="sales" & skill=="High"
replace custserv=0 if ((missingskill1 ==3 | missingskill2 ==3)
& occupation=="sales" & skill=="High") | (occupation=="sales" & skill=="Low")

gen cpr=1 if (missingskill1 !=3 & missingskill2 !=3) & occupation=="security" & skill=="High"
replace cpr=0 if ((missingskill1 ==3 | missingskill2 ==3)
& occupation=="security" & skill=="High") | (occupation=="security" & skill=="Low")

gen techskills=1 if (missingskill1 !=3 & missingskill2 !=3)
& occupation=="janitor" & skill=="High" & (template1==1|template2==1)
replace techskills=0 if ((missingskill1==3 | missingskill2==3)
& occupation=="janitor" & skill=="High" & (template1==1|template2==1)) | (occupation=="janitor" & skill=="Low")

replace techskills=1 if (missingskill1 !=2 & missingskill2 !=2)
& occupation=="janitor" & skill=="High" & (template3==1)
replace techskills=0 if ((missingskill1==2 | missingskill2==2)
& occupation=="janitor" & skill=="High" & (template3==1)) | (occupation=="janitor" & skill=="Low")

gen wpm=1 if (missingskill1 !=3 & missingskill2 !=3) & occupation=="admin" & skill=="High"
replace wpm=0 if ((missingskill1 ==3 | missingskill2 ==3)
& occupation=="admin" & skill=="High") | (occupation=="admin" & skill=="Low")
```

```
* Adding Spanish skill to the cases where it appeared by accident due to coding error;
replace spanish=1 if missingskill1==1 & missingskill2==2
replace spanish=1 if missingskill1==2 & missingskill2==1
replace spanish=1 if missingskill1==1 & missingskill2==3
replace spanish=1 if missingskill1==3 & missingskill2==1

* Removing the occupation-specific skills that got replaced by spanish;
replace computer=0 if missingskill1==1 & missingskill2==2
replace computer=0 if missingskill1==2 & missingskill2==1
replace computer=0 if missingskill1==1 & missingskill2==3
replace computer=0 if missingskill1==3 & missingskill2==1

replace license=0 if missingskill1==1 & missingskill2==2
replace license=0 if missingskill1==2 & missingskill2==1
replace license=0 if missingskill1==1 & missingskill2==3
replace license=0 if missingskill1==3 & missingskill2==1

replace cert=0 if missingskill1==1 & missingskill2==2
replace cert=0 if missingskill1==2 & missingskill2==1
replace cert=0 if missingskill1==1 & missingskill2==3
replace cert=0 if missingskill1==3 & missingskill2==1

replace custserv=0 if missingskill1==1 & missingskill2==2
replace custserv=0 if missingskill1==2 & missingskill2==1
replace custserv=0 if missingskill1==1 & missingskill2==3
replace custserv=0 if missingskill1==3 & missingskill2==1

replace cpr=0 if missingskill1==1 & missingskill2==2
replace cpr=0 if missingskill1==2 & missingskill2==1
replace cpr=0 if missingskill1==1 & missingskill2==3
replace cpr=0 if missingskill1==3 & missingskill2==1

replace techskills=0 if missingskill1==1 & missingskill2==2
replace techskills=0 if missingskill1==2 & missingskill2==1
replace techskills=0 if missingskill1==1 & missingskill2==3
replace techskills=0 if missingskill1==3 & missingskill2==1

replace wpm=0 if missingskill1==1 & missingskill2==2
replace wpm=0 if missingskill1==2 & missingskill2==1
replace wpm=0 if missingskill1==1 & missingskill2==3
replace wpm=0 if missingskill1==3 & missingskill2==1

compress

save ${cleaneddata}, replace

log close
```

descriptivestatistics.do

```
    /*
descriptivestatistics.do

*Authors:
        -Justine Nayral with some parts borrowed from Neumark, Burn, Putton (2016)

*This program :
                 provides summary statistics
                -replicates and extends table 1
        Input:
                -£{datapath}\mergefinal.dta
        Output:
                - Tables A.1, A.2.1, A.2.2 : descriptive statistics saved into £output
                - Table 4.1 : augmented replication of table 1 saved into £output
                - Table C.1: replication of table 1 with data for women saved into £output
*/

use ${cleaneddata}, clear

**#Necessary variables for tables

*Age categories
gen cat_age=0 if young==1
replace cat_age=1 if middle==1
replace cat_age=2 if old==1
label define age_label 0 "Young" 1 "Middle" 2 "Old"
label values cat_age age_label

*Gender categories
gen cat_sex=0 if gender=="Male"
replace cat_sex=1 if gender=="Female"
label define sex_label 0 "Male" 1 "Female"
label values cat_sex sex_label
label variable cat_sex "Female"

*Dummy for employment
gen cat_empl=1 if employment=="Employment"
replace cat_empl=0 if gender=="Unemployment"
label define empl_label 0 "Employment" 1 "Unemployment"
label values cat_empl empl_label
label variable cat_sex "Employed"

*Label dummies for skills
label variable spanish "Spanish"
label variable grammar "Grammar"
label variable college "College"
```

```
label variable emplmon "Employee of the month"
label variable vol "Volunteer"
label variable custserv "Customer service"
label variable cpr "CPR"
label variable license "License"
label variable techskills "Technical skills"
label variable cert "Certificate"
label variable wpm "WPM"
label variable computer "Computer"
label variable cat_age "Age"

**#Appendix A

*Descriptive data:
preserve
log using "${output}\Description.log", replace
drop if cat_age==.
sort cat_age

********************************************************************************
                                *Table A.1
********************************************************************************

**#Table A.1: proportion of sex within each occupation
est clear
estpost tab cat_sex occupation
ereturn list

esttab using "$output/tableA.1.tex", replace ////
 cells("b colpct") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Number" "Percentage")

tab occupation cat_sex
tab occupation cat_age if cat_sex==0, freq
tab occupation cat_age if cat_sex==1, freq
*no women in security and no men in administration.
*A few women in janitor, we consider only the case with men in Janitor.

********************************************************************************
                                *Tables A.2.1 and A.2.2
********************************************************************************

*Men & janitor
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol techskills cert
if occupation=="janitor" & cat_sex==0

est clear
```

```
estpost tabstat highskill spanish grammar college emplmon vol techskills cert
if occupation=="janitor" & cat_sex==0, by(cat_age)  stat(mean)
ereturn list
local vars=e(vars)

esttab using "$output/table1.1_men.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College" "Employee of the month"
   "Volunteer" "Technical skills" "Certificate")

*Women & janitor
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol techskills cert
if occupation=="janitor" & cat_sex==1

est clear
estpost tabstat highskill spanish grammar college emplmon vol techskills cert
if occupation=="janitor" & cat_sex==1, by(cat_age)  stat(mean)
ereturn list
local vars=e(vars)

esttab using "$output/table1.1_women.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College"
   "Employee of the month" "Volunteer" "Technical skills" "Certificate")


*Men and security
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol cpr license if occupation=="security"

est clear
estpost tabstat highskill spanish grammar college
emplmon vol cpr license if occupation=="security", by(cat_age)  stat(mean)
ereturn list
local vars=e(vars)

esttab using "$output/table1.2.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College" "Employee of the month" "Volunteer" "CPR" "License")

*Sales
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol computer custserv if occupation=="sales"

est clear
estpost tabstat highskill spanish grammar college emplmon vol computer custserv
if occupation=="sales", by(cat_age)  stat(mean)
```

```
ereturn list
local vars=e(vars)

esttab using "$output/table1.3.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College"
   "Employee of the month" "Volunteer" "Computer" "Customer service")

*Men and sales:
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol computer custserv
if occupation=="sales" & cat_sex==0

est clear
estpost tabstat highskill spanish grammar college emplmon vol computer custserv
if occupation=="sales" & cat_sex==0, by(cat_age)  stat(mean)
ereturn list
local vars=e(vars)

esttab using "$output/table1.3.men.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College"
   "Employee of the month" "Volunteer" "Computer" "Customer service")

*Women and sales:
by cat_age : sum cat_sex highskill spanish grammar college emplmon vol computer custserv
if occupation=="sales" & cat_sex==1

est clear
estpost tabstat highskill spanish grammar college emplmon vol computer custserv
if occupation=="sales" & cat_sex==1, by(cat_age)  stat(mean)
ereturn list
local vars=e(vars)

esttab using "$output/table1.3.women.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College"
   "Employee of the month" "Volunteer" "Computer" "Customer service")

*Administration and women
bysort cat_age : sum cat_sex highskill spanish grammar college emplmon vol computer wpm if occupation=="admin"

est clear
estpost tabstat highskill spanish grammar college emplmon vol computer wpm
if occupation=="admin", by(cat_age)  stat(mean)
ereturn list
```

```
local vars=e(vars)

esttab using "$output/table1.4.tex", replace ////
 cells("`vars'") nonumber ///
  nomtitle nonote noobs label booktabs ///
   collabels("Highskill" "Spanish" "Grammar" "College"
   "Employee of the month" "Volunteer" "Computer" "WPM")

log close
restore

********************************************************************************
                                *Table 4.1
********************************************************************************

*Replication of Table 1. I borrowed the original code from Neumark, Burn, Putton (2016)
*corrected for the presence of women and Janitors
* and augmented it to provide additional information:
log using "${output}\Table1.1.log", replace

*****1. Original table 1: piece of code from Neumark, Burn, Putton (2016)
*corrected for the presence of women in Janitor for the table for men.

* Sales--male;

tab callback resbyage if sales & (young|old) & female==0, col chi2 exact
*p-value young/old: 0.000

* Security;

tab callback resbyage if security & (young|old), col chi2 exact
*p-value young/old: 0.123

* Janitor;

tab callback resbyage if janitor & (young|old), col chi2 exact
*p-value young/old: 0.025

*** Young/old only, and exclude low exper resumes;

tab callback resbyage if janitor & ((old==1 & olres==0)|middle==0) & olres~=1, col chi2 exact
*p-value young/old: 0.481

***Correction of the code***: the code of the author include the observations for women. We must include them
tab callback resbyage if janitor & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, col chi2 exact
*p-value young/old: 0.528
```

```
**2. I augmented table 1 for men adding middle age category
*and p-value computed for each combination of age group:

* Sales--male;

tab callback resbyage if sales & female==0, col chi2 exact
*p-value young/old/middle: 0.000

tab callback resbyage if sales & female==0 & (middle|old), col chi2 exact
*p-value old/middle: 0.000

tab callback resbyage if sales & female==0 & (middle|young), col chi2 exact
*p-value young/middle: 0.902

* Security;

tab callback resbyage if security , col chi2 exact
*p-value young/old/middle: 0.163

tab callback resbyage if security & (middle|old), col chi2 exact
*p-value old/middle: 0.926

tab callback resbyage if security & (middle|young), col chi2 exact
*p-value young/middle: 0.094

* Janitor -Male;

tab callback resbyage if janitor & female==0, col chi2 exact
*p-value young/old/middle: 0.012

tab callback resbyage if janitor & female==0 & (middle|old), col chi2 exact
*p-value old/middle: 0.654

tab callback resbyage if janitor & female==0 & (middle|young), col chi2 exact
*p-value young/middle: 0.654


*** Janitor exclude low exper resumes -*** Janitor exclude low exper resumes;
tab callback resbyage if janitor & olres~=1 & mlres ~=1 & female==0, col chi2 exact
*p-value young/old/middle: 0.810

tab callback resbyage if janitor & olres~=1 & (middle|old) & mlres ~=1 & female==0, col chi2 exact
*p-value old/middle: 0.647

tab callback resbyage if janitor & (middle|young) & mlres ~=1 & female==0, col chi2 exact
*p-value young/middle:  1.000

log close
```

```
********************************************************************************
                                *Table C.1
********************************************************************************

*Table C.1: I generated an analog table 4.1 for women
log using "${output}\Table1.2.log", replace

* Sales--women;

tab callback resbyage if sales & female==1, col chi2 exact
*p-value old/middle/young: 0.000

tab callback resbyage if sales & female==1 & (young|old), col chi2 exact
*p-value young/old: 0.000

tab callback resbyage if sales & female==1 & (middle|young), col chi2 exact
*p-value young/middle: 0.113

tab callback resbyage if sales & female==1 & (old|middle), col chi2 exact
*p-value old/middle: 0.000

* Administration;

tab callback resbyage if occupation=="admin" & female==1, col chi2 exact
*p-value old/middle/young: 0.000

tab callback resbyage if occupation=="admin" & female==1 & (young|old), col chi2 exact
*p-value young/old: 0.000

tab callback resbyage if occupation=="admin" & female==1 & (middle|young), col chi2 exact
*p-value young/middle: 0.000

tab callback resbyage if occupation=="admin" & female==1 & (old|middle), col chi2 exact
*p-value old/middle: 0.000

log close
```

analytictables

```
    /*
analytictable.do

*Authors:
        -Justine Nayral with some parts borrowed from Neumark, Burn, Putton (2016)

*This program :
                -replicates tables 2 and 3 from the original papers
                while correcting the code for the presence of women in Janitors
                - run some robutsness checks (tables B)
                -provides an original extension (tables and graphs C)

        Input:
                -£{datapath}\mergefinal.dta
        Output:
                -table 4.2 and 4.3 saved into £output
                -tables B.1, B.2, B.3, B.4, B.5 saved into £output
                -tables C.1, C.2, C.3 saved into £output
                -graphs C.4, C.5 saved into £output
*/

use ${cleaneddata}, clear


tab multiplecontacts, gen(mc)
gen multcont=1 if mc1==1|mc2==1|mc3==1|mc4==1
replace multcont=0 if multcont==. & callback~=.

sum multcont
tab multcont resbyage if matchlevel~=2, col chi2 exact
tab multcont resbyage if old==0 & matchlevel~=2, col chi2 exact
tab multcont resbyage if middle==0 & matchlevel~=2, col chi2 exact
tab multcont resbyage if young==0 & matchlevel~=2, col chi2 exact

tab multcont resbyage if matchlevel~=2 & callback==1, col chi2 exact
tab multcont resbyage if matchlevel~=2 & callback==1 & old==0, col chi2 exact
tab multcont resbyage if matchlevel~=2 & callback==1 & middle==0, col chi2 exact
tab multcont resbyage if matchlevel~=2 & callback==1 & young==0, col chi2 exact

*****;

**#Necessary variables for graphs:

* By occupation;

global restypes "mhres mhbres mlres ohres ohberes ohblres olres"
```

```
global restypesjan "mhres mlres ohres olres"
global restypesrestricthigh "mhexpres mlres ohexpres olres"
global occs "sales security janitor"

global controls "city1-city11 orderdv2 orderdv3 unemployed"


global fullcontrols "template2 template3 email1 email2 scriptsubjectdv2
"scriptsubjectdv3 scriptopeningdv2 scriptbodydv2 scriptbodydv3 scriptsigndv2"
"saveformatdv2 saveformatdv3 emailformatdv2 emailformatdv3"
global adminskills "spanish grammar college emplmon vol computer wpm"
global salesskills "spanish grammar college emplmon vol computer custserv"
global secskills "spanish grammar college emplmon vol cpr license"
global janskills "spanish grammar college emplmon vol techskills cert"
global allskills "spanish grammar college emplmon vol computer wpm custserv cpr license techskills cert"
global agebyskill "middlehighsk oldhighsk"

* Create all interactions;
gen oldspanish=old*spanish
gen oldgrammar=old*grammar
gen oldcollege=old*college
gen oldemplmon=old*emplmon
gen oldvol=old*vol
gen oldcomputer=old*computer
gen oldwpm=old*wpm
gen oldcustserv=old*custserv
gen oldcpr=old*cpr
gen oldlicense=old*license
gen oldtechskills=old*techskills
gen oldcert=old*cert
gen oldunempl=old*unemployed
gen oldorderdv2=old*orderdv2
gen oldorderdv3=old*orderdv3
gen oldhighskill=old*highskill
drop oldfemale
gen oldfemale=old*female

gen oldcity1=old*city1
gen oldcity2=old*city2
gen oldcity3=old*city3
gen oldcity4=old*city4
gen oldcity5=old*city5
gen oldcity6=old*city6
gen oldcity7=old*city7
gen oldcity8=old*city8
gen oldcity9=old*city9
gen oldcity10=old*city10
gen oldcity11=old*city11
```

```
gen oldadmin=old*admin
gen oldsales=old*sales
gen oldjanitor=old*janitor
gen oldsecurity=old*security


global salesinterold "oldspanish oldgrammar oldcollege oldemplmon oldvol oldcomputer oldcustserv"
"oldunempl oldorderdv2 oldorderdv3 oldcity1-oldcity11"

global secinterold "oldspanish oldgrammar oldcollege oldemplmon oldvol"
"oldcpr oldlicense  oldunempl oldorderdv2 oldorderdv3 oldcity1-oldcity11"

global janinterold "oldspanish oldgrammar oldcollege oldemplmon oldvol"
"oldtechskills oldcert oldunempl oldorderdv2 oldorderdv3 oldcity1-oldcity11"

global admiinterold "oldspanish oldgrammar oldcollege oldemplmon oldvol oldwpm"
"oldcomputer oldunempl oldorderdv2 oldorderdv3 oldcity1-oldcity11"

global controlsnoorder "city1-city11 unemployed"

*******************************************************************************
                                *Table 4.2
*******************************************************************************

*Replication of the original table 2:  Piece of code from the original paper but
*I corrected the initial code for the presence of women in Janitors

*** Sales--Male;

* Start by using all interactions;

est clear

*With control of the authors: marginal effect
eststo r1: dprobit callback old $controls $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)


*** Security--using all skill variables;

* Start by using all interactions;
*With control of the authors

eststo r3: dprobit callback old $controls $secskills $secinterold
if security==1& (old==1|middle==0), vce(cluster email)
```

```
*** Janitors--using all skill variables; , dropping old, low experience resumes;

* Start by using all interactions; I corrected the code of the author to exclude women.

*With control of the authors

eststo r5: dprobit callback old $controls $janskills $janinterold   if janitor==1
& ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)


esttab, main(dfdx) aux(se_dfdx)

esttab using "$output/Table2.tex", replace  ///
 main(dfdx) aux(se_dfdx) nomtitle label star(* 0.10 ** 0.05 *** 0.01) ///
 booktabs  ///

 ********************************************************************************
                                *Table B1
********************************************************************************

*I added to the original table, additionnal control and
*I corrected the initial code for the presence of women in Janitors
*** Sales--Male;

* Start by using all interactions;

est clear

*With full control: marginal effect
eststo r2: dprobit callback old $controls $fullcontrols $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)


*** Security--using all skill variables;

* Start by using all interactions;

*With full control:
eststo r4: dprobit callback old $controls $fullcontrols $secskills $secinterold
if security==1 & (old==1|middle==0), vce(cluster email)


*** Janitors--using all skill variables; , dropping old, low experience resumes;

* Start by using all interactions; I corrected the code of the author to exclude women.

*With full control:
```

```
eststo r6: dprobit callback old $controls $fullcontrols $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)


esttab, main(dfdx) aux(se_dfdx)

esttab using "$output/TableC2.tex", replace  ///
 main(dfdx) aux(se_dfdx) nomtitle label star(* 0.10 ** 0.05 *** 0.01) ///
 booktabs  ///


 ******************************************************************************
                                *Table B2
******************************************************************************

*Robustness check: I generated an analog table as table 4.2 with logit,
*controls from the authors and additionnal controls
*** Sales--Male;

* Start by using all interactions;

est clear

*With control: overall effect

*With control of the authorq: marginal effect
qui logit callback old $controls $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)
eststo r1 :margins, dydx(*) post
esttab, main(b) aux(se)



*With full control: overall effect

*With full control: marginal effect
qui logit callback old $controls $fullcontrols $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)
eststo r2 :margins, dydx(*) post


*** Security--using all skill variables;

* Start by using all interactions;
*With control of the authors

qui logit callback old $controls $secskills $secinterold
if security==1 & (old==1|middle==0), vce(cluster email)
```

```
eststo r3 :margins, dydx(*) post


*With full control:
qui logit callback old $controls $fullcontrols $secskills $secinterold
if security==1 & (old==1|middle==0), vce(cluster email)
eststo r4 :margins, dydx(*) post



*** Janitors--using all skill variables; , dropping old, low experience resumes;

* Start by using all interactions; I corrected the code of the author to exclude women.

*With control of the authors

qui logit callback old $controls $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)
eststo r5 :margins, dydx(*) post


*With full control:

qui logit callback old $controls $fullcontrols $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)
eststo r6 :margins, dydx(*) post



esttab using "$output/TableC1.tex", replace  ///
 main(b) aux(se) nomtitle label star(* 0.10 ** 0.05 *** 0.01)t(4) ///
 booktabs  ///

 ******************************************************************************
                               *Table 4.3
******************************************************************************

*Replication of table 3 - Men : piece of code borrowed from the original paper
*but corrected for the presence of women in Janitors

log using "${output}\table3.log", replace
*Sales--Male
probit callback old $controls $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)

*Overidentification test
testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])=
_b[computer]/(_b[oldcomputer]+_b[computer])= _b[grammar]/(_b[oldgrammar]+_b[grammar])=
```

```
_b[college]/(_b[oldcollege]+_b[college])=_b[vol]/(_b[oldvol]+_b[vol])
= _b[custserv]/(_b[oldcustserv]+_b[custserv])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])= _b[city3]/(_b[oldcity3]+_b[city3])
= _b[city4]/(_b[oldcity4]+_b[city4])= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])= _b[city9]/(_b[oldcity9]+_b[city9])
= _b[city10]/(_b[oldcity10]+_b[city10])= _b[city11]/(_b[oldcity11]+_b[city11])

*Panel A: probit estimates
global X old $controls $salesskills
global Z old
dprobit callback $X if sales==1 & female==0 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

*Panel B: Heteroskedastic probit estimates
version 12: hetprob callback $X if sales==1 & female==0 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])

*Standard deviation of unobservables, old/young
scalar di sdbosdw

*Test: ratio of standard deviation =1
testnl exp(_b[lnsigma2:old]) = 1
```

```
drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part : Old level (marginal)
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part : Old-variance (marginal)
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))



*Security--using all skill variables;

* Start by using all interactions;

probit callback old $controls $secskills $secinterold if security==1 & (old==1|middle==0),   vce(cluster email)
```

```
testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
= _b[license]/(_b[oldlicense]+_b[license])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])= _b[cpr]/(_b[oldcpr]+_b[cpr])
=     _b[unempl]/(_b[oldunempl]+_b[unempl])= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])
= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])= _b[city1]/(_b[oldcity1]+_b[city1])
= _b[city2]/(_b[oldcity2]+_b[city2])= _b[city3]/(_b[oldcity3]+_b[city3])
= _b[city4]/(_b[oldcity4]+_b[city4])= _b[city5]/(_b[oldcity5]+_b[city5])
= _b[city6]/(_b[oldcity6]+_b[city6])= _b[city7]/(_b[oldcity7]+_b[city7])
= _b[city8]/(_b[oldcity8]+_b[city8])= _b[city9]/(_b[oldcity9]+_b[city9])
= _b[city10]/(_b[oldcity10]+_b[city10])= _b[city11]/(_b[oldcity11]+_b[city11])


global X old $controls $secskills
global Z old
dprobit callback $X if security==1 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

version 12: hetprob callback $X if security==1 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])
scalar di sdbosdw
testnl exp(_b[lnsigma2:old]) = 1

drop linxb
```

```
* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative;
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part ;
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part ;
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))

*** Janitors, dropping old, low experience resumes;

* Start by using all interactions: correction of the code by excluding women

* Check;

sum $restypes if janitor==1 & female==0 & (old==1|middle==0)

sum $restypes if janitor==1 & female==0 & ((old==1 & olres==0)|middle==0) & olres~=1
```

```
dprobit callback old $controls $janskills
if janitor==1 & (old==1|middle==0) & female==0, vce(cluster email)

dprobit callback old $controls $janskills
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0, vce(cluster email)

dprobit callback old $controls $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0, vce(cluster email)


probit callback old $controls $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0,   vce(cluster email)

testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
= _b[techskills]/(_b[oldtechskills]+_b[techskills])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])
= _b[cert]/(_b[oldcert]+_b[cert])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])
= _b[city3]/(_b[oldcity3]+_b[city3])= _b[city4]/(_b[oldcity4]+_b[city4])
= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])
= _b[city9]/(_b[oldcity9]+_b[city9])= _b[city10]/(_b[oldcity10]+_b[city10])
= _b[city11]/(_b[oldcity11]+_b[city11])


global X old $controls $janskills
global Z old
dprobit callback $X if janitor==1 & ((old==1 & olres==0)|middle==0)
& olres~=1 & female ==0, classic vce(cluster email)
scalar llprob=e(ll)

version 12: hetprob callback $X if janitor==1 & ((old==1 & olres==0)|middle==0)
& olres~=1 & female ==0, het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)
```

```
scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])
scalar di sdbosdw
testnl exp(_b[lnsigma2:old]) = 1

drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative;
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )
```

```
* Linear part ;
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part ;
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))

log close

 *******************************************************************************
                                *Table B.3
*******************************************************************************

*Robustness check: I generated the standard probit model with and without bootstrapped standard error
*** Sales--Male;

* Start by using all interactions;

est clear

*With control: overall effect

*With control of the author: marginal effect
qui probit callback old $controls $salesskills if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)
eststo r1 : margins, dydx(*) post
esttab, main(b) aux(se)

bootstrap, reps(1000): qui probit callback old $controls $salesskills
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)
eststo r2 : margins, dydx(*) post
esttab, main(b) aux(se)

*** Security--using all skill variables;

* Start by using all interactions;
*With control of the authors

 qui probit callback old $controls $secskills  if security==1 & (old==1|middle==0), vce(cluster email)
eststo r3 :margins, dydx(*) post

bootstrap, reps(1000): qui probit callback old $controls $secskills
if security==1 & (old==1|middle==0), vce(cluster email)
eststo r4 :margins, dydx(*) post


*** Janitors--using all skill variables; , dropping old, low experience resumes;

* Start by using all interactions; I corrected the code of the author to exclude women.
```

```
*With control of the authors

 qui probit callback old $controls $janskills
 if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)
eststo r5 :margins, dydx(*) post

bootstrap, reps(1000): qui probit callback old $controls $janskills
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female==0, vce(cluster email)
eststo r6 :margins, dydx(*) post

esttab using "${output}/TableC4.1.tex", replace  ///
 main(b) aux(se) nomtitle label star(* 0.10 ** 0.05 *** 0.01) ///
 booktabs

 ******************************************************************************
                                *Table B.4
******************************************************************************

*I generated the table with coefficients without interraction for the heteroskedastic model
log using "$output\tableC3.txt", replace
est clear
*Sales -- Only men:
global X old $controls $salesskills
global Z old
version 12: hetprob callback $X if sales==1 & female==0 &
(old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete


*Security--using
global X old $controls $secskills
global Z old
version 12: hetprob callback $X if security==1 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete


*Janitor: only men, excuding old, low resumees

global X old $controls $janskills
global Z old
version 12: hetprob callback $X if janitor==1 &
((old==1 & olres==0)|middle==0) & olres~=1 & female ==0, het($Z) cluster(email)
scalar llhetprob=e(ll)
 mehetprob, nodiscrete

log close
```

```
********************************************************************************
                                *Table B.5
********************************************************************************

*Robustness check: I generated Table 4.3 with additionnal controls.
log using "${output}\table3_control.log", replace

*Sales--Male
probit callback old $controls $fullcontrols $salesskills $salesinterold
if sales==1 & female==0 & (old==1|middle==0),  vce(cluster email)

*Overidentification test
testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
=_b[computer]/(_b[oldcomputer]+_b[computer])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])
= _b[custserv]/(_b[oldcustserv]+_b[custserv])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])
= _b[city3]/(_b[oldcity3]+_b[city3])= _b[city4]/(_b[oldcity4]+_b[city4])
= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])
= _b[city9]/(_b[oldcity9]+_b[city9])= _b[city10]/(_b[oldcity10]+_b[city10])
= _b[city11]/(_b[oldcity11]+_b[city11])

*Panel A: probit estimates
global X old $controls $fullcontrols $salesskills
global Z old
dprobit callback $X if sales==1 & female==0 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

*Panel B: Heteroskedastic probit estimates
version 12: hetprob callback $X if sales==1 & female==0 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)
```

```
scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])

*Standard deviation of unobservables, old/young
scalar di sdbosdw

*Test: ratio of standard deviation =1
testnl exp(_b[lnsigma2:old]) = 1

drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"
```

```
* Overall partial derivative
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part : Old level (marginal)
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part : Old-variance (marginal)
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))



*Security--using all skill variables;

* Start by using all interactions;

probit callback old $controls $fullcontrols $secskills $secinterold
if security==1 & (old==1|middle==0),   vce(cluster email)

testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
= _b[license]/(_b[oldlicense]+_b[license])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college]) = _b[vol]/(_b[oldvol]+_b[vol])= _b[cpr]/(_b[oldcpr]+_b[cpr])
=     _b[unempl]/(_b[oldunempl]+_b[unempl])= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])
= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])= _b[city1]/(_b[oldcity1]+_b[city1])
= _b[city2]/(_b[oldcity2]+_b[city2])= _b[city3]/(_b[oldcity3]+_b[city3])
= _b[city4]/(_b[oldcity4]+_b[city4])= _b[city5]/(_b[oldcity5]+_b[city5])
= _b[city6]/(_b[oldcity6]+_b[city6])= _b[city7]/(_b[oldcity7]+_b[city7])
= _b[city8]/(_b[oldcity8]+_b[city8])= _b[city9]/(_b[oldcity9]+_b[city9])
= _b[city10]/(_b[oldcity10]+_b[city10])= _b[city11]/(_b[oldcity11]+_b[city11])

*Panel A: probit estimates
global X old $controls $fullcontrols $secskills
global Z old
dprobit callback $X if security==1 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

*Panel B: Heteroskedastic probit estimates
version 12: hetprob callback $X if security==1 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
```

```
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])

*Standard deviation of unobservables, old/young
scalar di sdbosdw

*Test: ratio of standard deviation =1
testnl exp(_b[lnsigma2:old]) = 1

drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}
```

```
di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative;
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part : Old level (marginal)
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part : Old variance (marginal)
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))

*** Janitors, dropping old, low experience resumes;

* Start by using all interactions: correction of the code by excluding women

* Check;

sum $restypes if janitor==1 & female==0 & (old==1|middle==0)

sum $restypes if janitor==1 & female==0 & ((old==1 & olres==0)|middle==0) & olres~=1

dprobit callback old $controls $fullcontrols $janskills
if janitor==1 & (old==1|middle==0) & female==0, vce(cluster email)

dprobit callback old $controls $fullcontrols $janskills
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0, vce(cluster email)

dprobit callback old $controls $fullcontrols $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0, vce(cluster email)


probit callback old $controls $fullcontrols $janskills $janinterold
if janitor==1 & ((old==1 & olres==0)|middle==0) & olres~=1 & female ==0,   vce(cluster email)

testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
= _b[techskills]/(_b[oldtechskills]+_b[techskills])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])
= _b[cert]/(_b[oldcert]+_b[cert])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])
= _b[city3]/(_b[oldcity3]+_b[city3])= _b[city4]/(_b[oldcity4]+_b[city4])
= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])
= _b[city9]/(_b[oldcity9]+_b[city9])= _b[city10]/(_b[oldcity10]+_b[city10])
```

```
= _b[city11]/(_b[oldcity11]+_b[city11])


global X old $controls $fullcontrols $janskills
global Z old
dprobit callback $X if janitor==1 & ((old==1 & olres==0)|middle==0)
& olres~=1 & female ==0, classic vce(cluster email)
scalar llprob=e(ll)

version 12: hetprob callback $X if janitor==1 & ((old==1 & olres==0)|middle==0)
& olres~=1 & female ==0, het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])
scalar di sdbosdw
testnl exp(_b[lnsigma2:old]) = 1

drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
```

```
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative;
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part ;
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part ;
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))

log close


**#Extension 1 : Replication with data for women


********************************************************************************
                                *Table C.2
********************************************************************************

*I used data for women to produce an analog of table 2
*with specification from the authors and additional controls.

*** Sales--Women;

* Start by using all interactions;
```

```
est clear


*With control of the authorq: marginal effect
eststo r1: dprobit callback old $controls $salesskills $salesinterold
if sales==1 & female==1 & (old==1|middle==0),  vce(cluster email)

*With full control: marginal effect
eststo r2: dprobit callback old $controls $fullcontrols $salesskills $salesinterold
if sales==1 & female==1 & (old==1|middle==0),  vce(cluster email)


*** Administration--using all skill variables;

* Start by using all interactions;
*With control of the authors

eststo r3: dprobit callback old $controls $adminskills $admiinterold
if admin==1 & (old==1|middle==0), vce(cluster email)

*With full control:
eststo r4: dprobit callback old $controls $fullcontrols $adminskills $admiinterold
if admin==1 & (old==1|middle==0), vce(cluster email)


esttab, main(dfdx) aux(se_dfdx)

esttab using "$output/Table2_W.tex", replace  ///
 main(dfdx) aux(se_dfdx) nomtitle label star(* 0.10 ** 0.05 *** 0.01) ///
 booktabs  t(3)  ///

*******************************************************************************
                                *Table C.3
*******************************************************************************

*I used data for women to produce an analog of table 3

log using "${output}\table3_w.log", replace
*Sales--Women
probit callback old $controls $salesskills $salesinterold
if sales==1 & female==1 & (old==1|middle==0),  vce(cluster email)

*Overidentification test
testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
=_b[computer]/(_b[oldcomputer]+_b[computer])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])
= _b[custserv]/(_b[oldcustserv]+_b[custserv])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
```

```
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])
= _b[city3]/(_b[oldcity3]+_b[city3])= _b[city4]/(_b[oldcity4]+_b[city4])
= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])
= _b[city9]/(_b[oldcity9]+_b[city9])= _b[city10]/(_b[oldcity10]+_b[city10])
= _b[city11]/(_b[oldcity11]+_b[city11])

*Panel A: probit estimates
global X old $controls $salesskills
global Z old
dprobit callback $X if sales==1 & female==1 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

*Panel B: Heteroskedastic probit estimates
version 12: hetprob callback $X if sales==1 & female==1 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])

*Standard deviation of unobservables, old/young
scalar di sdbosdw

*Test: ratio of standard deviation =1
testnl exp(_b[lnsigma2:old]) = 1
```

```
drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part : Old level (marginal)
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part : Old-variance (marginal)
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))


*Administration--Women
probit callback old $controls $adminskills $admiinterold
if admin==1 & female==1 & (old==1|middle==0),  vce(cluster email)

*Overidentification test
testnl _b[spanish]/(_b[oldspanish]+_b[spanish])= _b[emplmon]/(_b[oldemplmon]+_b[emplmon])
=_b[computer]/(_b[oldcomputer]+_b[computer])= _b[grammar]/(_b[oldgrammar]+_b[grammar])
= _b[college]/(_b[oldcollege]+_b[college])= _b[vol]/(_b[oldvol]+_b[vol])
```

```
= _b[wpm]/(_b[oldwpm]+_b[wpm])= _b[unempl]/(_b[oldunempl]+_b[unempl])
= _b[orderdv2]/(_b[oldorderdv2]+_b[orderdv2])= _b[orderdv3]/(_b[oldorderdv3]+_b[orderdv3])
= _b[city1]/(_b[oldcity1]+_b[city1])= _b[city2]/(_b[oldcity2]+_b[city2])
= _b[city3]/(_b[oldcity3]+_b[city3])= _b[city4]/(_b[oldcity4]+_b[city4])
= _b[city5]/(_b[oldcity5]+_b[city5])= _b[city6]/(_b[oldcity6]+_b[city6])
= _b[city7]/(_b[oldcity7]+_b[city7])= _b[city8]/(_b[oldcity8]+_b[city8])
= _b[city9]/(_b[oldcity9]+_b[city9])= _b[city10]/(_b[oldcity10]+_b[city10])
= _b[city11]/(_b[oldcity11]+_b[city11])

*Panel A: probit estimates
global X old $controls $adminskills
global Z old
dprobit callback $X if admin==1 & female==1 & (old==1|middle==0), classic vce(cluster email)
scalar llprob=e(ll)

*Panel B: Heteroskedastic probit estimates
version 12: hetprob callback $X if admin==1 & female==1 & (old==1|middle==0), het($Z) cluster(email)
scalar llhetprob=e(ll)
mehetprob, nodiscrete

scalar lltest=1-chi2(1,2*(llhetprob-llprob))
scalar di lltest

* Replicate marginal effect of old and calculate separate pieces;

predict linxb if e(sample), xb
sum old if e(sample)
scalar mold=r(mean)

sum linxb
scalar mxb=r(mean)

scalar msd=exp(_b[lnsigma2:old]*mold)

scalar pd=normalden(mxb/msd)*((_b[callback:old]-mxb*_b[lnsigma2:old])/msd)

scalar di pd

scalar pdlin=normalden(mxb/msd)*((_b[callback:old])/msd)
scalar pdvar=normalden(mxb/msd)*((-mxb*_b[lnsigma2:old])/msd)
scalar di pdlin pdvar

scalar sdbosdw=exp(_b[lnsigma2:old])

*Standard deviation of unobservables, old/young
scalar di sdbosdw

*Test: ratio of standard deviation =1
```

```
testnl exp(_b[lnsigma2:old]) = 1

drop linxb

* with nlcom;

* Create locals with mean values of regressors;

foreach X of varlist $X $Z{
 sum `X' if e(sample)
 local m`X'=r(mean)
}

* Create a local containing linear combinations Xb and Zg;

local xb _b[_cons]

foreach X of varlist $X{
 local xb `xb' + `m`X''*_b[`X']
}

local zg 0

foreach X of varlist $Z{
 local zg `zg' + `m`X''*[lnsigma2]_b[`X']
}

di "The local xb contains: `xb'"

di "The local zg contains: `zg'"


* Overall partial derivative
nlcom normalden((`xb')/exp(`zg'))*( (_b[old]-(`xb')*[lnsigma2]_b[old])/exp(`zg') )

* Linear part : Old level (marginal)
nlcom normalden((`xb')/exp(`zg'))*_b[old]/exp(`zg')

* Variance part : Old-variance (marginal)
nlcom normalden((`xb')/exp(`zg'))*(-(`xb')*[lnsigma2]_b[old]/exp(`zg'))


log close

**#Extension 2: exploring further the time to respond


use ${cleaneddata}, clear
```

```
sum matchlevel

drop if matchlevel==2

tab timetorespond


********************************************************************************
                                *Graphs C.5
********************************************************************************
*This table calculate the hazard rate for the time to respond (i.e. the probability that an applicants
*received a callback given that he has not received it yet)

preserve
count
gen numb=1
gen cat_age="Y" if young==1
count if cat_age=="Y" //13,023
count if cat_age=="Y" & callback==1 //2,127
replace cat_age="O" if old==1
count if cat_age=="O" //13,871
count if cat_age=="O" & callback==1  //1593
replace cat_age="M" if middle==1
count if cat_age=="M" // 12,467
count if cat_age=="M" & callback==1  //1697
collapse (sum) numb, by(timetorespond cat_age)
bysort cat_age: egen total=sum(numb)
by cat_age: gen f=numb/total //density function
gsort cat_age -timetorespond
by cat_age: gen cum=sum(numb)
by cat_age: gen S=cum/total //Survival rate: P(X>=x)
by cat_age: gen H=f/S
sort cat_age timetorespond
by cat_age: gen cdf=sum(numb)

twoway line H timetorespond if timetorespond<30 & cat_age=="Y", scheme(s1mono) ytitle("Hazard")
xtitle("Tenure") title("Young applicants")
graph export "$output/hazard_Y.pdf", replace
twoway line H timetorespond if timetorespond<30 & cat_age=="M", scheme(s1mono) ytitle("Hazard")
xtitle("Tenure") title("Middle applicants")
graph export "$output/hazard_M.pdf", replace
twoway line H timetorespond if timetorespond<30 & cat_age=="O", scheme(s1mono) ytitle("Hazard")
xtitle("Tenure") title("Old applicants")
graph export "$output/hazard_O.pdf", replace
restore

preserve
count //39,419
```

```
gen numb=1
count if callback==1 //5,320
collapse (sum) numb, by(timetorespond)
 egen total=sum(numb)
gen f=numb/total //density function
gsort -timetorespond
gen cum=sum(numb)
gen S=cum/total //Survival rate: P(X>=x)
gen H=f/S
sort timetorespond
gen cdf=sum(numb)

twoway line H timetorespond if timetorespond<30, scheme(s1mono)
ytitle("Hazard") xtitle("Tenure") title("All applicants")
graph export "$output/hazard_all.pdf", replace

restore

********************************************************************************
                                *Graph C.4
********************************************************************************

*This graph provides more information about the cumulative frequency of people receiving a response per days:

*The piece of code below is borrowed from Neumark, Burn and Button (2016)

sum timetorespond if young==1 & callback==1
sum timetorespond if middle==1 & callback==1
sum timetorespond if old==1 & callback==1

tab timetorespond if young==1 & callback==1
tab timetorespond if middle==1 & callback==1
tab timetorespond if old==1 & callback==1

* Long tail likely with little variation, so create categories;

gen ttr0=1 if timetorespond==0
replace ttr0=0 if timetorespond~=0 & timetorespond~=.

gen ttr1=1 if timetorespond==1
replace ttr1=0 if timetorespond~=1 & timetorespond~=.

gen ttr2t5=1 if timetorespond>=1 & timetorespond<=5
replace ttr2t5=0 if (timetorespond<2 | timetorespond>5) & timetorespond~=.

gen ttr6t10=1 if timetorespond>=6 & timetorespond<=10
replace ttr6t10=0 if (timetorespond<6 | timetorespond>10) & timetorespond~=.
```

```
gen ttr11p=1 if timetorespond>=11 & timetorespond~=.
replace ttr11p=0 if timetorespond<11 | timetorespond==.

sum ttr* if young==1 & callback==1
sum ttr* if middle==1 & callback==1
sum ttr* if old==1 & callback==1

gen ttryoung=timetorespond if young==1 & callback==1
gen ttrmiddle=timetorespond if middle==1 & callback==1
gen ttrold=timetorespond if old==1 & callback==1

cumul ttryoung if young==1 & callback==1, gen(Young) equal
cumul ttrmiddle if middle==1 & callback==1, gen(Middle) equal
cumul ttrold if old==1 & callback==1, gen(Old) equal

line Young ttryoung, sort
line Middle ttrmiddle, sort
line Old ttrold, sort

stack Young ttryoung Middle ttrmiddle Old ttrold, into(c timeresp) wide clear

line Young Middle Old timeresp, sort ytitle("Cumulative frequency of applicants") xtitle("Days to respond")
lpattern(shortdash longdash solid) legend(cols(3))
graph export "$output/cdf.pdf", replace
```