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Reducing discrimination against job seekers with and without employment gaps

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Past research shows that decision-makers discriminate against applicants with career breaks. Career breaks are common due to caring responsibilities, especially for working mothers, thereby leaving job seekers with employment gaps on their résumés. In a preregistered audit field experiment in the United Kingdom (n = 9,022), we show that rewriting a résumé so that previously held jobs are listed with the number of years worked (instead of employment dates) increases callbacks from real employers compared to résumés without employment gaps by approximately 8%, and with employment gaps by 15%. A series of lab studies (an online pilot and two preregistered experiments; n = 2,650) shows that this effect holds for both female and male applicants—even when compared to applicants without employment gaps—as well as and for applicants with less and more total job experience. The effect is driven by making the applicant's job experience salient, not as a result of novelty or ease of reading.

Many people experience voluntary or involuntary career breaks at some point during their working lives[1], leading to employment gaps on their résumés. Such employment gaps may be caused by external shocks (for example, sickness or downsizing due to the COVID-19 pandemic[2,3]) or career and lifestyle choices. Women are particularly affected by employment gaps when they take family-related leaves; for example, in the United Kingdom, over 70% of previously full-time working women take between 6 and 18 months out of paid employment after the birth of a child[4].

Even when employment gaps are transitory, workers may face discrimination upon work re-entry if these gaps are evident on their résumés[5–10]. Whereas traditionally structural unemployment (for example, skill shortages) is a major concern to the economy and society at large[11], frictional unemployment (for example, short gaps between jobs or short-term leave) may pose challenges for individuals—in particular, the scarring effects of short-term unemployment gaps[12]. Indeed, this underemployment in itself is a problem due to inefficiency, but could also lead to more structural problems if those job seekers decide to leave the labour market permanently. While penalties associated with employment gaps have been shown to affect male and female workers[6,7,13], motherhood penalties may particularly penalize women for childcare-related leaves[5]. There is a long literature noting the scarring effects of gaps in employment and a closely aligned literature exploring the impact of maternity leave and adjacent career breaks on individuals' career trajectories[12]. In fact, these additional barriers to re-entry for mothers may contribute to the well-known, persistent gender wage gap[12,14–16] as well as to women's lower representation in the upper echelons of companies[17–20]. These effects are likely compounded further by other factors that also contribute to gender inequalities in the labour market, including occupational segregation and differential job entry[21,22], hiring agencies' pre-emptive sorting by gender and industries[23], bias and discrimination within the workplace[24], negotiation decisions[25] and differential career advancement[26].

In this article, we focus on an early stage of the process: the initial screening of résumés—the first 'gateway'—when companies hire for a new position. To study discrimination during the hiring process against workers with employment gaps, researchers have in the past turned to audit studies. Audit studies[27] have been used extensively to examine the effects of gender (such as discrimination against women[28,29]), race (such as discrimination against non-whites[30]), unemployment (that

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is, discrimination against those who are unemployed)[6,7,31,32], and more recently, parenthood and childcare-related leave (that is, discrimination against parents taking time out of the workforce to care for their children[5,10,33]); for a comprehensive register of discrimination of various characteristics during hiring in audit experiments, see Baert[27]. These studies measure the effects of applicant characteristics on 'callbacks' (that is, an employer invitation to the next stage in the recruitment process—often a job interview).

While reduced opportunities for workers with employment gaps have been widely documented, little research has explored ways to overcome these barriers and biases. Some research has focused on reducing bias towards female applicants and working mothers. Of these interventions, employer strategies require manager training[34,35], suppressing biases and taking more time to review applicants[36], or overhauling current assessment processes[37]. Employee strategies encourage applicants to explain their employment gaps[8,38,39], highlight volunteer work[40] or deliberately manage others' impressions[28,41]. Although these interventions have shown promise, they also tend to require substantial extra effort from applicants and employers; some of these strategies may even create backlash or social penalties by creating incongruence with behavioural expectations for women[41].

To reduce these burdens, we develop and test a costless intervention applicants can adopt to facilitate workforce re-entry without backlash. Our intervention is informed by research from psychology and the field of judgement and decision-making, which shows that people inherently categorize people into groups, particularly when the category is easily accessible and representative[42,43]. Stereotype activation is an automatic process, but reliance on these stereotypes is also greater in contexts of high uncertainty and high subjectivity[44–47], which characterizes many personnel selection processes[48]. In addition to reliance on stereotypes (for example, mothers are less committed to their jobs and less productive than their child-free and male counterparts, unemployed applicants are lower quality and less productive than employed persons, etc.), employers may also be comparing applicants to prototypical workers.

We therefore hypothesize that employees with employment gaps contrast with conceptions of the 'ideal worker' who begins employment in early adulthood, continuing full-time without interruption for several decades[49]. Whether it is a mother who has taken a caregiving leave or a person who became unemployed due to job loss —the two most common reasons for disrupted employment—career breaks undermine decision-makers' impressions of applicant job experience by breaking this pattern of continuous employment[50,51].

Employers may still attend to career breaks (and may even discount previous work experience) despite the break's potential irrelevance for the quality of the worker; we therefore argue that it is desirable to obscure this information from decision-makers. Our intervention removes the career-break information from job-seekers' résumés, while still conveying job-relevant information. Specifically, to decrease the salience of the employment gap and to increase the salience of applicant experience, our intervention displays work experience in a different format: the number of years of experience for each job held (Supplementary Fig. 1b) instead of the standard 'date format' (Supplementary Fig. 1a). That is, instead of an applicant's résumé listing the two calendar dates between which the applicant started and finished a job (for example, 'March 2011–March 2016'), the treatment résumé displays a single number indicating the number of years the applicant worked in each job (for example, '5 years'). As a result, the intervention draws attention to the applicants' job experience while also obfuscating employment gaps by omission.

We hypothesize that our intervention will increase the likelihood of a qualified applicant advancing to the next stage of selection (such as receiving a callback in Study 1, or receiving increased ratings of perceived hireability in Studies 2–3). To test our theorized mechanism—perceived job experience—we also measure recalled years of experience (Studies 2–3). A related but separate research question that we do not address here is whether applicants in the treatment group are treated differently from the control group once they progress past the first gateway (for example, at an in-person interview). While unequal treatment can still occur at the interview stage[52–54], other research aims to reduce bias during this stage of the application process[55,56]. The powerful, lasting effects of first impressions and the necessity of passing the first gateway to get to the second gateway[57] further underlines the importance of the current research.

Given the high prevalence of employment gaps among women due to family-related leave—which also remains a critical contributor to workplace gender inequalities—a key focus of our studies is on mothers returning to work. Studying discrimination against mothers (and fathers) has been a particular focus in the literature. Notably, Correll and colleagues found evidence of discrimination against mothers who received half as many callbacks as child-free women but no callback penalties for fathers (versus child-free men)[5]. Weisshaar[10] found no statistically significant gender differences in callbacks. However, employed parents (versus unemployed parents who were laid off) received approximately 1.8 times more callbacks, and were approximately three times more likely to get a callback (versus parents who voluntarily left to take care of their children)[10]. Although our later studies also include men, this was primarily intended to test potential boundary conditions of our intervention. However, results from these additional studies show that the intervention appears to be useful for a range of job seekers: for men and women with various reasons for employment gaps and lengths of job experience.

Results

In a real-world setting with actual employers, Study 1 revealed that displaying the number of years of job experience (Years condition) on a résumé garnered more callbacks for job-seeking mothers than any other condition (Fig. 1). The other conditions are No Gap, where the résumé had the most recent employment date running from 'July 2015 to Present'; an Unexplained Gap condition, where the last date in employment ended 2.5 years before the résumé was sent out, and an Explained Gap condition, where the last date in employment ended 2.5 years before the résumé was sent out, followed by the sentence, 'Left to become a full-time mother and look after my children'.

Using linear probability models controlling for working pattern and region (as described in the preregistration), both the Unexplained Gap ($b = -0.049$, standard error (s.e.) = 0.014, $t(9{,}003) = -3.52$, $P < 0.001$; effect size (d) = −0.10, 95% confidence interval (CI) −0.18 to −0.02) and Explained Gap ($b = -0.050$, s.e = 0.014, $t(9{,}003) = -3.61$, $P < 0.001$; $d = -0.10$, 95% CI −0.18 to −0.02) conditions led to significantly lower callbacks than the Years condition. Furthermore, even the No Gap condition, which served as a conservative benchmark, received fewer callbacks ($b = -0.029$, s.e = 0.014, $t(9{,}003) = -2.07$, $P = 0.038$; $d = -0.06$, 95% CI −0.14 to 0.02) than the Years condition. All results hold when including job types and county fixed effects, as well as when using a logistic regression model (Supplementary Table 2b). In sum, and as predicted, the redesigned résumé improved job prospects for mothers returning to paid employment in a large-scale field experiment, even when compared to similar mothers without employment gaps.

Our first study offers evidence that the Years intervention led to more callbacks for applicants in a real-world setting with real employers. To better understand the mechanism through which the Years résumé operates, we turned to controlled online vignette studies[58]. We were particularly interested in capturing how the Years intervention is perceived along a number of dimensions (measured through Likert scales, Methods) in contrast to the standard résumé, although we also sought to capture a hypothetical proxy for our outcome variable (callback) in the field study. We used a 'hireability' outcome[59], measured on a scale from 0 to 100, which captured the likelihood that

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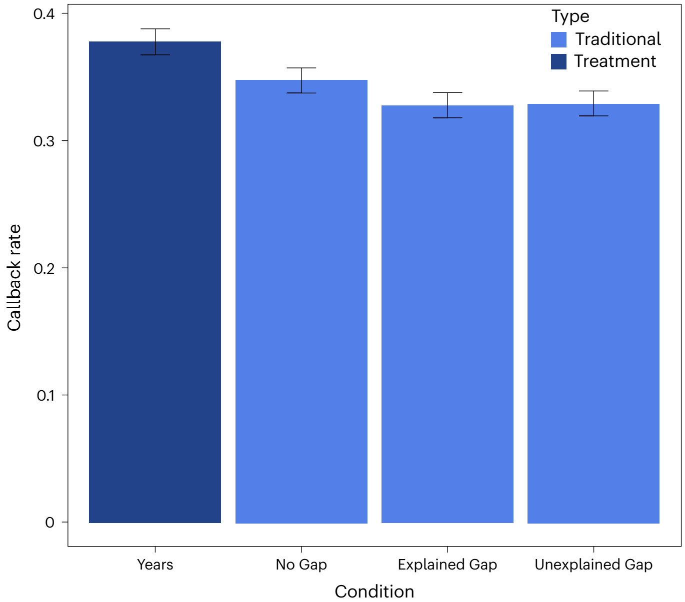

Fig. 1 | Callback rates by condition. The graph shows the percentage of callbacks per condition. Using a linear probability model, we find that the Years condition (n = 2,255) received significantly more callbacks than the No Gap condition (n = 2,255), the Explained Gap condition (n = 2,256) and the Unexplained Gap condition (n = 2,256). The error bars represent standard errors from the mean. The Unexplained Gap (b = −0.049, s.e. = 0.014, t(9,003) = −3.52, P < 0.001; d = −0.10, 95% CI −0.18 to −0.02) and Explained Gap (b = −0.050, s.e. = 0.014, t(9,003) = −3.61, P < 0.001; d = −0.10, 95% CI −0.18 to −0.02) conditions led to significantly lower callbacks than the Years condition. Furthermore, even the No Gap condition, which served as a conservative benchmark, received fewer callbacks (b = −0.029, s.e. = 0.014, t(9,003) = −2.07, P = 0.038, d = −0.06, 95%CI −0.14 to 0.02) than the Years condition. These results can also be found in Supplementary Table 2A.

the study participant would advance the applicant to the next stage of the application process.

We first explored the possible mechanisms with an online pilot study, in which we found no evidence in support of the most parsimonious explanations, namely, that the Years treatment is seen as easier to read (b = 0.08, s.e. = 0.15, t(248) = 0.51, P = 0.61; d = 0.01, 95% CI −0.34 to 0.36) or more novel (b = 0.01, s.e. = 0.16, t(248) = 0.06, P = 0.95; d = 0.06, 95% CI −0.30 to 0.41). Suggestive evidence for the mechanism emerged as increased perceptions of overall applicant experience in the treatment (b = 0.37, s.e. = 0.12, t(248) = 3.19, P = 0.002; d = 0.40, 95% CI 0.04 to 0.76) and years of applicant experience that participants recalled (b = 0.59, s.e. = 0.29, t(248) = 2.00, P = 0.047; d = 0.25, 95% CI −0.11 to 0.61). For the full regression results, see Supplementary Table 3.

Our preregistered Study 2 aimed to test this mechanism of increased perceptions of experience more explicitly and with a larger sample (n = 800). Study 2 was similar in many ways to Study 1 but differed from it in that we expanded it to also include résumés from male applicants. In particular, because the intervention in Study 1 was successful for applicants without an employment gap, we also sought to test whether the intervention would be moderated by, or would interact with, applicant gender.

Study 2 replicated and extended the effect of the Years condition, demonstrating that there was no statistically significant moderation by applicant gender: the redesigned résumé led applicants to be evaluated as more likely to be hired than applicants using a standard résumé, both when controlling for applicant gender (treatment: b = 2.13, s.e. = 0.94, t(758) = 2.25, P = 0.025; d = 0.16, 95% CI −0.04 to 0.36; applicant gender: b = −1.31, s.e. = 0.94, t(758) = −1.39, P = 0.17; d = −0.10, 95% CI −0.30 to 0.10; see Supplementary Table 4a, columns 1 and 2) and when including an interaction term between applicant gender and the intervention (treatment: b = 3.29, s.e. = 1.33, t(757) = 2.47, P = 0.01; gender: b = −0.12, s.e. = 1.35, t(757) = −0.09, P = 0.93; and treatment × gender interaction: b = −2.34, s.e. = 1.89, t(757) = −1.24, P = 0.22; see Supplementary Table 4a, column 3). Furthermore, Supplementary Table 4a, column 4 shows the robustness of the results by including both the interaction term and job fixed effects, while column 5 shows robustness by additionally excluding participants whose responses were outliers in the top 1% for the variable of years recalled.

We also confirmed the role of years of experience as a key mechanism: while the actual amount of job experience was 10 cumulative years for applicants in both conditions, participants who evaluated a résumé in the Years treatment more accurately recalled the number of years of experience that the applicant had (mean (M) = 9.41, s.e. = 0.34) than those in the standard résumé condition (M = 8.35, s.e. = 0.24; b = 1.06, t(759) = 3.16, P = 0.002; d = 0.23, 95% CI 0.03 to 0.43). This finding held after controlling for applicant gender and job type (Supplementary Table 4b) and was not significantly moderated by either or both factors.

In our preregistration, we said that we would exclude those who failed the gender manipulation check because we figured that those individuals would not be paying sufficient attention to the task at hand. For robustness, we provide the intention-to-treat (ITT) analysis without those exclusions; however, we expect adding in these additional inattentive participants would introduce noise to our analysis. In the ITT analysis, the treatment effect on applicant advancement becomes slightly marginal in two specifications (Supplementary Table 4c: P = 0.054 in our baseline specification with the treatment dummy in column 1; and P = 0.056 with job fixed effects in column 2) and remains significant in the two remaining specifications (Supplementary Table 4c: P = 0.021 when we include the interaction term in column 3; and P = 0.021 when we include both the interaction term and job fixed effects in column 4). Furthermore, in the ITT analysis, the treatment effect on recalled years of applicant experience is significant across all specifications (Supplementary Table 4d). In sum, the findings from the robustness analyses are broadly consistent with our preregistered analyses, although the estimates in some specifications are noisier, which we discuss in more detail below.

Finally, we sought to explore a policy-relevant boundary condition of the intervention. As the Years intervention focuses hiring managers' attention on applicants' amount of accumulated experience, it is plausible that the effect becomes less pronounced for more experienced workers (whose prior experience may be sufficiently long to be imprinted on hiring managers even with the standard résumé) or for less experienced workers (whose prior experience is too short to be highlighted effectively with the Years intervention).

Our preregistered Study 3 (n = 1,600) demonstrated that neither of these potential boundary conditions is of particular concern: the Years intervention worked successfully for applicants with 5 years or 15 years of experience, increasing hireability for applicants with fewer years of experience (5 years) (b = 2.36, s.e. = 1.03, t(762) = 2.29, P = 0.023; d = 0.17, 95% CI −0.02 to 0.32, Supplementary Table 5a, column 1) and with a greater number of years of experience (15 years) (b = 2.21, s.e. = 0.99, t(755) = 2.23, P = 0.026; d = 0.16, 95% CI 0.02 to 0.29, Supplementary Table 5a, column 2). In our preregistration, we said that we would exclude those who failed the gender manipulation check; however, for robustness, we include the ITT analysis without those exclusions (Supplementary Table 5b). All results remain significant except the probability of applicant advancement for 15 years of experience, which is marginal (P = 0.052). In sum, the findings from these robustness analyses are broadly consistent with our preregistered analyses.

Discussion

While the onus should not be on unemployed applicants to prevent others' bias against them, ample evidence has demonstrated that applicants with employment gaps face lower employment prospects, and therefore would benefit from seeking ways to remain competitive when re-entering the workforce. For working mothers in particular, a frequently recommended strategy is to 'explain the gap'[39]. Despite this proactive attempt to reframe the conversation—highlighting the skills, dedication and hard work needed to be a caregiver—we found no empirical support that this strategy works any better than an unexplained gap in our large-scale audit experiment in Study 1 (Supplementary Table 2c). However, our results from the field experiment offer applicants a promising and effective strategy to overcome barriers to work re-entry. Low-effort and costless, our intervention replaces the standard employment dates on the résumé with the length of time of employment and thereby highlights applicants' experience to prospective employers, eliminating employment gap penalties that hinder these applicants' advancement beyond the first gateway of the selection process. Furthermore, by conducting this study in a field setting, we prioritize high external validity. However, in a field setting it can be more difficult (and more expensive) to test mechanism and boundary conditions. Therefore, we combined these findings with additional studies in a more controlled 'online lab' setting for Studies 2 and 3 (ref. [60]).

Given the positive callback outcomes of the redesigned résumé for women in Study 1 compared to both No Gap and Gap résumés, we expanded this research to also include male applicants. In an online study, we tested and found that the intervention works well; also, its success is not moderated by the gender of the applicant, even when compared to résumés without an employment gap. These results suggest that résumés could be improved for a variety of applicants. And while there was no evidence that the treatment had an effect on perceptions of novelty or ease of reading, Study 2 demonstrated that the redesigned résumés facilitated reviewers' recall of applicants' years of job experience. Our final Study 3 provided additional evidence that this treatment can work for applicants with shorter and longer job experience, further suggesting that this intervention is fairly generalizable for various types of applicants. Because findings from our field studies and online vignette studies converge, we believe this is promising for the validity of our results[60].

Our research makes several contributions. First, this intervention provides a blueprint for how the judgement and decision-making literature can theoretically and practically contribute to practical interventions in the real world: by taking into account the mental machinery of hiring managers, we show how the kinds of mental shortcuts that can lead to bias (for example, seeing only gaps in employment) can instead be redirected to focus on positive associations (for example, helping hiring managers appreciate applicants' accumulated experience). Our research further contributes to the literature on gender discrimination, demonstrating a costless way for returning working mothers to show their potential to hiring managers and have a chance to proceed past the first gateway. Finally, our research contributes to understanding the wider experiences of discrimination for men and women who were temporarily unemployed. Helping people return to work after a prolonged unemployment spell is critical for public policy and social welfare support processes.

While this intervention predicted more callbacks and greater hireability, it is possible that this progress could be undone later in the interview process. For example, hiring managers might enquire about the exact dates of employment during an interview and, if learning about an employment gap, treat these applicants more negatively. However, it is also possible that interviewers rely less on stereotypes at this later stage, thus granting applicants a fairer, more merit-based opportunity. We encourage future research to explore this possibility. Furthermore, as hiring managers seem to assume that applicants with the standard 'dates' résumé have less experience than those with the 'years' résumé, future research should also attempt to quantify exactly how many years of experience the intervention can compensate for.

Our studies necessarily involved several design choices that other researchers may choose to explore differently. First, we focused on between-subject designs for our studies. While both between-subject and within-subject designs have their respective strengths and weaknesses, by not exposing participants to both treatment and control sequentially, the between-subject design is often a 'cleaner' if statistically less efficient test of causality[61,62]. On the other hand, we cannot speak to whether the same decision-maker would make different choices between the two résumés, which we encourage future research to explore. An additional consideration for choosing the between-subject design in the field context was that it reduces the burden on each individual employer (that is, the same employer is not sent multiple fictitious résumés). Second, we chose to replicate our field findings using online subject samples. While moving from the field into the 'online lab' reduces external validity, it also offers more experimental control and the potential to explore underlying mechanisms (for example, via survey scales)[63]. We chose to run our studies on Prolific Academic because it enabled us to reach a sample of working adults in the United Kingdom, which was similar to our field experiment sample[64]. Additionally, recent research on data quality across multiple platforms has shown Prolific to be of substantially higher quality than alternative platforms[65]. Because our results converge in both the field and online settings, it heightens our confidence in these findings.

However, there are also several limitations of this work. First, we only tested this intervention in the United Kingdom; however, we believe these findings should generalize because of the mechanism we identified. The 'years' résumé seems to operate on a cognitive level, not a cultural level. Therefore, we would expect this intervention to be effective in countries with less generous parental leave policies (for example, the United States) or more generous policies (for example, Scandinavian countries). That said, we encourage researchers to experimentally test the effectiveness of the intervention in other countries. Furthermore, as we only tested four specific levels of job experience (that is, 5, 9, 10 and 15 years), it is possible that there may be a lower bound of experience (for example, ≤1 year) below which the 'years' résumé might actually make a résumé appear less impressive than the standard 'dates' résumé. We also believe that the positive effects of this intervention may be limited to fields where more years is a proxy for more experience, and thus viewed favourably. If, however, a job applicant had a career break in certain fields (for example, while finishing a PhD in an academic context), the 'years' résumé might call attention to the extended timeframe, potentially triggering a negative effect (for example, signalling low motivation)[13]. Another potential limitation is in Studies 2 and 3 where we preregistered our analysis to exclude participants who did not pay sufficient attention and failed the attention check in the study. Doing so reduces the extent to which our results allow for a causal interpretation for all participants; rather they represent the causal treatment effect for participants who paid attention (that is, treatment-on-treated). However, our results are largely robust—with two out of eight regression specifications becoming marginally significant and the other six specifications remaining significant—to including even participants who did not pay sufficient attention in the study. Finally, a potential limitation of our design in Study 1 is that both the CV and the cover letter changed, introducing a potential confound. While this means that we cannot precisely identify which element in Study 1 caused our main effect, there is additional evidence that is consistent with our conclusion about the 'years' résumé: we replicated the main effect in online studies, where we only manipulated the résumés and did not provide a cover letter.

Our audit study was primarily conducted before the onset of COVID-19, yet it might offer insights into how employees can navigate a pandemic-induced employment gap. Due to the COVID-19 pandemic, millions of women and men now have employment gaps on their résumés[66], especially previously working mothers[3]. While hiring penalties may be lower for applicants whose employment gaps are due to external forces[10], the intervention tested here could theoretically help all applicants to receive appropriate recognition for their years of job experience.

While our results primarily speak to applicants, we believe this research also contributes to understanding ways stereotyping can be overcome and helping organizations with the design of their hiring processes. Hiring managers can add this intervention to their toolbox of 'debiasing' strategies (that is, by explicitly requesting that all résumés be submitted with years instead of dates), just as 'blinding' résumés has become commonplace in many settings[24]. While the general equilibrium effect of this intervention is an important question for future research if this intervention becomes more widely adopted, we predict that it would generally contribute to levelling the playing field if adopted more widely across applicants with and without employment gaps. In this way, applicants with equal experience receive equal employment opportunities, without the biasing stereotypes that more salient gaps may evoke.

Methods

Materials, data and code for all studies are available at https://osf.io/3gahc. Ethics oversight for the field experiment was provided by the Behavioural Insights Team's internal ethics process, and ethics oversight for the online lab experiments was provided by the University of Exeter ethics committee (eUEBS003871) and the Harvard University IRB (IRB20-1467). It is worth noting that the initial field study (Study 1) did not obtain explicit informed consent due to the impossibility of mitigating deception in this design; there was also no debriefing, which the research team deemed would create more harm than benefit. Moreover, the email inboxes and phones were monitored daily, and the research team politely declined any positive callbacks within one working day to reduce the potential burden on employers. Participants in the online studies did provide informed consent.

Study 1

We aimed to send 9,000 applications to detect an effect size of $d = 0.08$ with 80% power. We manipulated the presentation of the applicant's prior experience in a job in the form of dates (as is the case on traditional résumés) or summarizing the number of years the applicant held the job (on the redesigned résumé). We sent one of four different résumés and cover letters (conditions described below) to 9,022 employers across eight different sectors representing high- and low-skill jobs, in both male- and female-dominated fields (that is, software engineering, human resources, call centre operations, warehouse operations, finance, manufacturing production management, administrative work and social care work) who were advertising vacancies on a job-search platform from October 2019 to March 2020 in the United Kingdom. We aimed to assess a broad range of jobs that vary in the representation of men and women as well as the extent to which the job requirements might be linked to the male or female gender[58].

All résumés belonged to a fictitious applicant who had 9 years of work experience, was employed in two previous roles and, most importantly, was a mother. We selected 9 years because the average age of women in the United Kingdom having their first child is 28.8 (ref. [67]) and 50% of the population start full-time employment by 19 years old[68], which implies approximately 9–10 years of work experience before the birth of a first child. The fictitious applicant was named 'Sarah Smith'. Sarah was selected because it is one of the most common first names for women born in the United Kingdom between 1984 and 1994 (ref. [69]) without strong associations with a particular social class[70] and 'Smith' is the most common last name in the United Kingdom[71]. Where there was a gap, we selected a 2.5-year gap, because it is the average amount of time out of the workforce taken by women who choose to leave paid employment (beyond maternity or shared parental leave) for childcare-related reasons in the United Kingdom and then seek to return to paid employment[72]. We tailored the highest level of education and specifics of work experience to slightly exceed the typical requirements of each role. We conveyed parental status in all conditions with parent–teacher association involvement on résumés and stating that applicants were relocating to the hiring city with their family in cover letters[5,10].

We randomly assigned employers to receive one of four résumés (and corresponding cover letters). Three conditions used the 'traditional' résumé format, listing previously held jobs with their corresponding dates of employment. We varied whether an employment gap was present and, if so, whether this gap was explained (by stating that the applicant took time out of the workforce to look after her children) or unexplained. In the No Gap condition, the résumé had the most recent employment date running from 'July 2015 to Present', along with a line in the cover letter that said, 'I am currently employed at [Organization]'. In the Unexplained Gap condition, the last date in employment ended 2.5 years before the résumé was sent out and there was no explanation in the cover letter. In the Explained Gap condition, the last date in employment ended 2.5 years before the résumé was sent out, followed by the sentence, 'Left to become a full-time mother and look after my children'. The Explained Gap condition also included the following sentence in the cover letter, 'I was most recently employed at [Organization] and left in [Date] to become a full-time mother and care for my children, and am now eager to return to work'. We included the Explained Gap condition because it is a frequently recommended 'solution' on job-seekers' websites and thus offers a useful comparison against a common real-world benchmark.

The fourth condition—the 'Years' condition—is our main treatment of interest, in which we replaced the dates of employment with the number of years in each role with no explicit mention of current employment in the cover letter. In this condition, employment gaps were, by design, not visible to the employer as this format conveys applicant job experience without revealing when the jobs were held.

We were interested in studying whether an application received a 'callback' from an employer. To capture callbacks, we assigned each condition a unique corresponding email address and phone number and monitored both. Following the literature[5,10,29], we defined a callback as the employer progressing the applicant to the next stage in the process (for example, invitation to an online test, an interview or an in-person assessment), demonstrating strong positive interest, inquiring about start date availability, requesting that the applicant get in touch again once she moved, or if there was more than one missed call from the same employer. Our preregistration can be accessed at https://aspredicted.org/z2s6w.pdf.

The vast majority of applications for Study 1 (92.9%) were submitted before March 2020 when the United Kingdom enacted social distancing measures related to COVID-19. However, our results are also robust if we exclude data from March 2020 from the analysis.

Online pilot

For this exploratory study, we recruited 250 employees with hiring experience (33.6% male, $M_{\mathrm{age}} = 35.62$, $SD_{\mathrm{age}} = 12.38$; see Supplementary information for details) from the United Kingdom through Prolific Academic and collected data using a Qualtrics survey. After being randomized to either the Traditional (no gap) or Years résumé of a female applicant, participants rated whether they found the resumé easy to read or novel and how much professional experience they thought the applicant had; participants also recalled the applicant's years of job experience and demographics (for example, gender).

Study 2

We aimed to recruit 800 full-time employees from the United Kingdom through Prolific Academic and collected data using a Qualtrics survey to be able to detect an effect size of $d = 0.20$ with 80% power. After excluding participants who failed manipulation checks, we were left with 761 participants (54.7% male, $M_{\mathrm{age}} = 36.15$, $SD_{\mathrm{age}} = 10.68$). We said we would exclude participants who failed the manipulation checks in our preregistration, so our main analysis here excludes them; however, we provide the full ITT analysis in the Supplementary information; these results are consistent with our main findings.

Participants saw one of two different job types (that is, software engineer, which is a traditionally male job, or human resources manager, which is a traditionally female job). Participants were then randomly assigned to view a male or a female applicant and a control (Traditional without a gap) or treatment (Years) résumé. After seeing the résumé, participants were asked, 'How likely are you to advance this candidate to the next stage in the process?' on a scale from 1 (Definitely not) to 100 (Definitely yes).

After seeing the résumé and rating the applicant, participants proceeded to the next page of the survey where they no longer saw the résumé and were asked to recall the number of years of experience the applicant had and the number of previous jobs the applicant held, as well as identify the gender of the applicant (a manipulation check). Our preregistration can be accessed at https://aspredicted.org/is2b7.pdf.

Study 3

We recruited participants residing in the United Kingdom through Prolific Academic and collected data using a Qualtrics survey. We aimed to recruit 1,600 participants to be able to detect an effect size of $d = 0.25$ with 80% power. We excluded participants who failed an attention check before randomization and those who failed the gender manipulation check. We were left with a sample of 1,521 participants (38.7% men, $M_{age} = 34.8$, $SD_{age} = 9.7$). Because in our preregistration, we said that we would exclude these participants, our main analysis here excludes them; however, we provide the full ITT analysis in the Supplementary information; these results are consistent with our main findings.

Participants were randomly assigned to view the control (Traditional without a gap) or Years résumé. Within each condition, participants were then randomly assigned to see a résumé with fewer years (5 years) or more years (15 years) of job experience. Participants were then asked to rate on a 1–100 scale how likely they would be to advance the applicant to the next stage in the application process. After seeing the résumé and rating the applicant, participants proceeded to the next page of the survey where they no longer saw the résumé and were asked to recall the applicant's number of years of job experience and their demographics (as in Study 2). Our preregistration can be accessed at https://aspredicted.org/id5m4.pdf.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data for all studies are available at https://osf.io/3gahc/?view_only=a8188dc8f9e8473e8722fd57b92484ba.

Code availability

Code for all studies is available at https://osf.io/3gahc/?view_only=a8188dc8f9e8473e8722fd57b92484ba.

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Author contributions

L.N. designed the intervention and field experiment; A.S.K. and O.P.H. input into the field experiment and designed the online experiments; A.S.K. performed the online experiment research; A.S.K. analysed the data; and all authors wrote the paper.

Competing interests

L.N. is employed by the Behavioural Insights Team. The rest of the authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41562-022-01485-6.

Correspondence and requests for materials should be addressed to Ariella S. Kristal or Oliver P. Hauser.

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Corresponding author(s): Ariella Kristal

Last updated by author(s): September 22, 2022

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☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
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☐	☒	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Qualtrics, Prolific Academic
Data analysis	Open source R Studio (version 4.1.2). Code available: https://osf.io/3gahc/?view_only=a8188dc8f9e8473e8722fd57b92484ba.

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	These are quantitative data collected in a randomized controlled trial as well as several online lab experiments. In the first field experiment,). We sent one of four different résumés and cover letters (conditions described below) to 9,022 employers across eight different sectors representing high and low-skill jobs, in both male- and female-dominated fields (i.e., software engineering, human resources, call center operations, warehouse operations, finance, manufacturing production management, administrative work, and social care work) who were advertising vacancies on a job-search platform from October 2019 to March 2020 in the U.K. We aimed to assess a broad range of jobs that vary in the representation of men and women as well as the extent to which the job requirements might be linked to the male or female gender. We randomly assigned employers to receive one of four résumés (and corresponding cover letters). Three conditions used the "traditional" résumé format, listing previously held jobs with their corresponding dates of employment. We varied whether an employment gap was present and, if so, whether this gap was explained (by stating that the applicant took time out of the workforce to look after her children) or unexplained. In the No Gap condition, the résumé had the most recent employment date running from "July 2015 to Present," along with a line in the cover letter that said, "I am currently employed at [Organization]." In the Unexplained Gap condition with the last date in employment ending two and a half years before the résumé was sent out and there was no explanation in the cover letter. In the Explained Gap condition, the last date in employment ended two and a half years before the résumé was sent out, followed by the sentence, "Left to become a full-time mother and look after my children." The Explained Gap condition also included the following sentence in the cover letter, "I was most recently employed at [Organization] and left in [Date] to become a full-time mother and care for my children, and am now eager to return to work." We included the Explained Gap condition because it is a frequently recommended "solution" on job seekers websites and thus offers a useful comparison against a common real-world benchmark. The fourth condition— the "Years" condition—is our main treatment of interest, in which we replaced the dates of employment with the number of years in each role with no explicit mention of current employment in the cover letter. In this condition, employment gaps were, by design, not visible to the employer since this format conveys applicant job experience without revealing when the jobs were held. We were interested in studying whether an application received a "callback" from an employer. To capture callbacks, we assigned each condition a unique corresponding email address and phone number and monitored both. In the two online lab experiments, we showed participants control and years resumes and asked about perceptions of experience and likelihood of hiring.
Research sample	The research sample includes hiring managers/employers in the UK for which we did not collect demographic information. Given this was a natural field experiment, this sample consists of actual decision-makers responsible for hiring in organizations. For the online samples, we recruited (a non-representative sample) of full-time employed adults who are members of Prolific Academic and based in the UK, to try to approximate the types of people from Study 1 and who could realistically be involved in hiring decisions. For Study 2 we had 761 participants (54.7% male, Mage = 36.15, SDage = 10.68) and for Study 3 we had 1,521 participants (38.7% men, Mage = 34.8, SDage = 9.7).
Sampling strategy	Power calculations were conducted to determine the sample size needed for these randomized experiments.
Data collection	For the field experiment in Study 1, participants were actual hiring managers or HR officials working in their regular workplace and were unaware of the fact that they were participating in an experiment. These workers either chose to advance our fictitious candidate to the next round by calling or emailing, or not. RAs blind to condition checked the given phone numbers for voicemails and the emails for hiring responses and collated that data in a spreadsheet. The online experimental data was collected using a Qualtrics survey and participants recruited from Prolific Academic completed the survey online without an experimenter present at the time and location of their choosing.
Timing	The field experiment took place between October 2019 - March 2020. The online data collection took places between September 2020-June 2021.
Data exclusions	No data was excluded from the field experiment, and only those who failed the pre-registered attention/manipulation checks were excluded from the online studies.
Non-participation	No participants dropped out.
Randomization	All randomization occurred at the individual level.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☐	☒	Human research participants
☒	☐	Clinical data
☒	☐	Dual use research of concern

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	We do not have the population characteristics of the field experiment participants - as resumes were sent to UK companies posting open positions. The online experiments consisted of full-time employees in the UK who use Prolific Academic. The demographics of the pilot are: 33.6% male, Mage = 35.62, SDage = 12.38; Study 2 demographics: 54.7% male, Mage = 36.15, SDage = 10.68; Study 3 demographics: 38.7% men, Mage = 34.8, SDage = 9.7
Recruitment	Because we did not actively recruit for the field experiment, but rather included all eligible employers in our sample, our study has a lower risk of selection-bias. Employers in the field study were selected by posting certain job openings for certain positions during the trial window. Online study participants were recruited through Prolific Academic.
Ethics oversight	Ethics oversight for the field experiment was provided by the Behavioural Insights Team's internal ethics process, and ethics oversight for the lab experiments was provided by the University of Exeter ethics committee (eUEBS003871) and the Harvard University IRB (IRB20-1467). It is worth noting that the initial field study (Study 1) did not obtain explicit informed consent due to the impossibility of mitigating deception in this design, nor was there was a debrief, which the research team deemed would create more harm than benefit.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

nature human behaviour

Article https://doi.org/10.1038/s41562-022-01485-6

Reducing discrimination against job seekers with and without employment gaps

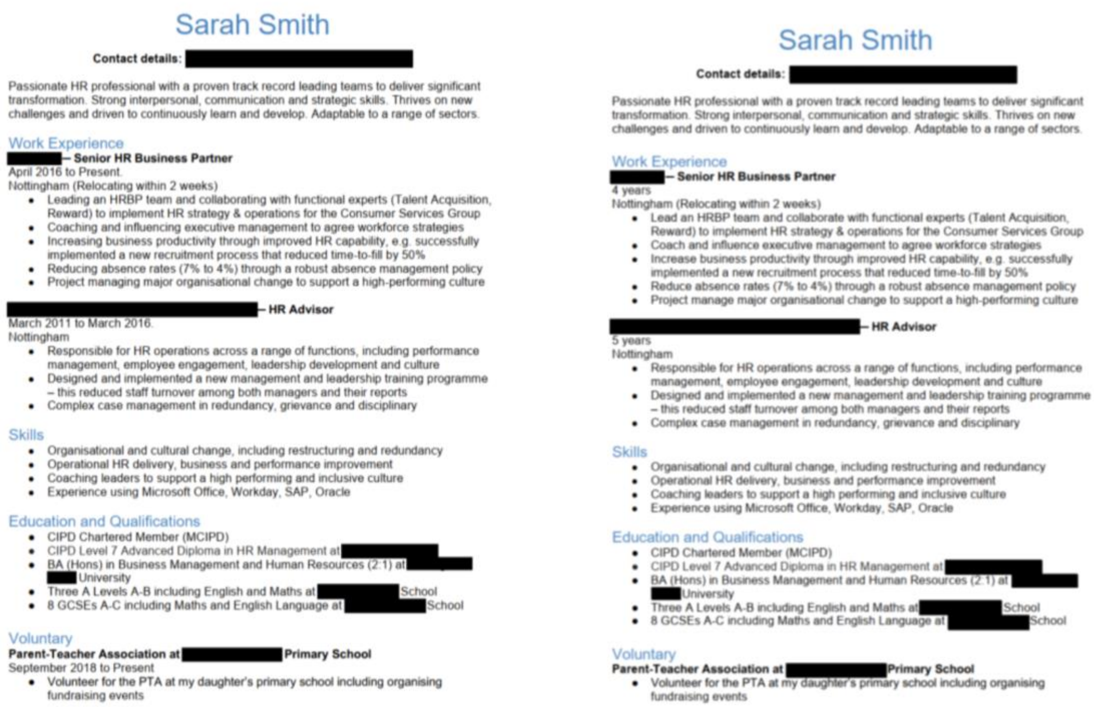
In the format provided by the authors and unedited

Table of Contents

Study 1 Additional Details

Supplementary Figure 1. Sample control and treatment résumés

A. **B.**



A.

Sarah Smith

Contact details: [redacted]

Passionate HR professional with a proven track record leading teams to deliver significant transformation. Strong interpersonal, communication and strategic skills. Thrives on new challenges and driven to continuously learn and develop. Adaptable to a range of sectors.

Work Experience

[redacted] **– Senior HR Business Partner**
April 2016 to Present.
Nottingham (Relocating within 2 weeks)
- Leading an HRBP team and collaborating with functional experts (Talent Acquisition, Reward) to implement HR strategy & operations for the Consumer Services Group
- Coaching and influencing executive management to agree workforce strategies
- Increasing business productivity through improved HR capability, e.g. successfully implemented a new recruitment process that reduced time-to-fill by 50%
- Reducing absence rates (7% to 4%) through a robust absence management policy
- Project managing major organisational change to support a high-performing culture

[redacted] **– HR Advisor**
March 2011 to March 2016.
Nottingham
- Responsible for HR operations across a range of functions, including performance management, employee engagement, leadership development and culture
- Designed and implemented a new management and leadership training programme – this reduced staff turnover among both managers and their reports
- Complex case management in redundancy, grievance and disciplinary

Skills
- Organisational and cultural change, including restructuring and redundancy
- Operational HR delivery, business and performance improvement
- Coaching leaders to support a high performing and inclusive culture
- Experience using Microsoft Office, Workday, SAP, Oracle

Education and Qualifications
- CIPD Chartered Member (MCIPD)
- CIPD Level 7 Advanced Diploma in HR Management at [redacted]
- BA (Hons) in Business Management and Human Resources (2:1) at [redacted] University
- Three A Levels A-B including English and Maths at [redacted] School
- 8 GCSEs A-C including Maths and English Language at [redacted] School

Voluntary

Parent-Teacher Association at [redacted] **Primary School**
September 2018 to Present
- Volunteer for the PTA at my daughter's primary school including organising fundraising events

B.

Sarah Smith

Contact details: [redacted]

Passionate HR professional with a proven track record leading teams to deliver significant transformation. Strong interpersonal, communication and strategic skills. Thrives on new challenges and driven to continuously learn and develop. Adaptable to a range of sectors.

Work Experience

[redacted] **– Senior HR Business Partner**
4 years
Nottingham (Relocating within 2 weeks)
- Lead an HRBP team and collaborate with functional experts (Talent Acquisition, Reward) to implement HR strategy & operations for the Consumer Services Group
- Coach and influence executive management to agree workforce strategies
- Increase business productivity through improved HR capability, e.g. successfully implemented a new recruitment process that reduced time-to-fill by 50%
- Reduce absence rates (7% to 4%) through a robust absence management policy
- Project manage major organisational change to support a high-performing culture

[redacted] **– HR Advisor**
5 years
Nottingham
- Responsible for HR operations across a range of functions, including performance management, employee engagement, leadership development and culture
- Designed and implemented a new management and leadership training programme – this reduced staff turnover among both managers and their reports
- Complex case management in redundancy, grievance and disciplinary

Skills
- Organisational and cultural change, including restructuring and redundancy
- Operational HR delivery, business and performance improvement
- Coaching leaders to support a high performing and inclusive culture
- Experience using Microsoft Office, Workday, SAP, Oracle

Education and Qualifications
- CIPD Chartered Member (MCIPD)
- CIPD Level 7 Advanced Diploma in HR Management at [redacted]
- BA (Hons) in Business Management and Human Resources (2:1) at [redacted] University
- Three A Levels A-B including English and Maths at [redacted] School
- 8 GCSEs A-C including Maths and English Language at [redacted] School

Voluntary

Parent-Teacher Association at [redacted] **Primary School**
- Volunteer for the PTA at my daughter's primary school including organising fundraising events

Results and Discussion

As specified in the preregistration (https://aspredicted.org/blind.php?x=i6k3se), we used a linear probability model to estimate the impact of the randomly assigned condition on callbacks and, as pre-registered, controlling for working pattern (full-time/ part-time) as well as for location (region-level fixed effects). The dependent variable callbacks is 1 if the response was positive (as defined above) and 0 otherwise. The independent variable takes one of four values: In the text, the baseline is our treatment of interest, the Years condition, against which the other three conditions are compared (No Gap, Unexplained Gap, Explained Gap). Here, we produce both regression tables using a linear probability model (Supplementary Table 2A) and a logistic regression for robustness (Supplementary Table 2B). We produce Supplementary Table 2C showing the same linear probability model using the Unexplained Gap condition as the baseline and showing how only the treatment significantly improves upon it. It is interesting to note that, unlike past research, we do not see a penalty for an employment gap in this context, relative to the Unexplained Gap condition.

While our randomization of the four conditions resulted in balance of our variables by construction (see Supplementary Table 1 for descriptive statistics), we nonetheless conducted a number of robustness analyses that ensured that no covariates were responsible for the treatment effect we observed.

Supplementary Table 1. Balance across conditions

	Years	No Gap	Explained Gap	Unexplained Gap
Administrative assistant	282	282	282	282
Call centre operative	282	282	282	282
Finance manager	282	282	282	282
Human resources manager	282	282	282	282
Product manager	282	282	282	282
Software engineer	281	282	282	282
Support worker	282	282	282	282
Warehouse operative	282	282	282	282
Full-time positions	1,253	1,259	1,296	1,253
Part-time positions	576	591	569	569
Working pattern not stated/other	426	405	391	434
Average salary advertised (SD)	£27,108 (£14,973)	£26,706 (£14,675)	£27,513 (£15,077)	£27,534 (£15,550)

Supplementary Table 2A. Impact of treatment on callbacks (linear probability model)

	(1) Callback	(2) Callback	(3) Callback	(4) Callback
No Gap	-0.029*	-0.029*	-0.029*	-0.029*
	(0.014)	(0.013)	(0.014)	(0.013)
	p = 0.036	p = 0.028	p = 0.038	p = 0.030
Explained Gap	-0.049***	-0.050***	-0.050***	-0.051***
	(0.014)	(0.013)	(0.014)	(0.013)
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Unexplained Gap	-0.050***	-0.049***	-0.049***	-0.049***
	(0.014)	(0.013)	(0.014)	(0.013)
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Mean (Years)	0.38	0.38	0.38	0.38
Working pattern controls	Y	Y	Y	Y
Job controls	N	Y	N	Y
Region	N	N	Y	Y
Observations	9,022	9,022	9,022	9,022
Adjusted R-squared	0.016	0.100	0.029	0.111

Supplementary Table 2B. Impact of treatment on callbacks (logistic regression)

	(1) Callback	(2) Callback	(3) Callback	(4) Callback
No Gap	-0.129*	-0.141*	-0.128*	-0.141*
	(0.062)	(0.065)	(0.063)	(0.066)
	p = 0.039	p = 0.031	p = 0.042	p = 0.032
Explained Gap	-0.216***	-0.242***	-0.225***	-0.254***
	(0.063)	(0.066)	(0.063)	(0.066)
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Unexplained Gap	-0.221***	-0.238***	-0.221***	-0.238***
	(0.063)	(0.066)	(0.063)	(0.066)
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Working pattern controls	Y	Y	Y	Y
Job controls	N	Y	N	Y
Region	N	N	Y	Y
Observations	9,022	9,022	9,022	9,022

Supplementary Table 2C. Conditions with Unexplained Gap condition as baseline (linear probability model)

	(1) **Callback**	(2) **Callback**	(3) **Callback**	(4) **Callback**
No Gap	0.20 (0.014) p = 0.150	0.20 (0.013) p = 0.144	0.20 (0.014) p = 0.147	0.20 (0.013) p = 0.140
Explained Gap	0.001 (0.014) p = 0.942	-0.001 (0.013) p = 0.970	-0.001 (0014) p = 0.929	-0.003 (0.013) p = 0.835
Years	0.050*** (0.014) p <0.001	0.049*** (0.013) p <0.001	0.049*** (0.014) p <0.001	0.049*** (0.013) p <0.001
Mean (Unexplained Gap)	0.33	0.33	0.33	0.33
Working pattern controls	Y	Y	Y	Y
Job controls	N	Y	N	Y
Region	N	N	Y	Y
Observations	9,022	9,022	9,022	9,022
Adjusted R-squared	0.016	0.100	0.029	0.111

Supplementary Table 2A-C Legend: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. No corrections were made for multiple comparisons.

Pilot Additional Details

Methods

Participants and procedure. We aimed to recruit 600 full-time employees from the United Kingdom (U.K.) through Prolific Academic to read. We planned to randomly assign participants to condition (control or treatment) for one of four different job types (i.e., software engineer, human resources manager, finance manager, and call centre operative), but due to a coding error, one of the job types (call centre operative) could not be analyzed. After excluding participants in both the control and treatment of the call centre operative, and excluding those who failed manipulation checks, we were left with 250 participants (33.6% male, $M_{\text{age}} = 35.62$, $SD_{\text{age}} = 12.38$).

After viewing one of three different job types, participants were randomly assigned to see a control (traditional dates without a gap) or a treatment (years) résumé. After seeing the résumé, participants were asked, “Overall, how much professional experience do you think this applicant has?” (1-7 Likert Scale ranging from “No experience” to “A lot of experience”). Participants were then asked two questions about the résumé: “To what extent do you think this CV is easy to read?” and “To what extent do you think this CV is novel” (1-7 Likert Scale ranging from “Definitely not” to “Definitely yes”). Then participants were asked to recall the number of years of professional experience the applicant had, to identify the gender of the applicant (a manipulation check), a series of exploratory questions (i.e., the gendered nature of the field of the job type and the new CRT scale; Thomson & Oppenheimer, 2016) and a comprehension check to ensure they understood the meaning of “novel” in this context (i.e., What is the definition of novel in the following context “The applicant’s CV was novel” and they could choose between “new,” “a book,” “fiction,” or “not sure”). Although we do not provide all exploratory analyses here, the full survey, dataset, and code can be found at https://osf.io/3gahc/?view_only=a8188dc8f9e8473e8722fd57b92484ba.

Results

As seen in Supplementary Table 3, the years résumé was not perceived as more novel (Column 1; $p = 0.952$) nor as easier to read (Column 2; $p = 0.611$). In contrast, the treatment résumé significantly increased perceptions of overall applicant experience (Column 3, $p = 0.002$) and the recalled years of experience (Column 4, $p = 0.047$).

Supplementary Table 3. Impact of résumé treatment on perceptions of résumés and applicants (OLS)

	(1) Résumé novelty	**(2) Résumé easy to read**	**(3) Overall experience**	**(4) Years of experience**
Treatment	0.010 (0.162) p = 0.952	0.078 (0.153) p = 0.611	0.369** (0.1116) p = 0.002	0.587* (0.294) p = 0.047
Constant	3.459*** (0.116) p < 0.001	5.508*** (0.109) p < 0.001	5.795*** (0.083) p < 0.001	9.475*** (0.210) p < 0.001
Observations	250	250	250	250
Adjusted R-squared	-0.004	-0.003	0.036	0.012

Supplementary Table 3 Legend: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. No corrections were made for multiple comparisons.

Study 2 Additional Details

Study 2 was designed to investigate whether the no dates version of a résumé has a differential effect for male applicants compared with female applicants and, therefore, could be extended to COVID-19 gaps. The pre-registration for Study 2 can be found at https://aspredicted.org/blind.php?x=4zq8a7.

Results

Replicating Study 2, we find evidence that the *Years* treatment increased perceptions of applicant experience. These effects held after controlling for gender or examining gender separately (see Supplementary Tables 4A-D for additional regression tables). Furthermore, we did not find a significant interaction between treatment and gender.

Supplementary Table 4A. Impact of résumé treatment on probability of applicant advancement and applicant gender (linear probability model)

	(1) Probability of advancing	**(2) Probability of advancing**	**(3) Probability of advancing**	**(4) Probability of advancing**	**(5) Probability of advancing (excluding top 1% outliers)**
Treatment	2.13* (0.94) p = 0.025	2.13* (0.94) p = 0.025	3.29* (1.33) p = 0.014	3.29* (1.33) p = 0.014	3.20* (1.34) p = 0.017
Male	-1.31 (0.94) p = 0.165	-1.31 (0.94) p = 0.163	-0.123 (1.35) p = 0.927	-0.13 (1.35) p = 0.923	-0.27 (1.35) p = 0.840
Treatment* Male	-	-	-2.34 (1.89) p = 0.216	-2.33 (1.89) p = 0.217	-2.20 (1.90) p = 0.248
Job Control	N	Y	N	Y	Y
Observations	761	761	761	761	748
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01

Supplementary Table 4B. Impact of résumé treatment on recalled years of applicant experience (linear probability model)

	(1) Recalled years of experience	(2) Recalled years of experience	(3) Recalled years of experience	(4) Recalled years of experience	(5) Recalled years of experience (excluding top 1% outliers)
Treatment	1.06** (0.34) p = 0.002	1.06** (0.34) p = 0.002	1.57*** (0.47) p < 0.001	1.57*** (0.47) p < 0.001	0.90*** (0.24) p < 0.001
Male	-0.42 (0.34) p = 0.211	-0.42 (0.34) p = 0.208	-0.10 (0.48) p = 0.832	0.10 (0.48) p = 0.841	-0.02 (0.24) p = 0.945
Treatment*Male	-	-	-1.03 (0.67) p = 0.127	-1.02 (0.67) p = 0.128	-0.30 (0.34) p = 0.374
Job Control	N	Y	N	Y	Y
Observations	761	761	761	761	748
Adjusted R-squared	0.01	0.01	0.01	0.02	0.04

Supplementary Table 4C. Impact of résumé treatment on probability of applicant advancement and applicant gender (ITT linear probability model)

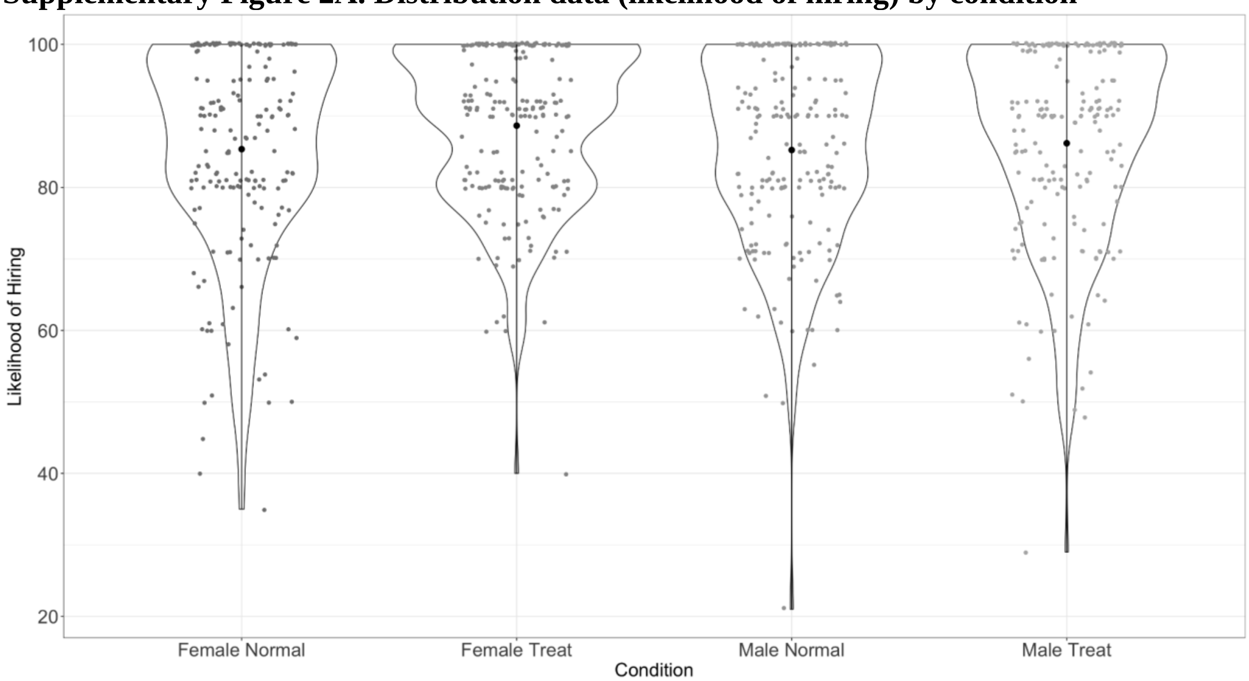
	(1) Probability of advancing	(2) Probability of advancing	(3) Probability of advancing	(4) Probability of advancing
Treatment	1.81† (0.94) p = 0.055	1.81† (0.95) p = 0.056	3.09* (1.33) p = 0.021	3.08* (1.33) p = 0.021
Male	-1.15 (0.94) p = 0.224	-1.16 (0.95) p = 0.222	-0.150 (1.34) p = 0.912	-0.143 (1.35) p = 0.916
Treatment* Male	-	-	-2.56 (1.89) p = 0.175	-2.56 (1.89) p = 0.176
Job Control	N	Y	N	Y
Observations	787	787	787	787
Adjusted R-squared	0.001	0.001	0.001	0.001

Supplementary Table 4D. Impact of résumé treatment on recalled years of applicant experience (ITT linear probability model)

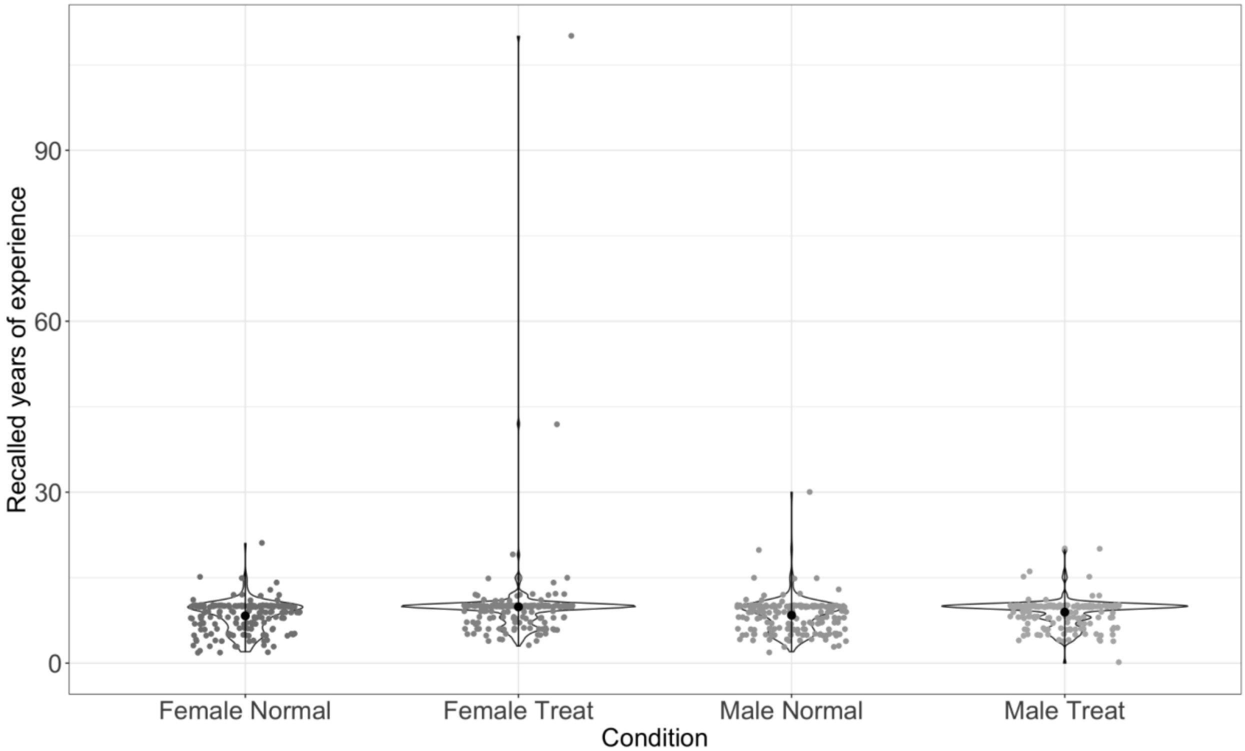
	(1) Recalled years of experience	(2) Recalled years of experience	(3) Recalled years of experience	(4) Recalled years of experience
Treatment	1.05** (0.33) p = 0.001	1.05** (0.34) p = 0.002	1.49*** (0.46) p = 0.001	1.48*** (0.46) p = 0.001
Male	-0.43 (0.33) p = 0.193	-0.43 (0.33) p = 0.188	0.015 (0.47) p = 0.974	0.01 (0.47) p = 0.983
Treatment*Male	-	-	-0.88 (0.66) p = 0.184	-0.87 (0.67) p = 0.184
Job Control	N	Y	N	Y
Observations	787	787	787	787
Adjusted R-squared	0.01	0.01	0.01	0.02

Supplementary Tables 4A-D Legend: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. No corrections were made for multiple comparisons.

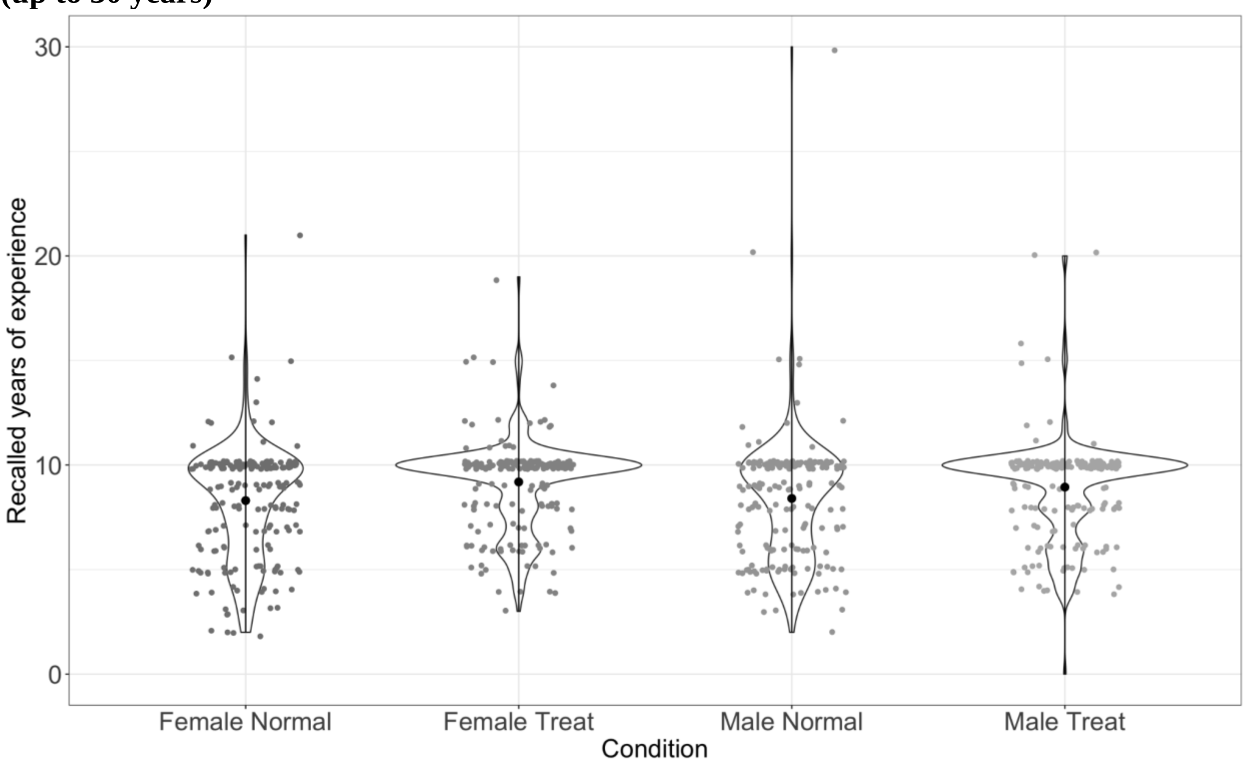
Supplementary Figure 2A. Distribution data (likelihood of hiring) by condition



Supplementary Figure 2B. Distribution of all data (recalled years of experience) by condition



Supplementary Figure 2C. Distribution of data (recalled years of experience) by condition (up to 30 years)



Study 3 Additional Details

Study 3 was designed to investigate whether the no dates version of a résumé would be effective for fewer (5 years) or a greater (15 years) number of years of experience. The pre-registration for Study 3 can be found at https://aspredicted.org/MY9_14Z.

Methods

Participants and procedure. We recruited participants residing in the U.K. through Prolific Academic. We aimed to recruit 1,600 participants to be able to detect an effect size of d = 0.25 with 80% power. We excluded participants who failed an attention check before randomization and those who failed the gender manipulation check. We were left with a sample of 1,521 participants (38.7% men, M_{age} = 34.8, SD_{age} = 9.7).

Participants were randomly assigned to view a control (traditional dates without a gap) or treatment (years) résumé. Within each condition participants were then randomly assigned to see a résumé with fewer years (5 years) or more years (15 years) of experience.

After seeing the résumé, participants were asked, "how likely are you to advance this candidate to the next stage in the process?" on a scale from 1 (Definitely not) to 100 (Definitely yes). Then, the participants were asked to recall the number of years of experience the applicant had and to identify the gender of the applicant (a manipulation check). See Supplementary Tables 5A-B. Column (5) shows the robustness of the results by excluding participants whose responses were outliers in the top 1% for the variable of years recalled.

Supplementary Table 5A. Impact of résumé treatment and years of experience on probability of advancement (linear probability model)

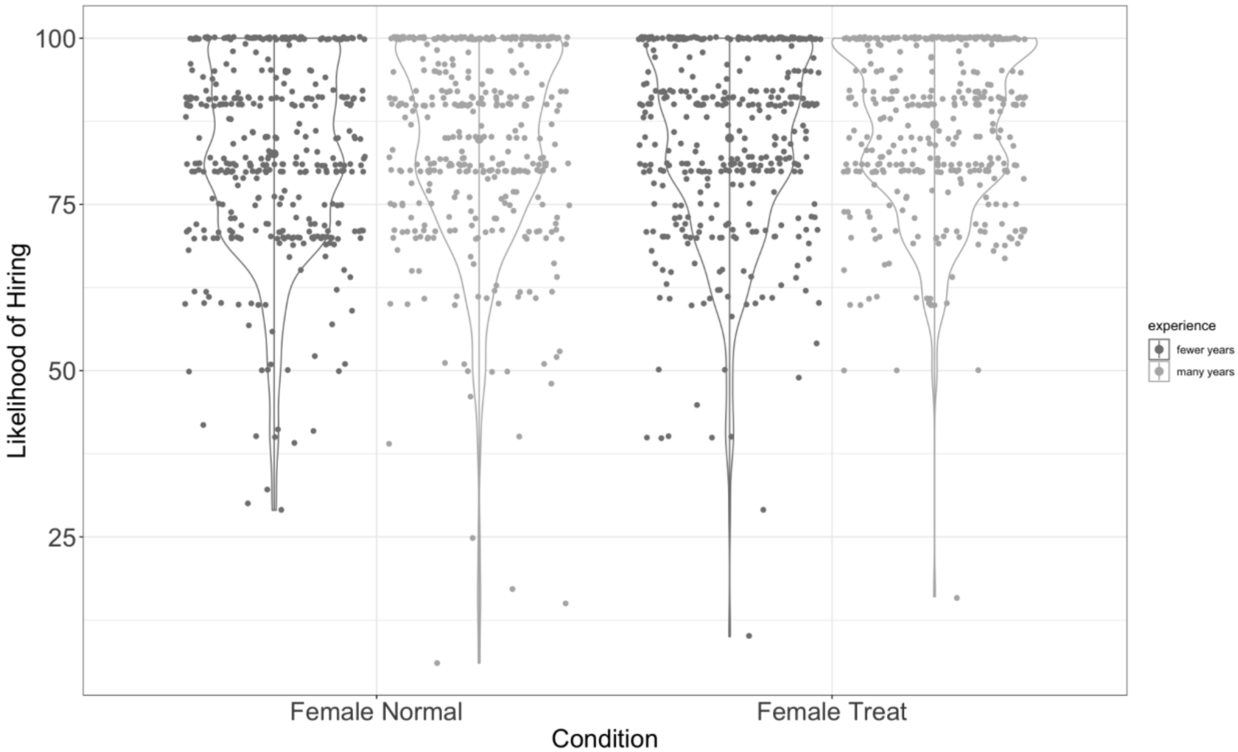
	(1) Probability of advancing (5 years)	(2) Probability of advancing (15 years)	(3) Probability of advancing	(4) Probability of advancing	(4) Probability of advancing (excluding top 1% outlier)
Treatment	2.36* (1.03) p = 0.023	2.21* (0.99) p = 0.026	2.29** (0.72) p = 0.001	2.36* (1.01) p = 0.020	2.55* (1.02) p = 0.012
Years	-	-	2.12** (0.72) p = 0.003	2.20* (1.01) p = 0.030	2.22* (1.01) p = 0.029
Treatment*Years	-	-	-	-0.15 (1.43) p = 0.918	-0.22 (1.44) p = 0.876
Observations	762	755	1,517	1,517	1,500
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01

Supplementary Table 5B. Impact of résumé treatment and years of experience on probability of advancement (ITT linear probability model)

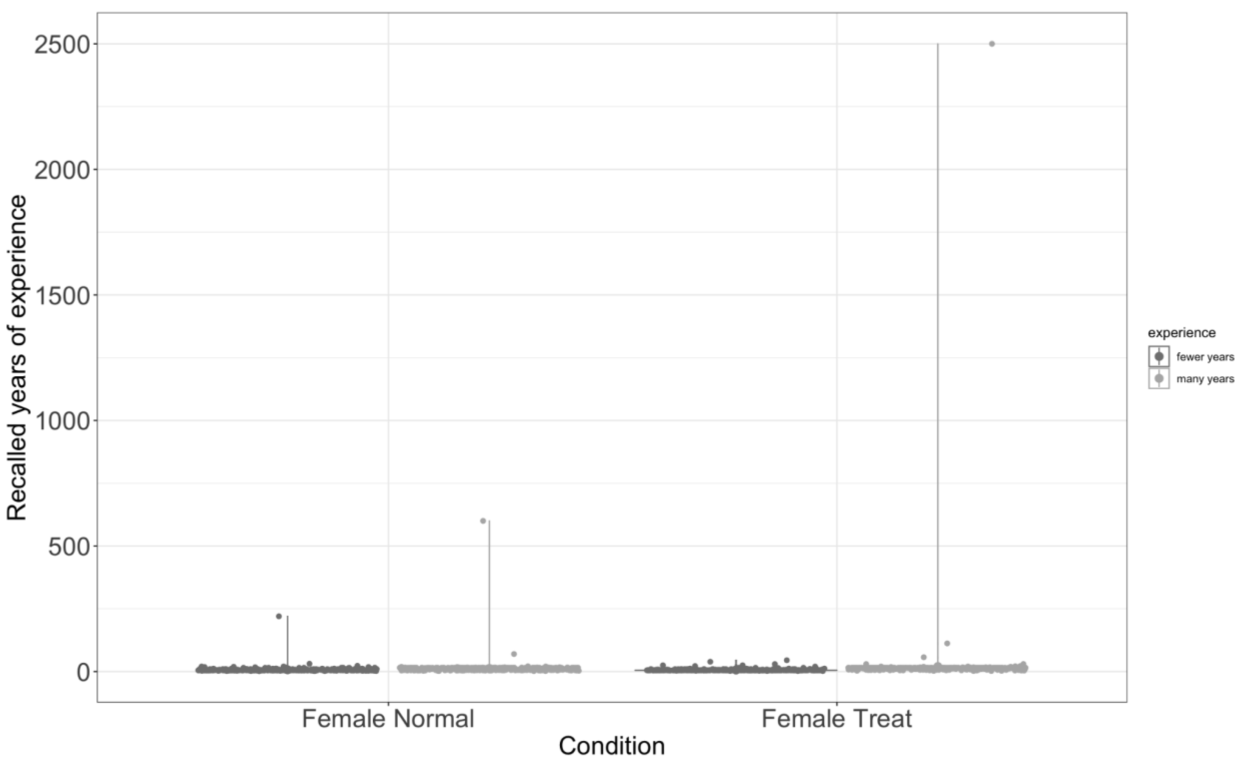
	(1) Probability of advancing (5 years)	(2) Probability of advancing (15 years)	(3) Probability of advancing	(4) Probability of advancing
Treatment	2.30* (1.02) p = 0.025	1.92† (0.99) p = 0.052	2.11** (0.71) p = 0.003	2.30* (1.00) p = 0.022
Years	-	-	2.31** (0.71) p = 0.001	2.50* (1.01) p = 0.013
Treatment*Years	-	-	-	-0.15 (1.43) p = 0.790
Observations	808	799	1,607	1,607
Adjusted R-squared	0.01	0.01	0.01	0.01

Supplementary Tables 5A-B Legend: † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. No corrections were made for multiple comparisons.

Supplementary Figure 3A. Distribution data (likelihood of hiring) by condition



Supplementary Figure 3B. Distribution of all data (recalled years of experience) by condition



Supplementary Figure 3C. Distribution of data (recalled years of experience) by condition (up to 30 years)