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Gender Orientation and Segregation of Ideas: #MeToo's Impact in Hollywood*

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Abstract

Does the #MeToo movement affect the gender orientation of ideas and who develops which types of ideas? We examine these questions in the context of Hollywood. Since #MeToo affected the entire industry, we use variation in whether producers had past collaborations with Harvey Weinstein to discern the movement's impact. We find that relative to non-associated producers, there is, on average, *no* significant change in the likelihood of developing female-protagonist stories by Weinstein-associated producers after #MeToo compared to before, despite the fact that they now work substantially more with female writers. This is because, among projects by Weinstein-associated producers, female writers are significantly *less* likely than male writers to work on female-protagonist stories after #MeToo. Moreover, compared to their non-associated counterparts, the depiction of female protagonists by Weinstein-associated producers after #MeToo is less traditionally feminine. Overall, our findings suggest that #MeToo may have helped mitigate the frictions and biases that prevent female talent from exploring parts of the idea space that are typically associated with men and may have shaped the nature of female-oriented works.

Keywords: Gender inequality; Gender segregation; Social movement; Direction of innovation; Creative industries

JEL Codes: D91; J16; M14; L82

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1 Introduction

While women have made considerable progress in the workplace, the gender gap is still significant and persistent on many fronts, particularly in the innovation, entrepreneurship, and creative sectors. For example, women represent only ten percent of inventors (Sugimoto et al., 2015); nine percent of venture capital (VC) investors and 11 percent of founders of VC-backed startups (Gompers and Wang, 2017); and only five percent of directors, 14 percent of writers, and 21 percent of producers of top-grossing films (Smith et al., 2020). Moreover, men and women also differ in the type of ideas and products they develop in these sectors. Female inventors account for ten percent of the inventors in chemical industries but for only two percent in engineering (Hoisl and Mariani, 2017); female-led startups are more likely to be in healthcare, education, and other service sectors, rather than in IT, finance, and manufacturing (Hebert, 2020); and female writers are more likely to write films in romance and drama genres than in action and sci-fi.[1]

Together, the general lack of female participation and the segregation by gender in the idea space suggest potential inefficiencies in idea development. First, the segregation may be due to female talent's preference for or advantage over male talent in developing ideas and products that are oriented towards women. Thus, the general lack of female participation may lead to an underdevelopment of female-oriented ideas (e.g., Koning et al., 2019). Second, this segregation may also reflect the constraints and stereotyping that women face in exploring technology and product types that are typically associated with men (e.g., Tak et al., 2019; Kanze et al., 2020). Such frictions or biases may lead to inefficiencies due to a potential mismatch between talent and ideas.

In this paper, we study the impact of the #MeToo movement on idea development. In particular, we ask two related questions: i) Has #MeToo changed the gender orientation of ideas that are developed? and ii) Has #MeToo changed the gender composition of talent that develops each type of idea? We examine these questions in the context of Hollywood and, in particular, by investigating producers' choice of new projects before and after #MeToo.

Seeded by activist Tarana Burke in 2006, the #MeToo movement took the world by storm following two exposés in October 2017 detailing decades of sexual harassment by Harvey Weinstein.[2] On October 15, 2017, actress Alyssa Milano asked women who had been sexually harassed or assaulted to write #MeToo on social media. Within 24 hours, Facebook reported that 45 percent of its users in the U.S. were friends with someone who had posted a "#Me Too" status; over 1.7 million tweets from 85 countries included the

[1] https://writersguild.org.uk/wp-content/uploads/2018/05/WGGB-Gender-Inequality-and-Screenwriters-Report.pdf

[2] "Harvey Weinstein Paid Off Sexual Harassment Accusers for Decades," by Jodi Kantor and Megan Twohey, October 5, 2017, *The New York Times*. "From aggressive overtures to sexual assault: Harvey Weinstein's accusers tell their stories," by Ronan Farrow, October 10, 2017, *The New Yorker*.

hashtag within the first week; and reports of sexual crimes began to increase in the next quarter (Levy and Mattsson, 2019). In addition to highlighting the pervasiveness of sexual harassment, the #MeToo movement brought the underlying causes of sexual misconduct to the forefront of the national discourse. These include the persistent gender disparities in representation, pay, and power, as well as the entrenched gender norms and stereotypes (Murnen et al., 2002; Dobbin and Kalev, 2017). Together with the increased public and media scrutiny, these conversations potentially resonated with both the decision makers in an organization and its various stakeholders and pushed individuals and organizations to enact change. Indeed, a year after the Weinstein scandal, at least 200 prominent men in a variety of sectors had lost their jobs after public allegations of sexual harassment, and half of their replacements were women.[3] Luo and Zhang (2020) also find that Hollywood producers became more likely to work with female writers after #MeToo. There is also anecdotal evidence of an increased awareness of gender stereotypes,[4] which may lead to changes that affect not only the number but also the types of opportunities women can pursue (Ceci et al., 2014).

Given the sheer breadth of the movement's reach, to disentangle #MeToo's impact from other societal trends that have separately but simultaneously affected the outcomes that interest us, we need to identify groups that are more affected by the movement from those less affected. Hollywood, the epicenter of the movement, provides a setting in which to address this question. As Luo and Zhang (2020) argue, while #MeToo is likely to affect Hollywood producers in general, those who had worked with Weinstein in the past are more affected. This may be because they are more likely to be (or perceived to be) complicit in the abusive culture or because their association with Weinstein may have made the issues highlighted by #MeToo especially salient for them personally. Thus, comparing producers who had worked with Weinstein (henceforth, Weinstein-associated producers) to those who had not (non-associated) helps to discern the effect of the movement.

Because Weinstein-associated producers tend to be significantly more experienced and are of higher status than non-associated producers, we use a matched sample of 1,977 new projects begun between January 2014 and September 2019 for which the two groups of producers are statistically similar in their observable characteristics. Our primary measure of the gender orientation of an idea is whether the story has a female protagonist, as it places a woman at the center of the story universe (Basinger, 1993). Consistent with the

[3] "#MeToo Brought Down 201 Powerful Men. Nearly Half of Their Replacements Are Women," October 23, 2018, *The New York Times*.

[4] For example, after #MeToo, high-school teachers began teaching students to have a better understanding of gender stereotypes, arguing that this is "one of the most effective ways to combat sexism" (source: https://www.wnyc.org/story/after-metoo-high-school-students-learn-about-gender-roles/). A recent federal appeals court reinstated charges in a sexual harassment case, arguing that traditional negative gender stereotypes are a form of sex discrimination. Experts say that the case reflects changing judicial attitudes towards sex stereotyping, which have been influenced by the #MeToo movement, and call for firms to "train employees not to use sex stereotyping when making decisions that affect workers' terms and conditions of employment" (Source: https://www.businessinsurance.com/article/20190219/NEWS06/912326747).

gender segregation of the idea space, projects written by female writers are 2.5 times as likely to feature female protagonists, compared to projects written by male writers (68.4 versus 27.3 percent).

We find that, on average, relative to non-associated producers, there is *no* significant change in the likelihood that Weinstein-associated producers will develop female-protagonist stories after #MeToo than before. This is despite the fact that they work substantially more—by about 35 percent—with female writers after #MeToo (Luo and Zhang, 2020). This contrast can be explained by the finding that, among projects by Weinstein-associated producers, female writers are significantly *less* likely than all-male writing teams to work on female-protagonist stories. This shift away from female-protagonist stories holds not only for teams with female writers, but also for teams with female producers. In contrast, if all of the writers and producers are men, Weinstein-associated producers are *more* likely to develop female-protagonist stories after #MeToo, relative to their non-associated counterparts. Quarter-specific triple-differences regression shows that this differential response by Weinstein-associated teams with and without any female writers or producers began in the second quarter after #MeToo and persisted until the end of our sample period. The difference is economically large, ranging between 14.7 and 45.6 percentage points.

Apart from the protagonist's gender, we also use the script's logline (short plot summary) to construct a measure that systematically captures how the protagonist is portrayed relative to a set of stereotypical feminine and masculine traits that is well-established in the gender-role literature (Bem, 1974). We find that relative to female-protagonist stories developed by non-associated producers, those developed by Weinstein-associated producers are significantly *less* traditionally feminine after #MeToo than before. We do not find any differential change in the portrayal of male protagonists due to Weinstein association.

Our findings suggest that while #MeToo, on average, has not changed the proportion of stories oriented towards female audiences, it has helped to reduce gender segregation in the idea space and has led to more portrayals of female characters that defy traditional gender stereotypes. While it is difficult to pin down the precise mechanisms, these results are consistent with several non-mutually exclusive interpretations. First, in our context, the high correlation between the gender of the talent and the gender orientation of ideas seems to be driven largely by constraints such as gender stereotypes that female talent face when exploring ideas that have been dominated by male talent, rather than by the female talent's own preference. #MeToo may have helped to relax these constraints. Second, consistent with its impact on counteracting gender stereotypes, the movement may have motivated producers to respond to an increased consumer demand for films with strong female leads, as evidenced by more favorable critic and user reviews of such movies released after #MeToo. Lastly, #MeToo may have compelled Weinstein-associated male producers—who may have faced greater difficulty than female producers in attracting female writers after #MeToo—to substitute the gender orientation of the idea for the gender of the writer as a means to mitigate economic risk.

2 Related Literature

Prior research in economics, psychology, and sociology has documented segregation by gender in various occupations and academic disciplines, as well as its underlying causes, such as preference for different types of work, family choices, discrimination (statistical and taste-based), and stereotypes (e.g., Blau et al., 2013; Ceci et al., 2014; Goldin, 2014). Our paper joins a small but growing number of studies that focus on the relationship between gender inequality and the types of ideas and products developed (Koning et al., 2019; Hebert, 2020; Kanze et al., 2020; Cao et al., 2020).[5] These studies consistently document a high correlation between the gender orientation of an idea and the gender of the talent. Our results highlight that the impact of organizational and policy levers aimed at reducing gender inequality on the types of ideas developed depends critically on the reasons underlying the gender segregation in a given context. In settings such as ours, in which the segregation is largely due to biases, stereotypes, and frictions (e.g., Heilman, 1983; Coffman, 2014; Bordalo et al., 2016), we may see increased employment opportunities for female talent and, at the same time, a lower tendency for women to work on female-oriented ideas. Consequently, we may not see an overall increase in female-oriented ideas. In contrast, in settings in which the segregation is driven primarily by comparative advantages and preferences, an increase in employment opportunities for female talent may also lead to more female-oriented ideas.

More generally, our study adds to our understanding of how the broader social context may influence the opportunities available to different types of talent and the types of innovations that are developed. Societal norms around openness to new ideas, diversity, and collaboration have been shown to influence the rate and direction of innovation (Jacobs, 1961; Florida et al., 2008; Bénabou et al., 2015; Vakili and Zhang, 2018). Our paper studies the impacts of social movements on the direction of ideas and the types of opportunities open to certain types of talent.[6] Scholars in sociology and political science have long studied the women's movement and its role in women's progress in the legal, social, and economic spheres (e.g., Davis, 1991; Lorber, 2010). Our paper, together with Luo and Zhang (2020), shows that social movements that aim to address gender inequality and stereotypes lead to an increase in female participation not only in general, but also in specific segments that have been traditionally dominated by men.

Finally, this paper also contributes to our understanding of the relationship between social movements

[5]This paper also relates to the extensive literature on gender inequality in representation, pay, and promotion in entrepreneurship and organizations, as well as their underlying demand-side and supply-side reasons (e.g., Botelho and Abraham, 2017; Correll et al., 2017; Sterling and Fernandez, 2018; Guzman and Kacperczyk, 2019). See Jennings and Brush (2013) and Fernandez-Mateo and Kaplan (2018) for overviews.

[6]More broadly, recent research in sociology and organizational theory has shown that social movements are capable of influencing corporate behavior such as impression management activities, operational and management practices, market entries and exits (e.g., Delmas and Toffel, 2008; Ingram et al., 2010; McDonnell and King, 2013). Research has found that the effects of social movements are likely to increase with (sustained) media attention (King, 2008), saliency of the issues (McDonnell and Werner, 2016), resources available (McCarthy and Zald, 1977), and society's receptivity to change (Amenta, 2006).

and the media. Prior research suggests that coverage of women's issues by the mainstream media has historically been sparse because of the predominance of male gatekeepers who have made news-selection decisions and the difficulty of covering substantive issues that were not tied to an event (Kahn and Goldenberg, 1991). Moreover, content analyses find that the media tend to perpetuate gender stereotypes (e.g., Tuchman et al., 1978; Strinati, 2004). Our paper highlights social media's ability to disseminate information, amplify issues, and facilitate public participation without gatekeepers (Sunstein, 2019). Our findings also show that social movements that make people reckon with deep-seated issues of gender inequality may help shift the media's portrayal of gender norms.

3 Selection of Movie Projects and Potential Impacts of #MeToo

Making a movie is a long, costly, and uncertain process. Producers—typically partners or executives of production companies and studios—manage this process. Their first task is to source ideas, by acquiring either finished scripts from screenwriters or the adaptation rights to pre-existing works (e.g., a novel) and hiring writers to adapt them into scripts. Once a script is in place, producers are tasked with hiring directors, assembling cast and crew, and, importantly, securing financing from major studios (e.g., Warner Bros.) or independent financiers. Luo et al. (2020) show that only about 16 percent of the projects are eventually produced and theatrically released; for released movies, the median time from the acquisition of a script to theatrical release is 2.1 years, and the median production budget is about $25 million.

Conceptually, #MeToo may affect a producer's project-selection decision—in particular, the gender-orientation of an idea—through two channels. First, #MeToo may incentivize a producer to provide more opportunities for female talent, which, in turn, affects the type of projects the producer chooses to develop. We focus our discussion on writing talent because writers are systematically identifiable for early-stage projects; in contrast, for half of our sample, directors and actors are not yet determined at the time of script acquisition. Moreover, projects with female writers are likely to attract other female talent, either because of the type of projects female writers tend to work on and/or because they help signal the producer's commitment to creating a female-friendly work environment. Second, #MeToo may also directly affect a producer's incentives to work on female-oriented ideas.

3.1 #MeToo's indirect effect on the gender orientation of ideas

3.1.1 Effect on a producer's incentive to work with female writers

As Luo and Zhang (2020) argue, #MeToo may have incentivized producers to provide more opportunities for female writers for three reasons. First, the expected costs (legal, market, and reputational) associated with harassment-related issues have credibly increased after #MeToo, given the higher likelihood of exposure of such incidences (Levy and Mattsson, 2019) and the increased reluctance by investors, talent, and consumers to invest in, participate, and consume products associated with these issues (Lins et al., 2019). Working with female writers may help mitigate such risks, because such a choice may lower the probability of harassment,[7] mitigate media scrutiny, and manage impressions. Second, producers may also be more intrinsically motivated to improve female representation. The increased awareness and saliency of issues around harassment and gender inequality after #MeToo may have made them feel guilty of being directly or indirectly complicit in the problematic culture and/or more sympathetic regarding the mistreatment of women and the barriers they face (Tarrow, 1998; Haidt, 2003). Third, even if the producers' own motivations do not change, they may want to take advantage of the increasing demand for projects involving female talent from consumers and other industry stakeholders.

While #MeToo may affect Hollywood producers in general, the impact is likely to be greater for producers who collaborated with Weinstein. First, many of Weinstein's past collaborators have received intense media and public scrutiny following the reporting.[8] This is not surprising given that associated producers are more likely than non-associated producers to be (or perceived to be) aware of Weinstein's behavior, to share similar traits with Weinstein, or to have a higher tolerance for misconduct in the workplace (e.g., McPherson et al., 2001; Pontikes et al., 2010).[9] Thus, they are likely to have a greater incentive to repair their reputations and mitigate economic risks. Second, associated producers may also be more intrinsically motivated to change than non-associated producers are. They may feel more guilt because they are more aware of Weinstein's behavior or more complicit in such behavior themselves. The association with Weinstein may also make them pay more attention to the types of issues highlighted by #MeToo, which may lead to a higher degree of sympathy (Dickert and Slovic, 2009).

The above arguments motivate the empirical strategy used by Luo and Zhang (2020) and in this paper: by comparing Weinstein-associated producers, who are more affected by #MeToo, with non-associated producers, who are less affected, we are able to discern the impact of #MeToo. Non-associated producers control for: (i) any industry-level impacts of #MeToo that affect associated and non-associated producers similarly; and (ii) other confounding factors that may have separately affected a producer's choice around the same time.[10] Indeed, Luo and Zhang (2020) find that, relative to non-associated producers, Weinstein-associated

[7]Projects by female writers tend to attract other female talent, and a greater presence of women tends to promote more respectful work environments and reduce the probability of harassment (Dobbin and Kalev, 2017).

[8]https://www.theguardian.com/film/2017/oct/09/harvey-weinstein-hollywood-men-actors-directors#img-1

[9]While some claimed that they were unaware of these allegations, many have since acknowledged knowing about Weinstein's transgressions to various extents. Source: https://www.huffpost.com/entry/meryl-streep-harvey-weinstein_n_59db5d87e4b072637c45420e; https://www.nytimes.com/2017/10/19/movies/tarantino-weinstein.html

[10]Other confounding factors include mass mobilizations such as the 2017 Women's March in the wake of the election of Donald Trump and the rise of sexism, as well as the increasing popularity of feminism that encourages women to focus on their personal empowerment and aspirations (e.g., Banet-Weiser (2018); and the notion of 'lean in' popularized by the 2013 book by Sheryl

producers are substantially more likely to work with female writers after #MeToo than before.[11]

3.1.2 Effect of more female writers on the gender-orientation of ideas

Whether this addition of female writers will lead to an increase in female-oriented ideas is, however, ambiguous. On the one hand, as mentioned, about 70 percent of the screenplays written by female writers feature female-oriented ideas. Thus, it seems intuitive to expect that the addition of female writers will lead to more female-oriented ideas because a producer is likely to have more female-oriented screenplays to choose from. In addition, if the gender of the talent and the gender orientation of the ideas are highly correlated primarily because female talent has a preference for female-oriented ideas or an advantage over male talent in developing such ideas—for example, due to exposure and awareness of different types of problems and life experiences—producers may also expect female-oriented ideas from female writers to be of higher quality than male-oriented ideas from female writers.[12]

On the other hand, the high correlation between the gender of the talent and the gender orientation of the ideas may be driven by constraints that female writers face in exploring male-oriented ideas. Female screenwriters have a long history of "writing to their gender" (Casella, 2017), and there are numerous industry accounts of Hollywood producers and studio executives having the perception that "women aren't capable of delivering films that will be successful with wide audiences" and women being typecast into writing, directing, producing female-oriented genres, which, on average, are also less expensive to make.[13] The lack-of-fit model of Heilman (1983) captures this phenomenon. Central to her arguments is the notion of gender stereotypes (e.g., men are thought to be assertive, bold, and aggressive, while women are thought to be relationship-based, nurturing, and kind). The mismatch between female stereotypes and the perceived requirements for success in typically male positions leads to negative expectations about women's ability and discriminatory behavior in their evaluation. Stereotyping is especially likely when ambiguity and uncertainty are high (e.g., the evaluation of creative and entrepreneurial projects), such that decision makers may

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Sandberg).

[11] Survey evidence suggests that some male managers may become less willing to hire women and more reluctant to work alone with, mentor, or socialize with women after #MeToo (see Cheng and Hsiaw (2020) for a formal model that illustrates the potential intended and unintended consequences of #MeToo). The findings in Luo and Zhang (2020) suggest that these liability concerns are relatively limited in Hollywood and are outweighed by the producers' increased incentive to work with women.

[12] While these different exposures and experience may themselves reflect biases and frictions in work and in life, for the purpose of this paper, we consider a person's preferences and abilities conditional on these past experiences and exposures; i.e., at a given point in time, does the female talent choose to develop female-oriented ideas because they want to or because they are forced to due to frictions or biases in the male segment of the idea space?

[13] https://lwlies.com/articles/where-are-all-the-women-screenwriters/. A recent report by the *New York Times* points out that "the higher the financial risk, though, the less confidence decision makers have in hiring women" and "the misconception that women are best at directing personal stories about women and romance, excluding them from opportunities to direct genres associated with men, like action, adventure, espionage, broad comedy, horror, sci-fi and others" (Source: https://www.nytimes.com/2019/04/14/movies/hollywood-female-directors.html). Disparity is also present among the producers; for example, women account for 23% of producers for movies budgeted under $5 million, but just 16% of films budgeted over $50 million (Source: https://stephenfollows.com/what-percentage-of-film-producers-are-women/).

overly rely on heuristics and readily observable factors as the basis for decision making.[14] Moreover, gender stereotypes not only shape one's assessment of others' ability, but also the belief about one's own ability. For example, Coffman (2014) shows that conditional on measured ability, people are less willing to contribute ideas in areas that are stereotypically outside of their gender's domain, and these decisions are largely driven by self-assessments.

As mentioned, in the wake of #MeToo, there is a greater acknowledgment that gender stereotypes contribute to sexual aggression and constraints on progress for women.[15] In Hollywood, in particular, decision makers may become more cognizant of implicit or explicit stereotyping, more motivated to systematically collect information to reduce uncertainty, and more deliberate in their decision-making.[16] These changes affect not only a producer's own evaluation of matching female writers to male-oriented ideas, but also the behavior of studio executives, independent financiers, and directing and acting talent whose assessment is critical to a project's success. Moreover, a greater awareness of stereotypes may also affect the talent's self-perception, making female writers more motivated to search for employment opportunities in gender-incongruent spaces. These forces may push female writers to work on male-oriented ideas, rendering the net effect of more female writers on the overall gender orientation of ideas ambiguous.

3.2 #MeToo's direct effect on the gender orientation of ideas

Apart from an indirect effect through changing a producer's incentive to work with female talent, the #MeToo movement may also directly affect a producer's incentives to develop female-oriented ideas and, potentially, to change how women are portrayed in film. As mentioned, prior research consistently finds a higher coverage of men than women in all types of popular and mass media; for films in particular, less than a third of all speaking characters in top-grossing films are female, and 28 percent of the films have a female lead or co-lead (Smith et al., 2020). In addition, films and other commercially-driven media products, such as TV, advertising, and comic books, have long been criticized for playing an important role in objectifying women, as well as normalizing gender stereotypes and violence against women (Gill and Orgad, 2018). Thus, the amplified discussions around harassment and gender inequality after #MeToo and the movement's calls for action may increase a producer's incentive to address the unequal coverage and stereotypical portrayals of

[14]Experimental evidence shows that consumers and investors penalize female entrepreneurs who develop technology and product types that are typically associated with men, holding other quality factors constant (Tak et al., 2019; Kanze et al., 2020).

[15]Research shows a strong correlation between gender stereotypes and sexual aggression (Murnen et al., 2002; Smith-Hunter et al., 2015). A 2016 CDC report argued that to combat sexual violence, we need strategies that would "influence both male and female gender norms" (Source: https://www.cdc.gov/violenceprevention/pdf/SV-Prevention-Technical-Package.pdf).

[16]In the film industry, people started to talk explicitly about the "cultural biases" that "help perpetuate myths about women and hold them back, much like the idea that women-driven shows and films don't attract viewers" (source: http://www.bu.edu/articles/2018/women-and-gender-bias-in-post-metoo-hollywood/) and taking the initiative to "hire women into roles that are traditionally male roles" (source: https://www.voanews.com/arts-culture/battle-gender-equality-hollywood). The hiring of screenwriter Phoebe Waller-Bridge to work on the latest James Bond film is one such an example (source: https://www.bbc.com/news/entertainment-arts-50331077).

women.[17]

Similar to changes in the producer's incentives to work with female talent, these changes may also be driven by economic considerations—such as mitigating risk or responding to potential changes in consumer demand—and by intrinsic motivations due to the recognition that cultural sectors have an obligation to create products that reflect changes in social norms and values. Moreover, these effects are also likely to be stronger for Weinstein-associated producers than for non-associated producers.

4 Data and Method

Our primary data source is Done Deal Pro (DDP), a database that tracks script transactions—both acquisitions of original screenplays and adaptation contracts—on a daily basis. DDP is recognized by various industry organizations as one of the leading movie project information sources, and, to the best of our knowledge, the timing of these transactions provides the earliest systematic measure of the start of new movie projects. The database contains 4,836 records from January 2014 to September 2019. We are left with 4,045 projects, after excluding i) 572 observations that have no information about the writers or the producers; ii) 76 additional observations by the Weinstein company or by producers who faced allegations of sexual harassment themselves after #MeToo;[18] and (iii) 143 additional observations missing information on the logline.

As explained above, our empirical strategy exploits the differential responses of Weinstein-associated producers versus non-associated producers after #MeToo. Utilizing cast and crew information from the Internet Movie Database, we define a production team as Weinstein-associated if at least one of the producers played any of the four major roles (producing, directing, acting, and writing) in a movie produced by Weinstein and released before October 2017. Out of the 5,342 unique producers, 11.9 percent had past collaborations with Weinstein. Because the majority (81 percent) of the projects involved more than one producer, 43.2 percent of the projects were managed by a Weinstein-associated production team.

The gender of the writers and the producers is determined by *genderize.io*, a commonly used gender-classification software based on a person's first name. If the confidence level of the predicted gender is below 95%, we manually confirm the person's gender using additional Internet sources. Out of the 3,650 unique writers, 23.30 percent are female. Because the majority of the projects (76.8 percent) involved a single writer, a similar percent (25.8 percent) of projects included at least one female writer. 26.0 percent of

[17] Anecdotally, "producers are seeing interest in more complex female characters, with writers relishing the freedom to depict women outside stereotypes," said Nina Tassler, the former head of CBS Entertainment who started a production company aimed at telling stories from diverse voices (source: https://www.reuters.com/article/us-television-women/after-metoo-hollywood-women-seize-power-behind-tv-camera-idUSKBN1L1119).

[18] *Vox* compiles a list of people who have been accused of sexual misconduct since April 2017 (https://www.vox.com/a/sexual-harassment-assault-allegations-list). We exclude these people and the Weinstein company itself because the negative publicity and potential litigations may have been sufficiently disruptive to drive them out of the market (The Weinstein company, for example, filed for bankruptcy.).

the 5,342 unique producers were female, and 50.1 percent of the projects were managed by production teams with at least one female producer.

Our primary measure of an idea's gender orientation—that is, whether an idea is more likely to appeal to a female audience than to a male audience—is the gender of the protagonist (i.e., the central character of a movie).[19] We construct this measure based on a script's logline, which typically consists of one to three sentences that describe the movie plot. While short, these loglines are the only source of content information that is systematically available for early-stage projects. For 77 percent of the projects, the pronoun or the name associated with the protagonist is clearly male or female. For the remaining 23 percent, we use supervised machine-learning techniques, trained on loglines for which the protagonist's gender is clearly coded, to predict whether a logline is likely to feature a female or a male protagonist. (See Section B.1 for a description of the prediction model and other details of the construction of this measure.) Combining manually coded and predicted classifications, 31.0 percent of the loglines feature only female protagonists; 62.1 percent feature only male protagonists; and the remaining 6.9 percent feature both female and male protagonists. Our key dependent variable, *female protagonists*, indicates projects with only female protagonists and projects with protagonists of both genders. As mentioned, the gender of the protagonist and the gender of the talent are highly positively correlated. In particular, projects with at least one female writer (25.8 percent of the projects) are 2.5 times as likely as projects written by all-male writers to feature a female protagonist (68.4 vs 27.3 percent, p-value is 0.000). Similarly, projects managed by teams with at least one female producer (50.1 percent of the projects) are also significantly more likely than projects managed by all-male production teams to feature female protagonists (44.2 vs 31.3 percent, p-value is 0.000).

Intuitively, by placing a woman at the center of the story universe, female-protagonist stories are more likely to appeal to a female audience than are male-protagonist stories. To empirically verify that the protagonist's gender, indeed, captures the gender orientation of an idea, we conduct two tests. First, we construct an alternative measure based on MTurk workers' ratings of how much a typical man (or woman) in the U.S. will like a movie based on a given logline. We create a variable, *gender appeal*, which categorizes the loglines as significantly more appealing to women than to men (22 percent of the loglines and coded as '1'); significantly more appealing to men than to women (26 percent of the loglines and coded as '-1'); and similarly appealing to either gender (the remaining 51 percent and coded as '0').[20] This demand-based

[19]We strive to capture the central character of a movie. Correspondingly, we instruct the coders that "a movie typically has a single central protagonist" and that "if both a male and a female character show up in a logline, typically, the one that shows up first is the protagonist (e.g., 'Pierre, a quietly resourceful bartender, returns to his hometown after the death of his parents. When he falls in love with the enigmatic Stella, he is unwittingly drawn into a circle of fate pitting him against the volatile criminal Shane.' In this example, Pierre is the protagonist.)" See Section B.1 for the detailed instructions we gave the coders to help them decide on the gender of the protagonist.

[20]In particular, for each logline, 15 unique respondents are asked to answer two questions: i) based on this logline, how much do you think a typical woman in the U.S. will like this movie (on a scale of 1-5)?; and ii) based on this logline, how much do you

measure is highly correlated with the protagonist's gender. For example, 44 percent of loglines featuring female protagonists are rated as significantly more appealing to women, whereas this is the case for only eight percent of loglines featuring male protagonists.[21] Second, using a different dataset of released movies, we find that female reviewers (both professional critics and *Rotten Tomatoes* users), relative to male reviewers, rate movies with a majority of female leads more favorably than movies with a majority of male leads (the results are presented in Appendix Table B.2). This result further corroborates that the protagonist's gender is a reasonable proxy for the gender orientation of an idea.

4.1 Empirical specification

We estimate the following difference-in-differences (DiD) style regressions:

$$Y_i = \alpha + \delta \text{Weinstein association}_i \times \text{Post shock}_t + \gamma \text{Weinstein association}_i + y_t + \beta X_i + \varepsilon_i, \quad (1)$$

where Y_i equals one if project i features female protagonists; Post shock$_t$ equals one for the time period after (and including) the fourth quarter of 2017; Weinstein association$_i$ indicates whether any producer on the production team had collaborations with Weinstein before the shock; X_i are control variables, including the experience and industry connections of the producers, a set of dummies indicating the major studio that is involved in the early stage of the projects, the characteristics of the writers and their agents, and the characteristics of the ideas, such as genre; and y_t are quarterly fixed effects. We cluster standard errors at the studio level. As discussed above, non-associated producers help to control for any industry-level changes in response to #MeToo and any confounding factors unrelated to the shock. Under the parallel-trend assumption, δ captures the average effect of #MeToo via the association with Weinstein.

A key identification challenge is that there may be variables that are related to both the association with Weinstein and the change in the outcome over time. This is a likely concern because the two groups of producers are observably different from each other: Weinstein-associated producers are significantly more experienced, have won or been nominated for more awards, and are more likely to work with major movie studios and large talent agencies (see Table A.1 for a summary of these variables by Weinstein association for the unmatched sample). Thus, any changes in the demand or supply of female-oriented projects during our sample period that are unrelated to #MeToo but may affect producers of different experience levels dif-

think a typical man in the U.S. will like this movie (on a scale of 1-5)? *Gender appeal* = 1 if the answers to the first question are significantly greater than those to the second question at the five percent level according to a one-sided paired t-test; = −1 if the answers to the second question are significantly greater; and = 0 if the answers to the two questions are statistically similar. Please see Section B.2 for a detailed explanation of the construction of this demand-based measure.

[21] We rely on the protagonist's gender as our primary measure in the paper because it is more precisely measured. The consumer appeal of a movie is notoriously difficult to predict for early-stage movie projects, let alone with only the short descriptions that we have. Nonetheless, we show that our baseline results are robust to using this alternative demand-based measure.

ferently would bias our estimates. To address this challenge, we use a matched sample that consists of 1,977 projects.[22] Table 1 shows that the two groups of projects are well-balanced along producer characteristics and most of the other variables. Moreover, as we show later with quarter-specific estimates, there are also no significant pre-trends, which further supports the parallel-trend assumption.

Finally, because all producers compete for the same pool of ideas and writers, it is possible that part of the differential response is due to a competition effect, whereby associated producers may compete certain types of projects away from non-associated producers. Thus, the differential change estimated from equation (1) should be interpreted as the relative change between the two groups due to #MeToo, rather than as an absolute change by the treatment group.

5 Results

5.1 The gender of the protagonist

The raw data show that, relative to non-associated producers, Weinstein-associated producers, on average, did *not* change their likelihood of developing female-protagonist stories after #MeToo compared to before. While the percentage of female-protagonist stories increased by six percentage points among Weinstein-associated producers (from 0.369 to 0.429, p-value is 0.101), it also increased by seven percentage points among non-associated producers (from 0.345 to 0.415, p-value is 0.054). The difference between these two changes is not statistically significant (p-value is 0.840). The regression results in Table 2 are consistent with the raw data. Column 1 includes the basic DiD variables in equation (1), and Column 2 adds additional controls. The DiD coefficient of interest is small and statistically insignificant in both specifications. Figure 1a plots the quarter-specific DiD coefficients estimated from an extended version of Column 2. The graph confirms both an absence of a pre-trend between the two groups of projects before #MeToo and a lack of differential change afterward.

The above results show that, on average, #MeToo does not appear to have led to a directional change in the gender orientation of ideas. This is despite the finding that Weinstein-associated producers are substantially more likely—by 8.9 percentage points (or 35 percent)—to work with female writers after #MeToo (Luo and Zhang, 2020). To explain these findings, we investigate potential changes in the gender orientation of ideas for female and male writers separately. As we discussed in Section 3.1, if female writers are more likely to work on male-oriented ideas after #MeToo, we may not see more female-oriented ideas, even

[22] This sample is consistent with the matched sample used by Luo and Zhang (2020), except that 81 observations are dropped because they do not have logline information. Luo and Zhang (2020) use coarsened exact matching (Iacus et al., 2012) to match production teams based on seven variables: Producer experience, Producer prior awards, Producer experience with major studios, Producer experience with top agencies, Include female producers, Producer team size, and Post shock. See the notes in Table 1 for the definitions of these variables.

though there are more female writers.

5.1.1 Effect by the gender of the writers

Columns 1 and 2 of Table 3 present the sub-sample results split by the writer's gender. Column 1 shows that, conditional on projects written by all-male writers, relative to non-associated producers, Weinstein-associated producers are similarly likely to develop female-protagonist stories after #MeToo compared to before. When there is at least one female writer, however, Weinstein-associated teams appear to be *less* likely to develop female-protagonist stories. While the DiD coeffiicent is not precisely estimated (p-value is 0.170), the economic magnitude of 11.0 percentage points is sizable, representing a 15-percent decrease relative to the pre-#MeToo level.[23] Column 3 combines the first two columns in a triple-differences regression:

$$\begin{aligned} Y_i \;=\; & \alpha + \delta \text{Weinstein association}_i \times \text{Female writers}_i \times \text{Post shock}_t + \gamma_1 \text{Weinstein association}_i \times \text{Post shock}_t \\ & + \gamma_2 \text{Weinstein association}_i \times \text{Female writers}_i + \gamma_3 \text{Post shock}_t \times \text{Female writers}_i \\ & + \gamma_4 \text{Female writers}_i + \gamma_5 \text{Weinstein association}_i + y_t + \beta X_i + \varepsilon_i. \end{aligned} \tag{2}$$

The triple-differences coefficient, -0.184 (p-value is 0.011), shows that projects by Weinstein-associated producers with at least one female writer are significantly *less* likely to feature female protagonists than if the writers are all male (and after controlling for the common trends that they share with their respective counterparts among the non-associated teams).[24]

Results in this section show that the increase in the representation of female writers on projects of Weinstein-associated producers is offset by a decrease in their female writers' tendency to work on female-oriented ideas. As a result, we do not observe any change in the overall proportion of female-oriented ideas. This result provides a first set of evidence that is consistent with the idea that #MeToo may have helped counteract gender stereotypes regarding female talent's ability to work on male-oriented ideas. Below, we examine whether such an effect may also be present for female producers, who, anecdotally, also suffer from such stereotyping about their ability to develop and manage male-oriented projects.

[23]Projects by Weinstein-associated producers written by female writers featured female protagonists about 74 percent of the time before #MeToo.

[24]We prefer to use linear probability models to examine the differential likelihoods of female-protagonist stories by Weinstein association conditional on the gender of the writer because they simplify the interpretation of the coefficients. An alternative specification is to employ a multinomial logit model for which the dependent variable is defined as four combinations of the gender of the writer and the gender of the protagonist. The results, presented in Table A.2, show that, relative to non-associated producers, Weinstein-associated producers are significantly more likely to choose "female writers & male protagonists" relative to the other three alternatives—"all-male writers & male protagonists," "all-male writers & female protagonists," and "female writers & female protagonists"—after #MeToo than before.

5.1.2 Effect by the gender of the writers and the producers

In Table 4, we further split the sample into four groups by the gender of both the writers and the producers. An interesting contrast emerges: the DiD coefficient is positive and economically large at 11.5 percentage points when the writers and the producers are all male (Column 1); in contrast, for teams with at least one female writer, one female producer, or both, the DiD coefficient is negative and economically large (Columns 2-4). To obtain a more precise estimate for teams with at least one woman, we group the three subsamples used in Columns 2-4 in Column 5. The DiD coefficient, which is 16.2 percentage points, becomes significant at the one-percent level.

In the last column of Table 4, we use a single triple-differences regression to confirm the above result that Weinstein-associated teams with at least one woman (either writer or producer) are significantly *less* likely to write female-protagonist stories, relative to all-male Weinstein-associated teams (and after controlling for the common trends that they share with their respective counterparts among the non-associated teams). The triple-differences coefficient is estimated to be 27.5 percentage points and is significant at the one-percent level.[25] Figure 1b plots the quarter-specific triple-differences coefficients estimated from an extended version of Column 6. The results show no obvious pre-trend; the triple-differences coefficients after #MeToo, though not all precisely estimated (likely due to many fewer observations in the quarterly data), are consistently negative and economically large, ranging from 14.7 to 45.6 percentage points.

Appendix Table A.4 shows that the triple-differences result in Column 6 of Table 4 is robust to a series of alternative specifications, including using only projects by single writers (77 percent of the sample) and only projects for which the director information is available (45 percent of the sample).[26] We also find consistent results using a continuous measure of Weinstein association (i.e., the total number of movies released by all the producers in the production team in collaboration with Weinstein before the focal project) instead of the binary variable used in the main specification. In addition, the result is robust to defining female-protagonist stories as those with only female protagonists, excluding those featuring protagonists of both genders. Finally, the result is robust to dropping projects for which the gender of the protagonist is predicted

[25] Appendix Table A.3 shows that our baseline results are qualitatively robust to using the unmatched sample. The triple-differences coefficients—either by whether female writers are included or by whether female writers or producers are included—are estimated to be about ten percentage points and statistically significant (or marginally significant; the p-value of the triple-differences coefficient in Column 3 is 0.100). Recall that we excluded Weinstein-associated production teams with the most industry experience and connections from the treatment group to form the matched sample. Under the premise that these producers were less constrained in their ability to explore different segments of the idea space prior to #MeToo, it is not surprising to find an economically smaller effect in the unmatched sample than in the matched sample on changing who develops which type of idea.

[26] Director information may be available at the time of script transactions because the agency that represents the writer often leverages its client portfolio and attaches key acting and/or directing talent to the project from the beginning (a practice called 'packaging'). 11 percent of these directors are female, and the correlation between the gender of the director and the gender of the writer is 0.5. In this triple-differences regression, we compare teams with at least one female writer, director, or producer with teams for which all the writers, producers, and director are male.

(25 percent of the matched sample) rather than manually coded based on the name or the pronoun associated with the protagonist.

The above results suggest that #MeToo may have helped counteract gender stereotypes for women in the film industry more generally, as we see this effect not only for female writers but also for female producers. Female producers, though among the decision makers at the time of initiating movie projects, may still be subject to the evaluations of the studio executives, financiers, and key talent who are critical to a project's success. In addition, we also find some, albeit weaker, evidence that all-male producing and writing teams are more likely to work on female-oriented ideas after #MeToo.[27] Thus, it appears that #MeToo has led to a reduction in the gender segregation of the idea space due to changes in both directions.

5.2 Alternative measures of gender orientation

In this section, we show that our core result that female talent is more likely to work on male-oriented ideas after #MeToo is robust to using two alternative measures of gender orientation. First, the first three columns of Appendix Table A.5 present results using the demand-based measure, *gender appeal*, as the dependent variable. Consistent with what we find with the gender of the protagonists, the results show that, on average, there is no significant change in a project's likely appeal to a particular gender by Weinstein-associated producers, relative to non-associated producers, after #MeToo. The reason is that Weinstein-associated teams with at least one female writer or producer are significantly more likely than their non-associated counterparts to shift towards content that is likely to be more appealing to men.

Columns 4 to 6 of Appendix Table A.5 examine whether changes in an idea's gender orientation is also reflected by shifts in genre. About 60 percent of the projects are categorized into more than one genre (e.g., action drama). The dependent variable, *female genres only*, indicates projects categorized exclusively as female genres (i.e., drama, romance, and romantic comedy) and not as male or neutral genres.[28] The results also show that, among teams with female writers or producers, Weinstein-associated teams are significantly more likely than their non-associated counterparts to shift away from exclusively female genres after #MeToo. In contrast, among all-male teams, Weinstein-associated producers are more likely to develop projects in exclusively female genres after #MeToo, relative to their non-associated counterparts (p-value is 0.101).

[27] For all-male writing and producing teams, while the coefficient of 'W Association × Post Shock' in Column 6 of Table 4 is not statistically significant, alternative specifications in Appendix Table A.4 show mostly significant or marginally significant estimates.

[28] We assign the gender orientation of genres based on Wühr et al. (2017), who survey men and women for their own preference for each movie genre. Based on their results, we assign drama, romance, and romantic comedy to female-oriented genres; action, adventure, horror, sci-fi, war, western, and sports to male-oriented genres; and crime, comedy, thriller, and family to neutral genres.

5.3 Gender stereotypes: feminine versus masculine characteristics

In this section, we take a closer look at the characterization of the protagonists beyond their gender. Because our results, so far, suggest that #MeToo may have helped counteract gender stereotypes for women in the film industry, we are especially interested in examining whether #MeToo has also had any impact on the depiction of female protagonists relative to traditional gender stereotypes.

Compared to studies analyzing a small number of completed movies,[29] our focus on a large number of early-stage projects with limited information on plots, characters, dialogues, and scenes constrains our ability to examine this question in depth. However, recent advances in machine-learning techniques allow us to use the loglines to construct a measure that captures the portrayals of the protagonists relative to gender stereotypes in a systematic way. The machine-learning model we use converts keywords, phrases, and paragraphs into multi-dimensional vectors.[30] In this vector space, we calculate the distance of the vector representing a given logline to a benchmark vector representing feminine characteristics, relative to a benchmark vector representing masculine characteristics.[31] These benchmark characteristics come from the Bem Sex-Role Inventory (BSRI) (Bem, 1974), which includes 20 masculine characteristics that are judged to be significantly more desirable for a man than for a woman and 20 feminine characteristics that are judged to be significantly more desirable for a woman than for a man.[32] The literature has interpreted these masculine characteristics to represent agentic or instrumental traits (e.g., "acts as a leader," "aggressive," and "assertive"), whereas the feminine characteristics represent communal or expressive traits (e.g., "affectionate," "compassionate," and "loyal"). We use BSRI both because it has been considered the gold standard in gender-role evaluation for the past 40 years (Dean and Tate, 2017) and because it is consistent with the traditional gender stereotypes central to Heilman's (1983) lack-of-fit model discussed above.[33]

[29]For example, Sutherland and Feltey (2017) analyze 18 feminist films through the lens of three types of power dynamics: 'power-over' (carrying out one's will over another, domination); 'power-to' (sense of personal control and self-efficacy); and 'power-with' (solidarity with other women to confront oppression and inequality).

[30]We use BERT models, created and published in 2018 by Jacob Devlin and his colleagues at Google (Devlin et al., 2018), in our paper. A key advantage of BERT models relative to word2vec models, which are commonly used natural language processing techniques to encode words, is that BERT models take into consideration the context of each word. For example, bank as a financial institute is different from bank of the river. BERT models will yield different vectors for the word 'bank' in these two different contexts, whereas word2vec models will produce the same vector.

[31]See Appendix B.3 for a detailed description of the construction of this measure. This measure is similar in spirit to that of Cao et al. (2020), who use word2vec techniques to construct a measure of the gender orientation of products by calculating the relative distance of the product description to three pairs of words—woman/man, she/he, and female/male—in a vector space.

[32]The 20 masculine characteristics are: "acts as a leader," "aggressive," "ambitious," "analytical," "assertive," "athletic," "competitive," "defends own beliefs," "dominant," "forceful," "has leadership abilities," " independent," "individualistic," "makes decisions easily," "masculine," "self-reliant," "self-sufficient," "strong personality," "willing to take a stand," "willing to take risks." The 20 feminine characteristics are: "affectionate," "cheerful," "childlike," "compassionate," "does not use harsh language," "eager to soothe hurt feelings," "feminine," "flatterable," "gentle," "gullible," "loves children," "loyal," "sensitive to the needs of others," "shy," "soft-spoken," "sympathetic," "tender," "understanding," "warm," "yielding."

[33]It is useful to note that by calculating the relative distance between a focal logline to these feminine and masculine characteristics, we are technically capturing not a specific character's personality traits but the overall description of the storyline. Nonetheless, it seems reasonable to interpret this measure as the depiction of the protagonist. This is likely because a logline centers mainly

Higher values of this gender-role measure indicate more feminine portrayals of the protagonists, and a zero value indicates that the logline is equally distant to masculine and feminine benchmarks. As we show in Appendix Figure B.1, while there is a high variance in how male and female protagonists are each portrayed based on this measure, the proportion of female-protagonist stories is monotone increasing as this measure increases, suggesting that it passes a basic validity test. A visual examination of the loglines associated with different parts of the distribution of this measure (see examples listed in Appendix Table B.6) also suggests that the measure does a reasonable job of capturing the relative femininity/masculinity of the protagonist.[34] Note that both the median and the mean of this measure are negative (i.e., closer to the BSRI masculine characteristics than to the feminine characteristics) for female-protagonist stories in our sample. This is consistent with findings in the literature that BSRI, constructed in the 1970s, are outdated in capturing the current gender norms associated with women (Donnelly and Twenge, 2017). Note that this criticism does not undermine our purpose, both because we want to capture traditional depictions of women and because what we care about is the direction of change before and after #MeToo.

Table 5 presents regression results in which the dependent variable, *feminine*, indicates whether the gender-role measure is above the sample median. Panel A restricts the sample to projects featuring female protagonists. Columns 1 shows that relative to female protagonists by non-associated producers, those by Weinstein-associated producers are significantly *less* traditionally feminine after #MeToo than before. Columns 2 and 3 show that this result holds for both all-male writing and producing teams and teams including at least one woman (writer or producer), with the magnitude being greater for the former. Columns 4 and 5 show that the shift of female-protagonist stories away from traditional female stereotypes holds for projects in both exclusively female genres and genre combinations that are not exclusively female. The magnitude of the change, however, is greater for the latter. Panel B presents the same set of regressions as Panel A, but for the subsample of projects featuring male protagonists. We find that there is no significant differential change due to Weinstein association in the portrayal of male protagonists, and this result holds regardless of the gender composition of the team and whether or not the project is in exclusively female genres.

That female protagonists are portrayed with fewer traditional feminine stereotypes after #MeToo is consistent with anecdotal evidence that film and TV productions have seen more strong female characters or

around the protagonist, and the natural language processing tool that we use does a reasonably good job of relating the general social and professional contexts and activities that are often described by verbs and nouns to the benchmark characteristics that are mostly adjectives.

[34] For example, films like Captain Marvel (*"Captain Marvel aka Carol Danvers is an air force pilot whose DNA is fused with that of an alien after an accident giving her superhuman strength and even the ability to fly."*), which features a female protagonist in a traditionally male plot line, scored at around the 15th percentile; however, the film Girl on the Train (*"A woman who is devastated by her recent divorce spends her daily commute fantasizing about the seemingly perfect couple who live in a house that her train passes every day until she sees something shocking happen there one morning and becomes entangled in the mystery that unfolds."*) scored at around the 85th percentile.

women portrayed in traditionally male plot lines.[35] This result is also consistent with the result that female talent appears to have made greater inroads in the male segment of the idea space, suggesting an overall impact of the #MeToo movement on mitigating gender stereotyping. The lack of change in the portrayal of men is consistent with the idea that #MeToo led primarily to discussions around the gender norms attached to women or that the portrayal of men is, by and large, consistent with what consumers demand.

5.4 Potential mechanisms

Overall, our results suggest that #MeToo has led to a reduction in the gender segregation of the idea space—driven mainly by female talent (writers or producers) taking up more male-oriented projects and, to a lesser extent, by all-male producing and writing teams working on more female-oriented ideas—and less-feminine portrayals of women in film. While it is difficult to pin down the precise mechanisms, we provide additional empirical results and contextual information in the following sections that help us interpret these results.

5.4.1 #MeToo and changes in consumer preference

In this section, we examine whether there were any significant changes in consumer preference around the time of #MeToo for female-protagonist stories and female protagonists that defy gender stereotypes. While such changes may or may not have been caused by #MeToo, the movement may have made Weinstein-associated producers more aware of or more prone to anticipate these demand-side shifts.[36]

To do so, we collect a dataset consisting of 761 movies *released* in theaters before and after #MeToo.[37] Columns 1-3 of Table A.6 show that, on average, relative to movies in which the majority of the leading cast are male, we do *not* see a differential change in the *Rotten Tomatoes* critic score or user score or in the U.S. box office performance for movies with a majority of female leading cast after #MeToo compared to before. These results suggest that there is no significant difference in the relative market demand for female-oriented versus male-oriented stories before and after #MeToo. This suggests that an anticipation of

[35] https://qrewcial.com/women-in-television-2018-female-character-roles-in-the-post-metoo-era/.

[36] Identifying the causal effect of #MeToo on end consumers is challenging. We do not find it convincing to use the variation in the producers' association with Weinstein because, while some consumers may recognize movies made by the Weinstein company or other filmmakers or actors who are directly accused of sexual misconduct (such as Kevin Spacey), it does not seem reasonable to assume that consumers would pay much attention to who the filmmakers are, let alone to differentiate films that are produced by people who had past collaborations with Weinstein. In contrast, journalists covering the film industry and industry insiders such as studio executives and talent (and their agents) are likely to have such information and, hence, may increase the associated producers' expected costs of inaction. Moreover, as we discussed in Section 3, the producers' motivation to make changes may also be intrinsic motivations due to a greater awareness of the issues highlighted by #MeToo because of past collaborations with Weinstein.

[37] We construct this sample as follows. *The-numbers.com* lists 2,872 movies that were released in U.S. theaters between January 2014 and September 2019. We are left with 1,450 movies after the following two steps: i) dropping people listed as cast and crew for which the confidence level of the prediction of *genderize.io* is below 90 percent; and ii) keeping movies with non-missing information on the leading cast, the writers, the director, and the producers (the dropped movies are mostly indie productions or foreign movies). We drop another i) 257 movies because we cannot find a match on *www.rottentomatoes.com*; ii) 375 movies because the earliest professional reviews listed on *www.rottentomatoes.com* were published more than 180 days before the U.S. theatrical dates (these movies are mostly re-releases of foreign movies); and iii) 57 movies because there is no review information on *www.rottentomatoes.com*. The final sample, thus, includes 761 movies.

end-consumer demand shift towards female-oriented stories does not seem to be the primary explanation for the all-male teams' choice of developing more female-oriented projects. However, given that producers are more likely to work with female writers after #MeToo, the fact that consumer demand for female-protagonist stories does not appear to have increased may partially explain why female writers are more likely to work on male-oriented stories.

Columns 4-6 of Table A.6 show that, among movies in which the majority of the leading cast are female, the critic and user scores become significantly lower after #MeToo for stories in which female protagonists are depicted as relatively feminine compared to those in which they are depicted as relatively masculine. The box office performance shifts in a consistent direction, but the change is not statistically significant. This result is consistent with the idea that producers anticipate a potential increase in demand for female characters that defy traditional female stereotypes, which could be influenced by #MeToo and/or other factors. As discussed above, while such changes may affect all producers in Hollywood, those associated with Weinstein may be more likely to pay attention and be more incentivized to respond to such changes. Consistent with the lack of change in the portrayal of male protagonists that we discuss in the previous section, the last three columns of Table A.6 show that, for released movies in which the majority of the leading cast is male, we do not see any significant changes by the movie's relative femininity in all three demand-side measures.

5.4.2 #MeToo and gender stereotypes

As discussed in Section 3.1, #MeToo may have helped to counteract gender stereotypes against women's ability to explore parts of the idea space that have traditionally been dominated by male writers and producers. This explanation is consistent with a majority of our results, including the increased likelihood of female talent developing male-protagonist stories, the shift in the depiction of female protagonists away from traditional female stereotypes, as well as an increase in consumer preference for movies with female leads that are less traditionally feminine. As discussed, this effect may be due to an increasing awareness of industry evaluators of potential biases in their decision-making process and their increased motivations to correct them; or it could be due to a change in female writers' and producers' self-perception and their increased motivations for seeking opportunities. We lack systematic data to provide more-precise insights regarding the relative importance of these more-nuanced mechanisms.

Finally, while it is theoretically possible that #MeToo may also have helped to mitigate gender stereotypes for male writers and producers, potentially explaining why all-male teams develop more female-oriented ideas after #MeToo, several pieces of evidence suggest that this explanation is less likely to be the primary driver of this result. First, even though the proportion of female writers is higher in female-protagonist stories than in male-protagonist stories, there are still more male writers than female writers working on female-protagonist projects (54 versus 44 percent). Second, as described above, we do not find any significant changes in consumer preference for or in the producers' choice of the depictions of male protagonists after #MeToo. As noted by Luo and Zhang (2020), all-male production teams may face greater difficulty than female producers in attracting female writers after #MeToo. Thus, a possible reason for this result is that all-male production teams may have substituted the gender orientation of the idea for the gender of the writers as a means to mitigate economic and reputational risk after #MeToo.

5.5 Discussion

5.5.1 Limitations

As discussed, we are limited in our ability to directly observe changes in behavior or the actions that various parties may have taken to address gender stereotypes. In addition, we are limited in our ability to observe the amount of resources devoted to these projects and their final outcomes, given that the median time to release is more than two years. Such information is critical to evaluate whether the changes we observe are also economically profitable. Finally, the overall welfare effect is also unclear. On the one hand, the finding that female talent is able to explore the male-oriented space seems to imply promising progress. On the other hand, given that stories with central female characters are significantly lacking relative to women's percentage of the population, #MeToo does not seem to help fill this void, at least not in the short run. Similarly, while the data suggest that producers' decision to develop female characters that defy traditional stereotypes is consistent with what the consumers demand, more in-depth analyses of these changes can shed further light on whether they substantively contribute to the public discourse on gender inequality or lead to any meaningful changes.[38]

5.5.2 Economic significance of these changes

While we lack information on the outcomes of these specific projects, several pieces of contextual information suggest that these changes are likely to be economically significant. First, based on movies that are released (for which information on resource allocation is available), we know that male-protagonist stories are substantially more expensive to make.[39] It is, thus, an economically significant change for teams with women to work on more male-protagonist stories after #MeToo. In addition, this change is driven primarily

[38] Not unlike the varying opinions of the value, goal, and approach of feminism, people's opinions differ in terms of what strong female characters mean and how to best characterize women and gender dynamics in film. Correspondingly, industry commentators have debated the merits and limitations of films that explore topics of sexual misconduct after #MeToo (e.g., Bombshell, The Assistant, and Promising Young Women), which vary in their approaches, narratives, and central themes, in terms of advancing women's causes. https://www.vulture.com/2020/02/me-too-movies-at-sundance-conflicted-stories-hit-hollywood.html

[39] For example, among the 761 released movies used in the previous subsection, movies with a majority males in leading roles are shown on 300 more screens than are movies with a majority of females in leading roles during the opening weekend (p-value is 0.007), which is a good proxy for a movie's budget level. Similarly, among movies for which the production budget data are available, male-protagonist movies are significantly more expensive than female-protagonist movies, by about 13.8 million).

by major studios—the most influential players in the industry and the financiers of higher-budget films—rather than by independent production companies (Columns 1-2 of Table A.7). Finally, this result holds not only in female genres but also in non-female genres, which tend to be associated with more-expensive projects (Columns 3-4 of Table A.7).[40]

5.5.3 External validity

Our core results suggest that social movements that motivate individuals and organizations to grapple with deep-seated issues around gender inequality may help fight gender stereotypes for women and reduce the constraints that women face in taking on roles and tasks in gender-incongruent sectors. Research suggests the presence of gender stereotypes and their potential impacts on a wide variety of occupational, creative, and academic outcomes (Blau et al., 2013; Ceci et al., 2014; Goldin, 2014; Hoisl and Mariani, 2017; Kanze et al., 2020; Hebert, 2020). While #MeToo may help increase the awareness of such biases in many of these settings, the extent of change is likely to be context-dependent. Hollywood seems to be an example of settings in which the movement is more likely to help women break the barriers to gender-incongruent spaces: the public and media attention in Hollywood is high, and it is the epicenter of the Weinstein scandal that triggered the #MeToo movement; there are more opportunities for change as projects are frequently set up, and the talent are hired on a non-permanent basis; and skills seem mostly transferable across female-oriented and male-oriented projects. In contrast, in settings that are subject to less attention, have fewer employment opportunities, and in which skills and qualifications are less transferable across domains (e.g., inventors trained in chemistry rather than in engineering), we expect that #MeToo will lead to a smaller increase in opportunities for women in general and that the opportunities will be concentrated in gender-congruent space, at least in the short run.

That #MeToo has led to the development of more female characters that defy traditional stereotypes also reflects the cultural nature of films. Similar types of changes may occur in other cultural industries that reflect and shape cultural and social norms. While we do not expect a direct effect on the characteristics of non-cultural products that primarily influence consumers' willingness to pay via their functionality, we may also see changes in how these products are advertised and promoted, particularly for products whose brand image is connected to social beliefs and values.

6 Conclusion

In this paper, we examine whether the #MeToo movement, spurred by the Harvey Weinstein scandal, led to any significant changes in the gender orientation of ideas and in who develops which type of ideas. We use

[40] Among the 761 released movies used in the previous subsection, the number of screens during the opening weekend was about 670 fewer for released movies in female genres than in male genres, and the production budget was about 16.7 million less.

the variation in the association with Weinstein to identify producers that are more versus less affected by the movement. We find that, while #MeToo, on average, has not significantly changed the gender-orientation of ideas, it appears to have led to a reduction in gender segregation in the idea space. In particular, Weinstein-associated teams with female writers or producers are significantly less likely to work on female-protagonist stories, relative to all-male Weinstein-associated teams. Moreover, consistent with a more favorable shift towards female characters that defy traditional stereotypes on the demand side, we find that female protagonists developed by Weinstein-associated teams are less traditionally feminine. Overall, our findings suggest that #MeToo, by uncovering deep-seated issues around gender inequality, helps counteract stereotypes and alleviates barriers faced by female talent in exploring parts of the idea space that are typically dominated by men. From an organization's perspective, our findings also highlight that inequality is multi-faceted, and policies that aim to address inequality need to consider not only the number, but also the types of opportunities, positions, and tasks that can be pursued by disadvantaged groups.

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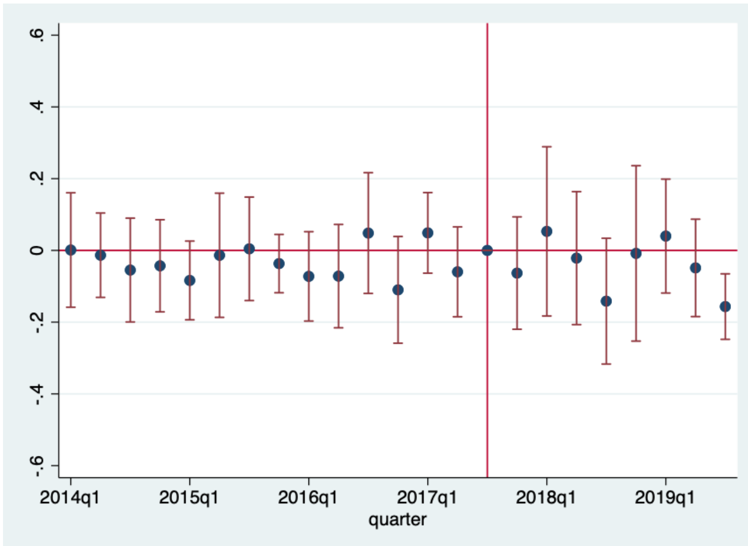
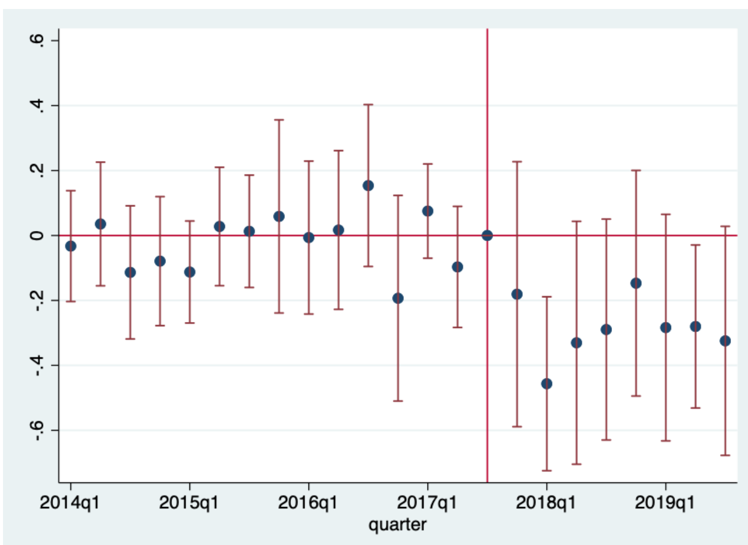
Figure 1: Effect on the likelihood of featuring female protagonists

(a) Quarter-specific difference-in-differences coefficients, by the association with Weinstein



(b) Quarter-specific triple-differences coefficients, by the association with Weinstein and inclusion of at least a female writer or producer



Note: Figure (a) plots the quarter-specific difference-in-differences coefficients estimated from an extended version of Column 2 of Table 2. Figure (b) plots the quarter-specific triple-differences coefficients estimated from an extended version of Column 6 of Table 4. The vertical line indicates the quarter before the reporting of the scandal and #MeToo.

Table 1: Summary statistics

	Weinstein association = 0			Weinstein association = 1			
	Obs	Mean	SD	Obs	Mean	SD	(p-value)
Female protagonists	981	0.36	0.48	996	0.38	0.469	(0.32)
Gender appeal	981	-0.09	0.70	996	-0.04	0.71	(0.09)
Female genre only	981	0.23	0.42	996	0.24	0.43	(0.54)
Feminine	981	0.48	0.50	996	0.52	0.50	(0.07)
Post shock	981	0.23	0.42	996	0.23	0.42	(0.85)
Include female writers	981	0.23	0.42	996	0.24	0.43	(0.58)
Include female producers	981	0.52	0.50	996	0.52	0.50	(0.86)
Producer experience	981	9.53	8.04	996	9.08	7.51	(0.20)
Producer prior awards	981	0.41	0.97	996	0.41	0.95	(0.94)
Producer exp. w/ major studios	981	0.65	0.39	996	0.66	0.37	(0.61)
Producer exp. w/ top agencies	981	0.73	0.28	996	0.74	0.28	(0.80)
Producer team size	981	3.43	1.78	996	3.51	1.76	(0.32)
Writer experience	981	0.93	1.66	996	0.92	1.66	(0.94)
Writer team size	981	1.28	0.51	996	1.23	0.48	(0.07)
Top four agencies	981	0.56	0.50	996	0.57	0.50	(0.51)
Original	981	0.61	0.49	996	0.64	0.48	(0.20)
Complete script	981	0.55	0.50	996	0.54	0.50	(0.68)
Talent attached	981	0.52	0.50	996	0.57	0.49	(0.01)
Rights purchase	981	0.17	0.38	996	0.17	0.37	(0.79)

Note: This table summarizes the variables by the association with Weinstein. The matched sample we use in this paper is based on the matched sample generated by Luo and Zhang (2020). 81 observations are dropped because they do not contain the logline information that is necessary to generate the dependent variables this paper focuses on.

Key variables: *Female protagonists* indicates whether the project features female protagonists; *Gender appeal* = 1 for loglines that are significantly more appealing to women than to men, = -1 for loglines that are significantly more appealing to men than to women, and = 0 for loglines that are similarly appealing to either gender; *Female genre only* indicates projects that are categorized as female genres (i.e., drama, romantic comedy, and romance) but not as male genres (i.e., action, adventure, sports, western, horror, sci-fi, and war) or neutral genres (i.e., comedy, crime, thriller, and family); *Feminine* indicates whether the gender-role measure is above the sample median; *Post-shock* indicates whether the project is set up after (and including) October 2017; *Include female writers* indicates whether the writer team includes at least one female writer; *Include female producers* indicates whether the production team includes at least one female producer.

Producer characteristics: *Producer experience* is the number of producing credits a producer obtained in the ten years before the focal project for movies distributed by the top-30 movie studios, with the maximum taken for teams with multiple producers; *Producer prior awards* is the number of Best Picture Academy Awards (the Oscars) a producer had won or been nominated for, with the maximum taken for teams with multiple producers; *Producer exp. w/ major studios* is the likelihood of working with major studios on past projects as captured by the DDP database since 2004, with the maximum taken for teams with multiple producers; *Producer exp. w/ top agencies* is the likelihood of working with the largest agencies on past projects as captured by the DDP database since 2004, with the maximum taken for teams with multiple producers; *Producer team size* is the total number of producers in a team.

Other control variables: *Writer experience* is the number of writing credits a writer obtained in the previous ten years for movies distributed by the top-30 movie studios, with the maximum taken for teams with multiple writers; *Top four agencies* indicate that at least one of the writers is represented by one of the four largest talent agencies in Hollywood; *Original* indicates that the script is based on original content rather than on existing properties such as books and short stories; *Talent attached* indicates that some directing and/or acting talent was committed at the time of the record; *Rights purchase* indicates that the transaction is about adaptation rights, and the writers are the authors or creators of the pre-existing properties. Additional control variables that are not summarized here include a set of dummy variables indicating 14 (non-mutually exclusive) genres and 28 movie studios.

Table 2: Effect on the gender of the protagonist

Dependent variable	Female protagonists	
	(1)	(2)
W Association × Post Shock	-0.008	-0.018
	(0.058)	(0.064)
W Association	0.025	0.011
	(0.029)	(0.023)
Includes female producers		0.130***
		(0.013)
Producer team size		-0.018**
		(0.008)
Producer experience		-0.000
		(0.001)
Producer prior awards		0.014
		(0.010)
Producer exp. w/ major studios		0.052***
		(0.016)
Producer exp. w/ top agencies		-0.048*
		(0.025)
Writer experience		-0.006
		(0.005)
Writer team size		-0.050***
		(0.017)
Top four agencies		0.004
		(0.021)
Original		-0.054*
		(0.031)
Complete script		0.017
		(0.051)
Talent attached		-0.000
		(0.030)
rights purchase		0.062**
		(0.026)
Genre FE	N	Y
Studio FE	N	Y
Quarter FE	Y	Y
Observations	1977	1977
R^2	0.013	0.123

Note: OLS regressions. The dependent variable of both columns is whether or not the project features female protagonists. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect on the gender of the protagonist, by the gender of the writers

Dependent variable	Female protagonists		
Sample	All-male writers	Incl. female writers	All
	(1)	(2)	(3)
W Association × Post Shock	-0.001	-0.110	-0.003
	(0.056)	(0.078)	(0.060)
W Association	0.003	0.055*	0.001
	(0.022)	(0.032)	(0.023)
W Association × Post Shock × Includes female writers			-0.184**
			(0.068)
Includes female writers × Post Shock			0.062
			(0.093)
Includes female writers × W Association			0.054*
			(0.031)
Includes female writers			0.386***
			(0.028)
Includes female producers	0.046***	0.088**	0.056***
	(0.015)	(0.038)	(0.017)
Other controls	Y	Y	Y
Genre FE	Y	Y	Y
Studio FE	Y	Y	Y
Quarter FE	Y	Y	Y
Observations	1511	466	1977
R^2	0.112	0.174	0.226

Note: OLS regressions. The dependent variable of all columns is whether or not the project features female protagonists. Columns 1 and 2 split the sample by whether the writers are all male or at least one of the writers is female. Column 3 combines the first two columns into a single triple-differences regression, comparing teams that include at least one female writer against all-male writing teams. All regressions use the same set of controls as in Column 2 of Table 2. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect on the gender of the protagonist, by the gender of the producers and the writers

Dependent variable	Female protagonists					
Sample	All-male producers		Include female producers		Include female writers or producers	All
	All-male writers	Include female writers	All-male writers	Include female writers		
	(1)	(2)	(3)	(4)	(5)	(6)
W Association × Post Shock	0.115	-0.313	-0.109*	-0.111	-0.162***	0.112
	(0.091)	(0.288)	(0.064)	(0.094)	(0.055)	(0.088)
W Association	-0.060*	0.177	0.054**	0.015	0.049***	-0.048
	(0.034)	(0.112)	(0.021)	(0.055)	(0.013)	(0.031)
Includes female writers					0.408***	0.409***
					(0.035)	(0.032)
Includes female producers					0.081**	0.063*
					(0.033)	(0.032)
W Association × Post Shock ×Includes female writers or producers						-0.275***
						(0.083)
Includes female writers or producers × Post Shock						0.101
						(0.069)
Includes female writers or producers × W Association						0.106***
						(0.029)
Includes female writers or producers						-0.054
						(0.046)
All other controls	Y	Y	Y	Y	Y	Y
Observations	820	129	691	337	1157	1977
R^2	0.129	0.535	0.168	0.219	0.253	0.229

Note: OLS regressions. The dependent variable of all columns is whether or not the project features female protagonists. Columns 1-4 split the sample in four ways: by the gender of the producers and by the gender of the writers. Column 5 combines the three subsamples used in Columns 2-4 into one group—i.e., teams that include at least one female writer or one female producer. Column 6 combines Columns 1 and 5 into a single triple-differences regression, comparing teams that include at least one female writer or producer against all-male writing and producing teams. All regressions use the same set of controls as in Column 2 of Table 2. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect on the portrayal of the protagonists relative to traditional gender stereotypes

(a) Projects featuring female protagonists

Dependent variable	Feminine				
Sample	All	All-male teams	Include female writers or producers	Female genres only	Non-female genres only
	(1)	(2)	(3)	(4)	(5)
W Association × Post Shock	-0.135***	-0.304**	-0.109**	-0.069*	-0.151***
	(0.036)	(0.132)	(0.048)	(0.034)	(0.053)
W Association	0.064*	0.112**	0.092*	0.072**	0.053
	(0.031)	(0.047)	(0.051)	(0.032)	(0.052)
Includes female writers	-0.040		-0.102**	0.016	-0.071
	(0.034)		(0.043)	(0.042)	(0.044)
Includes female producers	0.037		-0.031	-0.049	0.082**
	(0.029)		(0.042)	(0.031)	(0.032)
All other controls	Y	Y	Y	Y	Y
Observations	735	195	540	209	526
R^2	0.216	0.440	0.248	0.334	0.241

(b) Projects featuring male protagonists

Dependent variable	Feminine				
Sample	All	All-male teams	Include female writers or producers	Female genres only	Non-female genres only
	(1)	(2)	(3)	(4)	(5)
W Association × Post Shock	0.003	-0.036	0.043	0.005	0.015
	(0.064)	(0.125)	(0.077)	(0.116)	(0.048)
W Association	0.018	0.009	0.016	-0.116**	0.048
	(0.025)	(0.035)	(0.032)	(0.051)	(0.031)
Includes female writers	0.037		0.079*	-0.028	0.037
	(0.028)		(0.044)	(0.087)	(0.044)
Includes female producers	0.066		0.172*	0.101*	0.058
	(0.043)		(0.093)	(0.049)	(0.038)
All other controls	Y	Y	Y	Y	Y
Observations	1242	625	617	250	992
R^2	0.179	0.216	0.264	0.214	0.186

Note: OLS regressions. The dependent variable of all columns, *feminine*, is a dummy variable indicating that the gender-role measure is above the sample median. Panel 1 uses projects featuring female protagonists. Columns 2 and 3 split this subsample by whether the project is developed by an all-male writing and producing team or a team including at least one female writer or producer. Columns 4-6 split this subsample by whether or not the project is categorized as female genres only. Panel 2 presents the same set of regressions as Panel 1 but for the subsample of projects featuring male protagonists. All regressions use the same set of controls as in Column 2 of Table 2. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendices (not for publication)

A Appendix Tables and Figures

Table A.1: Summary statistics, unmatched sample

	Weinstein association = 0			Weinstein association = 1			
	Obs	Mean	SD	Obs	Mean	SD	(p-value)
Female protagonists	2295	0.38	0.48	1750	0.38	0.49	(0.73)
Gender appeal	2295	-0.03	0.70	1750	-0.06	0.70	(0.16)
Female genre only	2295	0.26	0.44	1750	0.26	0.44	(0.85)
Feminine	2295	0.51	0.50	1750	0.51	0.50	(0.99)
Post shock	2295	0.25	0.43	1750	0.27	0.44	(0.26)
Include female writers	2295	0.26	0.44	1750	0.25	0.43	(0.50)
Include female producers	2295	0.49	0.50	1750	0.54	0.50	(0.00)
Producer experience	2295	6.29	7.44	1750	11.87	9.35	(0.00)
Producer prior awards	2295	0.30	0.94	1750	1.23	2.05	(0.00)
Producer exp. w/ major studios	2295	0.49	0.43	1750	0.66	0.35	(0.00)
Producer exp. w/ top agencies	2295	0.55	0.39	1750	0.76	0.25	(0.00)
Producer team size	2295	2.79	1.70	1750	3.86	2.09	(0.00)
Writer experience	2295	0.78	1.51	1750	1.02	1.70	(0.00)
Writer team size	2295	1.27	0.50	1750	1.24	0.49	(0.10)
Top four agencies	2295	0.47	0.50	1750	0.59	0.49	(0.00)
Original	2295	0.64	0.48	1750	0.64	0.48	(0.93)
Complete script	2295	0.58	0.49	1750	0.55	0.50	(0.04)
Talent attached	2295	0.54	0.50	1750	0.59	0.49	(0.00)
Rights purchase	2295	0.18	0.38	1750	0.17	0.37	(0.36)

Note: This table summarizes the variables by the association with Weinstein using the unmatched sample. The sample is based on the unmatched sample used in Luo and Zhang (2020), dropping 143 observations that do not have the logline information that we use to generate the dependent variables that this paper focuses on. See Notes in Table 1 in the paper for the definitions of the variables.

Table A.2: The gender of the writer and the gender of the protagonist

	(1)	(2)
Baseline choice: All-male writers & male protagonists		
Alternative choice 1: All-male writers & female protagonists		
W Association × Post Shock	-0.118	-0.127
	(0.259)	(0.297)
W Association	0.108	0.014
	(0.147)	(0.124)
Alternative choice 2: Include female writers & male protagonists		
W Association × Post Shock	1.042***	0.971***
	(0.220)	(0.267)
W Association	-0.291**	-0.210*
	(0.119)	(0.117)
Alternative choice 3: Include female writers & female protagonists		
W Association × Post Shock	0.345	0.324
	(0.281)	(0.384)
W Association	0.046	0.068
	(0.147)	(0.156)
Other controls	N	Y
Quater FE	Y	Y
Observations	1977	1977

Note: Multinomial logit regressions (matched sample). The dependent variable indicates four options that vary by the gender of the writers and the gender of the protagonists: the baseline option of "all-male writers and male protagonists" and three alternative options, which are "all-male writers and female protagonists," "include female writers and male protagonists," and "include female writers and female protagonists." Results from Column 2 show that, relative to non-associated producers, the relative risk ratio of the alternative "include female writers & male protagonists" versus the baseline choice "all-male writers & male protagonists" for Weinstein-associated producers increased by $exp(0.97) = 2.64$ times after #MeToo compared to before (p-value is 0.000). The relative risk ratio of "include female writers & male protagonists" versus the alternative "include female writers & female protagonists" increased differentially for Weinstein-associated producers by $exp(0.97-0.32) = 1.91$ times (p-value is 0.0548), and the relative risk ratio of "include female writers & male protagonists" versus the alternative "male writers & female protagonists" increased differentially for Weinstein-associated producers by $exp(0.97+0.13) = 3.00$ times (p-value is 0.001). Moreover, the Hausman test cannot reject the null hypothesis of independence of irrelevant alternatives; that is, we do not observe systematic changes in the coefficients after excluding any one of the outcomes from the model. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Effect on the gender of the protagonist (unmatched sample)

DV	Whether female protagonists		
	(1)	(2)	(3)
W Association × Post Shock	0.021	0.014	0.046
	(0.040)	(0.035)	(0.050)
W Association	0.007	0.004	-0.018
	(0.014)	(0.011)	(0.020)
W Association × Post Shock		-0.098**	
×Includes female writers		(0.041)	
Includes female writers × Post Shock		0.066**	
		(0.030)	
Includes female writers × W Association		0.044**	
		(0.018)	
Includes female writers		0.356***	0.396***
		(0.017)	(0.027)
W Association × Post Shock			-0.098
×Includes female writers or producers			(0.058)
Includes female writers or producers			0.051
× Post Shock			(0.048)
Includes female writers or producers			0.055*
× W Association			(0.028)
Includes female writers or producers			-0.067
			(0.047)
Includes female producers	0.124***	0.061***	0.093***
	(0.008)	(0.008)	(0.029)
All other controls	Y	Y	Y
Observations	4045	4045	4045
R^2	0.095	0.195	0.196

Note: OLS regressions (unmatched sample). Column 1 replicates Column 2 of Table 2; Column 2 replicates Column 3 of Table 3; and Column 3 replicates Column 6 of Table 4. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Effect on the gender of the protagonist, robustness

Dependent variable		Female protagonists		Female protagonists only	Female protagonists	Female protagonists only
Sample	Single writer	Director available	All	All	Exclude cases with predicted protagonist gender	
	(1)	(2)	(3)	(4)	(5)	(6)
W Association × Post Shock × Includes female writers or producers	-0.351***			-0.300***	-0.264**	-0.310***
	(0.094)			(0.075)	(0.106)	(0.100)
W Association × Post Shock	0.220**	0.259**		0.156*	0.127	0.184**
	(0.092)	(0.106)		(0.087)	(0.084)	(0.077)
Includes female writers or producers × Post Shock	0.156**		0.015	0.106*	0.062	0.076
	(0.063)		(0.059)	(0.053)	(0.081)	(0.059)
Includes female writers or producers × W Association	0.111***			0.106***	0.064*	0.072*
	(0.037)			(0.027)	(0.034)	(0.036)
W Association	-0.065*	-0.104*		-0.076**	-0.027	-0.066***
	(0.032)	(0.052)		(0.035)	(0.026)	(0.022)
Includes female writers	0.439***	0.244***	0.406***	0.454***	0.435***	0.496***
	(0.032)	(0.058)	(0.033)	(0.018)	(0.049)	(0.025)
Includes female writers or producers	-0.078		-0.014	-0.125***	-0.033	-0.117*
	(0.061)		(0.044)	(0.042)	(0.070)	(0.057)
Includes female writers	0.078*	0.036	0.063*	0.125***	0.080	0.152***
	(0.039)	(0.057)	(0.033)	(0.029)	(0.061)	(0.055)
W Association × Post Shock × Includes female writers, directors, or producers		-0.440***				
		(0.096)				
W Association (total) × Post Shock × Includes female writers or producers			-0.040***			
			(0.012)			
W Association (total) × Post Shock			0.027*			
			(0.014)			
Other controls	Y	Y	Y	Y	Y	Y
Genre FE	Y	Y	Y	Y	Y	Y
Studio FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Observations	1526	896	1977	1977	1480	1480
R^2	0.246	0.220	0.227	0.234	0.260	0.268

Note: OLS regressions (matched sample). Column 1 uses projects with single writers. Column 2 uses projects for which the director information is available. This regression compares teams with at least one female writer, director, or producer with all-male teams. Column 3 uses a continuous measure of the association with Weinstein, W Association (total), which is the total number of past released movies on which all the producers in the team had collaborated with Weinstein before the focal project was set up. Columns 2 and 3 both include a full set of their respective double-interaction terms, some of which are not reported in the table due to the space constraint. Column 4 uses an indicator for stories featuring female protagonists only (those featuring protagonists of both genders are coded as zero). Columns 5 and 6 drop projects for which the gender of the protagonists is predicted (25 percent of the matched sample) rather than manually coded based on the pronouns and names associated with the protagonists. All regressions use the same set of controls as in Column 2 of Table 2. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Alternative measures of an idea's gender orientation

Dependent variable	Gender appeal			Female genres only		
Sample	All	All-male teams	Incl. female writers or producers	All	All-male teams	Incl. female writers or producers
	(1)	(2)	(3)	(4)	(5)	(6)
W Association × Post Shock	-0.004	0.047	-0.112**	-0.016	0.058	-0.067**
	(0.047)	(0.053)	(0.042)	(0.024)	(0.034)	(0.025)
W Association	0.028	-0.073*	0.103***	0.003	-0.034**	0.037**
	(0.026)	(0.036)	(0.029)	(0.015)	(0.015)	(0.015)
Includes female producers	0.185***		0.175**	0.024**		0.027
	(0.032)		(0.066)	(0.010)		(0.032)
Includes female writers			0.452***			0.023
			(0.058)			(0.017)
All other controls	Y	Y	Y	Y	Y	Y
Observations	1977	820	1157	1977	820	1157
R^2	0.261	0.247	0.330	0.656	0.611	0.701

Note: OLS regressions (matched sample). The dependent variable of the first three columns is the gender appeal of a project, which equals 1 if rated as significantly more appealing to women, -1 if significantly more appealing to men, and 0 if similarly appealing to both genders. Columns 2 and 3 split the sample by whether the writers and the producers are all male or at least one of them is female. The last three columns replicate the first three columns but use Female genres only—an indicator for projects categorized only as female genres and not as male or neutral genres—as the dependent variable. All regressions use the same set of controls as in Column 2 of Table 2. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Box office performance and critic/user ratings before and after #MeToo

Dependent variable	Critic score	User score	log(US B.O.)	Critic score	User score	log(US B.O.)	Critic score	User score	log(US B.O.)
Sample		All			Feature female protagonists			Feature male protagonists	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Majority female leads × Released post #MeToo	-1.997	-3.675	0.145						
	(4.858)	(2.756)	(0.169)						
Released post #MeToo	-13.866*	-11.627*	0.629	-5.651	-7.015	1.110*	-13.360	-12.126*	0.635
	(7.882)	(5.882)	(0.489)	(17.029)	(9.829)	(0.545)	(9.196)	(6.373)	(0.929)
Majority female leads	-2.440	-1.697	-0.087						
	(2.464)	(1.168)	(0.073)						
Feminine × Released post #MeToo				-12.565**	-11.196*	-0.372	-0.416	-1.275	0.201
				(5.915)	(6.440)	(0.382)	(3.886)	(2.120)	(0.171)
Feminine				8.788**	7.392***	-0.054	4.110	1.388	0.175
				(3.497)	(2.202)	(0.155)	(2.608)	(1.852)	(0.109)
Include female writers	1.808	1.217	0.140	-0.782	-0.866	0.033	4.432	3.218	0.240
	(1.520)	(1.558)	(0.086)	(3.544)	(2.719)	(0.184)	(2.896)	(2.058)	(0.160)
Include female directors	7.555**	0.994	-0.361*	8.951**	1.701	-0.651**	6.148*	0.570	-0.080
	(2.916)	(1.794)	(0.184)	(3.784)	(3.638)	(0.277)	(3.191)	(3.431)	(0.203)
Include female producers	1.820	-0.233	-0.149	-3.569	-2.869	-0.074	4.186	0.952	-0.111
	(1.913)	(1.512)	(0.093)	(2.865)	(1.855)	(0.129)	(2.917)	(1.677)	(0.122)
Maximum screen #	-0.876***	-0.098	0.138***	-0.765***	-0.004	0.143***	-0.894***	-0.148	0.145***
	(0.147)	(0.100)	(0.020)	(0.255)	(0.153)	(0.023)	(0.151)	(0.123)	(0.021)
# of critics	0.196***		0.004**	0.202***		0.004**	0.203***		0.003**
	(0.010)		(0.001)	(0.017)		(0.002)	(0.019)		(0.001)
# of users		2.029***	0.005		1.913***	-0.028		2.131***	0.020
		(0.181)	(0.022)		(0.400)	(0.043)		(0.296)	(0.018)
Genre FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Studio FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	759	759	759	292	292	292	467	467	467
R^2	0.431	0.316	0.854	0.477	0.386	0.864	0.467	0.342	0.869

Note: OLS regressions, using movies released in theaters between January 2014 and September 2019. We construct this sample as follows. *The-numbers.com* lists 2,872 movies that were released in U.S. theaters between January 2014 and September 2019. We are left with 1,450 movies after the following two steps: i) dropping people listed as cast and crew for which the confidence level of the prediction of *genderize.io*, a commonly used gender-classification software, based on a person's first name, is below 90 percent; and ii) keeping movies with non-missing information on the leading cast, the writers, the director, and the producers (the dropped movies are mostly indie productions or foreign movies). We drop another i) 257 movies because we cannot find a match on *www.rottentomatoes.com*; ii) 375 movies because the earliest professional reviews listed on *www.rottentomatoes.com* were published more than 180 days before the U.S. theatrical dates (these movies are mostly re-releases of foreign movies); and iii) 57 movies because there is no review information on *www.rottentomatoes.com*. The final sample, thus, includes 761 movies (2 observations are dropped out of the regressions).

Dependent variables: critic and user scores are movie-level scores displayed on a movie page on *rottentomatoes.com*, and both variables range from 0 to 100. The U.S. box office (B.O.) performance is obtained from *the-numbers.com*.

Other variables: according to *the-numbers.com*, leading cast are determined based on whether they appear on the movie's theatrical posters or are credited at the top of the posters if the posters show no actors or actresses at all. In these regressions, *Majority female leads* equals one if the majority of the leading cast are female. The majority of the leading cast are female for 38 percent of the movies. The results are robust to using a dummy variable indicating that the first listed lead is female. *Released post #MeToo* is an indicator if the movie was released after October 15th 2017. *Max screen #* is the maximum number of screens the movie is shown on throughout its theatrical run. Because budget information is not available for all movies, we use *max screen #* to proxy for the amount of resources allocated to the movie. This is a reasonable proxy, as for 514 movies with budget information, the correlation between max screen and budget is 0.76. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Additional results on the gender of the protagonist

Dependent variable	Female protagonists			
Sample	Non-major studios	Major studios	Non-female genres only	Female genres only
	(1)	(2)	(3)	(4)
W Association × Post Shock	-0.125	-0.267***	-0.135*	-0.180**
	(0.092)	(0.084)	(0.075)	(0.064)
W Association	0.021	0.052**	0.066*	0.038
	(0.046)	(0.019)	(0.037)	(0.039)
Include female writers	0.433***	0.363***	0.353***	0.478***
	(0.047)	(0.061)	(0.041)	(0.066)
Include female producers	0.090	0.105	-0.001	0.207**
	(0.069)	(0.075)	(0.061)	(0.076)
Other controls	Y	Y	Y	Y
Genre FE	Y	Y	Y	Y
Studio FE	N	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Observations	580	577	831	326
R^2	0.250	0.342	0.232	0.340

Note: OLS regressions using projects in the matched sample by teams with at least one female writer or producer. The dependent variable of all regressions is whether or not the project features female protagonists. Columns 1 and 2 split this subsample by whether or not a major studio was involved at the time of the DDP records. Columns 3 and 4 split this subsample by whether or not a project is categorized as female genre only. All regressions use the same set of controls as in Column 2 of Table 2, except for Column 1 in which studio fixed effects are not included. Standard errors clustered at the studio level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Construction of the Outcome Variables

We use the logline of a script, a short summary typically consisting of one to three sentences, that is recorded in the Done Deal Pro database to construct the three variables that we use to characterize content: i) the gender of the protagonists; ii) the appeal of the movie to a typical man and a typical woman in the U.S.; and iii) how the protagonist is portrayed relative to traditional perceptions of gender stereotypes.

B.1 Female protagonists

B.1.1 Mechanical Turk (MTurk) survey question

We ask MTurk workers to help us classify the gender of the protagonists. In particular, we ask the following question:

> Based on the following logline:
>
> *Pierre, a quietly resourceful bartender, returns to his hometown after the death of his parents. When he falls in love with the enigmatic Stella, he is unwittingly drawn into a circle of fate pitting him against the volatile criminal, Shane.*
>
> I think the gender of the protagonist is:
>
> ○ Female ○ Male ○ Both female and male (if multiple protagonists) ○ Unclear

We provide the following instructions that help MTurkers decide:

> Please help us classify the gender of the protagonist (lead character) of a movie, based on its logline (1-2 sentence summary). The following are a few notes that might help you decide:
>
> - A movie typically has a single central protagonist, so please select the third option only if you are sure that there are multiple central protagonists.
> - If both a male and a female character show up in a logline, typically, the one that shows up first is the protagonist (e.g., "Pierre, a quietly resourceful bartender, returns to his hometown after the death of his parents. When he falls in love with the enigmatic Stella, he is unwittingly drawn into a circle of fate pitting him against the volatile criminal, Shane." In this example, Pierre is the protagonist.)
> - Sometimes, you have to read to the end of the logline before you realize the gender of the protagonist (e.g., "Aiman, a young correctional officer, befriends older colleague Koon, an executioner at the prison, and Aiman must grapple with the possibility that he may have to take over the older man's job." In this example, "he" is used to refer to Aiman, the lead character, and this gender pronoun shows up at the end.)
> - Apart from gender pronouns, you can sometimes make inferences from the name of the lead character (e.g., if the protagonist's name is Emily, the protagonist is clearly female). Please indicate "unclear" if you are not sure about the gender of the name of the protagonist.

- Please do not classify the gender purely based on the person's profession, unless you are absolutely sure (for example, a U.S. sports figure could be a male or a female. If this is the only information available, please indicate "unclear.")
- Please click "unclear" if there is not enough information to tell whether the protagonist is a man or a woman or if the logline does not refer to a man or a woman.

The payment per assignment, which asks the above question about a single logline, is $0.04. We restrict the respondents to workers who have approval rates greater than 95 percent, have the number of Human Intelligence Tasks (HITs) approved to be greater than 500, and are located in the United States.

B.1.2 Construction of the variable *female protagonists*

We construct the variable, *female protagonists*, via a two-step process.

In Step 1, we construct a variable to capture the gender of the protagonist based on MTurk workers' answers to the above question through an iterative process. We ask two different MTurk workers to classify the gender of the protagonist for each of the 4,045 loglines in the unmatched sample. If their answers coincide, we code the gender of the protagonist accordingly. For loglines for which the two answers differ (1011 in total, and 25 percent of the entire sample), we ask a third MTurk worker the same question independently to break the tie. For these loglines, if two out of the three answers are consistent with each other, we code the gender of the protagonist accordingly. For a small number of loglines for which all three answers differ (242 in total, and six percent of the entire sample), we ask a fourth MTurk worker independently. For these loglines, if two out of the four answers are the same, we code the gender of the protagonist accordingly. For loglines for which all four answers differ (28 observations in total), we (the authors) code up the final answer.

The variable *protagonist gender* generated via the above process categorizes 26.58 percent of the loglines as featuring female protagonists; 43.26 percent as featuring male protagonists; 6.85 percent as featuring both female and male protagonists; and 23.31 percent as unclear.

For a validity check, the left panel of Table B.1 summarizes the percentage of loglines in each category that are written by female writers. It is intuitive that the percentage of female writers is substantially higher for loglines with female protagonists compared to loglines that are categorized as featuring male protagonists (54 versus 13 percent, p-value is = 0.0000). 17 percent of the loglines that are categorized as unclear are written by female writers, which suggests that the majority of these "unclear" cases are likely to feature male protagonists, even though the short summary does not have clear gender pronouns or protagonist names that are clearly female or male. This is consistent with our manual examination of a randomly selected subset of "unclear" cases: for the majority of these loglines, the contextual information strongly suggests that the protagonist is male.

In Step 2, to better utilize observations in the 'unclear' category, which comprise 23.31 percent of the sample, we employ machine-learning techniques to predict whether a given logline is likely to feature female or male protagonists based on the contextual information. In particular, we use the subset of loglines that are clearly identified as featuring female and male protagonists as the input into a supervised machine-learning model.[41] A random 80 percent of the clearly labeled loglines are allocated to the training set and the other

[41] We chose not to include cases with both male and female protagonists, mainly because they made up of a very small percentage

Table B.1: Percentage of female writers, by the gender of the protagonist

Step 1			Step 2		
Protagonist gender	N	Percentage of female writers	Protagonist gender	N	Percentage of female writers
Female	1075	53.8%			
Male	1750	13.0%			
Both	277	27.0%			
Unclear	943	17.3%	Female (predicted)	180	33.3%
			Male (predicted)	763	13.6%
Total	4045	26.0%			

Note: In Step 1, MTurk workers classify the gender of the protagonist based on the pronouns and names associated with the protagonist. For 23.31 percent of the loglines for which the gender of the protagonist is not immediately clear, we use supervised machine-learning method, based on observations that are clearly coded as featuring male or female protagonists in Step 1, to predict the gender of the protagonist.

20 percent to the testing set.

To implement the procedure, we first encode the loglines into vectors. Recent advancements in natural language processing allow us to encode sentences or words in more meaningful forms than simply counting the frequency of the actual words used in the texts, taking into consideration the semantic and syntactic information of words.[42] The word2vec techniques and Bidirectional Encoder Representations from Transformers (BERT) language models are two important ones.[43] We use BERT models, created and published in 2018 by Jacob Devlin and his colleagues at Google (Devlin et al., 2018), in our paper. A key advantage of BERT models relative to word2vec models is that the former takes into consideration the context of each word. For example, bank as a financial institute is different from bank of the river. BERT models will yield different vectors for the word 'bank' in these two different contexts, whereas word2vec will produce the same vector. In addition, BERT models will transform an entire paragraph into a vector in a single step, whereas with word2vec, one needs to transform each word into a vector first and then aggregate all the word vectors included in a logline to a single vector.

We use a pre-trained BERT model to convert each logline into a 768-dimension vector and then run a logistic regression to train the supervised learning classification. The label (female and male protagonist) is the dichotomous dependent variable, and the logline vectors are the predictors. The trained model achieves an accuracy rate of 98.04% for the training set and 94.86% for the testing set.

We then use the trained model to predict the gender of the protagonists for loglines that are categorized as 'unclear' in Step 1. Among the 943 loglines, 180 (19 percent) are predicted to feature female protagonists, and the other 763 (81 percent) are predicted to feature male protagonists. Such a split is consistent with the above statistic and our manual inspection that a vast majority of the unclear loglines likely feature male protagonists. To provide a reality check of this prediction, the right panel of Table B.1 tabulates the share of female writers for each predicted category: this percentage is 13.6 percent for loglines that are predicted to

of the total sample, and it is possible that the coders were less stringent about finding a single central character in these cases.

[42] These vectors are known to capture analogical reasoning—for example, king − men + women = queen—or capture meaningful relationships with other vectors (e.g., the vector of dog will be quite similar to the vector of cat or domestic).

[43] The original models are trained on the BooksCorpus with 800M words and a version of the English Wikipedia with 2,500M words. BERT has achieved state-of-the-art performance on a number of NPL tasks.

feature male protagonists, which is virtually the same as the percentage of female writers for loglines that are clearly identified as featuring male protagonists in Step 1. The percentage of female writers is 33.3 percent for loglines that are predicted to feature female protagonists, which is closer to the same percentage for loglines categorized as 'both' in Step 1 than to that for loglines that are clearly identified as featuring female protagonists in Step 1. The difference in the percentage of female writers for the two predicted categories among all the "unclear" loglines (33.3 versus 13.6 percent) is statistically significant (the p-value is 0.0000).

Finally, the main outcome variable that we use in this paper, *female protagonists*, equals one if the protagonist's gender is classified as 'female' or 'both' by MTurk workers in Step 1, or if the protagonist's gender is 'unclear' in Step 1 and is predicted to feature female protagonists in Step 2. In the paper, we show the robustness of our core results to an alternative definition of 'female protagonist only' and to excluding all the "unclear" cases from the analysis.

Conceptually, what we mean by the gender orientation of an idea is that it is more likely to appeal to an audience of a given gender. At the intuitive level, by placing a woman at the center of the story universe, female-protagonist stories are likely appeal to a female audience. To verify this concept, we also construct a variable that is intended to capture the movie's likely appeal to an audience of a given gender more directly. We explain the construction of this variable in detail in the next section and show that the gender of the protagonists is highly correlated with this demand-side measure. Finally, we conduct an analysis using *Rotten Tomatoes* critic and user review data, which are presented in Table B.2. The results show that female reviewers (both critics and users) are more likely than male reviewers to rate movies with a majority of female leads more favorably compared to movies with a majority of male leads.

Table B.2: Critic and user reviews, by the gender of the protagonist

DV	Critic rating	User rating
	(1)	(2)
Female critic × Majority female leads	0.016**	
	(0.007)	
Female users × Majority female leads		0.123**
		(0.062)
Movie fixed effects	Y	Y
Critic (user) fixed effects	Y	Y
Observations	109498	464200
R^2	0.366	0.315

Note: OLS regressions using critic-movie- and user-movie-level data of 761 movies released in theaters between January 2014 and the third quarter of 2019. See the notes in Table A.6 for a detailed description of the construction of this dataset. The dependent variable of Column 1 is a dummy variable indicating 'fresh' (positive) versus 'rotten' (negative), which is a binary rating scheme that *Rotten Tomatoes* uses to translate the reviews by professional critics. The dependent variable of Column 2 is the user rating that ranges from 0 to 5. The regressions include movie fixed effects and critic (or user) fixed effects. Standard errors clustered at the movie level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Gender appeal

As mentioned above, we construct a variable intended to capture the movie's likely appeal to an audience of a given gender. While this measure captures the gender orientation of an idea directly from the demand perspective, we rely on the gender of the protagonist as our primary measure in the paper because it is more precisely measured. Consumer appeal of a movie is notoriously difficult to predict for early-stage movie projects, let alone with the short descriptions that we have. Nonetheless, we show below that the gender of the protagonists is highly correlated with the demand-side measure. In Appendix Table A.5 (Columns 1-3), we show that our baseline results are consistent when using this appeal measure instead.

B.2.1 MTurk survey design

MTurk workers are asked to classify the appeal of a logline separately for men and women at a 1-5 scale. Below is an example of a task:

> Below is a logline, which is a short summary of a movie. Using your best judgement, please help us rate the appeal of the movie for men and women:
>
> *An American civilian turned self-taught spy works with the FBI to bring down a Russian intelligence agent on American soil.*
>
> 1. Based on this logline, how much do you think a typical ***woman*** in the U.S. will like this movie?
>
> ◯ Really Dislike ◯ Dislike ◯ Neither Like or Dislike ◯ Like ◯ Really Like
>
> 2. Based on this logline, how much do you think a typical ***man*** in the U.S. will like this movie?
>
> ◯ Really Dislike ◯ Dislike ◯ Neither Like or Dislike ◯ Like ◯ Really Like
>
> 3. How do you identify your gender?
>
> ◯ Woman ◯ Man ◯ Transgender ◯ Non-conforming ◯ Prefer not to respond

We ask the respondents to rate a movie's appeal based on their beliefs of how much a typical man or woman may like the movie, rather than on their own preferences because we want to capture the social perception of a movie's gender appeal. This is also likely to correspond with what the producers may perceive as a movie's appeal to consumers of a given gender. This method also does not require us to specify the respondents' gender ex-ante, which would have significantly raised the cost of soliciting respondents on MTurk. Wühr et al. (2017) conduct two separate studies that compare men's and women's own preferences with their evaluations of the preference of a typical man or a typical woman for 17 movie genres. The results show that for the majority of the genres, the perception of others' preferences is consistent in direction with one's own preferences (e.g., both surveys show that women prefer romance more than men), even though it tends to overestimate the actual gender differences.

The payment per assignment, which asks the above questions about a single logline, is \$0.07. We restrict the workers to those who have approval rates greater than 95 percent, have the number of Human Intelligence Tasks (HITs) approved to be greater than 500, and are located in the United States to minimize differences in perceptions of appeal across cultures.

Each logline is classified 15 times by unique MTurk workers. After dropping classifications with very low work times (i.e., completion time less than ten seconds), we are left with a total of 50,163 usable classifications for 4,045 loglines. About 37 percent of the classifications were completed by women and 61 percent by men. Compared to male MTurk workers, female MTurk workers tend to rate a logline as having slightly higher female appeal (by 0.03) and lower male appeal (by 0.07). We do not think this systematic difference between female and male MTurkers is concerning. Because we randomize the order of the loglines, there are no reasons to expect that the share of female MTurkers rating a given logline will differ systematically by the key variables we use in the paper, such as the gender of the protagonists, the writers, or the producers. Moreover, the share of female MTurkers is not significantly correlated with the gender appeal measure we construct based on these answers. On average, loglines are rated as having higher appeal to men than to women (by 0.06), which is not surprising given that a greater proportion of the loglines are developed primarily for a male audience (e.g., having a male protagonist).

B.2.2 Construction of the variable *gender appeal*

For each logline, we conduct paired t-tests comparing the answers to the above two gender-appeal questions by the same MTurker.[44] We define a *gender appeal* variable that equals -1 if a logline is rated significantly more appealing to men than to women at the five percent level based on one-sided p-values; 1 if a logline is rated significantly more appealing to women than to men at the five percent level based on one-sided p-values; 0 for the remaining loglines.

Among the 4,045 projects, 22 percent are rated as significantly more appealing to women than to men; 26 percent are rated as significantly more appealing to men than to women; and the remaining 51 percent are likely to attract women and men to a (statistically) similar degree. Table B.3 tabulates the percentage of writers within each category of gender appeal that are female. Also consistent with what we expect, this percentage is increasing monotonically as we move from projects that are rated as more appealing to men to more appealing to women.

Table B.3: Percentage of female writers, by the appeal to a given gender

Gender appeal	N	Percentage of female writers
More appealing to men	1,079	10%
Similarly appealing to both genders	2,073	22%
More appealing to women	893	51%
Total	4,045	26%

The correlation between *gender appeal* and *female protagonists* is 0.47 (p-value = 0.000). Table B.4 tabulates the two measures of gender orientation. 48.13 percent of movies featuring female protagonists are rated as significantly more appealing to women, whereas this percentage is only 8.36 for movies featuring male protagonists). Similarly, 38.96 percent of movies featuring male protagonists are rated as significantly more appealing to men, whereas this percentage is only 4.06 for movies featuring female protagonists).

[44]Recall that our survey asks the same MTurk worker to rate the appeal of a given logline to both men and women. This allows us to conduct paired t-tests that help remove the baseline differences among the respondents.

Table B.4: Tabulation by gender appeal and by the gender of the protagonist

		Gender appeal			
		More appealing to men	Similarly appealing to both genders	More appealing to women	Total
Female protagonists	N	51	600	604	1,255
	Percent	4.06%	47.81%	48.13%	100%
Male protagonists	N	979	1,324	210	2,513
	Percent	38.96%	52.69%	8.36%	100%
Both female and male protagonists	N	49	149	79	277
	Percent	17.69%	53.79%	28.52%	100%

B.3 Gender-role measure: feminine-masculine characteristics

B.3.1 The construction of the measure

We aim to construct a measure that captures how a protagonist is portrayed relative to the traditional perception of gender stereotypes. To achieve this goal, we use the set of feminine and masculine characteristics in the Bem Sex-Role Inventory (BSRI) as the benchmark (Bem, 1974). We then create a measure that calculates a focal logline's distance to the feminine keywords relative to the masculine keywords in the vector space.

The Bem Sex-Role Inventory (BSRI) inventory is considered the gold standard of gender-role evaluation and has been used in thousands of studies in the more than 40 years since it was developed (Dean and Tate, 2017). Table B.5 lists the full set of feminine and masculine characteristics in Table 1 of Bem (1974).[45]

As Bem (1974) notes, these characteristics are selected as masculine or feminine on the basis of sex-typed social desirability (that is, a characteristic qualified as masculine if it is judged in American society to be more desirable in a man than in a woman, and as feminine if it is judged to be more desirable in a woman than in a man). In general, masculinity has been associated with instrumental traits, a cognitive focus on "getting the job done;" and femininity has been associated with expressive traits, an affective concern for the welfare of others. As Dean and Tate (2017) discuss, later work also characterizes masculine traits as agentic and feminine traits as communal, applying these concepts to a variety of contexts, such as the effectiveness and acceptability of styles of male and female leaders and how people's perception of self in relation to agency and communion attributes influences different social outcomes, such as attraction to different academic and professional fields.

It is useful to note a few caveats when interpreting the measure. First, as we explain below, by calcu-

[45] Bem (1974) arrived at the list of 40 feminine and masculine characteristics as follows. She started off with a set of personality characteristics that she and a group of students deemed to be positive in value and either masculine or feminine in tone (400 in total, with 200 for each gender). 100 judges were asked to rate each of the 400 characteristics according to questions such as: "In American society, how desirable is it for a man to be truthful?" or "In American society, how desirable is it for a woman to be sincere?" The judges were asked to answer each question based on a 7-point scale, ranging from 1 ("Not at all desirable") to 7 ("Extremely desirable"). A personality characteristic qualified as masculine if it was judged to be significantly more desirable for a man than for a woman ($p < 0.05$). Similarly, a personality characteristic qualified as feminine if it was judged to be significantly more desirable for a woman than for a man. Of the characteristics that satisfied these criteria, 20 were selected for the masculinity scale and 20 were selected as the femininity scale.

lating the relative distance between a focal logline and these feminine and masculine characteristics, we are technically capturing not a specific character's personality traits but the overall description of the storyline. Nonetheless, as we discuss in the next section, it seems reasonable to interpret this measure as the depiction of the protagonist. This is likely because a logline centers mainly on the protagonist, and because the natural language processing tool that we use does a reasonably good job in relating the general social and professional contexts and activities that are often described by verbs and nouns to the benchmark characteristics that are mostly adjectives. Second, the BSRI inventory has been criticized in recent years as being outdated in depicting societal gender norms—for example, Donnelly and Twenge (2017) reviewed a large collection of studies that apply BSRI and show that women's femininity scores have decreased significantly over the years. This is not very concerning for our purpose both because we want to capture a more traditional depiction of stereotypical women and because what we care about is the direction of change (both before and after the #MeToo movement and by Weinstein association).

Table B.5: BSRI masculine and feminine characteristics from Table 1 of Bem (1974)

Masculine items	Feminine items
Acts as a leader	Affectionate
Aggressive	Cheerful
Ambitious	Childlike
Analytical	Compassionate
Assertive	Does not use harsh language
Athletic	Eager to soothe hurt feelings
Competitive	Feminine
Defends own beliefs	Flatterable
Dominant	Gentle
Forceful	Gullible
Has leadership abilities	Loves children
Independent	Loyal
Individualistic	Sensitive to the needs of others
Makes decisions easily	Shy
Masculine	Soft spoken
Self-reliant	Sympathetic
Self-sufficient	Tender
Strong personality	Understanding
Willing to take a stand	Warm
Willing to take risks	Yielding

We construct this gender-role measure as follows:

- In Step 1, we use a BERT pre-trained model, as explained in the previous section, to convert each of the characteristics in the BSRI masculinity and femininity scales to a 738-dimension vector. Then, we create v_f, a single vector that represents feminine characteristics, by taking the average of all the vectors associated with the BSRI feminine characteristics. Similarly, we create v_m, which represents masculine characteristics, by taking the average of all the vectors associated with the BSRI masculine characteristics. We normalize both v_f and v_m to have unit length.

- In Step 2, we use the same BERT pre-trained model to convert each logline to a vector, v_l. Note that to avoid mechanical relationships between any gendered words in a logline and the benchmark characteristics, we replace a gendered word in a logline with a corresponding gender-inclusive word. For example, “she/he” is replaced with “they;” “woman/man” is replaced with “person;” and “wife/husband” is replaced with “spouse.”[46]

- In Step 3, we want to construct a measure that ranks different loglines based on their relative distances to the benchmark feminine and the masculine vectors. One such measure can be calculated as follows (Cao et al., 2020):

$$G^l = \frac{Cos(v_l - v_m, v_f - v_m) \cdot |v_l - v_m|}{|v_f - v_m|} - \frac{1}{2} = \frac{\langle v_f - v_m, v_l - v_m \rangle}{|v_f - v_m|^2} - \frac{1}{2}. \tag{3}$$

  Geometrically, this measure is equal to the ratio between the length of the projection of the difference vector $(v_l - v_m)$ onto the difference vector $(v_f - v_m)$ and the length of the difference vector $(v_f - v_m)$, minus 0.5. The higher this measure, the closer the logline is to the benchmark feminine vector relative to the masculine vector. If a logline vector is equally distant to the two benchmark vectors, for example, the projection of $(v_l - v_m)$ onto $(v_f - v_m)$ would land in the middle between v_f and v_m. After deducting 0.5, the above measure would be zero. For loglines that are closer to the benchmark feminine vector than to the masculine vector, this measure would be positive, whereas for loglines closer to the masculine vector than to the feminine vector, this measure would be negative.

B.3.2 Description of the gender-role measure

Figure B.1a plots the percentage of female-protagonist stories for each bin of this measure. Consistent with what we might expect, the relationship is monotone positive. Figure B.1b shows that the density of this measure for female-protagonist stories is to the right of that for male-protagonist stories, though it exhibits a high variance for both sets of stories. The mean value of this measure is -4.11 for female-protagonist loglines and -6.21 for male-protagonist loglines (p-value is 0.000). That the mean of this measure is negative even for female-protagonist stories is consistent with the idea that the characteristics included in BSRI are likely to be too outdated to depict the current gender norms associated with women (Donnelly and Twenge, 2017).[47]

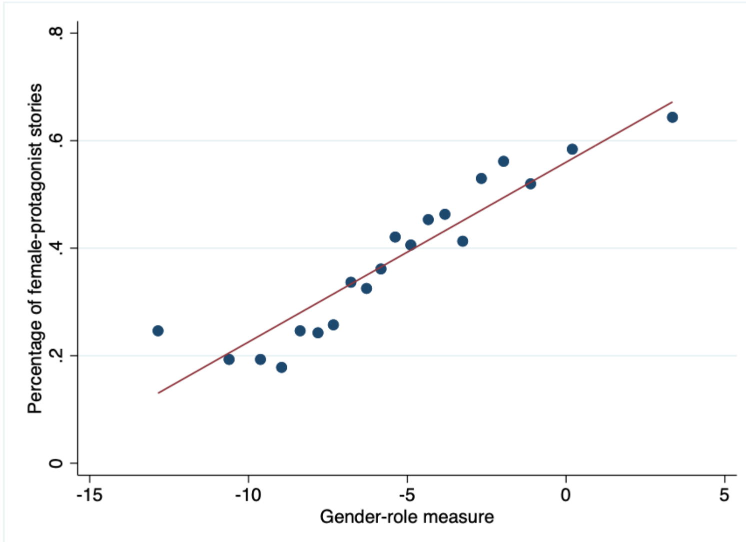
To give some sense of how this measure corresponds to the content of the logline, we provide several examples of loglines with male and female protagonists at different parts of the distribution in Table B.6. Note that these displayed loglines are prior to the removal of gendered pronouns and nouns (as described in Step 2 above). For context, films such as Captain Marvel (*“Captain Marvel aka Carol Danvers is an air force pilot whose DNA is fused with that of an alien after an accident giving her superhuman strength and even the ability to fly.”*), which features a female protagonist in a traditionally male plot line scored at around the 15th percentile; however, the film Girl on the Train (*“A woman who is devastated by her recent divorce spends her daily commute fantasizing about the seemingly perfect couple who live in a house that her train*

[46]We use the following webpage of Springfield college for a list of gendered pronouns and nouns, available at https://springfield.edu/gender-pronouns#: :text=Pronouns%20can%20be%20in%20the,or%20she%2Fher%2Fhers.

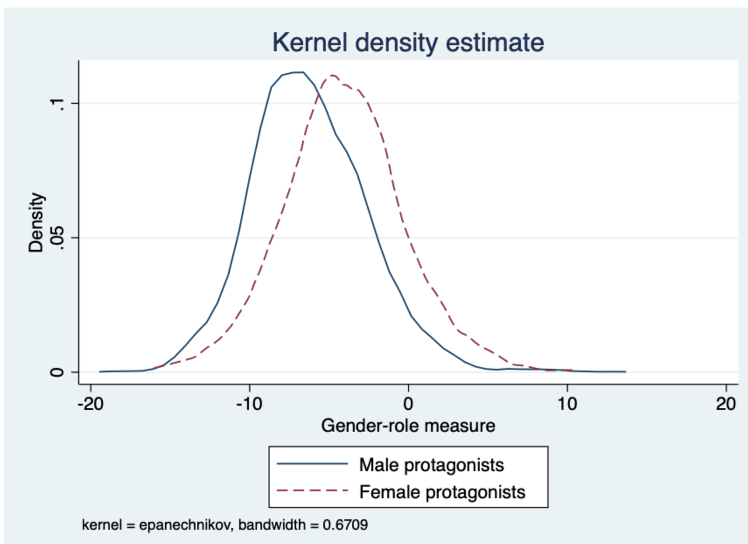
[47]Note, also, that because the measure is based on the entire logline, rather than on a specific character’s personality description, it is also hard to interpret the value of this measure in relation to zero. Again, this is all right in our study because, as discussed, we care about the direction of change before and after #MeToo.

Figure B.1: Description of the gender-role measure

(a) Female-protagonist stories and the gender-role measure



(b) Kernel densities by female- and male-protagonist stories



Note: Based on the 4,045 observations in the unmatched sample.

passes every day until she sees something shocking happen there one morning and becomes entangled in the mystery that unfolds.") scored at around the 85th percentile.

Table B.6: Examples of loglines across the distribution of the gender-role measure

Percentile	Male-protagonist loglines	Female-protagonist loglines
5th	*"A newly released prison gangster is forced by the leaders of his gang to orchestrate a major crime with a brutal rival gang on the streets of Southern California."*	*"Seeker. Only when it's too late does she discover she will be using her new found knowledge and training to become an assassin. The events take her around the globe from remote estate in Scotland to a bustling futuristic Hong Kong."*
25th	*"A young boy travels the world with his scientist father, adopted brother from India, Bandit the bulldog, and a government agent assigned to protect them as they go on their adventures investigating scientific mysteries."*	*"A woman returns from combat and befriends a family in New York City. When a gang of thieves plot to take the family's valuables she fights to defend the family."*
50th	*"A 30-year-old guy meets the woman of his dreams and life could not be better, but right before his wedding he gets a knock at his door and a 66-year-old man walks in and says do not marry this girl because she will ruin your life."*	*"A Wall Street financial adviser who has recently lost her job adopts a dog which has been adopted twice and returned twice for being too unruly. The woman cannot find another job and starts training Roo! who wins a special award for the best mixed-breed dog at the Westminster Dog show's first-ever agility competition, marking the first time mixed-breed dogs have appeared at the show."*
75th	*"Rickie, a sensitive and intelligent young man with an intense imagination, sets out full of hope to become a writer. Giving up his aspirations and opting for convention and marriage to Agnes, he gradually finds himself sinking into conformity and bitter disappointment until he once again realizes his dreams of literary ambition."*	*"A former pageant queen embarks on an all-night adventure with four unlikely friends she meets while volunteering at a women's shelter."*
95th	*"After 20 years of marriage, a lawyer goes to great lengths to prove his love to his wife, a music lover, and save their relationship by taking piano lessons from a free-spirited female teacher to learn Robert Schumann's Traumerei, a tricky piece that is also his wife's favorite song."*	*"A woman loves her daughter, but after years of expulsions and strained home schooling, her precarious health and sanity are weakening day by day. The battle of wills between mother and daughter ultimately reveal the frailty and falsehood of familial bonds."*

Note: The distribution cutoff is uniform rather than specific to the gender of the protagonist. As explained in the previous section, we replaced gendered pronouns and nouns with their gender-inclusive counterparts before constructing the gender-role measure. We display the original loglines here for clarity.