Reject and resubmit:
A formal analysis of gender differences in reapplication and their contribution to women's presence in talent pipelines

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ABSTRACT

A common explanation for women's underrepresentation in many economic contexts is that women exit talent pipelines at higher rates than men. Recent empirical findings reveal that, in male-dominated selection contexts, women are less likely than men to reapply after being rejected for an opportunity. We examine the conditions under which this gender difference contributes to women's underrepresentation in talent pipelines over time. We formally model and analyze the population dynamics of a generic selection context, which we then ground using three distinct empirical settings. We show that gender differences in reapplication are an important mechanism of gender segregation in some selection contexts but negligible in others. The extent to which gender differences in reapplication contribute to women's underrepresentation is driven in part by the rejection rate. Higher rejection rates increase the stock of rejected applicants, which in turn enables gender differences in reapplication to disproportionally reduce women's representation. The results demonstrate that interactions between individuals' choices on the supply-side and screeners' behavior on the demand-side may have consequences for gender inequality even if we were able to fully eliminate demand-side biases. We discuss the theoretical and policy implications of our research for understanding women's underrepresentation in talent pipelines. We also interrogate the effectiveness of common interventions focused on encouraging women to apply for opportunities in male-dominated domains.

INTRODUCTION

Women are underrepresented in top management positions, entrepreneurship, science, and many other economic contexts (Catalyst 2018; Guzman and Kacperczyk 2019; Huang et al. 2020). One common explanation for this phenomenon is that there is a limited pipeline of women available to apply for the most rewarding opportunities (Carli and Eagly 2001; Helfat, Harris, and Wolfson 2006; Ding, Murray, and Stuart 2013). In the last few years, scholars have started to document a novel contributor to this problem: after being rejected in a male-dominated selection context, women are less likely to reapply for future opportunities within that context. The finding has been reported in a wide range of settings, including hiring processes (Dlugos and Keller 2021; Brands and Fernandez-Mateo 2017; Yang et al. 2019), entrepreneurial crowdfunding projects (Greenberg et al. 2019), patent applications (Jensen et al. 2018), and research grant proposals (Kolev et al. 2019). The ubiquity of this tendency raises questions, both from a theoretical and a policy perspective, about its implications for gender inequality. Intuitively, the implications appear obvious: women's lower likelihood of reapplying after being rejected should significantly contribute to their underrepresentation in talent pipelines over time. Likewise, interventions that directly encourage women to reapply should help to improve gender diversity.

However, such intuitions implicitly assume that gender differences in individual behavior yield predictable outcomes at the talent pipeline level. This assumption overlooks the interdependency between individuals' choices to apply for opportunities and organizations' processes for selecting candidates – i.e., between the supply-side and the demand-side of the market. Recent studies have demonstrated that what often looks like solely a supply-side process (e.g., women's reluctance to apply for jobs or to start a new venture) may also be influenced by the demand-side (e.g., the criteria used to select candidates) (Fernandez-Mateo and Kaplan 2018). Even if we consider the application decision to be a purely supply-side phenomenon, and the selection decision to be a purely demand-side phenomenon, reapplication following rejection necessarily involves both supply- and demand-side processes. Such interdependency makes it challenging to isolate the theoretical impact of gender differences in reapplication. The challenge is not unique to the specific phenomenon of reapplication choices; it applies to any attempt to understand the dynamics of talent pipelines.

Uncovering the dynamic effects of a complex system of interactions among actors is far from straightforward. We address this challenge here, by using formal modeling to build theory about the consequences of gender differences in reapplication for women's representation in talent pipelines. Although the use of formal models is not yet widespread among scholars of gender inequality, it can offer a powerful tool to isolate the effect of specific theoretical mechanisms, as well as to examine how interdependencies between supply-side and demand-side processes shape gender inequality (Rubineau and Fernandez 2015; Kogut et al. 2014). Leveraging this approach, we examine three key questions regarding the operation and consequences of gender differences in reapplication. First: Can gender differences in reapplication after rejection lead to substantial segregating effects[1] over time? Second: What contextual factors attenuate or amplify the segregating effects of gender differences in reapplication? Third: How do common interventions – such as including more women in the applicant pool – interact with gender differences in reapplication to increase gender parity?

In order to address these questions, we build a formal model of the population dynamics (e.g., Hirsch et al. 2012) of a generic selection context that represents individuals' application, selection/rejection, and reapplication. We start with the simplest possible model to isolate the effect of gender differences in reapplication on women's representation in this generic context over time (i.e., at equilibrium). The model's parameters represent key features of the selection context: women's share of first-time applicants, the rate of reapplication by rejected women, and the overall rejection rate. The overall rejection rate is the same for men and women, in order to isolate the effect of gender differences in reapplication net of any demand-side gender bias.

After defining and describing the model, our analysis unfolds in two stages. First, we explore the model's parameter space to assess how women's share of the applicant pool at equilibrium varies with different values of the parameters. We then develop two propositions regarding the features of the selection context that determine whether reapplication rates contribute substantially to women's

[1] Gender differences in reapplication can contribute to reducing the share of women in a talent pipeline below their share of first-time applicants, as women would be less likely than men to apply over time. We describe reductions in women's representation in the talent pipeline resulting from these differences as the *segregating effects* of gender differences in reapplication.

representation. Second, in order to provide real-world parameter ranges, we ground the model (Harrison et al. 2007) using three empirical cases – executive search, crowdfunding, and patenting. Finally, we discuss how the results of the model help us to scrutinize the effects of a popular intervention for increasing gender parity in talent pipelines: increasing the number of women in the applicant pool.

The main theoretical insights of our analysis are twofold. First, while in some contexts gender differences in reapplication do contribute substantially to the reduction of women's presence in the talent pipeline, in other contexts the segregating effects of this mechanism are negligible. This point runs counter to common intuition that women's lower likelihood of reapplication after rejection would necessarily exacerbate female underrepresentation over time. Second, and surprisingly so, whether gender differences in reapplication matter in the long run depends not only on the magnitude of these gender differences, but also, critically, on a demand-side attribute – namely, the overall rejection rate of the selection context. Higher rejection rates increase the stock of rejected applicants who are at risk of reapplying, thus boosting the proportion of previously rejected applicants in the pool. Because of women's lower likelihood of reapplying, these previously rejected applicants are disproportionally men. Hence, a higher rejection rate exacerbates the potential for gender differences in reapplication to reduce women's representation in the applicant pool. Conversely, in contexts where the rejection rate is low, gender differences in reapplication – even very large differences – do not have the opportunity to generate substantial reductions in women's representation over time.

Our paper makes several contributions to research on gender inequality. An emerging body of work suggests that gender differences in reapplication are an important supply-side mechanism contributing to women's underrepresentation in talent pipelines. Our formal modeling approach allows us to show that this is true only under certain conditions. Whether supply-side gender differences in reapplication produce meaningful segregating effects in the long run greatly depends on demand-side rejection rates (even if these rejection rates are *unbiased*). This possibility, which has thus far not been considered in the literature, has two important implications. First, it opens up new theoretical avenues to examine how various features of selection contexts on the demand-side interact with individuals' behavior on the supply-side to exacerbate or attenuate gender inequality in talent

pipelines. Second, it suggests hitherto unexplored consequences for policy. Namely, our model questions the long-term effectiveness of popular approaches to increase women's representation by expanding and diversifying the applicant pool. It also suggests that demand-side interventions – such as those that act on the rejection rate – may sometimes be an alternative to the most obvious practice of encouraging women to reapply.

THEORETICAL BACKGROUND

The underrepresentation of women in many economic contexts is a topic of growing interest in management research, from studies of gender diversity in firms' upper echelons (Dezsö and Ross 2012; Post and Byron 2014) to research on the scarcity of women entrepreneurs and innovators (Ding et al. 2006; Thébaud 2015; Lerchenmueller and Sorenson 2018; Guzman and Kacperczyk 2019). Although progress has been made to increase female participation in male-dominated contexts, an enduring concern is the dwindling number of women as opportunities become more rewarding (Preston 1994; Catalyst 2018). A common explanation for this phenomenon is that there is a problem with the pipeline of women available and willing to apply for these opportunities over time (Carli and Eagly 2001; Helfat, Harris, and Wolfson 2006; Ding, Murray, and Stuart 2013). Attaining the most rewarding positions within a given context requires one to participate in a series of sequential selection processes. For example, to reach an organization's highest echelons, individuals must win a series of competitions for jobs (Rosenbaum 1979). Likewise, aspiring entrepreneurs often must solicit funding for their ventures over multiple rounds (Neher 1999; Tian 2011). Careers in science and technology similarly involve a series of points at which individuals choose to apply for opportunities (Xie and Shauman 2003; Penner and Willer 2019). In most male-dominated settings, the proportion of women among candidates for these opportunities declines from each selection stage to the next – thereby contributing to gender disparity in the most coveted roles.

From the perspective of organizations or institutions seeking to increase women's presence in a given context, filling talent pipelines with enough female candidates is a dynamic problem of resource accumulation (Dierickx and Cool 1989; Rahmandad and Repenning 2016). It takes time to build a stock of women, and the accumulation process depends on the flow of female candidates entering and leaving each selection stage. Any mechanism by which women are (at each stage) either

less likely to be selected or less likely to apply will result in decreasing female representation over time. A large amount of research has presented evidence for both types of mechanisms. On the demand side of the market, screeners are less likely to select women for opportunities that are traditionally male and more rewarding (Blau et al. 2006; Fernandez-Mateo and King 2011; Brooks et al. 2014). On the supply side, women are less likely to apply for positions in male-dominated selection contexts, and they tend to drop out from talent pipelines at a higher rate than men (Barbulescu and Bidwell 2013; Shahriar 2018; Huang et al. 2020).

An emerging body of research has reported a supply-side process by which women drop out from talent pipelines: women are less likely to reapply for opportunities following a rejection. This phenomenon has been documented in several labor market contexts, both within organizations as well as in recruitment mediated by intermediaries. Dlugos and Keller (2021) report lower rates of reapplication after rejection for internal jobs among women in a large organization. Brands and Fernandez-Mateo (2017) find that female candidates are less willing than male candidates to be considered for top management jobs by an executive search firm after having been rejected for a similar position. Yang, Leung, and Bao (2019) study an online labor market, where women who are rejected for jobs in information technology and programming are less likely than men to apply subsequently for similar jobs through the platform. Similarly, Bapna, Benson, and Funk (2021) show that women rejected by a temporary staffing firm are much less likely than men to reapply for jobs – a difference that could be reduced by framing rejection in terms of fit with the job.

Beyond the labor market, women's lower likelihood of reapplying has also been documented in science, technology, and entrepreneurship. Using data from US patent applications, Jensen, Kovács, and Sorenson (2018) report that rejected patent application teams including women inventors are less likely to appeal a patent rejection than are rejected teams that do not include women. Kolev, Fuentes-Medel, and Murray's (2019) study of research grant proposals submitted to the Gates Foundation shows that women are less likely to reapply if their proposal had been rejected previously. In the entrepreneurial context, Greenberg, Kuppuswamy, and Mollick (2019) show that aspiring women entrepreneurs who fail to achieve their funding goal via a crowdfunding platform are less likely than men to pursue another entrepreneurial attempt on the same platform.

Despite the contextual differences across these various settings, they all entail individuals who participate in selection processes to access opportunities, often repeatedly over time. Candidates who are rejected typically face the choice of trying again: either for the same opportunity or for subsequent similar opportunities. That is, the possibility of reapplication is a feature of many selection contexts. This is certainly the case in settings such as research grant proposals, patenting, academic journal submissions, and entrepreneurial funding. For example, Kolev et al. report that repeat applications for grants are 20.4% of all proposals. Similarly, about half of patent applicants who receive a "request for a re-examination" are likely to do so (Jensen et al. 2018). In the labor market, hiring studies suggest that reapplying to the same organization (either for the same or a similar vacancy) is not a rare occurrence either. Research by Fernandez and colleagues using firms' archival data report that between 10% and 25% of applications are repeat applications (e.g., Fernandez and Sosa 2005; Fernandez and Fernandez-Mateo 2006; Fernandez and Mors 2008; Fernandez and Galperin 2014). More recent work studying staffing firms and internal labor markets find rates of reapplication to the same firm that vary from around 7% (Bapna et al. 2021) to as much as 46.4% in some selection contexts (Dlugos and Keller 2021).

We define a *selection context* as a screening stage that involves candidates' evaluation, selection/rejection and the possibility of reapplication. This term is intended to include the wide range of empirical settings where gender differences in reapplication have been detected. We focus on the consequences of men and women's behavioral choices for the gender segregation of the talent pipeline within a given selection context (e.g. a hiring firm, an online platform, a research grants programme). The observed behavior that women are less likely to reapply after rejection is similar across all these contexts, although its cognitive or psychological drivers may vary across settings. For example, while Brands and Fernandez-Mateo (2017) focus on gendered perceptions of procedural justice, Greenberg, Kuppuswamy, and Mollick (2019) highlight gender differences in interpreting failure signals. In the context of patent applications, it may even be that gender differences in reapplication after rejection stem from actors other than the inventors themselves – for instance, patent lawyers. The underlying psychological or cognitive sources of gender differences in reapplication are not important for our purposes, since our unit of analysis is the selection context (i.e.

the population level dynamics) rather than the individual applicant. The striking behavioral similarity across such diverse contexts raises the question of how this behavioral tendency may shape the dynamics of inequality in talent pipelines.

Intuitively, it seems obvious that individuals' application choices will necessarily aggregate to the talent pipeline level. Namely, as most previous studies of this phenomenon assume, women's lower likelihood to continue applying in a selection context after rejection should significantly contribute to their underrepresentation in that context over time. However, there is ample evidence that reliance on human intuition for understanding dynamic systems may yield false conclusions (Forrester 1971). This is because dynamic systems with even very low levels of complexity can exhibit counterintuitive behavior that prompts dysfunctional responses (Sterman 2001). A better understanding of the pipeline problem requires that we consider the dynamic effects of a given segregation mechanism on the stocks and flows of women available as candidates for selection in a given selection context. Crucially, these stocks and flows depend not only on individuals' application behavior, but also on their interdependency with processes on the demand-side of the market. Examining these dynamic interdependencies is an insufficiently explored theoretical frontier in the literature. Yet, absent an understanding of such dynamics, intuitively compelling interventions could give rise to unintended (and perhaps even perverse) consequences. To address this problem, we use formal modelling as a tool to examine the dynamic, population-level implications of reapplication rates for gender inequality in talent pipelines.

FORMAL MODEL OF GENDER DIFFERENCES IN REAPPLICATION

We build a formal model of the population dynamics of a selection context with gender differences in reapplication after rejection. Model construction requires making trade-offs between simplicity and realism (Levins 1966; Burton and Obel 1995; Coen 2009). There is no one correct resolution to these trade-offs; rather, the modeler's choice is informed by the research question at hand (Burton and Obel 1995; Coen 2009; Csazar 2019). We seek to gain an initial dynamic understanding of the effects of gender differences in reapplication after rejection in a generic selection context – and, if possible, to identify what types of interventions may ameliorate these effects. Of course, many processes and mechanisms shape the gender composition of any real-world selection

context, but our goal here is not to build a complete model with direct predictive accuracy. Therefore, we set aside other segregating mechanisms and instead build a highly simplified – but hopefully useful – formal model of the specific process of interest (e.g., Akerlof 1970). We base our modeling choices on empirical evidence, when available, and conduct robustness checks in the form of model variants when empirical evidence is lacking. When two similarly justifiable modeling choices exist, we choose the one that yields a more conservative answer.

Our formal model represents the application, selection/rejection, and reapplication of a generic selection context as a dynamical system. The model is a paired set of differential equations for the population dynamics of men and women[2] within that generic selection context (e.g., Rubineau and Fernandez 2015). The only source of gender differences is the gender difference in reapplication after rejection. The selection process is otherwise unbiased; that is, male and female applicants all face the same rejection probability. Our modeling procedure is the mathematical equivalent of simulation approaches used in system dynamics (Levy 1994; Rahmandad and Sterman 2008). The model is rendered formally in Table 1 and is illustrated schematically, as a stylized diagram of the "stock and flow" type, in Figure 1.[3] There are two stocks each for men and women (indicated by the subscripts *M*, and *W*, respectively) – applicants (*A*) and those who are rejected and at risk of reapplying (*R*). The model's outcome is the women's share of the applicant pool, $A_W/(A_W + A_M)$, at equilibrium.

[[INSERT Table 1 about Here]]

[[INSERT Figure 1 about Here]]

A single round of the modeled selection context is as follows: Men and women apply for an opportunity. The parameter *p* captures the share of women among first-time applicants, and it takes values between 0 and 1. All applicants are either selected or rejected. The parameter *r* (also between 0

[2] In our mathematical examination of gender segregation in talent pipelines, we adopt the gender binary as a simplifying assumption. Gender is not exclusively binary (Hyde et al. 2019), and as nonbinary identification and data about the same grow (e.g., Statistics Canada 2022), more inclusive approaches to understanding gender segregation become possible.

[3] The code for the model, its solutions, all model calculations, and the generation of model output tables and figures is publicly available online here: https://htmlpreview.github.io/?https://github.com/brubineau/genderReapplyDiffs/blob/master/appendixOrgSci20220630.html.

and 1) stands for the unbiased rejection rate[4] experienced by both men and women (equivalently, 1-*r* of applicants are selected). All selected applicants exit the model and do not reapply. All rejected applicants move to the stock of rejected applicants at risk of reapplying. The rejected applicants in this stock either reapply (and move back to the applicant stock) or exit the model (and can no longer reapply). Reapplying applicants join the applicant stock in the next round along with additional first-time applicants; and all applicants are (again) subject to the same unbiased rejection rate, *r*. The model's *b* parameter, whose value also lies between 0 and 1, represents the baseline rate of reapplication for rejected applicants who are at risk of reapplying. We define this baseline rate as the reapplication rate of rejected women.

The parameter *g* reflects the gender difference in reapplication after rejection, represented as the odds ratio of men's higher reapplication rate relative to women. This odds ratio relates to women's reapplication rate (*b*) and men's reapplication rate (*m*) as follows: $g = m*(1-b)/(b*(1-m))$. Equivalently, men's reapplication rate (*m*) is a function of the baseline women's reapplication rate (*b*) and the gendered odds ratio (*g*): $m = bg/(1-b+bg)$. We operationalize the reapplication rates for men and women as functions of a baseline (*b*) and a gender difference odds ratio (*g*) for two reasons. First, this formulation gives us a single gender difference parameter, *g*, rather than trying to relate two distinct parameters. Second, we use odds ratios because simple multiples are not practical when comparing rates. For example, men's reapplication rate may be double that of women if women's rate is 0.1 and men's rate is 0.2, but men's reapplication rate can never be double that of women if women's rate is 0.6. Using an odds ratio as our gender difference term allows for comparable gender differences across the whole range of reapplication rates. When $g = 1$, the same reapplication rate (*b*) applies to both men and women; when $g > 1$, men reapply at a higher rate than women. We therefore model *g* as having values no less than 1, with men exhibiting either the same or higher reapplication

[4] The rates described in the model come from probabilities (i.e., probability of being rejected, probability of reapplying) at the individual level, and represent the proportion of the corresponding stock being rejected or reapplying. For example, a rejection rate of 0.8 comes from a rejection probability for each applicant of 0.8. Thus, 80% is the expected percentage of the stock of applicants that are rejected. The same holds for reapplication rates. For this reason, the rates described in the model can only take on values in the range of 0 to 1.

rate than women. Rejected applicants who do not reapply exit the model entirely. Rejected women exit the model at the rate of $1-b$. Rejected men exit the model at the rate of $(1 - b)/(1 - b + bg)$.

Our model outcome is the women's share of the applicant pool at equilibrium, $A_W/(A_W + A_M)$. At time zero (t=0), the women's share of the applicant pool is defined by parameter p (women's share of first-time applicants). At equilibrium, the women's share of the applicant pool will be some value less than p, as rejections, reapplications, and gender differences in reapplications take place as described. The parameter g, which captures the gender difference in reapplication after rejection, is our model's sole source of gender differences. When $g = 1$, the women's share of the applicant pool begins and remains at the initial women's share of first-time applicants (p), as men and women reapply at the same rate (b). Any other value of g would result in some deviation from that initial share. Our formal model has an analytical solution (provided in the online Appendix).

MODEL RESULTS

Model behavior across the parameter space

We first examine the model's behavior across its parameter space. In our four parameter model, three parameters: p, r, and b, corresponding to women's share of first-time applicants, the unbiased rejection rate experienced by both applying men and women, and the baseline (women's) reapplication rate, respectively, each range from zero to one. The odds ratio of men's higher reapplication rate, g, begins at 1, and can take larger values as the gender difference increases. In empirical studies of this phenomenon, observed values of g range from 1 (no gender difference) to as much as 1.86 (calculated from Bapna, Benson, and Funk (2021)). We consider the full range of values for parameters r (rejection rate) and b (baseline reapplication rate). The women's share of first-time applicants (p) ranges from 0 to 0.5, in order to model the full range of male-dominated selection contexts.[5] Although we analyze our model's behavior for the full range of b and g, we limit the plots of our model results to the range of 1 to 2 for the gender difference in reapplication parameter, g. This range of values of g corresponds to current empirical estimates. Conceptually, the odds ratio of men's

[5] We restrict our analysis to selection contexts where men are in the majority because the pipeline problem is an issue only in those cases. In addition, there is no evidence that women are more likely than men to reapply in women-dominated domains – they are just equally likely (e.g., see Yang et al. 2019).

higher reapplication rate (g) can take on very large positive values, as women's reapplication rates approach 0 and men's reapplication rates approach 1. In practice, such large values are not observed.

We plot our outcome – women's share of the applicant pool at equilibrium – as a colored contour map[6] in Figure 2. The gender difference in reapplication parameter, g (the odds ratio of men's higher reapplication rate), is the horizontal axis. The baseline (women's) reapplication rate, b, is the vertical axis. Because the gender difference g can only reduce women's share in the applicant pool over time, not increase it, the only possible deviation from the women's share of first-time applicants, p, is towards an applicant pool at equilibrium with more men and fewer women than p.

A single contour map must fix the values of the other two model parameters: the women's share of first-time applicants, p, and the unbiased rejection rate, r. In Figure 2, we use as an initial example a 30% women's share of first-time applicants (p=0.30), and a 70% rejection rate (r=0.70). These parameter values are for illustrative purposes only. Each contour line in Figure 2 maps the parameter values associated with an additional 1 percentage point change in the women's share of the applicant pool at equilibrium. The shades deviating most from the blue shade at the left side of the figure (when g=1, and thus when the women's share at equilibrium equals p=0.30 in Figure 2) indicate that the largest gender segregating effects appear near the vertical center of the rightmost edge of Figure 2, when g is at its highest value, and thus when the difference between women's reapplication rate and men's reapplication rate is greatest. At the right edge of Figure 2, the small contour corresponds to a women's share of the applicant pool at equilibrium of 26% – a 4 percentage-point drop from the 30% women's share of first-time applicants (p).

[[INSERT Figure 2 about Here]]

To illustrate the model's behavior while varying the two parameters that must be fixed within a single contour map (p and r in Figure 2), we next plot a grid of contour maps in Figure 3. Each column uses a single value of the women's share of first-time applicants, p, starting with p=0.1 (10% women's share) at the left side of the grid, and ending with p=0.5 (50% women's share) at the right

[6] Contour maps are a way to present three dimensions of information. In a contour map, both horizontal and vertical axes are independent variables, and the dependent variable is plotted as a color in the plane at the corresponding point. The contours represent the lines of equal value for the dependent variable in the plane.

side of the grid. Each row uses a single value of the unbiased rejection rate, *r*, starting with *r*=0.1 (10% rejection rate) at the top of the grid, and ending with *r*=0.9 (90% rejection rate) at the bottom of the grid. As with Figure 2, shades more different from those appearing on the left edge of each panel indicate greater deviations (towards more men and fewer women at equilibrium) from the women's share of first-time applicants, *p*. The contour lines within each of the panels in Figure 3 represent a 1 percentage point change each in the women's share of the applicant pool at equilibrium. Note that the contour map in Figure 2 appears as one of the panels in Figure 3 (middle column, penultimate row). The range of colors in Figure 3 (and Figure 2) map directly to the values of the women's share at equilibrium, from 0.10 (yellow) to 0.30 (blue), and 0.50 (red).

[[INSERT Figure 3 about Here]]

Two notable patterns appear in the grid of contour plots in Figure 3. First, the figure demonstrates the absence of large gender segregating effects across much of the parameter space. Almost a third (8 of 25) of the contour plots in Figure 3 are wholly monochromatic and lack even a single contour line. In these plots, gender differences in reapplication do not change the gender composition of the applicant pool over time by even a single full percentage point. Similarly, each column in Figure 3 has a distinct and dominant color. This means that for much of the parameter space depicted, there is not a lot of deviation from the women's share of first-time applicants, *p*. This pattern helps us answer our first motivating question: Do gender differences in reapplication after rejection lead to meaningful segregating effects? For much of the parameter space, the answer to this question is – surprisingly – no.

The second notable pattern in Figure 3 relates to the sections of the parameter space that *do* present visible gender segregating effects at equilibrium. Greater ranges of color and more contour lines appear within the contour plots themselves (versus color changes between the columns) as we descend the rows of Figure 3. Descending the rows of Figure 3 corresponds to increasing the rejection rate, *r*. The contour plots in the topmost row are all monochromatic, without even a single contour line. Each subsequent row, indicating an increase in the rejection rate *r* experienced by both men and women, has a greater color range and more contour lines – corresponding to more segregating effects.

This pattern indicates that even unbiased rejection can be an important contributing factor to segregating effects in the presence of gender differences in reapplication.

Gender differences in reapplication after rejection obviously require a positive rejection rate to generate segregating effects. As the rejection rate approaches zero, these differences will cease to have any effect on the talent pipeline. In such a situation, the women's share of the applicant pool will be the same as the women's share of first-time applicants, and the segregating effects approach zero as well. As the rejection rate approaches (but does not reach) one, gender differences in reapplication have their maximum effect in reshaping the applicant pool. An increasing rejection rate – even when that rejection rate is the same for men and women – monotonically increases the segregating effects of gender differences in reapplication. Although we do not observe these extreme rejection rates (neither zero nor one) in the real world, we can still observe a larger (smaller) segregating effect of gender differences in reapplication in selection contexts with higher (lower) rejection rates.

We are of course not claiming that real world selection decisions are unbiased (i.e. that rejection rates are always the same for men and women). There exists voluminous empirical evidence of gender biases in selection processes. Rather, we use an unbiased rejection rate in order to isolate the segregating effects of gender differences in reapplication. Our model suggests that simply increasing this unbiased rejection rate parameter r, without any changes to the other parameters, will increase the segregating effect of gender differences in reapplication (as long as $g > 1$). Intuitively, we would not necessarily expect an unbiased selection process to increase gender segregation. Yet our model shows just that – in selection contexts with gender differences in reapplication, higher rejection rates increase the stock of rejected applicants, which enables gender differences in reapplication to reduce women's representation. This pattern provides one answer to our second question: What contextual factors attenuate or amplify the segregating effects of gender differences in reapplication? The overall rejection rate in a selection context – even in the absence of gender bias – is an important factor that amplifies the segregating effects of gender differences in reapplication.

In addition to the two patterns just described, Figure 3 includes an additional pattern that merits explanation. Notice that, within the rows of contour plots, moving from left to right across the columns (corresponding to increasing values of the women's share of first-time applicants, p), the

plots below the first row show more lines and colors the farther to the right – indicating greater changes in the women's share of the applicant pool at equilibrium. The plot in Figure 3 with the most contour lines and greatest color change is the plot in the bottom-right of the grid (when p = 0.5 and r = 0.9). This direct relationship between increases in p and increases in the segregating effects of gender differences in reapplication is to be expected. When there are very few women among first-time applicants (i.e., when p is small), large changes in women's share at equilibrium are not possible. For example, when p=0.10, at most 9 contour lines indicating changes of 1 percentage point are possible. On the other hand, when p=0.50, at most 49 such contour lines are possible. That higher values of p allow for greater changes in women's share at equilibrium is simply a mathematical necessity, dictated by the percentage-point approach to describing the results of the model.

The percentage-point approach is the most straightforward way of showing the magnitude of the segregating effects arising from gender differences in reapplication, as revealed by the model. However, it has the drawback of highlighting a relationship between the women's share of first-time applicants (p) and the women's share of the applicant pool that is a mathematical necessity, as just described. In addition, it is difficult to assess whether the magnitude of the model's segregating effects is substantial. To address both issues, we next offer an alternative approach to presenting the results of our model – a sex bias equivalence analysis. This approach compares the segregating effects of gender differences in reapplication revealed by our model to those produced by demand-side sex biases that have been empirically documented in prior work.

Sex bias equivalence analysis

In our model, men and women experience the same rejection rate by design, in order to isolate the segregating effects of gender differences in reapplication in a hypothetical selection context free from demand-side bias. Alternatively, we can calculate how sex bias in selection decisions would affect the women's share of selected applicants, in a parallel hypothetical selection context free from gender differences in reapplication. To isolate the segregating effects of sex bias in selection, this hypothetical context would not include reapplication or any other features that may otherwise influence the women's share of selected applicants. Using this approach, we can derive the amount of explicit sex bias in selection needed to yield the same segregating effects that arise from gender

differences in reapplication (for a particular set of model parameter values). This *sex bias equivalence analysis* (see Rubineau and Fernandez 2013) leverages prior findings of gender biases in selection (where reapplication is typically absent or ignored) to determine more objectively whether and when the segregating effects of gender differences in reapplication are substantial.

The outcome measure for the sex bias equivalence analysis is the odds ratio favoring men in selection (from the parallel context with sex bias in selection) that yields a women's share of selected applicants equal to the women's share of the applicant pool at equilibrium (from the context with gender differences in reapplication). The odds ratio favoring men in selection is often reported (or is calculable from data provided) in studies examining sex bias within a given selection context. It is determined by an estimated probability of selecting a woman s_w, and an estimated probability of selecting a man s_m. Based on these two probabilities, the odds ratio favoring men in selection is: $OR_M = (s_m/(1- s_m))/(s_w/(1- s_w))$. In a selection context where women's share of first-time applicants is p, the women's share of selected applicants will be: $p \cdot s_w /(p \cdot s_w + (1-p) \cdot s_m)$. This resulting share of selected applicants, as compared to the initial women's share of p, is the segregating effect of the gender-biased selection process defined by the odds ratio favoring men in selection.

The segregating effects of gender bias in selection from this analysis can be compared directly with the segregating effects of gender differences in reapplication from our model. The common contextual parameters across the two analyses are the women's share of first-time applicants, p, and the rejection rate, r. Unlike the unbiased rejection rate used in our model, the rejection rate in the sex bias equivalence analysis comes from the two gender-specific selection probabilities. The overall rejection rate combines those two probabilities as follows: $r = 1 - (p \cdot s_w + (1-p) \cdot s_m)$. We can now calculate the odds ratio favoring men in selection that produces a segregating effect at equilibrium equivalent to that produced by gender differences in reapplication (OR_M). We do this by setting the share of women applicants at equilibrium ($\%W^*$) equal to the women's share of selected applicants under gender-biased selection: $p \cdot s_w /(p \cdot s_w + (1-p) \cdot s_m)$. We can then solve for OR_M as a function of p, r, and $\%W^*$. This function, also given in Table 1 and substituting "w" for "$\%W^*$" for readability, is: $OR_M = ((w-1)*(p+(r*w)-w))/(w*(p+(r*w)-r-w))$.

For example, in Figure 2, the women's share of first-time applicants, *p*, is 0.3, and the overall rejection rate, *r*, is 0.7. The range of the other two model parameters – *b*: the baseline (women's) reapplication rate, and *g*: the gender difference in reapplication – yields women's shares of the applicant pool at equilibrium ranging from 30% (when g = 1), to 26% (when *b* is 0.6 and *g* is 2). We use these equilibrium values to calculate the odds ratio favoring men in selection (OR_M) that yields the same women's share at equilibrium in a context where there is only gender bias in selection. In this context, the women's share of first-time applicants is again 0.3, and the overall rejection rate is 0.7. The results of this sex bias equivalence analysis are illustrated in Figure 4, which shows a portion of the model results from Figure 2 (where the gender difference in reapplication parameter, *g*, varies from 1 to 1.5), and its corresponding sex bias equivalence for the same portion of parameter space.

To demonstrate this correspondence, both contour plots and the Table in Figure 4 include four points as illustrative examples: A, B, C, and D. Each of these specifies a point in the model's parameter space (p = 0.30, r = 0.70, b = 0.50, and g = 1.1, 1.2, 1.3, and 1.4, respectively), which yields a calculated women's share of the applicant pool at equilibrium (left panel of Figure 4). Each point also has a corresponding outcome of the odds ratio favoring men in selection that yields that same women's share at equilibrium as in our model (right panel of Figure 4). That is, the right panel simply represents a different outcome variable plotted along the same parameter space as the results on the left panel.

At the model parameter values indicated by point A, the women's share of applicants at equilibrium is 29.5%. This share is less than a one percentage point deviation from the original women's share of first-time applicants of 30%. Therefore, in the left panel of Figure 4, point A is in the blue region indicating outcome values in the women's share of applicants at equilibrium from 30% to 29%. What level of sex bias (that favors applying men in selection) would yield the same 29.5% women's share of selected applicants when the women's share of first-time applicants is 30% and the overall rejection rate is 70%? That value, an odds ratio of 1.038 favoring men in selection, is plotted in the right panel of Figure 4, and is described numerically in the table between the two panels. Recall that an odds ratio favoring men in selection of 1 corresponds to no sex bias, such that the women's share of selected applicants at equilibrium is the same as the women's share of first-time

applicants (30%). The contour lines in the sex bias equivalent plot on the right are drawn at every 0.1 point change in the outcome variable of that plot: the odds ratio favoring men in selection. Because 1.038 is less than a 0.1 deviation from an odds ratio of 1, point A is in the orange region of the contour plot, indicating outcomes that are between 1 and 1.1.[7]

[[INSERT Figure 4 about Here]]

Next, Figure 5 plots the model effects in terms of equivalent sex bias for the same parameter space used in Figure 3. The colors in Figure 5 are unrelated to the colors used in Figure 3, as the outcome variables are different. In Figure 5, the composition effects associated with different levels of *p* seen in Figure 3 are largely gone – i.e., the columns appear very similar to each other. Instead, Figure 5 highlights the row-based pattern that the greatest segregating effects correspond to rows with the largest values of the rejection rate, *r*. This figure thus makes it clear that, when the overall rejection rate is high, even small gender differences in reapplication rates (*g*) can yield large segregating effects. This is the case regardless of the value of the initial women's share of first-time applicants, *p*. Highlighting this key result was the first goal of our sex bias equivalence analysis, which was obscured using the percentage-point outcome approach shown in Figures 2 and 3. The second goal is to determine whether the magnitude of the model's segregating effects is substantial, using a threshold based on prior empirical work.

[[INSERT Figure 5 about Here]]

Assessing the substantial importance of the model's segregating effects

How do we determine whether the segregating effects of gender differences in reapplication meet a threshold that can be called substantial? The sex bias equivalence analysis can help us make this assessment. There is a sizeable literature showing demand-side gender bias in selection processes, which has reported a range of odds ratios favoring men in selection across contexts. Some of these studies show statistically significant differences in selection decisions by applicant gender, while

[7] Similarly, points B, C, and D show equilibrium values of women's share in the applicant pool (%W*) of 29%, 28.5%, and 28.1%; which are also the women's share of selected applicants in a selection context where only demand-side sex bias is present and when the odds ratio favoring men in selection (OR_M) are 1.079, 1.109, and 1.143, respectively.

others are statistically insignificant. We define sex bias in selection to be substantial when the difference in selection by gender is statistically significant, and sex bias in selection to be non-substantial when the difference in selection by gender is statistically insignificant.[8] We then consider gender differences in reapplication to have a substantial segregating effect over time only when the equivalent segregating effects from sex bias in selection are substantial.

Table 2 reports a sample of recent studies of gender bias in selection decisions, with their empirical estimates of odds ratios favoring men in selection across a variety of male-dominated selection contexts.[9] Several studies analyzed more than one male-dominated selection context; hence they have multiple entries in Table 2. Among studies finding statistically significant gender bias in selection, the range of the calculated odds ratios favoring men in selection from the published estimates is: 1.18 – 1.42. The range of calculated odds ratios from studies finding non-significant gender bias in selection is: 0.84 – 1.07. We can see that odds ratios below 1.2 may be statistically significant or not, but all odds ratios of 1.2 or greater are statistically significant. We therefore choose an odds ratio favoring men in selection of 1.2 or greater as a useful, while admittedly subjective and imperfect, threshold for claiming substantial segregating effects.

[[INSERT Table 2 about Here]]

In Figure 5, the 1.2 odds ratio line is the second contour line from the left edge of each contour plot, as contour lines are plotted in increments of 0.1. The areas of the contour plots to the right of these 1.2 odds ratio contour lines are the regions of the parameter space with segregating effects that we classify as substantial, while the area to the left of these 1.2 odds ratio contour lines reflect regions of the parameter space with less than substantial segregating effects. Notice that the women's share of first-time applicants, *p*, plays only a small role in determining whether the segregating effects of gender differences in reapplication are substantial. We can see this in the

[8] Statistical significance and effect size are separate concerns (Bettis et al. 2016). We only link them here as an initial attempt to identify an empirically grounded threshold.

[9] There are examples of male-dominated contexts where women appear to be favored in selection (Williams and Ceci 2015; Parasurama, Ghose, and Ipeirotis 2020). The purpose of Table 2 is not to provide a comprehensive review of gender bias in male-dominated selection contexts, but rather to derive an empirically supported threshold for 'substantial' sex bias in selection contexts that do favor men over women. Thus, we limit the focus of Table 2 to examples of selection contexts where men are favored over women.

similarities of each column of contour plots in Figure 5. The rejection rate parameter *r*, however, remains a primary determining factor for whether gender differences in reapplication yield substantial segregating effects or not. In contexts with higher (>0.5) rejection rates, much of the parameter space (excluding both values of $g \leq 1.3$ and extreme values of *b*) gives rise to substantial segregating effects. These segregating effects require gender differences in reapplication, and the effects of these differences are amplified by the rejection rate. Still, gender differences in reapplication appear also to have a threshold. In Figure 5, only values of *g* greater than 1.3 give rise to above-threshold segregating effects.[10] In contexts with low rejection rates, most of the parameter space (excluding high values of *g* and values of *b* a little over 0.5) does *not* give rise to substantial segregating effects.

In our next set of analyses, we add more specificity to our inferences from Figure 5, by deriving clear thresholds necessary for each parameter to produce substantial segregating effects. Relying on our definition of *substantial* segregating effects as above, we estimate the probability of finding substantial segregating effects at equilibrium when a model parameter takes a specific value. To do so, we fix the value of a parameter of interest (e.g., r = 0.5) and randomly sample a large number of points (10,000) in the remaining parameter space around that given parameter value (e.g., $r = 0.5$, $b \in (0..1)$, $g \in (1..2)$, $p \in (0..1)$). At each sampled point, we calculate the sex bias equivalent odds ratio favoring men in selection (OR_M). In turn, using the large sample of randomly selected points, we can determine the probability that a random point with a fixed parameter value yields substantial segregation at equilibrium; that is, it has segregating effects equivalent to an odds ratio favoring men in selection of 1.2 or greater. Figure 6 plots the results of this sampling-based approach, with one panel for each of our model parameters. The curves in each panel show the proportion of calculated OR_M values that meet or exceed the threshold for substantial segregating effects at different parameter values along the horizontal axis. Figure 6 more clearly reveals critical parameter thresholds and in turn, the parameter-specific implications of our model.

[10] In parameter space beyond that which is plotted in Figure 5, there are edge cases (e.g., rejection rates approaching 1, and women's reapplication rates around 0.8) where values of g as low as 1.25 can give rise to above threshold segregating effects. These edge cases are unlikely to be informative for real world situations.

The panel plotting the effects of parameter p – women's share of first-time applicants – has two key implications. One, that parameter p plays little role in determining whether or not the segregating effects of gender differences in reapplication are substantial, and two, that only about 15% of the parameter space yields substantial segregating effects. The other three panels of Figure 6 show the values of the model parameters below which substantial segregating effects are almost never observed. These values for parameters r, b, and g are 0.2, 0.2, and 1.3, respectively. If any one of these three parameters has a value below those respective values, substantial segregating effects are unlikely. Substantial segregating effects are expected only when those parameters have values at or above those thresholds.

Figure 7 plots the results of a similar parameter space-sampling procedure that examines the likelihood of substantial segregating effects for different values of the rejection rate parameter, r, when the rest of the parameter space (b and g) is more constrained. Specifically, we constrain the rest of the parameter space to parameter ranges conducive to substantial segregating effects – $b \geq 0.2$ and $g \geq 1.3$ – as identified in Figure 6. We re-estimate the probability of substantial segregating effects for specific values of the rejection rate (r), using a large random sample of points (10,000) from the more constrained parameter space [$b \in (0.2..1)$, $g \in (1.3..2)$, $p \in (0..1)$] around each value of r. When the plotted curve in Figure 7 passes the horizontal line of 50%, it reveals a subset of the parameter space where substantial segregation is observed more often than not. We see that when the rejection rate is high (above 0.81), substantial segregating effects are observed in more than 50% of the randomly and uniformly sampled parameter space.

PROPOSITIONS

Having fully explored the model's parameter space, we can now specify the precise conditions where gender differences in reapplication can produce substantial segregating effects. Formal models are tools for theory building. In our case, we aim to develop theory about the consequences of gender differences in reapplication for women's presence in talent pipelines over time. If our model captures even an approximation of these dynamics, then our expectations about where the segregating effects of gender differences in reapplication are substantial (and where they are not) should be observable in

the real-world. Based on the model results above, we make these expectations explicit via two propositions:

- **Proposition 1:** Substantial segregating effects from gender differences in reapplication are likely in selection contexts where gender differences in reapplication are characterized by odds ratio of men's higher reapplication rate of 1.3 or higher, where overall rejection rates are high (i.e., >80%), *and* where the baseline (women's) reapplication rate is above 20%.
- **Proposition 2:** In the presence of significant gender differences in reapplication, variation in overall rejection rates will be directly associated with variation in the segregating effects of these differences across selection contexts.

These propositions entail testable predictions about the conditions under which we expect to observe substantial segregating effects from gender differences in reapplication. For example, consider the empirical finding that, after failing a STEM class, men are more likely than women to re-take the failed class (Penner and Willer 2019). Our first proposition would predict that this gender difference in re-taking failed STEM classes itself is unlikely to contribute substantively to women's underrepresentation in STEM. This prediction derives from the fact that failing a course (the analogue to rejection) tends to happen infrequently. When the rejection rate is low, we are unlikely to observe substantial segregating effects from real-world gender differences in reapplication. In the following section, we examine several cases where significant gender differences in reapplication have been documented. This allows us to ground our model with empirical estimates from real-world regions of the parameter space.

GROUNDING THE MODEL

We identified three selection contexts with well-documented instances of gender differences in reapplication and that allow the calculation of our model parameters: executive search, patenting, and crowdfunding. First, Brands and Fernandez-Mateo (2017) use longitudinal data from an executive search firm. Women are 16% of first-time candidates and, on average, are not more likely than men to be rejected. The authors use individual fixed-effects models to account for unobserved heterogeneity and find that being rejected for a position has a stronger effect on declining future interviews with the search firm for women than it does for men. Second, Jensen, Kovács, and Sorenson (2018) analyze

data from 2.5 million US patent applications; these authors report that teams with more female inventors are more likely to have their application rejected and are also less likely to appeal those rejections. The effects are similar when including a host of quality controls and limiting the analysis to the subset of applications with a single inventor. Finally, in an unpublished study, Greenberg, Kuppuswamy, and Mollick (2019) examine second entrepreneurial attempts in the context of Kickstarter, a large crowdfunding platform. Crowdfunding is a type of seed capital that enables direct appeals from entrepreneurs to the public (Schwienbacher and Larralde 2012; Greenberg and Mollick 2017). In this context, failure to reach one's fundraising goal indicates that the crowd rejected the entrepreneur's idea. Crowdfunding is often a source of "last resort" funding for entrepreneurs who lack access to other sources of capital (Mollick and Kuppuswamy 2016). Although women are underrepresented here as well (accounting for 30% of the project creators on Kickstarter), crowdfunding is one of the few entrepreneurial settings where women are more likely than men to obtain funding (Marom et al. 2016; Greenberg and Mollick 2017). Yet, despite experiencing a lower rejection rate, women are less likely to pursue a second attempt within the platform following an unsuccessful first attempt (Greenberg et al. 2019).

These selection contexts are different from each other in several ways. For example, in executive search, the talent making the reapplication decision is an individual. In crowdfunding and patenting, the talent may be a team of people. The decision makers for patent reapplications may even include actors other than the inventors (e.g., patent lawyers). The social or psychological processes generating gender differences in reapplication, although a fertile area for research, are beside the point of our study. We instead seek to understand the segregating effects of these behavioral differences, however they arise. These selection contexts also vary in whether the number of applicants that can be selected is fixed (as in executive search, where only one applicant can typically be selected for a single opportunity) or open (as in patenting and crowdfunding, where selection is not zero-sum). As we explain below, this distinction has meaningful policy implications.

Table 3 reports the model parameter values calculated from each of the three cases, and the segregating effects entailed when entering these values into our model and performing the sex bias equivalence analysis. Each of the three cases showed statistically significant gender differences in

reapplication (*g*). However, our model analysis suggests that only for one of these three cases – executive search – can the segregating effects of these differences be considered substantial. Applying the calculated parameters from the executive search case to our model yields a change from the initial 16% women's share of first-time applicants to a women's share of 13.8% at equilibrium. A gender-biased selection context with the same *p* ($p = 0.16$) and *r* ($r = 0.96$) parameter values would require an odds ratio favoring men in selection of 1.20 to produce that same shift (from 16% to 13.8%) in the women's share of selected applicants. This odds ratio is at our threshold of 1.2 for denoting substantial segregating effects. For the other two empirical cases, patenting and crowdfunding, the sex bias equivalent odds ratios are both below the 1.2 threshold – at 1.05 and 1.03, respectively.

[[INSERT Table 3 about Here]]

The three empirical cases provide useful comparisons for illustrating the implications of our theoretical model. Comparing executive search with patenting, we can see the expected importance of gender differences in reapplication. The two cases are similar in having high rejection rates, *r*: 0.96 and 0.86, respectively; and high baseline (women's) reapplication rates, *b*: 0.64 and 0.54, respectively, although executive search has the higher values for both parameters. But the gender differences in reapplication, as captured by the odds ratio of men's higher reapplication rate (*g*) are quite different: 1.34 and 1.11, respectively. Based on these values, the segregating effects of these two cases using the sex bias equivalence analysis yields an odds ratio favoring men in selection of 1.20 for executive search but only 1.05 for patenting.

However, the gender difference in reapplication is not the only factor driving segregating effects. Comparing now executive search with crowdfunding, we see that the two cases have similar values for the gender difference in reapplication parameter, *g*: 1.34 and 1.30, respectively, but very different segregating effects at equilibrium: the odds ratio favoring men in selection is 1.20 for executive search but only 1.03 for crowdfunding. Two features that differ between the two cases (other than the *g* parameter) make the segregating effects in crowdfunding trivial. First, executive search has a very high rejection rate ($r = 0.96$) while the rejection rate for crowdfunding is lower (r=0.64). Second, the baseline (women's) reapplication rate is also high for executive search ($b = 0.64$), but low for crowdfunding ($b = 0.11$). This comparison of cases reveals that the relative

magnitude of the gender difference in reapplication is not the sole or even the single most important factor for determining the relative segregating effects of this difference. Variation in two other model parameters – both the overall rejection rate and the baseline (women's) reapplication rate – can each change the substantial nature of the segregating effects of gender differences in reapplication.

Illustrating the results of our model for real-world sections of the parameter space, as we just did, is the main goal of our grounding exercise. In addition, this exercise allows us to determine whether the gender differences in reapplication found by each of the studies are expected to substantively contribute to gender segregation over time in their respective contexts. Studies documenting gender differences in reapplication generally conclude that these differences could worsen gender segregation, but those studies were not designed to directly evaluate their segregating effects. Our model analysis gives us a way to do so, by classifying the segregating effects of gender differences in reapplication as substantial or non-substantial for the three specific selection contexts. The three empirical cases reveal a range of real-world gender differences in reapplication (g), from 1.11 to 1.34. The 1.11 value of g in our patenting case is unlikely to yield substantial segregating effects, and the calculated sex bias equivalent for patenting is 1.05 – well below the 1.2 threshold. Both the crowdfunding and executive search cases have values of g at or above the 1.3 level. However, the baseline rate of women's reapplication for crowdfunding, 0.11, is below the 0.2 minimum identified in our model analysis, and the calculated sex bias equivalent for crowdfunding is 1.03, also below the 1.2 threshold for substantial segregating effects. Only the executive search case meets our criteria for substantial segregating effects on all three parameters, and its calculated sex bias equivalent is at our 1.2 threshold for substantial segregating effects. The model analysis would thus allow us to predict that gender differences in reapplication can yield appreciable decreases in the proportion of women over time only in the executive search context. Although gender differences in reapplication do contribute to decreases in the proportion of women over time in the other two cases as well, those decreases are too small and too slow to be appreciable. For example, a tub may have a leaky drain, but if that leak is too small and too slow to reduce the water level noticeably over the course of a bath, then that leak is not substantial as far as the bather is concerned.

The calculated parameter values in Table 3 come from empirical studies, and thus they are uncertain. In additional analyses, we employ numerical simulations to determine a 95% confidence interval for the gender difference in reapplication parameter (g) in each of our three cases (see online Appendix for details). We use this interval to calculate an upper and lower value of the segregating effects for each case. These intervals are shown in Table 3. If the true value of gender differences in reapplication, g, in the executive search case is less than the observed 1.34, then the segregating effects of this selection context would also be below the threshold we set for being substantial.

In addition to providing more detail on the confidence intervals for the grounding of our model, we consider several model variations in the Online Appendix. Specifically, we model the stocks of selected candidates rather than applicants, we discuss interactions between reapplication decisions and applicants' quality, and we evaluate the possibility of gender differences in the selection rates of reapplicants. We conclude that these variations either have no different effects from the ones presented here or make our analysis the most conservative version of the model.

DISCUSSION

What do our model results and theoretical propositions entail for understanding and addressing women's underrepresentation in talent pipelines? We first consider the implications for the effectiveness of common interventions to achieve gender parity – i.e. including more women in the applicant pool. We then describe some suggestive empirical evidence for our theory and finish by discussing the broader contributions of this study to the literature on gender inequality.

Implications for the "expanded pool" approach

The importance of overall rejection rates revealed by our model presents a challenge for one popular intervention to address women's underrepresentation in talent pipelines – expanding and diversifying the applicant pool (see e.g., Bilimoria and Buch 2010; Rivera 2012; Williams and Wade-Golden 2013; Fernandez and Campero 2017). The rationale for this type of intervention is that an expanded and more diverse applicant pool can yield a more diverse set of selected applicants, even without favoring female candidates at the selection stage (Fernandez-Mateo and Fernandez 2016). However, expanded applicant pools can increase the overall rejection rate. For selection contexts where the number of applicants that can be selected is fixed (as in hiring), a higher rejection rate is a

necessary outcome of an expanded pool. For selection contexts where the number of applicants that can be selected is open (as in patenting and crowdfunding), expanded pools may or may not increase the rejection rate. So, while expanded and diversified applicant pools can help increase the diversity of selected applicants initially, the rejected women in that expanded pool are less likely to reapply subsequently than the rejected men. By increasing the effective rejection rate, expanded pool strategies in selection contexts with a fixed number of opportunities can also perversely *increase* the segregating effects of gender differences in reapplication. This may be particularly so for interventions primarily aimed at expanding the overall applicant pool, for example by posting job opportunities within internal labor markets (see Keller 2018). While the risk is lower with interventions that increase the proportion of women in the applicant pool (e.g., outreach to passive female candidates, tailoring of job advertisements, etc.), it is still important to consider their potential unexpected consequences.

To understand the practical importance of this argument, consider a hypothetical organization with parameters matching that of our executive search case – where gender differences in reapplication are likely to have substantial segregating effects. At those parameter values, the women's share of the applicant pool at equilibrium is 13.8%. In practice, a given organization likely observes its applicant pool near its equilibrium. This is because reapplication after rejection has been occurring throughout the organization's recruiting efforts. Therefore, our hypothetical organization likely observes its pool comprising of 13.8% female applicants. What goal would such an organization set for itself when working to expand and diversify its applicant pool? Arguably, getting 15% of female applicants into the applicant pool would likely be seen as an improvement. After all, the greater gender diversity in the applicant pool would be expected to increase the gender diversity post-selection, ceteris paribus. But is this expectation accurate?

In the presence of gender differences in reapplication after rejection, even a steady input of first-time applicants with a women's share of p can result in a steady-state applicant pool whose women's share is less than p – because the steady-state applicant pool also contains reapplying applicants, which are disproportionately men. In our hypothetical organization, the 13.8% female applicant pool is the result of an input stream of first-time applicants that is 16% women. If the

organization were able to attract a set of applicants with a women's share approaching 16%, it is clear from our model that this effort will provide little enduring benefit in terms of increasing gender diversity (and may make things worse by increasing the rejection rate if the overall size of the pool is expanded). From an observed applicant pool that includes 13.8% women, the expanded and diversified applicant pool of first-time applicants must thus enduringly include *more than 16% women among first-time applicants* in order to overcome the segregating effects of gender differences in reapplication after rejection. In selection contexts where the number of positions is fixed, the women's share must be even higher than 16% to overcome the additional segregating effects of a larger rejection rate resulting from an increase in the size of the applicant pool.

The necessary implication of these results is that policies aiming to achieve applicant pools that include more women than current pools may not actually increase women's representation over time. This is another surprising and counterintuitive contribution of our model, one that can inform efforts to promote gender diversity. The critical value of the women's share of first-time applicants (p) required to increase gender diversity is calculated using a conceptual reversal of our initial model: given model parameters r, b, and g, what value of p yields a particular equilibrium women's share of the applicant pool? The p so calculated is the critical value for the women's share of first-time applicants that expanded pool efforts must surpass if they are to increase women's representation. For our three cases, the p parameter for each case shown in Table 3 is this critical value based on the equilibrium women's share of the applicant pool for each case (also in Table 3). For example: in the executive search case, where the women's share at equilibrium is 13.8%, the women's share of first-time applicants must exceed the critical value of 16% simply to begin promoting gender integration.

Therefore, although conventional wisdom suggests that any marginal increase in the share of women applicants can increase gender diversity, our analysis reveals that this is not so in the presence of gender differences in reapplication. Diversity-promoting efforts that do not exceed the critical value are not expected to overcome the segregating effects of gender differences in reapplication. In fact, they could *reduce* gender diversity in the long run. This previously unappreciated obstacle facing a popular approach to increase women's representation in talent pipelines may well add to the observed difficulties in countering gender segregation (Valian 1999; England et al. 2020). Our

analysis highlights that the size and composition of applicant pools can have unexpected effects on gender diversity (see also Leung and Koppman 2018), while also representing a potential policy lever to increase women's representation.

An initial empirical assessment

The goal of this paper is to build theory, as expressed in our propositions. Nevertheless, we would also like to discuss here an initial empirical assessment of Proposition 2, which allows us to offer some suggestive evidence for the plausibility of our theory. If we were able to observe a set of selection contexts that exhibit gender differences in reapplication and that are similar along many dimensions, then Proposition 2 predicts that variation in overall rejection rates will be directly associated with variation in gender segregation over time within those contexts. That is, contexts with higher rejection rates will have larger declines in their shares of women over time than those with lower rejection rates – everything else being equal.

One of our three empirical cases, patenting, is structured in just this way. Each patent application is evaluated within a single patent class (among more than 400 such classes). Beds, cutlery, heating, and robots are examples of distinct patent classes. Each patent class can be seen as a kind of distinct selection context, with its own pipeline of potential inventors.[11] We can calculate the overall rejection rate within each patent class. We can also calculate the difference in the women's share of first-time patent applicants and the women's share of patent awardees within each class. This difference serves as a reasonable measure of the magnitude of gender segregation within each class over time. Proposition 2 implies that patent classes with higher rejection rates will also exhibit larger changes in the women's share from initial applicants to awardees – i.e. that these two measures will be positively correlated.

One of the scholars who conducted the study from which we obtained parameter values for the patenting case provided us with the correlation between within-class rejection rates and the magnitude of change in women's share of patent applicants (from initial applicants to awardees)

[11] Inventors can pursue distinct patents via multiple patent applications in several classes simultaneously (or separated in time), but the empirically observed tendency is toward specialization and within-class innovation (Jones 2009).

across the 400+ patent classes. This correlation is -0.23 ($p < 0.0001$; B. Kovács, personal communication). The correlation and the underlying data points from the patent classes are illustrated in Figure 8. This significant correlation is predicted by and consistent with Proposition 2 from our model analysis. As the rejection rate increases across patent classes, women's share of patent applicants exhibits larger declines. That is, in the inventor pipelines defined by patent classes, the pipelines with higher overall rejection rates also tend to show higher gender segregating effects.

[[INSERT Figure 8 about Here]]

Three observations regarding this descriptive finding merit note. First, identifying a segregating role for overall rejection rates is a novel contribution. In their exceedingly thorough examination of gender differences in patenting outcomes, Jensen et al. (2018) do not consider overall rejection rates as a potential contributor to gender inequality. Our formal model uncovered this possibility. Second, the magnitude of the correlation means that variation in patent class rejection rates alone may explain more than 5% (i.e., the square of the correlation, 0.23^2) of the variation in the magnitude of gender segregation across patent classes. To be sure, there are many other contributing factors to the declining share of women from initial application to patent award. Yet our analysis reveals a previously overlooked (and non-trivial in magnitude) contributing factor. Third, this preliminary test is conservative. Patenting was one of the two cases where our model finds that gender differences in reapplication play a less-than-substantial role in gender segregation (the sex bias equivalent male-favoring odds ratio is only 1.05). We examined the association between rejection rate and gender segregation in the patenting case simply because the data were available to do so, not because we anticipated a strong effect. And yet the presence of a sizeable observed correlation is consistent with the predictions of our model.

Contributions

Recent studies documenting gender differences in reapplication implicitly or explicitly assume that this mechanism will exacerbate women's underrepresentation in male-dominated selection contexts (see Brands and Fernandez-Mateo 2017; Kolev et al. 2019). Whether and when this is the case, however, has until now been merely a topic of speculation. Using a formal model, we find that the gender segregating effects of reapplication differences are substantial for some contexts, while for

others they are negligible. In addition, the segregating effects of this supply-side behavior are, surprisingly, driven importantly by a demand-side feature of the selection context – namely, the overall rejection rate.

Our study has theoretical and policy implications for the literature on gender inequality. From a theoretical standpoint, grounding our formal model with field data allows us to assess the substantial importance of a documented behavioral tendency and to deepen our understanding of its effects. Although it is possible to intuitively grasp the theoretical importance of a mechanism by using empirical data only, it is much harder to understand its dynamic implications – particularly its possible interactions with other segregation mechanisms. Formal modeling is well suited to this task (Hannah, Tidhar, and Eisenhardt 2021). In our case, the results underscore how interactions between the supply side (applicants' behavior) and the demand side (screeners' behavior) affect the dynamics of gender segregation in selection contexts. This is critical because, although many studies focus on disentangling supply from demand sources of inequality, we still lack research on how these interact with each other (Fernandez-Mateo and Kaplan 2018).

In particular, we show that a gender-undifferentiated demand-side factor (i.e., overall rejection rates) plays a lead role in determining the magnitude of the segregating effects of a supply-side behavioral tendency (i.e., gender differences in reapplication). This conclusion, which would not have been easily reached absent the insights provided by our formal model, yields a novel and testable theoretical hypothesis: If there are gender differences in reapplication then, *ceteris paribus*, selection contexts with higher overall rejection rates will exhibit more gender segregation. This has implications for *where* gender differences in reapplication have the potential to operate as a powerful segregating mechanism. Although sizeable gender differences in reapplication have been identified in a wide range of empirical settings, this mechanism *per se* is unlikely to contribute to women's underrepresentation in talent pipelines where rejection rates do not reach a high enough threshold (e.g. crowdfunding or patenting). In contrast, women's lower tendency to reapply after rejection can be an

important contributor to female underrepresentation in selection contexts where rejection rates are typically very high, such as in hiring processes.[12]

Although the primary goal of this paper is to build theory, our effort is grounded in real-world dynamics and has important implications for policy. As a general rule, faced with evidence of the mechanisms contributing to gender segregation, academics and practitioners seek to design targeted interventions. If there is evidence of biased behavior on the demand-side (e.g., screeners are less likely to select women), one would aim at reducing such bias, for example by introducing blind reviews (Goldin and Rouse 2000), implicit bias training, or formalized selection processes (Kalev et al. 2006). If there is evidence of biased behavior on the supply-side (e.g., women are less likely to apply for certain roles or pursue certain opportunities), common practices are to reach out to female candidates (Fernandez-Mateo and Fernandez 2016) or to encourage women's participation (Dutt and Kaplan 2018). These targeted interventions can be important levers to increase gender equity. However, our study suggests alternative and complementary approaches.

First, we note that encouraging women to "persist" (i.e., to reapply) may not generate meaningful diversity improvements in contexts where gender differences in reapplication have negligible long-term effects on women's representation. As evidenced by our analysis, this is likely to be the case for a non-trivial number of selection contexts. If so, it might be advisable to instead devote limited organizational resources to other types of diversity interventions. Second, under certain circumstances, acting on the demand side by reducing overall rejection rates may be a useful complement to gender integrating efforts on the supply side – even if those interventions were not necessarily designed with diversity goals in mind. For instance, when the selection context is a platform (e.g., on-demand labor markets, crowdfunding, etc.), applicants often face rejection due to poor visibility, stemming from screeners' high search costs. Consequently, interventions that reduce

[12] Rejection rates in hiring routinely exceed 85%. For example, Brands and Fernandez-Mateo (2017) report an overall rejection rate for executive positions of 96%. At the other end of the spectrum, entry-level jobs at production plants, call-centers, and retail establishments have rejection rates between 91% and 95.5% (Castilla 2005; Fernandez and Fernandez-Mateo 2006; Autor and Scarborough 2008). Evidence supporting high rejection rates in hiring also comes from audit studies on employers' preferences, which often report interview call-back rates of 15% or lower (Kacperczyk and Younkin 2022; Deming et al. 2016; Pager and Quillian 2005; Bertrand and Mullainathan 2004).

search costs can often lower the overall rejection rate. In crowdfunding, Kickstarter recognized that search costs were greatest during the middle phase of crowdfunding campaigns (Kuppuswamy and Bayus 2018), which particularly reduced the success rate associated with longer campaigns. Therefore, in 2011, Kickstarter reduced the maximum campaign length from 90 to 60 days, to lower the overall rejection rate and increase the likelihood of fundraising success for all entrepreneurs.[13] Our analysis suggests that these kinds of efforts can aid in fostering gender diversity, even if they do not directly encourage women's persistence.

While lowering rejection rates is most straightforward in selection contexts where the number of opportunities is not fixed (e.g., crowdfunding and patenting), it is more complicated when these opportunities are limited and fixed (e.g. hiring). In such cases, one can devise tools to better align the attributes of those that do decide to apply and the demands of screeners, such as realistic job previews that provide applicants with an accurate picture of the job for which they are interviewing (Meglino, Ravlin, and DeNisi 1997). For example, employers may show details of a typical day on the job, share employee interviews, or use online games to preview the opportunity to prospective applicants. Practitioners recognize that the number of applicants will drop when a realistic job preview is presented, yet those who do apply are better suited to the job and the rejection rate is lower. Job try-outs (Sterling and Fernandez 2018) may have similar effects on lowering rejection rates for certain positions. Our study suggests that lower rejection rates should help increase gender diversity in the long run through its effect in decreasing the segregating effects of gender differences in reapplication. However, if taking these approaches, one should also consider that deterring applicants may not be a gender neutral intervention in itself, since increased barriers to entry can effectively *reduce* women's participation (Ehrlinger and Dunning 2003; Mohr 2014; De Paola et al. 2015). More generally, any intervention aimed at reducing rejection rates needs to carefully consider the potential biases that such intervention may introduce. The balance of costs and benefits will vary across cases.

We do not suggest that strategies for reducing rejection rates should be the sole method, or even the most consequential method, for increasing women's representation in talent pipelines.

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[13] https://www.kickstarter.com/blog/shortening-the-maximum-project-length

Reducing gender differences in reapplication is still a feasible course of action. One method to do so is the provision of feedback after a rejection, which has been shown to increase future engagement (Fernandez-Mateo and Coh 2015; Piezunka and Dahlander 2019). A recent study by Bapna et al. (2021) finds that women who were rejected with messages citing fit with the job were significantly more likely to reapply for jobs than those who were rejected with messages citing quality or those rejected without a reason. Tailoring rejection messages can thus be a lever to reduce the gender gap in reapplications. Similarly, organizations may even eliminate the need to reapply, by having candidates consent at the time of application to being considered for other, relevant opportunities, in the near future.[14] Prior research has suggested that making competition the default choice can increase women's participation (He, Kang, and Lacetera, 2021). Our study simply suggests that, in addition to these types of supply-side measures, lowering rejection rates can be an alternative (and largely unappreciated) demand-side opportunity to help increase gender diversity in selection contexts characterized by substantial gender differences in reapplication.

Conclusion and implications for future research

This study opens up new avenues for research on how gender differences in reapplication shape gender diversity. There is much that we do not know about this phenomenon. It is plausible that this mechanism interacts with other supply-side and demand-side factors, such as applicants' quality and screeners' gendered perceptions of rejected applicants (we examine some of these in the online Appendix). There are also questions about volition. For example, some scholars have suggested that diversity in internal labor markets would be helped if organizations consider *all* employees determined by Human Resources as eligible – that is, rather than having each employee decide whether or not to apply (Bosquet et al. 2019). From the perspective of volition, this approach differs markedly from the approach of advertising internal job opportunities more widely (Keller 2018). In both approaches, increasing the number of applicants necessarily increases the rejection rate. But would removing the choice to apply alter reapplication and segregation dynamics?

[14] We thank an anonymous reviewer for this suggestion.

Additional work is also needed to reveal how gender differences in reapplication interact with other talent pipeline processes. Our initial dynamic examination focuses narrowly on gender differences in reapplication in isolation. We did not consider interactions with feedback from changes in gender composition, and the like. Similarly, our model focuses on a single generic selection context within a given domain. We speculate that the dynamics that we uncover at the level of the selection context should have implications for talent pipelines at the domain level of analysis (i.e., a given occupation/area of work). Yet, it is certainly true that individuals who are rejected in a selection context can often reapply to other selection contexts within the same domain. This is most evident in the labor market, where women applicants might disproportionally apply to other firms instead than the one that rejected them – perhaps in anticipation of obtaining better outcomes. Indeed, recent evidence on the job search behavior of people in underrepresented groups suggests that people in such groups, anticipating potential discriminatory outcomes, may cast a broader net when looking for jobs (Pager and Pedulla 2015; Obukhova and Kleinbaum 2020). Interestingly, this kind phenomenon is less likely to play a role in two of the three selection contexts that we use to ground our model – i.e. patenting and crowdfunding – where the organizations that we examine are the single dominant option for applicants in that domain.[15] Nevertheless, the extent to which multi-firm dynamics operate in reapplication behaviors and may shape overall segregation in the labor market is an open empirical question. Along similar lines, macro-level changes potentially affecting rejection rates across multiple firms - such as business cycle changes - may make only very small changes to rejection rates. The current model cannot answer whether the effects of these very small changes in rejection rates across the labor market accumulate to appreciable changes in segregation outcomes. Addressing the possible domain-level or labor market effects of such broad but likely small changes requires future research.

[15] In the case of patenting, an inventor whose patent application has been rejected by the US Patent Office is unlikely to apply to another patent authority. A patent under a different patent authority would represent protection under a different jurisdiction. Similarly, Kickstarter is the largest and most popular crowdfunding platform, with Indiegogo a distant second. Entrepreneurs who wish to re-launch a crowdfunding campaign are likely to seek repeat support from contributors to their first (failed) attempt. To validate this preference for reattempts on Kickstarter, we randomly selected 100 unsuccessful Kickstarter campaigns (from our sample of crowdfunding projects in the Online Appendix). We supplemented existing data on Kickstarter reattempts for these entrepreneurs by manually searching and coding instances of second attempts on Indiegogo. Entrepreneurs were three times more likely to reapply for funding on Kickstarter (12%; 9 men and 3 women) than on Indiegogo (4%; 3 men and 1 women).

Finally, we would like to stress the benefits of our methodological approach for exploring the underrepresentation of women in talent pipelines. Grounding our formal model with field data allows us not only to assess the significance of a given theoretical mechanism, but also to deepen our understanding of its effects. Although one can grasp the theoretical importance of a mechanism using empirical data only, our counterintuitive conclusion – that modifying selection practices may increase diversity more effectively than does encouraging women to "lean in" by reapplying more – would have remained elusive without the insights generated by our formal model. Formal analysis can thus play a crucial role in evaluating the effectiveness of various policy prescriptions (Hannah, Tidhar, and Eisenhardt 2021; Kogut et al. 2014; Rubineau and Fernandez 2015). After all, decades' worth of data have accumulated that speak to the causes and consequences of women's underrepresentation in the economy. Hence the time is ripe for organizational scholars to reorient the conversation toward using both theory and evidence to design effective solutions.

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Table 1: Equations for the formal mathematical model of gender differences in reapplication after rejection.

Stock	Men	Women
Applicants	$\frac{dA_M}{dt} = -A_M + 1 - p + \frac{R_M bg}{1 - b + bg}$	$\frac{dA_W}{dt} = -A_W + p + R_W b$
Rejected applicants at risk of reapplying	$\frac{dR_M}{dt} = rA_M - R_M$	$\frac{dR_W}{dt} = rA_W - R_W$
Model outcome	Share of women applicants at equilibrium (%W*) = $\frac{A_W}{A_W + A_M}$	
Sex Bias Equivalence	Odds ratio favoring men in selection (OR_M, and rewriting %W* as w) = $\frac{(w-1)(p+rw-w)}{w(p+rw-r-w)}$	

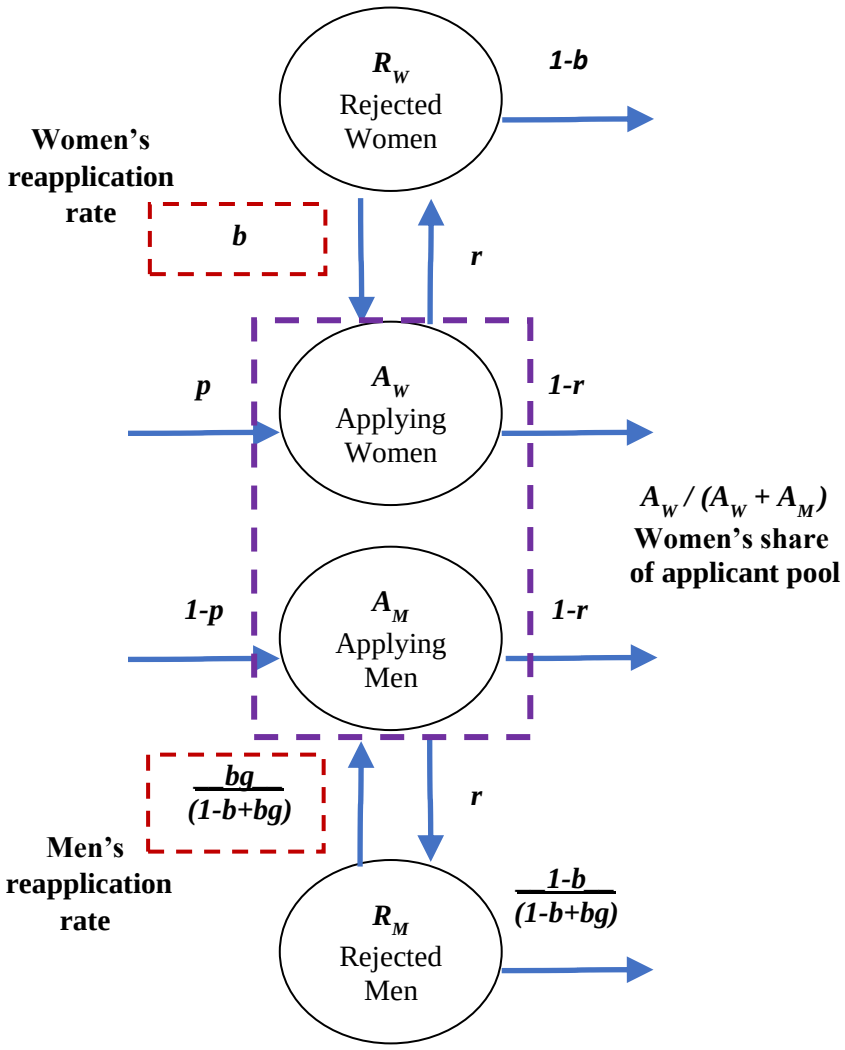
Table 2. Empirical estimates and statistical significance of odds ratios favoring men's selection (OR_M) in a variety of contexts from several recent studies.

OR_M	Sig. level	Women's share of applicants	N	Selection Context	Source
0.84	ns	31%	6,320	Selection for job offer (conditional on interview) for IT/engineering jobs	Fernandez and Campero (2017)
0.90	ns	9%	12,190	Selection for hire by an executive search firm	Fernandez-Mateo and Fernandez (2016)
1.00	ns	36%	226,137	Selection for job interview among all job applicants across 441 high-tech firms	Fernandez and Campero (2017)
1.00	ns	31%	3,588	Selection for grant funding in the 'Project' program (2014-2016)	Witteman, Hendricks, Straus, and Tannenbaum (2019)
1.07	ns	35%	18,205	Selection for grant funding in the 'Traditional' program (2011-2014)	Witteman, Hendricks, Straus, and Tannenbaum (2019)
1.18	$p < 0.05$	N/A	N/A	Selection for grant funding (within a larger meta-analysis of academic productivity across scientists) [N = 27 studies with grant results]	Astegiano, Sebastian-Gonzalez, and Castanho (2019)
1.20	$p < 0.05$	47%	19,857	Selection for job offer (conditional on interview) across all job types	Fernandez and Campero (2017)
1.25	$p < 0.001$	1%-25%	57,251	Selection for job interview across all male-dominated job types	Campero and Fernandez (2019)
1.27	$p < 0.001$	1%-25%	48,008	Selection for job interview in male-dominated IT/engineering jobs	Campero and Fernandez (2019)
1.32	$p < 0.001$	22%	1,875,087	Selection for VC financing	Guzman and Kacperczyk (2019)
1.35	$p < 0.05$	11%	12,551	Selection for interview by executive search search firm	Fernandez-Mateo and Fernandez (2016)
1.42	$p < 0.05$	33%	2,125	Selection for grant funding in the 'Foundation' program (2014-2016), focusing on PI	Witteman, Hendricks, Straus, and Tannenbaum (2019)
1.42	$p < 0.05$	21%	67,816	Selection for job interview for IT/engineering jobs	Fernandez and Campero (2017)

Table 3. Model parameters observed in the 3 analysed cases and the interpretation of the segregating impact of the gender difference in reapplication after rejection mechanism

	Case 1 Executive search	**Case 2** Patenting	**Case 3** Crowdfunding
Model parameters			
p: women's share of first-time applicants	0.16	0.088	0.29
r: rejection rate (same for men and women)	0.96	0.86	0.64
b: rate of reapplication by rejected women	0.64	0.53	0.11
g: Odds Ratio of men's higher reapplication rate	1.34	1.11	1.30
g_{CI}: 95% confidence interval for *g*	(1.19,1.48)	(1.10,1.11)	(1.24,1.36)
Segregating impact			
$\%W^*$: Women's share of applicant pool at equilibrium	0.138	0.085	0.286
Absolute change in women's share of applicant pool	–2.2%	–0.32%	–0.40%
Relative change in women's share of applicant pool	–13.8%	–3.62 %	–1.38%
Sex-bias equivalence			
Selection rate for men	4.10%	14.05%	36.2%
Selection rate for women	3.45%	13.49%	35.5%
OR_M: Odds ratio favoring men in selection	1.20	1.05	1.03
95% CI for odds ratio favoring men in selection	(1.12,1.28)	(1.04,1.05)	(1.03,1.04)

Figure 1: The model diagrammed via stocks and flows



<u>Parameters</u>

p = women's share of first-time applicants
r = rejection rate (same for men and women)
b = rate of reapplication by rejected women
g = gender difference in reapplication rates, as the odds ratio of men's higher reapplication rate

Figure 2. Absolute change in the women's share of the applicant pool at equilibrium. Effects on the women's share of the applicant pool at equilibrium (%W*) from gender differences in reapplication (*g*, horizontal axis, as the Odds Ratio of men's higher reapplication rate) and the baseline (women's) reapplication rate (*b*, vertical axis) plotted as a contour plot. The women's share of first-time applicants (*p*) in this figure is 0.30, or 30%. The rejection rate experienced by all applicants (*r*) in this figure is 0.70, or 70%. Each contour line in the panel represents a 1 percentage point change (0.01) from the initial women's share of first-time applicants (*p* = 0.30) to the women's share of the applicant pool at equilibrium (%W*).

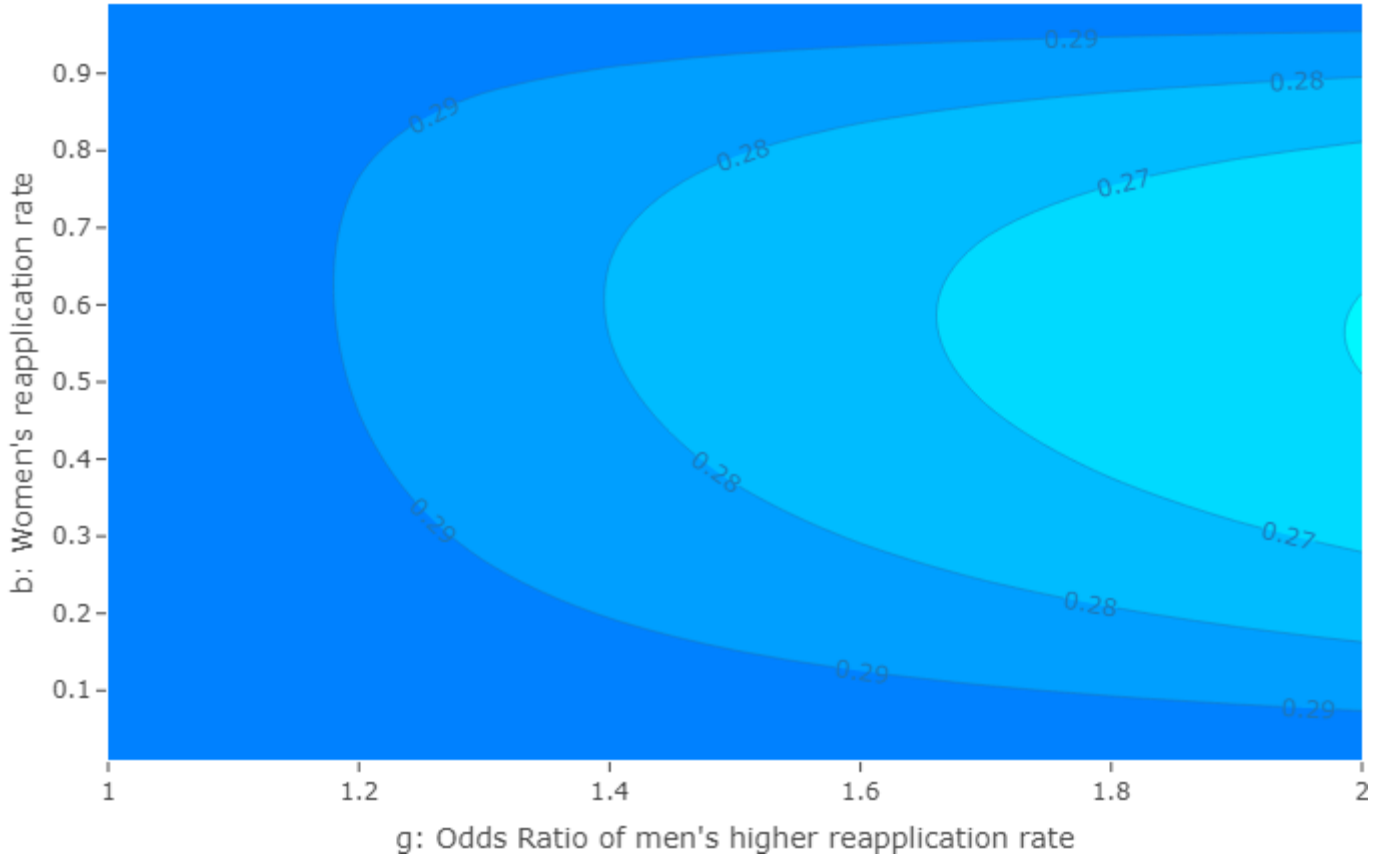


Figure 3. Absolute change in women's share of the applicant pool at equilibrium when varying the 4 model parameters. Effects on the women's share of the applicant pool at equilibrium (%W*) from gender differences in reapplication (*g*, horizontal axis for each contour plot panel) and the three other model parameters: baseline (women's) reapplication rate (*b*, vertical axis for each contour plot panel), women's share of first-time applicants (*p*, increasing horizontally across panel columns), and rejection rate experienced by all applicants (*r*, decreasing vertically across panel rows). Each row of panels has the same rejection rate (*r*). Each column of panels has the same women's share of first-time applicants (*p*). Each contour line within the panels represents a 1 percentage point change (0.01) from the initial women's share of first-time applicants (*p*) for that panel to the women's share (%W*) of the applicant pool at equilibrium.

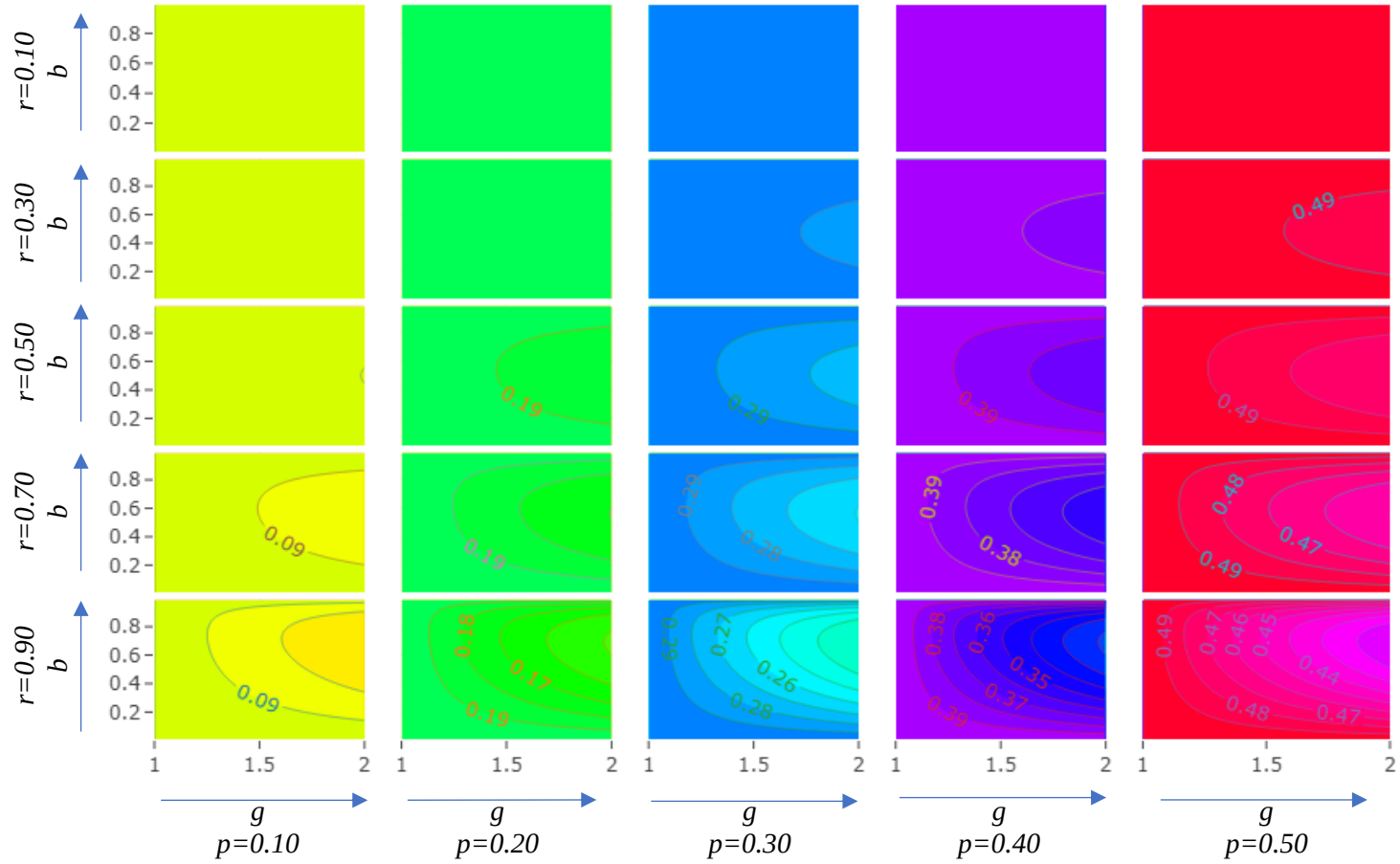
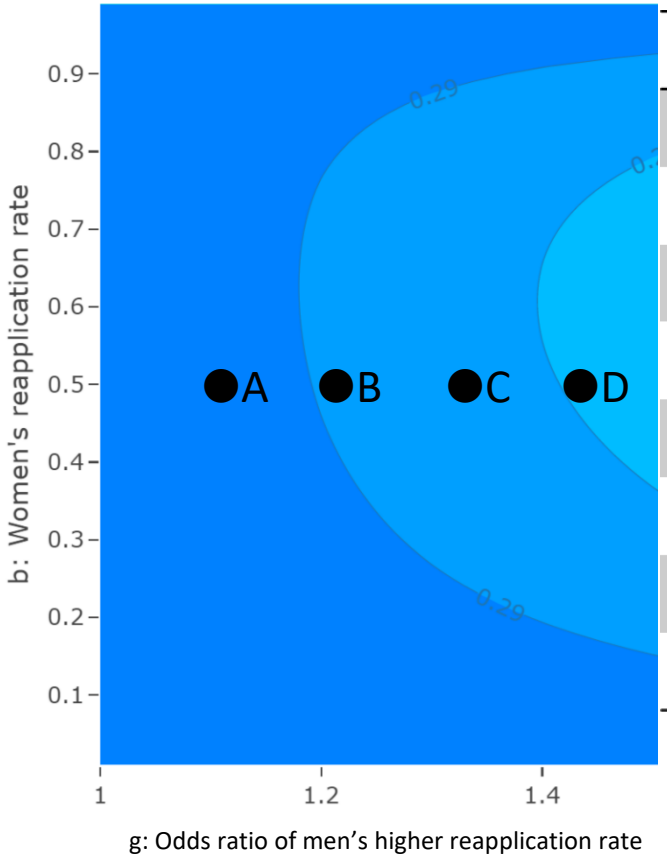


Figure 4. Illustration of the translation of model effects into the equivalent level of sex bias. Left part of figure is a portion of the same contour plot from Figure 2. For the same range of model parameters, the right contour plot gives the **Odds Ratio** favoring men in selection (OR_M) that yields the same women's share of selected applicants as the women's share of the applicant pool at equilibrium from model parameters (%W*). The horizontal axis for both panels is the gender difference in reapplication (*g*), and the vertical axis is the baseline (women's) reapplication rate (*b*). The women's share of first-time applicants (*p*) for this figure is set at 30%, and the rejection rate experienced by all applicants (*r*) is set at 70%. The contour line in the right figure represents a 0.1 change in the OR_M from an unbiased OR_M of 1. That is, the OR_M =1.1 contour.

The 4 corresponding points (A, B, C, and D) on the two figures and the table in between illustrate how points from the model in terms of the women's share at equilibrium (e.g., Figures 2 and 3) correspond directly to a calculated level of men-favoring sex bias in selection that yields an identical equilibrium in terms of the women's share of selected applicants.



	A	B	C	D
p	0.3	0.3	0.3	0.3
r	0.7	0.7	0.7	0.7
b	0.5	0.5	0.5	0.5
g	1.1	1.2	1.3	1.4
%W*	29.5	29.0	28.5	28.1
	↓	↓	↓	↓
OR_M	1.038	1.074	1.109	1.143
%W*	29.5	29.0	28.5	28.1

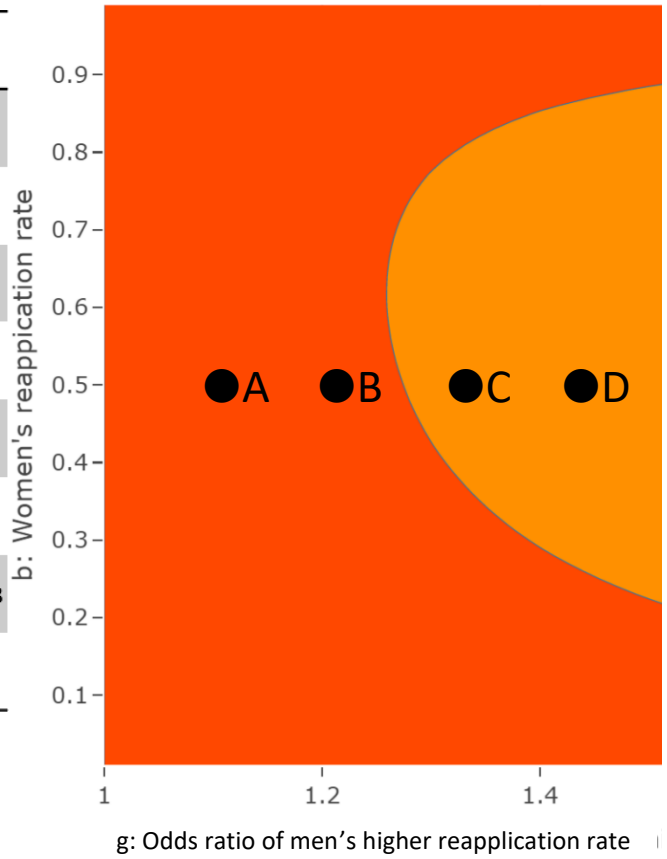


Figure 5. Sex bias equivalence of women's share of the applicant pool at equilibrium when varying the 4 model parameters. Panels plot the Odds Ratio (OR_M) favoring men in selection that yields the same women's share of selected applicants as the women's share of the applicant pool at equilibrium (%W*) from gender differences in reapplication (*g*, horizontal axes within each contour plot panel) and the three other model parameters: baseline (women's) reapplication rate (*b*, vertical axes within each contour plot panel), women's share of first-time applicants (*p*, increasing horizontally across panel columns), and rejection rate experienced by all applicants (*r*, decreasing vertically across panel rows). Each row of panels has the same rejection rate (*r*). Each column of panels has the same women's share of first-time applicants (*p*). Each contour line in the panels represents a 0.1 change in the OR_M from an unbiased OR_M of 1.

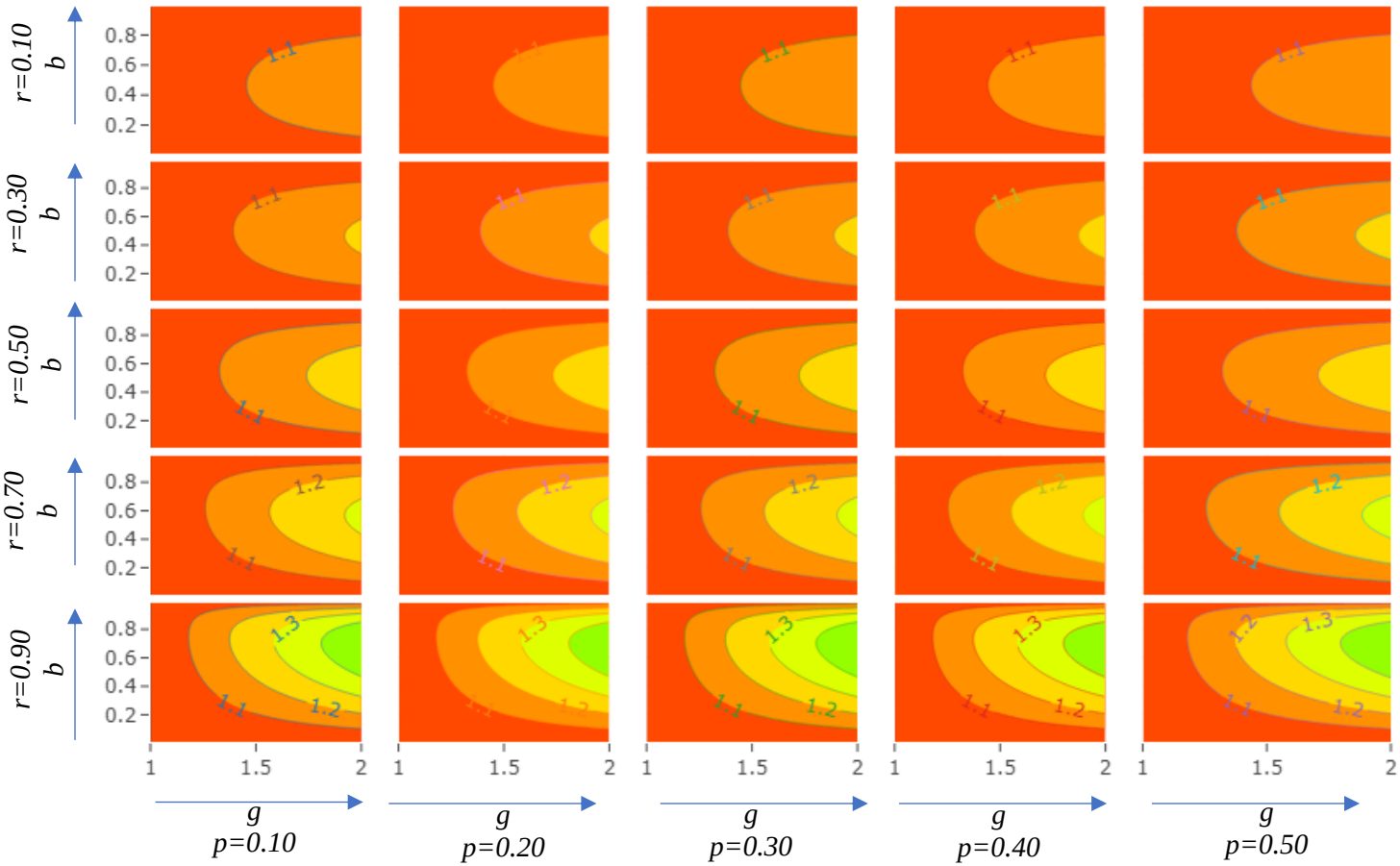


Figure 6. Relationship between individual model parameters and the portion of the remaining parameter space that shows substantial segregating effects. In each panel, each point along the horizontal axis identifies a particular parameter value. The remaining three model parameters are sampled at random and uniformly from their distributions [$r \in (0..1)$, $b \in (0..1)$, $g \in (1..2)$, $p \in (0..1)$]. The sex bias equivalent odds ratio favoring men in selection ($\boldsymbol{OR_M}$) is calculated. For each point along the horizontal axis, this sampling and $\boldsymbol{OR_M}$ calculation is repeated 10,000 times. The portion of calculated $\boldsymbol{OR_M}$ values that are at or above the 1.2 threshold for substantial segregating effects is plotted to give the curves in each panel.

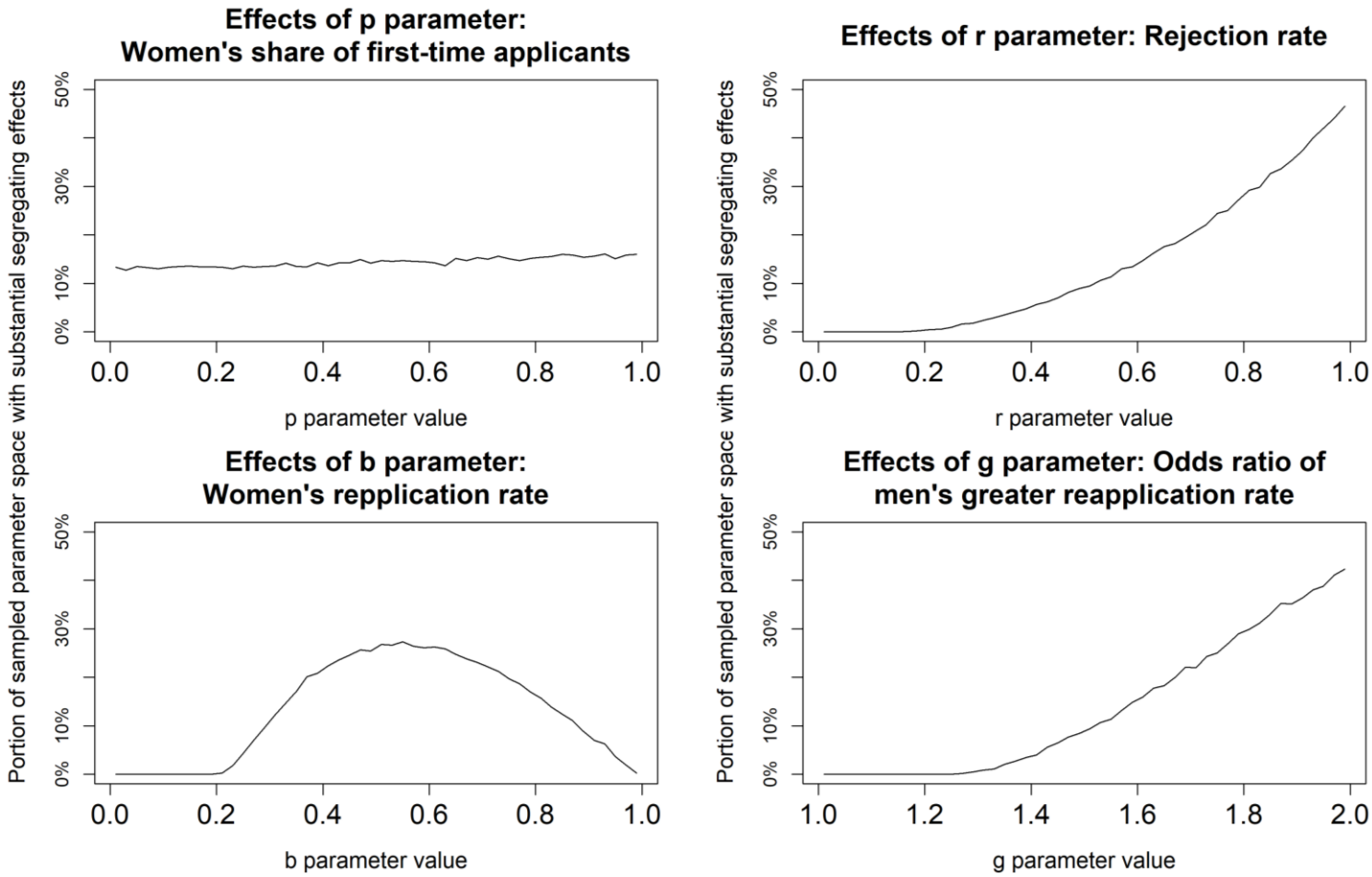


Figure 7. Relationship between model parameter *r*, overall rejection rate, and the portion of the remaining parameter space that shows substantial segregating effects when the ranges of the *b* and *g* parameters are constrained to be within the set of values shown in Figure 6 to yield some substantial segregating effects. Each point along the horizontal axis identifies a particular rejection rate value. The remaining three model parameters are sampled at random and uniformly from a more constrained range in their distributions [$b \in (0.2..1)$, $g \in (1.3..2)$, $p \in (0..1)$]. The sex bias equivalent odds ratio favoring men in selection ($\boldsymbol{OR_M}$) is calculated. For each point along the horizontal axis, this sampling and $\boldsymbol{OR_M}$ calculation is repeated 10,000 times. The portion of calculated $\boldsymbol{OR_M}$ values that are at or above the 1.2 threshold for substantial segregating effects is plotted. Where the plotted curve exceeds the horizontal line of 50%, the majority of parameter space for those values of *r* exhibit substantial segregating effects.

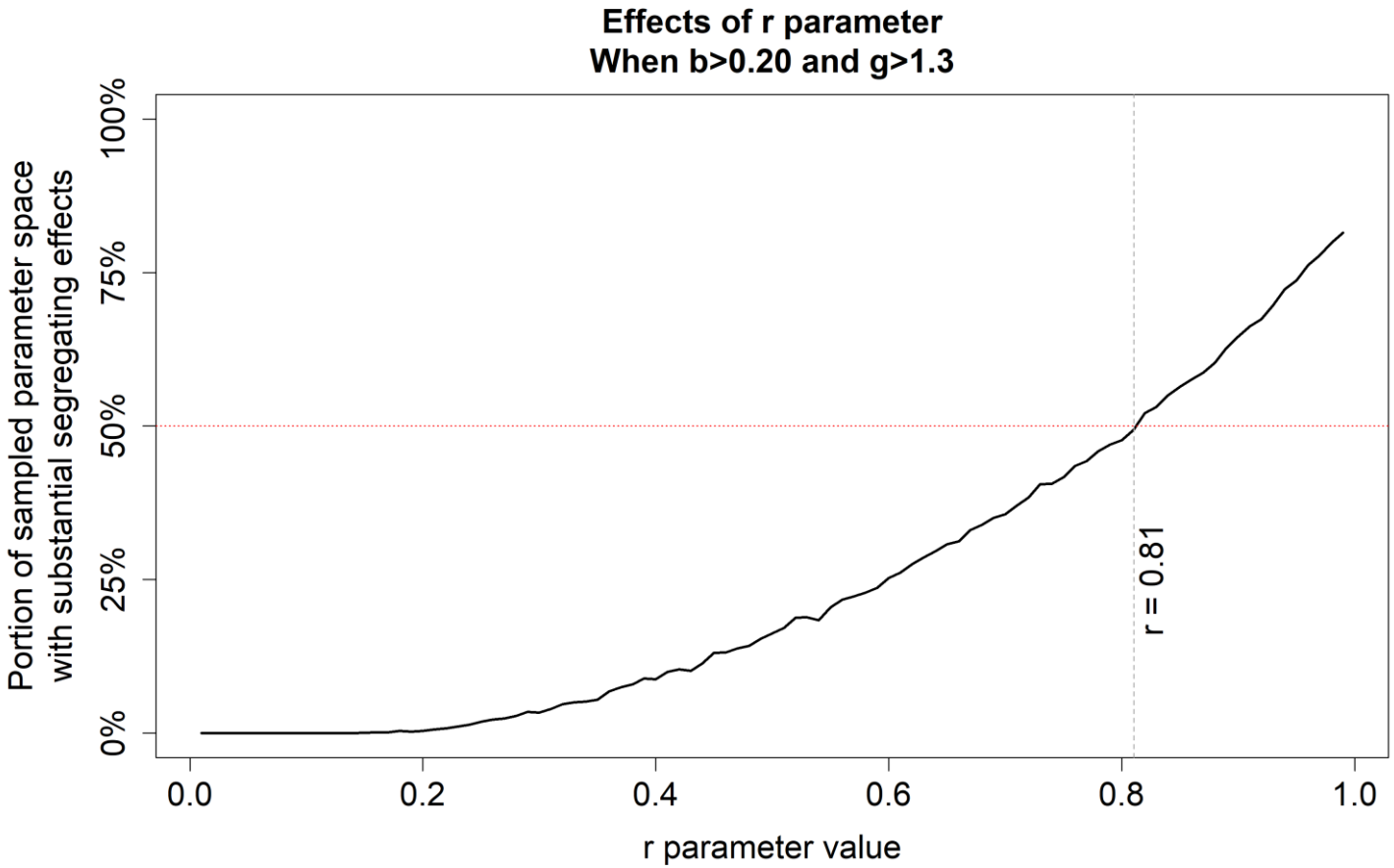


Figure 8. Correlation between within patent class rejection rates and the change in women's share of patent applicants from first application to patent awards. Both variables are standardized. Correlation is -0.23, N = 433, $p < 0.0001$.