Gender Bias in Competitive Music Composition Evaluation: An Experimental Study

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Abstract

Women's underrepresentation in science has drawn attention from scholars in many disciplines. Our study aims to advance understanding on this issue through examining the extreme case of gender imbalance in music composition. We conducted an audit experiment to examine whether such gender imbalance is due to unfair judgment in evaluative settings. We invited composition faculty to rate new compositions with randomly assigned gendered names along with live recordings directed by the same conductor. Contrary to our hypotheses, we do not observe gender bias against women. Instead, there is evidence that compositions associated with female names are rated higher than those with male names. There is no evidence of in-group bias either: reviewers do not favor compositions from composers of their genders. In the heterogeneity analysis, we find suggestive evidence that male faculty and senior faculty favor female composers in both general and structured evaluations.

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1. Introduction

The underrepresentation of women in various academic fields is a persistent problem of growing concern worldwide. Much of the discussion on this issue has focused on STEM fields, yet women are also underrepresented in non-STEM fields, such as economics and philosophy. As of the mid-2000s, women accounted for less than 35 percent of PhD students and 30 percent of assistant professors in economics (Lundberg and Stearns 2019). This gender imbalance has sparked lively discussion about the disparate treatment of women and gender-biased atmosphere in the economics profession (Wu 2018; Wu 2020) and instigated new research on gender bias published in economics journals and presented at economics conferences (Hengel, 2018; Hospido and Sanz, 2019; Chari and Goldsmith-Pinkham, 2017; Card et al., 2020). In 2019, the *Journal of Economic Perspective* hosted a special symposium on women in economics (Bayer and Rouse, 2016; Avilova and Goldin, 2018; Boustan and Langan, 2019; Lundberg and Stearns, 2019; Buckles, 2019). One of the leading explanations presented at this symposium for the field's gender imbalance is that female candidates are not equally evaluated in selection processes, including interviews and peer reviews. This unequal treatment can be attributed to discriminatory biases against minority groups (Greenwald and Banaji, 1995; Greenwald and Krieger, 2006; Bayer and Rouse, 2016)[1] and "in-group bias," where people favor in-group members, such as men favoring other men in a male-dominated field (Tajfel et al., 1971; Bernhard et al., 2006; Chen and Li, 2009; Goette et al., 2012; Sandberg, 2018). Leslie et al.'s (2015) nationwide study across 30 disciplines, furthermore, found that fields with strong belief in innate talent (field-specific abilities that cannot be learned), such as Mathematics and Physics, tend to hold negative stereotypes against woman, which may in part

[1] Bayer and Rouse (2016) provides a review in this demand side explanation for understanding diversity in the economics profession.

explain women's underrepresentation in these academic fields. These factors combine to form barriers for women, limiting their opportunities for career advancement.

Given this background, we believe that a study of gender representation in professional music composition would provide insights on the origins of gender representation disparities in a non-STEM field. The field of music composition exhibits extreme underrepresentation of women, even surpassing other traditionally male-dominated disciplines. In 2011, only about 16 percent of U.S. doctorates in music composition were awarded to women, the lowest percentage among all fields in Leslie et al.'s (2015) study – lower than physics (18%), computer science (19%), and economics (35%) (Leslie et al., 2015: Fig. 1). This gender gap grows even wider in the professional realm. Women held only 15 percent of the U.S. composition faculty positions in 2014, and only 9 percent of the prestigious composition prizes had been awarded to women (O'Bannon, 2014). A recent study revealed that only 2% of the works performed by symphony orchestras worldwide in 2018 – 2019 were written by women (Brown, 2018).

Beyond the statistics, research has shown the great extent of systemic gender discrimination toward woman in the music composition profession, such that female composers conceal their gender identities to mitigate disadvantageous outcomes (Bennett et al. 2018, Bennett et al. 2019, Cannizzo and Strong 2020). Gender bias in music evaluations (Goldin & Rouse, 2000; Leonard, 2007; Miller 2016), which has been well-documented in the literature, is certainly a component of gender discrimination. Despite this, we have witnessed more conversations about gender and diversity issues in composition and some small steps have been made (Robin, 2017; McClary and de Boise 2019). For instance, the number of female composers who have joined prestigious programs in recent years has increased. In 2017 all three finalists for the Pulitzer Prize for Music

were women, a historic achievement. A social movement to promote diversity in music is also growing via social media, with the hashtag #HearAllComposers gaining traction.

We designed an audit experiment to examine whether college composition faculty members evaluate compositions fairly when the music is randomly associated with a gendered name, and whether the evaluations differ with more structured evaluation methods, such as giving detailed ratings on various musical dimensions. We recruited composition faculty members at U.S. higher education institutions to evaluate four orchestral compositions as if they were judging a composition competition. Faculty members were recruited from 377 music institutions that participated in the 2013–14 National Association of Schools of Music (NASM) Higher Education Arts Data Services (HEADS) project, and all of the participants have a training background in composition. Participants were randomly assigned to one of the two groups, with randomization done at the institutional level, meaning that faculty at the same school were assigned to the same survey. In Survey Group A, compositions appeared with the gendered name sequence of M, F, M, F. In Survey Group B, the exact same compositions appeared with the opposite sequence of F, M, F, M. All music pieces are brand new, last between 8 to 10 minutes, and each was composed by a different professional composer with a doctoral degree in composition. In the evaluation, we provided both the music scores and the audio recordings from live performances under the same conductor and university orchestras to ensure equivalent quality of recordings and performances. Our experimental design replicates the setting of similar competitions.

Our paper contributes to the literature on discrimination. A substantial number of studies in this literature finds evidence of discrimination against racial, ethnic, and gender minority groups (see the review of field experiments on discrimination by Bertrand and Duflo, 2016). The leading

economic models describing discrimination are the Becker's taste-based model (Becker, 1957; Charles and Guryan, 2008) and the statistical discrimination model (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). According to Becker's model, in the labor market some people have non-pecuniary aversion to hiring members from minority groups. The statistical discrimination model is based on the rational perception of skill distribution among different groups and predicts that employers or evaluators would favor majority groups (e.g., white and male) because of their perceived higher productivity. Literature on the belief-based model—a dynamic statistical discrimination model—is also relevant (Fryer 2007; Bohren et al. 2019). This model describes discrimination toward the minority group in the initial stage, but when reviewers receive new information and the minority group gains more reputation, evaluators would update their beliefs and thus discrimination would disappear or even reverse. These models often observe gender bias favoring male, as documented in the literature on underrepresentation of women in academia (for surveys of the evidence: see Greenwald and Banaji, 1995; Greenwald and Krieger, 2006; Bayer and Rouse, 2016). A large number of the field experiments, however, lack information on employers' identities, making it difficult to examine the mechanisms of discrimination. In our experiemnt, we examine gender bias in a distinct field with a large gender imbalance and are able to record the identities of evaluators and evaluatees.

In-group bias is another potentially significant explanation for observed gender discrimination. If in-group bias exists in evaluation, the dominant group (e.g. males) in a particular discipline will perpetuate unbalanced representation. Our experiment, one that mimics a real-world music competition, would add to the literature on in-group bias. Most evidence of in-group bias has come from experiments in laboratory settings, which have shown that in-group favoritism will arise in both natural social groupings and artificially created groupings (Tajfel et al., 1971; Bernhard et al.,

2006; Leider et al., 2009; Chen and Li, 2009; Chen and Chen, 2011; Goette et al., 2012; Chen et al, 2014; Currarini and Mengel, 2016; Dickinson et al., 2018). It is challenging to test to what extent this favoritism persists in real-world settings. Studies have, so far, found mixed results. In the professional sports setting, for instance, scholars have found discrimination toward other racial ethnic groups (Price and Wolfers, 2010; Parsons et al., 2011) and favoritism to the same nationality but no in-group bias in favor of gender (Sandberg, 2018). In judicial decision-making, there is evidence of racial or ethnic in-group bias (Shayo and Zussman, 2011, 2017; Anwar et al., 2012), while Depew et al., (2017) find the opposite result of racial out-group bias in juvenile court cases. Racial in-group bias can also be found in policing (Antonovics and Knight, 2009; West, 2018), lending decisions (Fisman et al. 2017), and equity analysis (Jannati et al. 2018). Gender in-group bias has been found in teaching evaluations (Boring 2017). Yet some research suggests no gender in-group bias in other contexts, such as journal reviews (Abrevaya and Hamermesh, 2012) and grading (Feld et al., 2016), and even out-group bias in Bar and Zussman's (2020) study of driving tests. Overall, the existence and extent of in-group bias on gender, race, and nationality is not conclusive and demands more empirics.

Our experiment crafts a "clean" non-laboratory setting to test in-group bias. We will outline below why it is challenging to test in-group bias outside of the laboratory setting and how our design circumvents these issues.

A primary challenge to testing in-group bias in real-world settings is that the evaluator's identity is often unknown in these settings. In most of the experimental studies on testing discrimination, researchers can only record the outcome, such as the callback rate in Bertrand and Mullainathan (2004) (See more review on field experiments in testing discrimination by Bertrand and Duflo

(2017)). In Goldin and Rouse's (2000) examination of orchestra audition outcomes, a context similar to ours, the researchers do not have information on the juries' identities. It is thus challenging to test potential sources of discrimination. In our study, we recruited the faculty reviewers based on certain criteria to ensure we selected the appropriate samples. We enlisted both male and female reviewers, and the demographics are similar in the two experimental groups.

Another challenge to testing in-group bias is the potential for correlation between evaluators' associated group identity (e.g., gender) and candidates' quality. In other words, the matching between evaluators and candidates is not random, making it difficult to identify in-group bias. This is a frequent concern, especially in observational studies in certain contexts, including journal review (Abrevaya and Hamermesh, 2012), tenure review (Bagues and Esteve-Volart, 2010), and professional sports competition (Price and Wolfers, 2010; Sandberg, 2018). In our audit experiment, all faculty reviewers were assigned to four identical compositions with randomly assigned gendered names (two female and two male names). The matched gender identity between evaluators and candidates is designed to circumvent identification challenges.

A third challenge arises when a group's identity (race and gender) is not exogenous, and thus the discriminatory effects in the market outcome could be overstated due to other unobserved variables (Siegelman and Heckman, 1993; Heckman, 1998). In other words, it is difficult to examine the causal effect of being "female" or "white" while keeping all else constant. In most non-laboratory studies the actual productivity/skill of the candidate is rarely observed directly and can be confounded with minority identities. In our experiment, we circumvent this problem by associating the same composition with both female and male names. For example, composition #1 is assigned

with a male name in randomization group A and with a female name in group B. The unobservable characteristics should cancel out to zero for the same audit pair.

A fourth difficulty in testing in-group bias comes from endogenous behaviors in typical hiring and evaluation studies. In hiring studies, for instance, it is possible that the interviewees' behaviors may be endogenous to the recruiter's race or gender. Even in audit studies, the trained interviewers know the purpose of the study and may thus unconsciously want to do a "good job." This demand side effect can generate confounding factors to the discriminatory effect. In our field experiment, we only rely on music scores and recordings rather than actual people, and are thus able to eliminate this endogenous behavioral factor and to more effectively distinguish gender bias or in-group bias.

Our results show that compositions associated with female names are rated higher than compositions associated with male names. This pattern persists in the more structured evaluations when participants assess compositions in different subcategories. We find some evidence of an out-group bias by which male evaluators favor female composers' music compositions. Senior faculty exhibit a greater preference for female composers than do junior faculty. Our results align with other studies that fail to find male favoritism in various contexts, such as academic evaluations (Broder, 1993; Bagues et al., 2017), hiring in the Spanish Judiciary (Bagues and Esteve-Volart, 2010), female dominated occupations in Australia (Booth and Leigh 2010),[2] and driving tests in Israel (Bar and Zussman, 2020).

[2] One has to be careful interpreting the result in Booth and Leigh (2010) as opposite gender favoritism because the hiring experiment is conducted in female dominated jobs, such as waitstaff, data-entry, customer service, and sales.

There are several implications to our findings. First, the common in-group bias may not hold outside laboratories as this preference may differ in real-world contexts. Second, even in a highly professional setting where gender imbalance persists, it is possible for evaluators to update their beliefs and even reverse gender bias. Finally, biases in treating a minority group may not be an essential explanation for the underrepresentation of women in the music composition profession. This finding urges us to also look closely at the "supply side" factors, including self-confidence, stereotypes, training pipelines, etc., to understand the underlying causes of inequalities (Bordalo et al, 2016; Bordalo et al, 2019).

The next section describes the contexts of composition competitions. Sections 3 and 4 introduce the experimental design and the estimation strategy. Section 5 discusses the results. Section 6 presents the robustness checks. Section 7 discusses the findings. Section 8 concludes.

2. Music Composition Competition

Composition competitions are important events for composers' career advancement. These competitions are the primary vehicles used to identify young talents ready to launch international careers (McCormick, 2009). The competitions are hosted frequently by various organizations and ensembles. A quick visit to *The Composer's Site*, an online information hub for composers, yielded 63 ongoing competitions in June 2020. A "call for scores" or composition competition is similar to an academic conference where young professionals present their works, build professional networks, establish creative portfolios, and develop potential employment opportunities. Composers' works are selected for performance through such competitions, and these performances often lead to future engagements and even commissions (Whitacre, 2009; Watts, 2018; Murphy, 2012; Doolittle, 2018). Research shows that prior success in music competitions

has strong implications for later success. Ginsburgh and Van Ours (2003)'s study on the participants of the Queen Elizabeth Competition, one of the most prestigious piano and violin competitions, showed that participants' prior success was predictive of subsequent market success.

Our experimental design follows the form of hosting a formal composition competition. The organizer sends out invitations to professional composers to participate as reviewers. The scores, often along with a recording, are uploaded to a digital platform and the reviewers give evaluations of the compositions. Although professional composers are able to judge the quality of a composition based solely on the music score, it is common for competition to provide recordings to facilitate the evaluation process. We adopted this same design in this study. One of the authors, a professional conductor, conducted and recorded all four pieces of music to ensure the quality of recordings are commensurate with professional standards. We could have created a control group without any composer names as the baseline, yet such anonymous design deviates from common practices in the profession. Esteemed and highly influential composition competitions, such as Guggenheim, Fromm, Koussevitzky, ASCAP, Barlow, are not anonymous, and we follow suit. Because our study focuses on a group of highly specialized professionals, it is distinctly challenging to find qualified subjects. We sought to maximize the results' statistical power by not adding another control group. Since our main purpose is to understand the relative level of gender bias and not the absolute level of bias, we keep with the standard practice of including composers' names.

3. Experimental Design

In this section, we present our experimental design to measure gender bias in the professional music composition setting. In this experiment we also aim to test the effects, if any, of same-gender

in-group bias as found in the experimental literature. Some research suggests that structured evaluation methods—ones that with clear rubrics—could reduce bias, and we test this claim in the experiment (Bragger et al., 2002; Brecher et al., 2006; Levashina et al., 2013). Our hypotheses were:

Hypothesis A: Reviewers favor compositions associated with a male name (gender discrimination hypothesis).

Hypothesis B: Reviewers would favor compositions associated with a name of their own gender, showing in-group gender bias (favoritism/in-group bias hypothesis).

Hypothesis C: Evidence of evaluation discrimination against female composers would be reduced or eliminated by structured evaluation.

Constructing the audit experiment in composition

Our main objective is to examine gender bias in music competitions by presenting compositions randomly assigned to male and female composer names. All compositions last between 8 and 10 minutes when performed and were composed by four different professional composers, all with a terminal doctoral degree in composition. All of the works were chosen by the same conductor using the same selection criteria, and they were all commissioned works by the Georgia Tech School of Music. The compositions had only been performed once in a regional concert in the southwestern U.S., and the reviewers were unfamiliar with the pieces of music before our experiment. This is a common practice in competitions, wherein composers submit recordings of performances or reading sessions at their affiliated institutions for consideration. Consistent with real composition competitions, we provided both the score and the recording of each piece for

reviewers. All the recordings were made during two performances in the same concert hall conducted by the same conductor in a two-month span. As male composers are more prevalent and established in this field, the recording quality and orchestral performance may endogenously correlate with this gender factor, resulting in compositions by male composers being perceived as more presentable. Our experiment is designed to isolate these noisy factors.

To test gender bias, we assigned two female (F) names and two male names (M) to the four compositions. The designated composers' names only appeared on the title page and the first page of the music score, as is the standard practice in composition competitions. We pre-tested the survey with faculty members who have served as composition competition judges. They agreed that this design is similar to real composition competitions and none detected that gender bias was being tested. A sample page of the score is in the Appendix.

Names were selected from the U.S. Social Security Administration's database of popular names in the 1970s with the most common last names from the 2000 census. We pre-tested and Google searched the names to make sure that 1) gender cue is easily recognized; 2) last names do not give extra racial/ethnic cues; 3) no actual composers have the same names in our experiment. We alternated the female and male names in two groups, A and B. The name assignment in group A is M, F, M, F, namely Michael Adams, Rebecca Moore, Sean Campbell, Tara Davis. Names used in group B were F, M, F, M, namely Tara Davis, Sean Campbell, Rebecca Moore, Michael Adams.

With limited gender cues, respondents in our pre-tested qualitative survey interviews were able to correctly recall the gender of the composers, indicating that subjects were truly "treated" in this design. Because this population is a highly white-dominated discipline, none of the respondents expressed any comments regarding the race of the composers' names. We tested the names using

NamePrism (Ye et al., 2017), a non-commercial ethnicity/nationality classification tool often used in economics studies (Diamond et al., 2019; Tang, 2020; Honigsberg and Jacob, 2021; Kempf and Tsoutsoura, 2021). Our pseudo names are unambiguously (around 90%) classified as white names.

Some observers may be concerned that the actual gender of the composers affects the "gendered" features of the compositions, yet we believe it unlikely that this is an issue in our study. The compositions in our sample are created by two females and two males, and we assign names to all of the compositions. According to the music experts, classical symphony compositions usually do not have easily identifiable gendered features, meaning that it is not easy to determine the gender of the composers based on the music alone. Edvenson's (2017) study, for instance, found that listeners could not accurately guess the gender of a composer based solely on listening to the classical music performed. Even if our compositions did exhibit gendered features, our fixed effects empirical design would control for individual composition factors. We are also able to compare results between the compositions created by females and those composed by males.

Recruitment

Faculty members were recruited from 377 music institutions that participated in the 2013-14 National Association of Schools of Music (NASM) Higher Education Arts Data Services (HEADS) project. To choose qualified reviewers, we searched the websites of these music schools and reviewed faculty members' profiles and CVs to identify all eligible participants with composition expertise – either composing experience or a music composition degree. We included faculty of all tenure-track ranks (assistant professors, associate professors, and full professors) as well as adjunct faculty. The final invitation list was comprised of 1,060 eligible faculty members. Faculty reviewers were randomly assigned to group A or B to evaluate four compositions as if they were

participating in a composition competition. Randomization was at the institution level to ensure that faculty members at each institution received compositions associated with the same female and male composer names, preventing sample contamination. We cross-checked for duplicate faculty names in case anyone were transitioning from one institution to another or if certain faculty were affiliated with more than two institutions, ensuring that each faculty member is invited only once per randomization group.

The survey was conducted between March and May 2018. Eligible faculty were invited to voluntarily participate (see the invitation email in Appendix B: Survey Materials for reference) via the Qualtric system through a personalized survey link sent in the invitation email. This study was approved by the Institutional Review Board (IRB) at Georgia Institute of Technology and the subjects were informed of the approval in the email invitation (Appendix B). The subjects would give consent when they filled out the online survey. The reviewers were rewarded with a $75 gift card upon completion of the evaluation. Only invited eligible faculty were able to complete an evaluation and receive a gift card for completing the survey. We use personalized links to ensure data quality and prevent sample corruption from ineligible faculty.

The final sample was comprised of 124 faculty reviewers (20 female, 103 male, 1 other). The response rate is 11.7%, which is normal for a highly selected group. Research has also shown that the result of the focal variable is not sensitive to the response rate if the sample demographics is similar to the underlying population (Williams and Ceci, 2015). Since we use the same procedure recruiting faculty reviewers in two randomized groups (the recruiting emails were sent on the same day with the same content), there is no difference in the attrition rate. The sample may still differ in other unobservable dimensions. Nonetheless, the music professionals in our sample still provide

meaningful insights as this setting has never been examined in the discrimination literature. The summary statistics of the final sample is in Table 1. We tested the difference in means among various covariates between randomization group A and group B. The covariates include demographic variables, such as gender, race, and, rank. We have also tested the average overall evaluation score between group A and group B. As Table 1 shows, our randomization works well since none of the differences between the two groups appear to be statistically significant.

Evaluation Survey

We disguised this survey as a simple music evaluation study without revealing to reviewers that it was a gender bias experiment. Reviewers were asked to judge the compositions as if they were judging a real competition. The composer names only appeared in the score and the final question where reviewers were asked to recommend a winner. This avoids experimenter effect, which may cause human subjects to change thheir behavior if they know that they are in an experimental setting. Some economists have concerns over using "deception" in audit studies and have proposed using new experimental methods to elicit preference without deception (Kessler et al., 2019). We contend that the use of deception is not problematic in our case. The first-order problem in resume studies is whether the fake resumes fundamentally differ from real resumes. We do not have this issue since all of our composition pieces are not "fake"—they are written by actual composers. Another common concern in resume studies regards the "callback rate", in which researchers worry that the employers' evaluation of the resume may confound with their expectation of the candidates' acceptance. Callback rates, for instance, are usually higher for unemployed candidates than for employed candidates, reflecting the influence of the employer's expectation of a

candidate's likelihood of acceptance. Our study is not subject to this problem as we ask evaluators to give scores to all compositions rather than make phone calls to disclose binary decisions.

The study's survey contained four parts: general evaluation, structured evaluation, winner recommendation, and demographic information. In conventional practice, overall evaluation is often the only judgement the reviewers give. The interpretation of gender bias should thus be highly weighted to this score. Overall evaluation was scored on a 0–10 scale.

Since the overall evaluation assessment is highly subjective, we added a structured evaluation in Part II so that reviewers could appraise compositions in more detail. This structured evaluation presumably would prompt reviewers to examine the works more closely when judging compositions and could eliminate arbitrary bias. The Part II evaluation consisted of five categories, namely (1) Form / Structure, (2) Tonality / Harmony, (3) Tempo / Rhythm, (4) Orchestration, and (5) Artistic Originality. These five dimensions were chosen because they consist of the basic elements of musical composition and were suggested by professional composers who have judged composition competitions. The five categories covered both the craft and creativity of music composition and were gender neutral terms. To ensure the integrity of Part II's evaluation, reviewers were given the score and recordings again and were not allowed (by our pre-set Qualtrics algorithm) to change their initial overall scores from Part I once they advanced to Part II.[3] The structured evaluation in Part II was based on a 1–5 Likert scale labeled "Extremely Weak," "Somewhat Weak," "Neutral," "Somewhat Strong," and "Extremely Strong." The scale was pre-

[3] The other potential experiment design is to separate Part II evaluation from Part I into other two randomization groups. Since the common evaluation practice always includes Part I-the overall evaluation, this design will make the survey too far from the composition competition norm.

tested among faculty who have judged music and they agreed that this chosen scale is commonly used. The survey questions are in Appendix B.

4. Estimation Strategy

In the summary statistics and the mean evaluation tests, we used the original 124 faculty reviewers as the unit of analysis to show the overall descriptive characteristics in the data. To perform gender bias analysis, we treated the unique combination of composition and reviewer as the unit of analysis. The total observations expanded to N = 496. Each reviewer evaluated four compositions and the standard errors may be correlated within the same reviewers, so we followed the standard practice of clustering our standard errors by reviewer. Our estimation equation is:

$$Score_{ic} = \beta Female_{ic} + \delta_c + \gamma_i + \varepsilon_{ic}$$

where $Score_{ic}$ is the evaluation score by reviewer i for composition c; $Female_{ic}$ is the dummy variable where it is equal to 1 if the composition is randomly assigned with a female name, and 0 if the composition is assigned with a male name; β is the coefficient for gender bias. δ_c controls for composition fixed effects; γ_i controls for reviewer fixed effects. This model controls for differences among compositions, so that we compare reviewers' evaluations within the same composition assigned with a female name and a male name. Controlling for reviewer fixed effects should eliminate confounding issues arising from unobservable differences between reviewers. We expected $\beta < 0$ if there is implicit gender bias in favor of male composers relative to female composers. We ran a similar analysis using 7 different evaluation scores as the dependent variable, namely, the overall score in survey Part I, the structured scores in 5 categories in survey Part II, and the average score of the 5 categories in Part II. We also estimated the same 7 sets of regressions

by gender, age, and rank to examine heterogeneity in gender bias. Since the scoring of the compositions is done by the same reviewers and may be correlated, we cluster the standard errors by reviewers.

To examine in-group bias, we estimate whether those reviewers would give higher scores to the compositions assigned with names that indicate the same gender as their own, as opposed to compositions assigned with opposite gendered names. Similar to the above equation, we estimate:

$$Score_{ic} = bSame\_gender_{ic} + \delta_c + \gamma_i + e_{ic}$$

where $Same\_gender_{ic}$ is the dummy variable which is equal to 1 if the assigned composers' names and the reviewers are of the same gender, and 0 if otherwise. If there is in-group bias among people within the same membership (i.e. gender), b should be larger than zero. We also controlled for several fixed effects, including composition fixed effects (δ_c) and reviewer fixed effects (γ_i). Similar to the previous specification, we clustered the standard errors by reviewers.

5. Results

Based on ratings of the same compositions with male and female names, we estimated gender bias through standard regression analysis, clustering standard errors. We employed additional controls for variables that might bias our results. We describe below the analysis's detailed results.

A. Is there gender bias in ratings?

Contrary to Hypothesis A, female composers were favored in all evaluations. Compositions appearing with female names received higher scores in both the general rating and structured rating (See Figure 1). Examining the overall ratings by gendered names, we find that female composers

scored on average 0.305 points higher on a 0-10 scale (See Figure 1 and Table 2). This differential bias is non-negligible, accounting for approximately 16% of the overall standard deviation. For comparison, in a separate professional evaluation context, Dressage in Olympics, the size of own-nationality bias is between 7.2% and 23.8% of the overall standard deviation (Sandberg 2018). When we ask the reviewers to pick winners, the compositions with female names were 1.6 times more likely to be selected the winners than were the same compositions associated with male names.

Differences were found in all five categories in the structured evaluation, with female composers receiving an average of 0.188 more points than did male composers on a 1-5 scale (See Figure 2 and Table 2). The precise difference was 0.158 in Form / Structure, 0.203 in Tonality / Harmony, 0.086 in Tempo / Rhythm, 0.247 in Orchestration, and 0.246 in Artistic Originality (statistically significant at 0.05 significance level, except for Form and Tempo and; See Figure2 and Table 2). These differential numbers favoring female composers correspond to 14.7% of the overall standard deviation in Form / Structure, 18.6% of the overall standard deviation in Tonality / Harmony, 6.8% of the overall standard deviation in Tempo / Rhythm, 21.4% of the overall standard deviation in Orchestration, and 22.6% of the overall standard deviation in Artistic Originality.

B. Is there in-group bias based on gender?

To test Hypothesis B, we tested whether reviewers exhibit in-group bias toward the same gender. Contrary to the literature (Nosek et al., 2002; Dovidio and Gaertner, 2004; Moss-Racusin, 2012) and the majority of past laboratory findings, our results show no evidence of in-group bias based on gender—reviewers did not give higher scores to composers of their own gender. In fact, we

found evidence of an out-group bias of male reviewers giving higher ratings to female names. This pattern appears in both general and structured evaluations.

Table 3 shows an opposite sign of in-group bias. Faculty reviewers give statistically significant higher scores to compositions produced by members of the opposite gender. The negative coefficient (-0.38) is nearly 20% of the overall standard deviation. This magnitude is a drastic difference from what is reported in current literature. Sandberg (2018) has, for instance, found that nationalistic in-group bias in the Olympic game is between +7.2% and +23.8% of the overall standard deviation, while our estimated coefficient is in the opposite direction with similar magnitude.

This result is mostly driven by the prevalence of male reviewers favoring female composers. Based on Table 4, male reviewers rated compositions with female names 0.402 points higher in the general rating (0-10 scale) as well as in all five musical dimensions in the structured evaluation, with an average of 0.244 points higher (1–5 scale). This is a sizable opposite-gender bias—0.402 points corresponds to approximately 21% of the overall standard deviation.

On the other hand, female reviewers were more likely to rate female composers lower in both evaluations, though on a smaller scale. Female faculty rated female composers 0.278 points lower than male composers in overall rating (0–10 scale) and an average of 0.141 points lower in the structured evaluation (1–5 scale).

We further test the rating difference between female and male faculty (See the interaction effect in Panel C Table 4). The difference in overall rating between female and male faculty reviewers is marginally statistically significant (p-value<0.1); yet the actual difference is sizable. The

difference in the average scores in the structured rating (column 7) between female and male faculty reviewers is statistically significant (p-value<0.01).

We note that female faculty gave 0.67 more points than did male faculty in the general evaluation and 0.22 more points in the structured evaluation (both are statistically significant), regardless of the composer's gender. In other words, female faculty were more generous and relatively unbiased graders, while male faculty tended to give lower scores and favored female composers.

C. Effects across the Distribution of Overall Evaluation

We follow Kessler et. al (2019) in implementing a counterfactual callback exercise. At each overall evaluation scoring level, we generate an equivalent counterfactual callback rate, treating each scoring level as the callback threshold (composers would be "called back" if their overall evaluation score is above that given score, as if in a hiring situation). Even though our study is not a hiring experiment, our granular measure—overall evaluation score—helps us explore whether evaluators' preferences would differ in the tails of the distribution. Unlike typical audit studies, the binary callback rate variable is sensitive to a low callback rate environment (Kessler et al. 2019).

Two analytical tools are used here. The first graph is the empirical cumulative distribution function (CDF) of the overall evaluation scores. In our study, we compare the CDFs of female composers and male composers. The second exercise generates counterfactual callback rates by assuming that evaluators would call back the composers if their overall evaluation scores were at or above a certain threshold. We can then observe the differences in callback rates across each scoring threshold through a linear probability model.

We plot the CDF of the ratings of hypothetical male and female composers (see Figure 3 panel a). We also show the differences in the counterfactual callback rates (Figure 3 panel b). We observe that, in Figure 3(b), the coefficients are higher than zero at almost all levels of selectivity (less pronounced at the tail), meaning that our result is qualitatively consistent across nearly the entire distribution of the overall score. We employ the same analysis by reviewers' gender in Figure 4. When reviewers are female, the difference in the counterfactual callback rates between female composers and male composers is nearly zero at all levels of the scoring threshold (Figure 4 Panel b). Yet when reviewers are male, callback rates for female composers are consistently higher than their male counterparts across the whole scoring distribution (Figure 4 Panel d), although this difference is less pronounced at the tail. This additional analysis supports our study's findings, showing our results to be generalizable: female names associated with music compositions influence reviewers' preferences throughout nearly the entire distribution of overall evaluation scores.

D. Other Characteristics

The data shows that senior faculty (45 years and older) preferred female composers and graded compositions with female names 0.536 points higher than the same compositions with male names in overall evaluation (0–10 scale), equivalent to 28% of the overall standard deviation. Senior faculty also rated female composers higher in all five musical dimensions by an average of 0.205 points (1–5 scale) in the structured evaluation. In contrast, there was no evidence of gender bias in younger faculty (under 45 years old) in their evaluations. All the results are consistent using regression analysis and can be found in Table 5 (See also Appendix Figure A-1). We test whether there is a statistically significant difference in evaluation scores between younger faculty and elder

faculty reviewers; Panel C in Table 5 shows that this difference is only at the marginal line of statistically significance in overall evaluation (P-value<0.1), and not significant in structured evaluation.

Table 6 presents results showing scoring separated out among participating faculty reviewers of differing tenure status: adjunct instructor, assistant professor, associate professor, and full professor. Gender bias was observed among full professor reviewers. They showed preferance for female composers in general evaluations and structured evaluations, and compositions associated with female names received higher ratings in all five musical dimensions (although scoring differences for tempo and orchestration were not statistically significant.). All the differences are presented in Table 6 (See also Appendix Figure A-1). Full professors showed the only statistically significant bias in favor of female composers of the reviewer tenure status groups. Compositions with female names were rated 0.852 points higher on average (0–10 scale) in general evaluation, and an average of 0.415 points higher in structured evaluation (1–5 scale). This bias toward female names in general evaluation corresponds to 44% of the overall standard deviation. All the lower-ranked professors, including adjunct professors, assistant professors, and associate professors did not exhibit a statistically significant gender bias. We further test whether there is a statistically significant difference in evaluation between tenured professors (Associate professor and above) and others. Panel C in Table 6 shows that this difference is only at the marginal line of statistical significance in overall evaluation (P-value<0.1) and not statistically signifcant in structured evaluation. We note that the patterns between the overall score and the average score (based on the structured evaluation) appear slightly different in Tables 5 and 6. We suspect that evaluators have differing opinions on what they consider to be a good composition. We explain more about

the general evaluation, which produced an overall score, versus the structured evaluation in the next section.

D. General versus Structured Evaluation

Hypothesis C predicted that discrimination against female composers would be reduced or eliminated by structured evaluation. A general preference for female composers was, however, found in both evaluation methods. Though the differences in magnitudes are non-comparable due to the measurement designs (0.294 points on 0–10 scale, 0.182 points on 1–5 scale), the results provide evidence that a similar bias persisted in structured evaluation.

In the structured evaluation, evidence of gender bias was found in the overall evaluation and all five music categories (although form/structure and tempo/rhythm are significant at 10% level). Reviewers who favored compositions associated with female names rated these pieces higher in every aspect of the evaluation: detailed and overall, on specific musical traits and on the complete work. Structured evaluation does not seem to affect faculty reviewers' gender preference. One may notice a small discrepancy between overall scores and the average scores of structured evaluation in the heterogeneity analysis. We attribute this discrepancy to the low statistical power, which makes the results less stable.

A caveat of our study is that we use a within-subjects test instead of a between-subjects test when comparing general versus structured evaluation. In an ideal scenario, we can assign some respondents to conduct only the overall evaluation survey, and others to conduct only the structured ones to create a between-subjects test. Yet we designed a within-subjects test for several reasons. First, with this unique population, we would be further constrained by the statistical power

if using a between-subjects test. Second, we did not want to ask respondents to evaluate only a structured evaluation because such evaluation is not conventional in composition competitions. Third, it would be imprudent to ask reviewers to evaluate only the overall evaluation either because this request would be at odds with our stated invitation purpose to study the criteria of evaluation.

We recognize the design limitation that would allow the reviewers to remember their overall evaluation scores and rate the structured evaluation to be consistent with their initial assessment. We raise barriers to this harmonization by making it impossible for reviewers to "go back to the previous page" and change their overall scores once they are in the structured section. In addition, the scales of the scores are different (i.e. overall evaluation (1-10) and structured evaluation (1-5)), making it more challenging to intentionally "fit" the two types of assessment.

6. Robustness Check

We conducted further robustness checks using different model specifications to see if our results are consistent and valid. Table 7 shows the response time. We thought it unlikely that response times would matter much in driving the results as some professional judges may simply have downloaded the scores and performed the evaluation offline making their response time appear very quick. To test the results' robustness, we simply drop those who have unusually short response times (less than 10% of the bottom tail). We find that these results are almost identical to the main results in Table 2. There is also no significant difference in the response times between our randomization group A and group B.

To assure our external validity, we coded the background information of more than one thousand respondents and non-respondents and test their differences. We are constrained by the basic

information available on faculty's website. Based on the results in Table 8, we find that our respondents are very similar to non-respondents in terms of the gender proportions, and whether the faculty's institution is public or private. We find that faculty members in our experiment are less likely to be tenured faculty. We do not know if this response rate difference is correlated with gender bias. Nonetheless, if our heterogeneity analysis holds (i.e. senior faculty favors female composers), our current results may underestimate female favoritism.

To address any concern that the results are driven by outliers, we re-estimate our main coefficients after dropping the observations that have overall scores below 1st and above 99th percentile. The results, shown in Table 9 and Table 10, are consistent with our main results.

7. Interpretation

To help understand our findings, we aim to interpret the mechanisms that underlie our observed results using different economic models of discrimination. The literature mostly discusses two primary models of discrimination: the taste-based discrimination model and statistical discrimination model. A relatively recent strand of literature, published over the past 15 years, cites biased belief to explain a dynamic model of discrimination, which is relevant in our context (Fryer, 2007; Fryer and Jackson, 2008; Schwartzstein 2014; Bohren et al., 2019; Bohren et al., 2022; Bohren et al., forthcoming). Our results are consistent with an extended version of the taste-based discrimination model, which indicates in/out-group bias. While our findings do not align with predictions from the classical statistical discrimination model, they are consistent with the "belief-based" model, where a belief updated at a later stage corrects or even reverses the initial

bias. Although we have limited information to adjudicate the exact mechanism, we provide highly plausible explanations in detail below.

7.1 Taste-based Discrimination and in/out-group bias

The taste-based discrimination mechanism was derived from Becker's utility-based discrimination model (Becker, 1957; Charles and Guryan, 2008), which shows that employers may prefer a certain type of group (e.g. white over black employees) because employers incur disutility from interacting with a different group, despite their equivalent abilities. Empirically, in-group or out-group bias can be viewed as an extended version of Becker's model. Bar and Zussman (2020), for instance, found that, in the driving tests, male testers generate utility from interacting with students of the opposite gender, resulting in a higher passing rate among female students. In this regard, our results may exhibit a similar taste-based gender bias, in which male reviewers incur utility by having more female composers winning awards, and thus they prefer female composers in the experiment. Card et al. (forthcoming) recognizes such a possibility, finding that the Econometric Society admitted more female than male fellows in the 2010-2018 period—flipping the historical negative to a positive benefit in favor of female scholars. They explain that fellows may exhibit positive values demonstrating more equal gender representation to showcase their values to the academic society.

7.2 Statistical Discrimination

The other model commonly used to explain discrimination is the statistical discrimination model with accurate belief. Under this framework, our empirical evidence would suggest that reviewers view female composers as more capable based on historical statistical evidence and thus rate them

higher than their male counterparts.[4] This explanation is unlikely the case, as we have ample evidence showing the opposite—unlike with certain musical instrument performance, such as piano or flute, the fields of composition and conducting are associated with a leading role in the orchestra and bear relatively negative stereotypes against women. Bennett et al. (2019) conducted a survey among female composers and found that most of them reported experiencing gender-related disadvantage in their composition careers. Many respondents stated that they try to strategically conceal their identity in their professional setting, such as composition competitions. The statistical discrimination model predicts that discrimination would be stronger among less experienced evaluators than it would be among more experienced evaluators. Our results do not support this common prediction. We therefore contend that our findings are not in line with the classical statistical discrimination model's predictions.

7.3 Belief-based Model

In the more recent "belief-based" literature, discrimination is dynamically updated with new information. There is evidence of settings, for instance, where evaluators hold initial discriminatory beliefs against a group (e.g. women) but quickly update them once they see evidence of good performance. Discrimination could be reduced or even reversed after the discriminated group earns a better reputation. Linking this literature to our results, it is possible that the evaluators have internalized how difficult it is to "make it" in the music world as a female composer. If this were the case, a previous stage of selection as well as a "belief update" would have already occurred. In the evaluators' updated belief, the compositions associated with female names are worthy of higher ratings as they are authored by women who have succeeded in

[4] Statistical discrimination often arises from the *correct* perception that one group, in our case, women composers, has a lower, or more precise, or less variant distribution compared to the other group, in this case, male composers.

becoming music composers. Our evidence suggesting that senior faculty are more favorable of female composers than are junior faculty would also fit well with the "belief update" mechanism.

The caveat, however, is that all the compositions we selected are commissioned pieces with our collaborated institution, and these composers may have already made it to the "later stage." We cannot directly observe evaluations among more junior level composers and thus cannot directly observe the belief update dynamics.

We note that our study is also relevant to the literature on joint versus separate evaluation. Bohnet et al. (2016) find that, with an "evaluation nudge," jointly evaluated resumes show less implicit bias against women than those evaluated sequentially. Given that our experiment treats every reviewer with two male names and two female names, the design may nudge the reviewers to mitigate their biases. We could not explore this mechanism thoroughly due to our experiment design but want to draw attention to this feature for future studies.

8. Conclusion

In this study, we replicated a composition competition, an important event in composers' careers, similar to conferences in other fields. The study used new compositions of equal quality created by professional composers and employed a simple 0–10 rating scale to evaluate the works. This design helped to eliminate potential endogenous unobservables between female and male candidates which is a common issue in observational studies.

This study adds to the discrimination and in-group bias literature. Contrary to the gender discrimination prediction, our audit study finds a bias favoring female names in professional settings. When we tested the in-group bias hypothesis, we found an out-group bias, in which male

reviewers give higher scores toward female composers. These results were consistent across general and structured evaluations.

Some may have concerns that our results are driven by the experiment demand effect. Faculty members, for instance, could have googled the name of the composition and figured out that this was a study about gender, resulting in the Hawthorne effect with male evaluators giving favored evaluations toward female composers. We contend that this effect is unlikely. The study's compositions are all newly commissioned works with no public info available online, so the actual composers' names cannot be revealed. We also double-checked that our fictitious names are not the same names as real composers. It is quite common that junior composers or composition students do not yet have a prominent online portfolio. One may also be concerned that the two-female-two-male design in our experiment leads to a subtle signaling effect for diversity. We cannot eliminate this factor but note that this design is not uncommon, as many female composers have advanced as finalists of multiple well-known competitions in recent years.

This study addresses the literature on women's underrepresentation in the academy, which focuses heavily on the STEM fields. Our study fills a critical gap in the literature by examining an extreme case of gender imbalance in a non-STEM field. The puzzling question remains: if we see little gender bias against women, what explains the extremely low representation of women composers? (O'Bannon, 2014, 2015, 2016; Brown, 2018; Doolittle, 2018; Ting, 2018). Our paper alone cannot answer this question, but it offers insights for further investigation. As for a concrete policy implication, our results align with Bagues et al. (2017) that having more female evaluators does not necessarily increase the odds for female candidates to succeed.

Despite the statistically significant results of our study, the findings should be interpreted carefully. We are reminded by the recent paper in the *Journal of Economic Perspectives* that discrimination can come in various forms (Small and Pager, 2020). The prevalent taste and statistical discrimination models may not capture all reasons and mechanisms behind differential treatment. Discrimination can be unintentional, institutional, historical, or come through mundane everyday interactions. Our study, which focuses on the assessment of sample compositions, observes only one arena for a composers' career advancement. We do not capture the larger institutional or historical dimensions of the problem. Our study does not rule out gender bias in other evaluation processes, including the review of resumes, curricula vitae, and letters of recommendation as investigated in other studies (Steinpreis et al., 1999; Bornmann et al., 2007; Knobloch-Westerwick et al., 2013; Moss-Racusin et al., 2012; Trix and Psenka, 2003). Another caveat is that our study is not a hiring experiment, and thus the results have limitations in translating into employment in music composition professions. Finally, our study does not capture temporal changes in this field. If the recent call for diversity is an explanation of our results, it may only "benefit" a small number of composers of a generation, and the broader inequality remains.

With these limitations in mind, our findings suggest that women's underrepresentation in professional composition is not due to unfair evaluation in composition competitions, or, at the very least, that demand side discrimination should not be seen as the only cause. Women's underrepresentation in this field may in part be a supply side issue, resulting from women's decisions to not apply or pursue such careers. Our results speak to other research showing zero or positive bias for females in academia (Ceci and Williams, 2015; Williams and Ceci, 2015; Breda

and Hillion, 2016; Card et al., forthcoming [5]), in which researchers argue that the underrepresentation of women in certain STEM fields is less about unfair evaluation in higher education or the labor market, and more a result of "pre-college factors and the subsequent likelihood of majoring in these fields." (Ceci et al., 2014). To what extent our insights can be applied to STEM fields and other professions remains an open question. Further research is required in other aspects of this profession, such as composers' employment, pay, and career advancement, to yield a more conclusive judgment.

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[5] Card et al. (forthcoming) examine the selection of Fellows of the Econometric Society. They found that there was gender gap in earlier decades, and the effect flips favoring women in the most recent decade.

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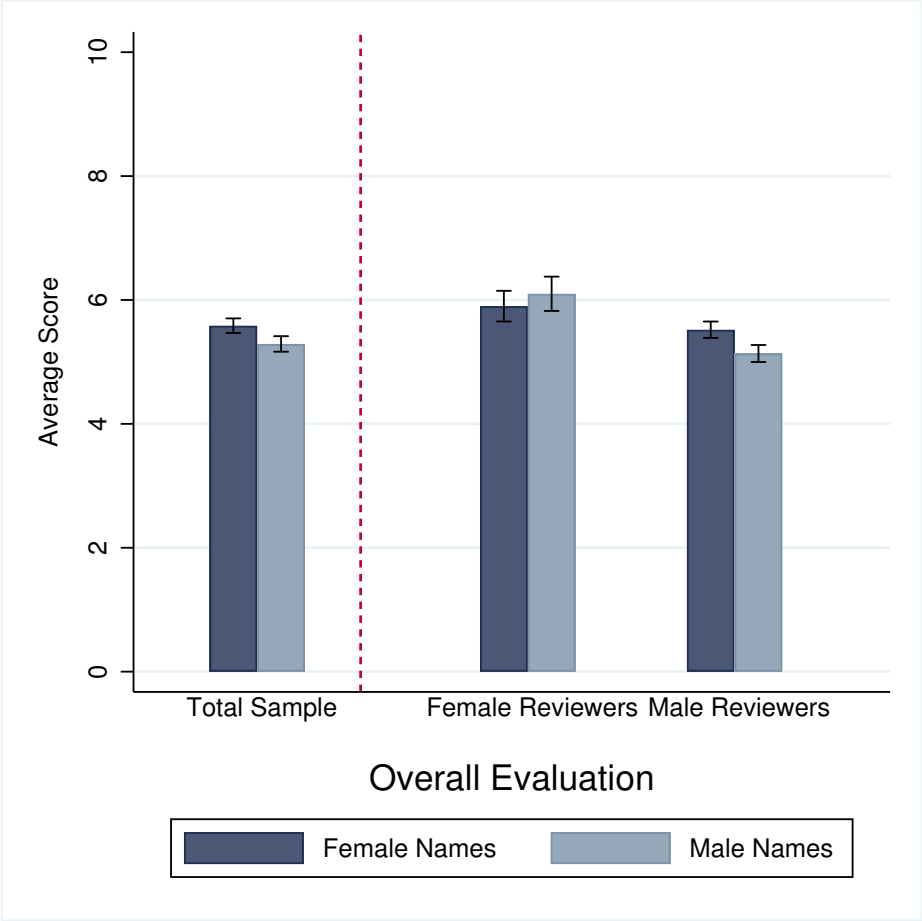
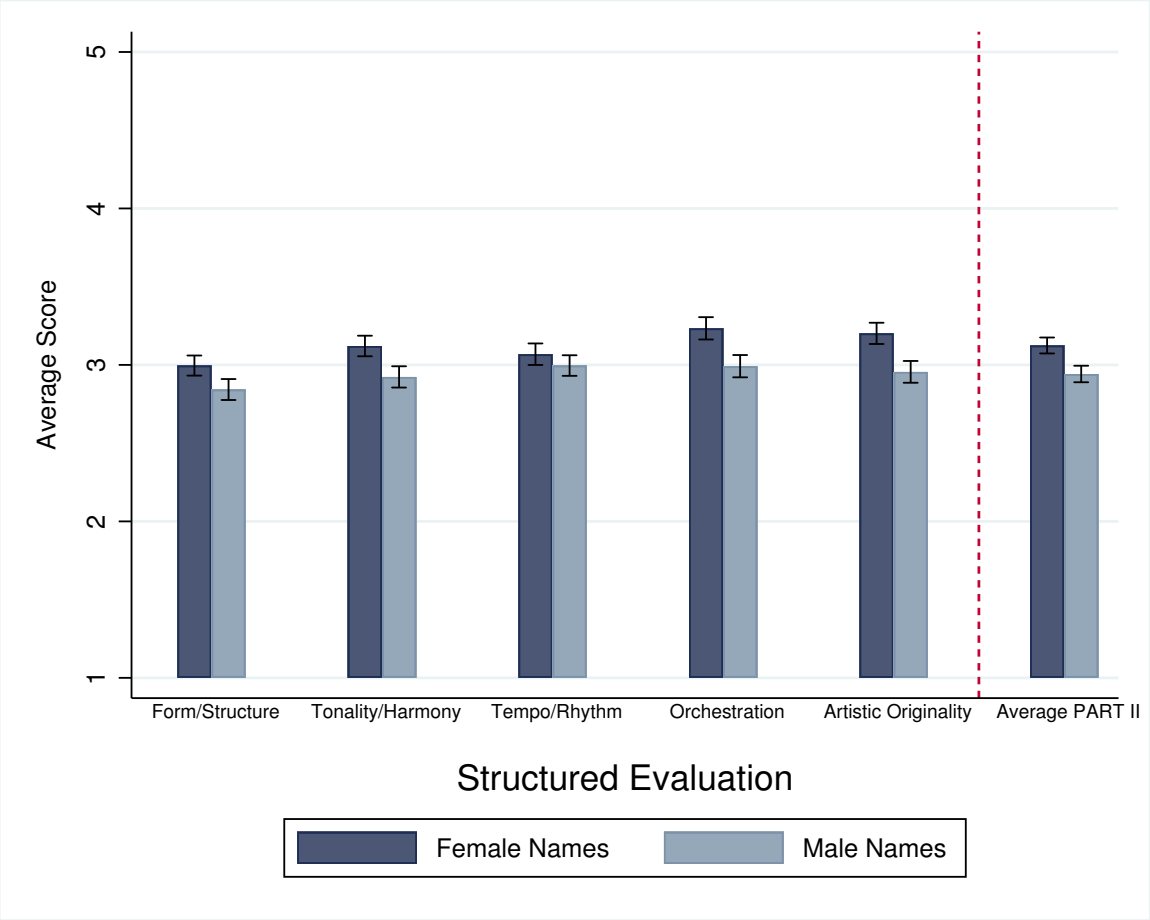
9 Figures and Tables

Figure 1: Graphical analysis of overall evaluation



Note: All the bars represent the average scores in Part I overall evaluation (0-10) for compositions associated with female names vs. male names. The left two bars are mean scores among the total sample; the middle two bars are mean scores among female reviewers; the right two bars are mean scores among male reviewers. Error bars represent standard errors.

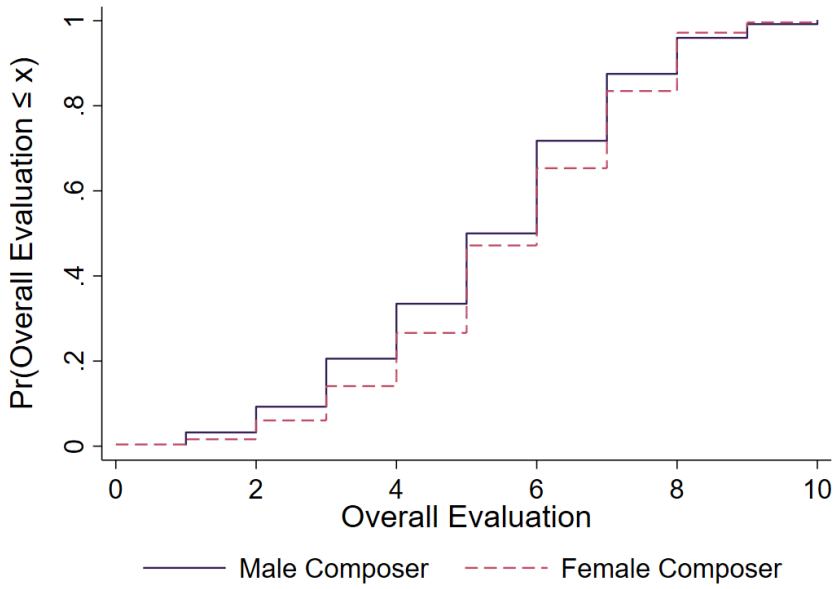
Figure 2: Graphical analysis of structured evaluation



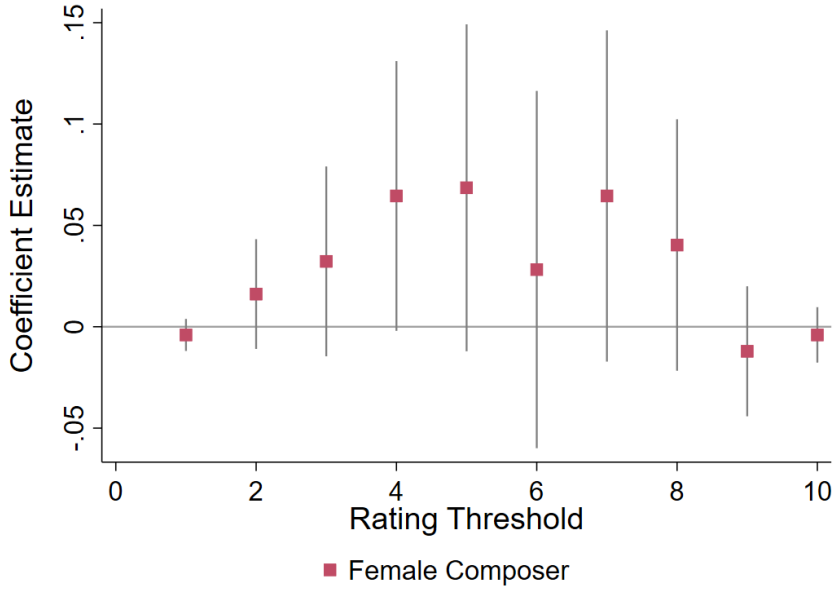
Note: All the bars represent the average scores in Part II structured evaluation (scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong") for compositions associated with female names vs. male names. Compositions are evaluated in five categories. The last right two bars correspond to the average scores of the five categories. Error bars represent standard errors.

Figure 3: Value of Composers' Gender over Selectivity Distribution

(a) Empirical CDF of Overall Evaluation



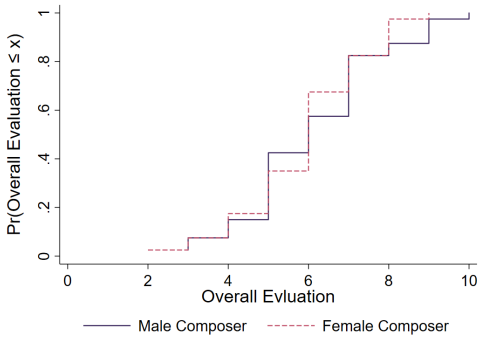
(b) Linear Probability Model for *Female Composers*



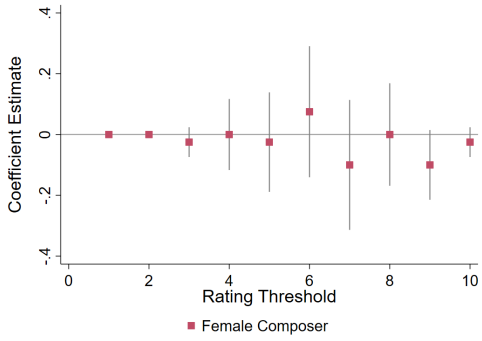
Note: Empirical CDF of *Overall Evaluation Score* is in panel (a). The CDFs show the share of compositions with each characteristic (ex: written by hypothetical male or female composers) with a overall evaluation score less than or equal to each value. The counterfactual callback rates for *female names* is in panel (b), which plot the equivalent "callback rate" for that group. That is, the composition for that group receive the score above the callback rate when it is set at any given rating threshold. Error bars represent 95% confidence intervals. The confidence intervals are calculated from a linear probability model where the dependent variable is an indicator for being at or above a threshold and the independent variable is a dummy variable indicating the composer's characteristic (i.e. female).

Figure 4: Composers' Gender by Reviewers' Gender over Selectivity Distribution

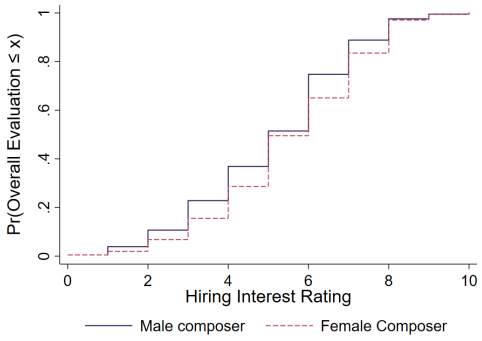
(a) Empirical CDF of Overall Evaluation, Female Reviewers



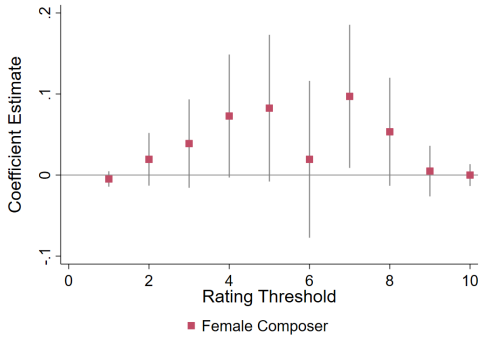
(b) Linear Probability Model for *Female Composers*, Female Reviewers



(c) Empirical CDF, Male Reviewers



(d) Linear Probability Model for *Female Composers*, Male Reviewers



Note: Empirical CDF of *Overall Evaluation Score* is in panel (a) and (c) and the counterfactual callback plot for *female names* is in panel (b) and (d). The top row shows the empirical CDF and counterfactual callback rate when the reviewers are female, while the bottom row shows similar figures when the reviewers are male. The CDFs show the share of compositions with each characteristic (ex: written by hypothetical male or female composers) with a overall evaluation score less than or equal to each value. The counterfactual callback plot shows the equivalent "callback rate" for that demographic group (in this case, female composers). That is, the share of the composers that would be called back if the rating threshold is set at any given value. Error bars represent 95% confidence intervals. The confidence intervals are calculated from a linear probability model where the dependent variable is an indicator for being at or above a threshold and the independent variable is the dummy variable indicating a composer's characteristic (i.e. female).

Table 1: Summary Statistics and Test for Randomization

	Overall	Randomization A (M,F,M,F)	Randomization B (F,M,F,M)	P-value for testing the difference of (2) and (3)
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	
	(1)	(2)	(3)	(4)
Female (0/1)	0.16	0.18	0.15	0.60
	(0.37)	(0.39)	(0.36)	
White (0/1)	0.86	0.89	0.84	0.48
	(0.35)	(0.32)	(0.37)	
Age younger than 45 (0/1)	0.52	0.44	0.60	0.07
	(0.50)	(0.50)	(0.49)	
Adjunct professor(0/1)	0.34	0.34	0.33	0.90
	(0.48)	(0.48)	(0.48)	
Assistant professor(0/1)	0.23	0.21	0.25	0.59
	(0.43)	(0.41)	(0.44)	
Associate professor(0/1)	0.18	0.16	0.19	0.70
	(0.38)	(0.37)	(0.40)	
Full professor(0/1)	0.22	0.21	0.22	0.90
	(0.41)	(0.41)	(0.42)	
Public school(0/1)	0.61	0.62	0.60	0.82
	(0.49)	(0.49)	(0.49)	
Average overall evaluation	5.44	5.48	5.39	0.72
	(1.42)	(1.38)	(1.46)	
Number of faculty reviewers	124	61	63	

Note: Standard deviations are in parenthesis. Four faculty reviewers are from the institutions that do not have the conventional rank system, making the four ranks added up <1.

Table 2: Overall Results for Gender Bias in Music Evaluation

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female names	0.305**	0.158	0.203**	0.0860	0.247**	0.246**	0.188***
	(0.147)	(0.103)	(0.0909)	(0.103)	(0.0961)	(0.0990)	(0.0703)
Average score of outcome variable	5.438	2.919	3.022	3.032	3.113	3.079	3.033
Standard deviation of outcome variable	1.920	1.036	1.057	1.059	1.128	1.088	0.822
Observations	496	496	496	496	496	496	496
R-squared	0.618	0.397	0.447	0.464	0.452	0.447	0.495

Note: All the results are based on regressions with female names dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variable. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top row represents the regression coefficient. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions.

Table 3: In-group Bias in Music Evaluation

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same gender	-0.380***	-0.200*	-0.251***	-0.184*	-0.245**	-0.250**	-0.226***
	(0.145)	(0.103)	(0.0903)	(0.102)	(0.0965)	(0.0996)	(0.0693)
Average score of outcome variable	5.438	2.919	3.022	3.032	3.113	3.079	3.033
Standard deviation of outcome variable	1.920	1.036	1.057	1.059	1.128	1.088	0.822
Observations	496	496	496	496	496	496	496
R-squared	0.621	0.400	0.452	0.470	0.451	0.447	0.500

Note: All the results are based on regressions with the same gender dummy (1 if reviewers and assigned composers are the same gender; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variable. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top row represents the regression coefficient. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions.

Table 4: Gender Bias in Music Evaluation - Female Heterogeneity

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Female Professor							
Female names	-0.278	-0.184	-0.157	-0.301*	-0.0379	-0.0278	-0.141
	(0.311)	(0.168)	(0.205)	(0.147)	(0.176)	(0.286)	(0.115)
Observations	80	80	80	80	80	80	80
R-squared	0.602	0.305	0.437	0.408	0.437	0.400	0.464
Panel B: Male Professor							
Female names	0.402**	0.208*	0.272***	0.161	0.289***	0.293***	0.244***
	(0.162)	(0.118)	(0.100)	(0.119)	(0.109)	(0.107)	(0.0796)
Observations	412	412	412	412	412	412	412
R-squared	0.624	0.419	0.456	0.478	0.450	0.459	0.504
Panel C: Total Sample							
Female names	0.402**	0.209*	0.273***	0.160	0.291***	0.293***	0.245***
	(0.162)	(0.118)	(0.100)	(0.119)	(0.109)	(0.107)	(0.0797)
DID result (Female names X Female Professor)	-0.668*	-0.368*	-0.409*	-0.470**	-0.299	-0.322	-0.374***
	(0.353)	(0.210)	(0.227)	(0.182)	(0.212)	(0.283)	(0.141)
Observations	492	492	492	492	492	492	492
R-squared	0.626	0.403	0.452	0.469	0.454	0.446	0.502

Note: All the results are based on regressions with female names dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variables. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top panel reports the regression coefficients for female faculty reviewers; The bottom panel reports the regression coefficients for male faculty reviewers. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 123 reviewers' evaluations for four compositions as one reviewer identified the gender question as "other."

Table 5: Gender Bias in Music Evaluation - Age Heterogeneity

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Younger Professor (<45)							
Female names	0.0261	0.106	0.191	0.0721	0.181	0.173	0.145*
	(0.185)	(0.146)	(0.122)	(0.132)	(0.140)	(0.128)	(0.0833)
Observations	260	260	260	260	260	260	260
R-squared	0.585	0.364	0.411	0.443	0.450	0.471	0.490
Panel B: Older Professor (≥45)							
Female names	0.536**	0.164	0.199	0.103	0.283**	0.278*	0.205*
	(0.239)	(0.155)	(0.134)	(0.158)	(0.128)	(0.159)	(0.118)
Observations	236	236	236	236	236	236	236
R-squared	0.656	0.427	0.501	0.479	0.453	0.455	0.504
Panel C: Total Sample							
Female names	0.571**	0.188	0.208	0.102	0.300**	0.301*	0.220*
	(0.236)	(0.153)	(0.134)	(0.155)	(0.127)	(0.155)	(0.116)
Panel C: Total Sample							
Female names	0.571**	0.188	0.208	0.102	0.300**	0.301*	0.220*
	(0.236)	(0.153)	(0.134)	(0.155)	(0.127)	(0.155)	(0.116)
DID result (Female names X Younger Professor)	-0.510*	-0.0572	-0.00792	-0.0311	-0.101	-0.105	-0.0606
	(0.304)	(0.214)	(0.180)	(0.204)	(0.189)	(0.205)	(0.145)
Observations	496	496	496	496	496	496	496
R-squared	0.622	0.397	0.447	0.464	0.452	0.447	0.495

Note: All the results are based on regressions with female names dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variables. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top panel reports the regression coefficients for younger faculty reviewers; The bottom panel reports the regression coefficients for older faculty reviewers. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions.

Table 6: Gender Bias in Music Evaluation - Rank Heterogeneity

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adjunct Professor							
Female names	-0.107	-0.0595	0.179	0	0.155	0	0.0548
	(0.232)	(0.179)	(0.174)	(0.187)	(0.186)	(0.164)	(0.122)
Observations	168	168	168	168	168	168	168
R-squared	0.626	0.365	0.378	0.438	0.431	0.380	0.460
Panel B: Assistant Professor							
Female names	0.406	0.387*	0.0793	0.286	0.242*	0.387**	0.276**
	(0.239)	(0.217)	(0.143)	(0.172)	(0.126)	(0.185)	(0.111)
Observations	116	116	116	116	116	116	116
R-squared	0.671	0.440	0.524	0.447	0.593	0.547	0.588
Panel C: Associate Professor							
Female names	0.425	-0.0458	0.196	-0.262	0.458*	0.162	0.102
	(0.359)	(0.191)	(0.248)	(0.190)	(0.246)	(0.233)	(0.138)
Observations	88	88	88	88	88	88	88
R-squared	0.634	0.385	0.418	0.547	0.527	0.471	0.521
Panel D: Full Professor							
Female names	0.852**	0.507**	0.430**	0.356	0.205	0.580**	0.415**
	(0.360)	(0.222)	(0.197)	(0.265)	(0.199)	(0.244)	(0.188)
Observations	108	108	108	108	108	108	108
R-squared	0.638	0.501	0.546	0.497	0.439	0.499	0.524
Panel E: Total Sample							
Female names	0.0915	0.102	0.128	0.0956	0.209*	0.153	0.138
	(0.167)	(0.135)	(0.111)	(0.128)	(0.122)	(0.118)	(0.0832)
DID result (Female names X Tenured Professor)	0.540*	0.142	0.190	-0.0243	0.0963	0.237	0.128
	(0.308)	(0.208)	(0.190)	(0.217)	(0.199)	(0.208)	(0.149)
Observations	496	496	496	496	496	496	496
R-squared	0.622	0.398	0.449	0.464	0.452	0.450	0.496

Note: All the results are based on regressions with female names dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variables. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top from the bottom panels reports, respectively, the regression coefficients for adjunct professors, assistant professors, associate professors, and full professors. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 120 reviewers' evaluations for four compositions. Four faculty reviewers are from the institutions that do not have the conventional rank system.

Table 7: Robustness Check: Dropping Those Whose Response Times are Short

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female names	0.284*	0.152	0.221**	0.0753	0.244**	0.221**	0.183***
	(0.148)	(0.106)	(0.0918)	(0.100)	(0.0991)	(0.0969)	(0.0697)
Average score of outcome variable	5.438	2.919	3.022	3.032	3.113	3.079	3.033
Standard deviation of outcome variable	1.920	1.036	1.057	1.059	1.128	1.088	0.822
Observations	472	472	472	472	472	472	472
R-squared	0.619	0.397	0.453	0.476	0.454	0.452	0.504

Note: All the results are based on regressions with female names dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variable. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." Those whose response times are less than 10% of the bottom tail are dropped. The top row represent the regression coefficient. All regressions are controlled for reviewer and composition fixed effects. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions.

Table 8: Robustness Check: Selection into the Survey

	In sample	Out of sample	Difference between those in sample and out sample
Female (0/1)	0.1612	0.1799	-0.019
	(0.0331)	(0.0124)	
Public School (0/1)	0.6363	0.6165	0.0198
	(0.0439)	(0.0157)	
Tenured (0/1)	0.4117	0.6842	-0.272***
	(0.0453)	(0.0164)	

Note: Those can we cannot identify the rank or the visiting professors are not included in this test. There are 167 out 1081 faculty members who we cannot identify the rank. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions.

Table 9: Robustness Check: Dropping Outliers (Gender Bias)

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female names	0.333**	0.169	0.210**	0.102	0.250**	0.255**	0.197***
	(0.150)	(0.104)	(0.0904)	(0.103)	(0.0967)	(0.101)	(0.0711)
Average score of outcome variable	5.438	2.919	3.022	3.032	3.113	3.079	3.033
Standard deviation of outcome variable	1.920	1.036	1.057	1.059	1.128	1.088	0.822
Observations	492	492	492	492	492	492	492
R-squared	0.611	0.395	0.448	0.465	0.451	0.447	0.495

Note: All the results are based on regressions with female assigned name dummy (1 if assigned with female names; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variable. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top row represent the regression coefficient. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions. In this robustness check, we dropped observations that have overall scores below the 1st and above the 99th percentile.

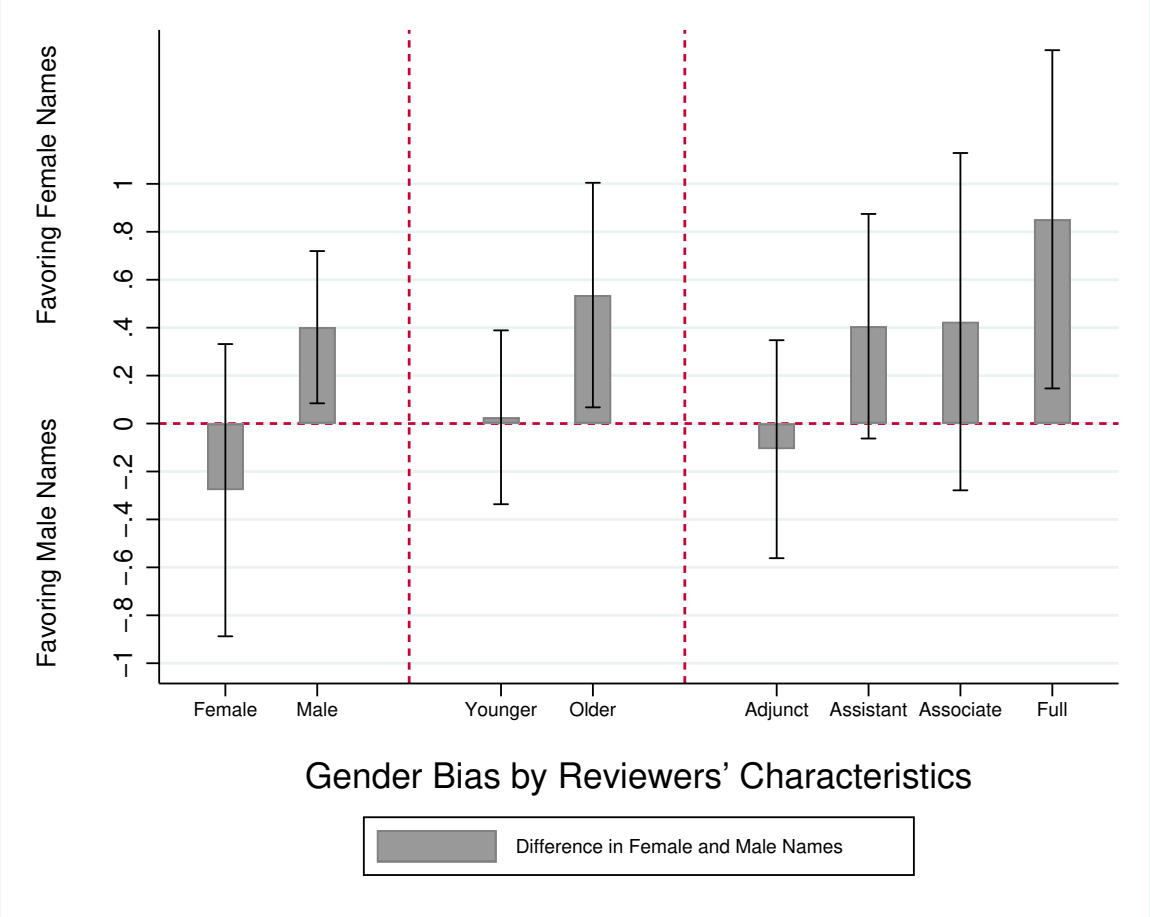
Table 10: Robustness Check: Dropping Outliers (In-group Bias)

VARIABLES	Overall	Form	Tonality	Tempo	Orch	Artistic	Average score (2)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same gender	-0.385**	-0.194*	-0.241***	-0.186*	-0.235**	-0.253**	-0.222***
	(0.148)	(0.104)	(0.0902)	(0.103)	(0.0973)	(0.101)	(0.0705)
Average score of outcome variable	5.438	2.919	3.022	3.032	3.113	3.079	3.033
Standard deviation of outcome variable	1.920	1.036	1.057	1.059	1.128	1.088	0.822
Observations	492	492	492	492	492	492	492
R-squared	0.614	0.397	0.451	0.470	0.449	0.447	0.498

Note: All the results are based on regressions with same gender dummy (1 if reviewers and assigned composers are the same gender; 0 otherwise) as the independent variable and all the scores in Part I and Part II as the outcome variable. Part I is the overall evaluation scored on a 0–10 scale. Part II is the structured evaluation scaled from 1 to 5, namely "Extremely Weak", "Somewhat Weak", "Neutral", "Somewhat Strong", "Extremely Strong." The top row represent the regression coefficient. Robust standard errors clustered with reviewers are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is the unique combination of composition and reviewer, based on 124 reviewers' evaluations for four compositions. In this robustness check, we dropped observations that have overall scores below the 1st and above the 99th percentile.

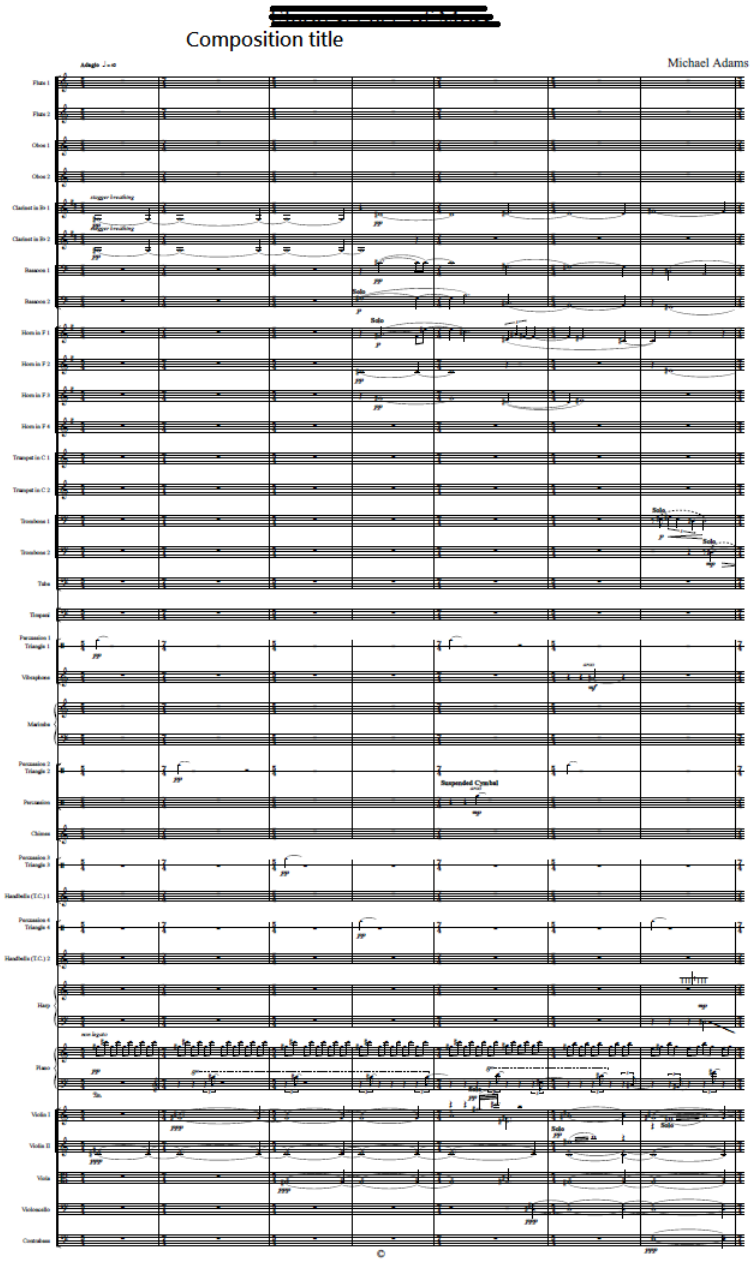
10 Appendix A: Figures and Tables

Figure A-1: Heterogeneity in gender bias



Note: All the bars represent the gender bias, calculated as the average score difference between compositions with female names and compositions with male names. Positive (negative) numbers indicate higher (lower) scores to female names than male names. All the gender bias numbers are estimated based on the regression analysis by different sub-samples based on reviewers' gender, age (45 years old as the cut-off), and rank. (see estimation strategy in the manuscript and Tables 5-7). Error bars represent 95% confidence intervals.

Figure A-2: One Example Page from The Score



11 Appendix B: Survey Materials

11.1 Invitation Letter

Dear Composition Faculty,

I would like to invite you to participate in a research study of composition evaluation conducted at xxx (anonymous institution). The purpose of this study is to better understand criterion used in assessing musical compositions. You will be asked to evaluate four 10-minute orchestral pieces, and the survey will take approximately 40-60 minutes to complete. To compensate for your time, we will provide a seventy-five dollars ($75) e-gift card upon completion of the survey.

The records of this study will be kept private, and your personal information will not be identifiable in any future reporting of results. Research records will be kept in password-protected files; only the researchers will have access to the records. The risks are no more than experienced in everyday life while using the internet. Study records will be kept confidential to the extent required by law.

To make sure that this research is being carried out in the proper way, the Georgia Institute of Technology IRB may review study records. The Office of Human Research Protections may also look at study records. If you have any questions about the study, you may contact Dr. xxx at telephone (xxx) xxx-xxxx, or xxx xxx.xxxx.edu.

If you have any questions about your rights as a research subject, you may contact Ms. xxx, xxx (anonymous institution) at (xxx) xxx-xxxx. Your participation in this study is voluntary. You do not have to be in this study if you don't want to be. You have the right to change your mind and leave the study at any time without giving any reason and without penalty. You will be given a copy of this consent form to keep. You do not waive any of your legal rights by agreeing to be in the study. Your completion of this survey provides your consent to participation.

Thank you for participating in this survey.

Please follow this link to the Survey:

Take the Survey

Or copy and paste the URL below into your internet browser:
https://xxxxx

Follow the link to opt out of future emails:
Click here to unsubscribe

(Email Signature)

11.2 Composition Evaluation Survey

Start of Block: Welcome Message

PART I Thank you for participating in our survey. We appreciate your time and expertise.

The purpose of this study is to better understand criterion used in assessing musical compositions. Below you will be asked to evaluate four (4) 10-min orchestral works. Please evaluate the compositions as if you were judging a final round of a Call for Score composition competition.

The survey takes approximately 40-60 minutes to complete. You can save your answers and return at a later time. Upon completion of the survey, you will be awarded a $75 gift card for your time.

Click the next button to get started!

End of Block: Welcome Message

Start of Block: (B1) Music Evaluation: General

Q1 Please evaluate the composition as if you were judging a composition competition, and provide your general recommendation for composition No.1.

Fluorescence of Moss_Score.pdf
Fluorescence of Moss_Recording.mp3

	0 1 2 3 4 5 6 7 8 9 10
Overall Recommendation ()	

Page Break

Q2 Please evaluate the composition as if you were judging a composition competition, and provide your general recommendation for composition No.2.

Stockholm_Score.pdf
Stockholm_Recording.mp3

	0 1 2 3 4 5 6 7 8 9 10
Overall Recommendation ()	

Page Break

Q3 Please evaluate the composition as if you were judging a composition competition, and provide your general recommendation for composition No.3.

The Irresistible Embrace of Singularity_Score.pdf
The Irresistible Embrace of Singularity_Accompanying Tape.mp3
The Irresistible Embrace of Singularity_Recording.mp3

	0 1 2 3 4 5 6 7 8 9 10
Overall Recommendation ()	

Page Break

Q4 Please evaluate the composition as if you were judging a composition competition, and provide your general recommendation for composition No.4.

FiddleSticks!_Score.pdf
FiddleSticks!_Recording.mp3

	0 1 2 3 4 5 6 7 8 9 10
Overall Recommendation ()	

End of Block: (B1) Music Evaluation: General

Start of Block: (B2) Music Evaluation: Specifics

PART II In the next section, you will be asked to provide detailed assessments of the four pieces as we are interested in understanding the criterion used in evaluating musical compositions. Please refer to the scores and recordings when providing your evaluation.

Page Break

Q5 For Musical Composition No.1, please rate the artistic achievement of the following:

Fluorescence of Moss_Score.pdf
Fluorescence of Moss_Recording.mp3

	Extremely Weak (1)	Somewhat Weak (2)	Neutral (3)	Somewhat Strong (4)	Extremely Strong (5)
Form / Structure (1)	○	○	○	○	○
Tonality / Harmony (2)	○	○	○	○	○
Tempo / Rhythm (3)	○	○	○	○	○
Orchestration (4)	○	○	○	○	○
Artistic Originality (5)	○	○	○	○	○

Page Break

Q6 For Musical Composition No.2, please rate the artistic achievement of the following:

Stockholm_Score.pdf
Stockholm_Recording.mp3

	Extremely Weak (1)	Somewhat Weak (2)	Neutral (3)	Somewhat Strong (4)	Extremely Strong (5)
Form / Structure (1)	○	○	○	○	○
Tonality / Harmony (2)	○	○	○	○	○
Tempo / Rhythm (3)	○	○	○	○	○
Orchestration (4)	○	○	○	○	○
Artistic Originality (5)	○	○	○	○	○

Page Break

Q7 For Musical Composition No.3, please rate the artistic achievement of the following:

The Irresistible Embrace of Singularity_Score.pdf
The Irresistible Embrace of Singularity_Accompanying Tape.mp3
The Irresistible Embrace os Singularity_Recording.mp3

	Extremely Weak (1)	Somewhat Weak (2)	Neutral (3)	Somewhat Strong (4)	Extremely Strong (5)
Form / Structure (1)	○	○	○	○	○
Tonality / Harmony (2)	○	○	○	○	○
Tempo / Rhythm (3)	○	○	○	○	○
Orchestration (4)	○	○	○	○	○
Artistic Originality (5)	○	○	○	○	○

Page Break

Q8 For Musical Composition No.4, please rate the artistic achievement of the following:

FiddleSticks!_Score.pdf
FiddleSticks!_Recording.mp3

	Extremely Weak (1)	Somewhat Weak (2)	Neutral (3)	Somewhat Strong (4)	Extremely Strong (5)
Form / Structure (1)	○	○	○	○	○
Tonality / Harmony (2)	○	○	○	○	○
Tempo / Rhythm (3)	○	○	○	○	○
Orchestration (4)	○	○	○	○	○
Artistic Originality (5)	○	○	○	○	○

Page Break

Q9 Finally, please make your final recommendation for the winner of the mock competition. (pick only one piece)

- Fluorescence of Moss (Michael Adams) (1)
- Stockholm (Rebecca Moore) (2)
- The Irresistible Embrace of Singularity (Sean Campbell) (3)
- FiddleSticks! (Tara Davis) (5)

End of Block: (B2) Music Evaluation: Specifics

Start of Block: Demographics

Q10 Please specify your age range.

- 18-24 years old (1)
- 25-34 years old (2)
- 35-44 years old (3)
- 45-54 years old (4)
- 55-64 years old (5)
- 65-74 years old (6)
- 75 years or older (7)

Q11 Please specify your gender.

- Female (1)
- Male (2)
- Other (3)

Q12 Please specify your ethnicity.

- White (1)
- Black or African American (2)
- American Indian or Alaska Native (3)
- Hispanic or Latino (4)
- Asian/Pacific Islander (5)
- Other (6)

End of Block: Demographics