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The Paradox of Minority Conformity: Same-gender Referencing among Female Financial Analysts

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ABSTRACT

The Paradox of Minority Conformity: Same-gender Referencing among Female Financial Analysts

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This paper examines minority actors' conformity behavior. I focus on the influence of minority token status, or "skewed proportions" of demographic distribution in a group as contextual factors of conformity. Through my analyses of financial analysts’ earnings forecasts, I find that minority actors, specifically female analysts, tend to conform to the consensus forecast of the entire analyst population due to their minority status. More interestingly, I also find that female analysts tend to conform, rather than deviate, to other female counterparts due to self-stereotyping. To examine the influence of culture as another contextual factor, I further conduct a cross-country difference between individualist vs. collectivist cultures. This same-gender conformity for female analysts, paradoxically, was greater in the U.S than in China. Extending prior socio-psychological research on culture, I argue that this same-gender conformity is contextually derived—an outcome of minority status which arises from the skewed gender distribution and cultural stereotypes towards gender role in the professional society.

Keywords: Conformity, Minority, Token Status, Diversity, Culture, Stereotypes, Female Analysts

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INTRODUCTION

“Shearson impressed me as an unusually good place for a woman; it had an unusually high percentage of women analysts. It had a unique ability to make women welcome in the department and make us feel in the mainstream socially. I never felt I had to pretend to be male to fit in here [emphasis added].”

–Miriam Cutler Willard (Lewis, cited in Groysberg & Roberts, 2005)

Minority groups’ behavioral and social uniqueness has been receiving an increasing amount of research attention (Westphal and Milton, 2000; Lyngsie and Foss, 2017; Chen, Crossland, & Huang, 2014; Green, Jegadeesh, & Tang, 2009). In particular, minorities’ conformity and deviance have been a major topic of interest to management scholars. Researchers have addressed the question of “who conforms and to whom” by focusing on the dispositional differences among demographic groups. Studies in psychology have explained dispositional variances in the susceptibility to conform among demographic groups, such as gender and race (Tuthill & Forsyth, 1982; Eagly & Wood, 1991; Blumer, 1958; Bonacich, 1973). A number of experimental research in cognitive psychology and behavioral economics also suggest that behavioral differences can arise from personality traits, such as risk tolerance, conservatism, and overconfidence, which are more or less associated with certain genders (Levin, Snyder, & Chapman, 1988; Powell & Ansic, 1997; Croson & Gneezy, 2009; Huang & Kisgen, 2013). Adopting this dispositional approach, some scholars in the management literature have examined differences in corporate
policies and strategic actions of female and male top managers, highlighting behavioral variances as gender effects (Krishnan & Park, 2005; Huang & Kisgen, 2013; Francoeur et al., 2008).

On the other hand, a stream of research has adopted a more sociological perspective by considering conformity as a result of social processes, for instance, an outcome of social comparison among actors sharing similar identities (Festinger, 1954) or positions within a social hierarchy (Hollander, 1958; Phillips & Zuckerman, 2001). According to these scholars, individuals use their social identity or status as a guide in their choice of social referents. Studies suggested that when conducting social comparison, individuals are likely to select comparison targets that are socially similar to them in terms of age, gender, or appearance (Merton & Rossi, 1968; Miller, 1982). These processes have been revealed among various social groups (Coleman, Katz, and Menzel, 1966; Park and Lessig, 1977; Clarke, Beeghley, & Cochran, 1990), including those of professional societies (Groysberg, 2010; Bosquet, de Goeji, & Smedts, 2014).

While demographic minorities within professional groups have received an increasing amount of attention in the management literature, extant studies do not sufficiently highlight how certain behaviors may be an outcome of individuals’ minority status and social comparison process. Although the minority-majority division is a relative interpretation based on numerical rarity, prior studies lack emphasis on how actors’ behaviors may be influenced because their demographic group is outnumbered. Alternatively, Kanter’s (1977) framework on skewed
demographic proportions elaborates on how the relative underrepresentation of demographic categories within a group can result in tokenism—when minorities are perceived as representatives of their social category through stereotyping rather than as individuals. Consistent with this framework, experimental studies on women in male-dominated professional groups and black token actors in white groups (Wolman & Frank, 1975; Taylor & Fiske, 1976) revealed how the behavioral distortions of minority actors could lead to conformity. Compared to other studies focusing on dispositional traits of a group, for instance, gender effects, this framework has high external validity as it can also explicate the conformity behavior of generally dominant demographic groups such as males in female-dominated sectors such as nursing, child-care, and flight attendant services (Segal, 1962; Seifert, 1974; Young & James, 2001).

Considering the framework of skewed distribution as an alternative lens to understanding conformity behavior, I examine how conformity is contingent on token status as well as cultural stereotypes, and thus contextually varies. This perspective departs from previous works on dispositional differences by integrating theory on the social comparison of token status actors. This study addresses how minority individuals may be more likely to show stronger conformity to the entire population in market forecasting due to the internalization of social stereotypes. Moreover, I examine whether token actors are more likely to select similar minorities as referents when market forecasting, and thus conform or deviate within their minority group as well. Since these topics have not received sufficient empirical
investigation, this paper contributes to the literature on minority behavior within and across organizations.

For the empirical context, I examine female analysts as minority actors in the professional community. The lack of diversity, or demographic skewness, of the finance industry has been well-acknowledged and problematized for the past decades. According to Brook (1973:108)’s account of the mid-sixties, “professionally, prejudice against women in the financial business was wide, deep, and largely unquestioned” (cited in Fisher, 2012:40). Although under the Equal Employment Opportunity Commission (EEOC), the number of female analysts has been increasing from a mere 14% in the 1960s, still, gender and ethnic minorities are largely underrepresented in the field. Recent statistics provided by the U.S. census poll (2016) report that the median male analysts’ wage was 27% greater than female analysts, while the average male analyst’s wage was approximately 54% greater than that of the average female analyst in 2016. Although this study examines female analysts as a suitable empirical context to test minority referencing and conformity behavior, the results will be generalizable to other minority professionals as well.

The goals of this research are threefold. First, the study examines if minority actors generally conform due to their token status. To measure conformity behavior, I measure analysts’ deviation from the mean earnings-per-share (EPS) forecast. By conducting a regression analysis using a panel data of sell-side financial analysts’ EPS forecast and background information, I find that female analysts are less likely to deviate compared to male analysts. Second, it is further investigated whether
minority actors are more likely to reference other minority actors within their social category. By measuring the analysts’ deviation from the prior consensus forecast of analysts of the same-gender, I find that female analysts are, surprisingly, more likely to conform rather than deviate from the consensus forecast of other female counterparts. By extending prior experimental evidence in the social psychology literature, I theorize that this is an outcome of token actors’ self-stereotyping. Third, this study examines the interaction effect of culture through a cross-cultural comparison between analysts located in the U.S. and China. The findings show that, paradoxically, female analysts in the U.S. are more likely to conform to the same-gender consensus due to stronger cultural tendencies to create distinct partitions between genders through stereotyping. Therefore, by investigating cross-country differences of the conformity behavior of female analysts to the entire population as well as among themselves, I argue that minority conformity arises due to contextual factors, such as skewed demographic proportions and cultural stereotypes, rather than dispositional traits.

THEORY AND HYPOTHESES

Dispositional and contextual views on conformity

In both management and finance literature, there has been a number of psychology-oriented research exploring systematic differences between female and male executives in terms of personalities, preferences, and decision-making behavior (e.g. Chen, Crossland, & Huang, 2014; Green, Jegadeesh, & Tang, 2009).
Management studies have suggested tendencies of female executives and board members to be less acquisitive and overconfident (Levi, Li, & Zhang, 2011; Chen, Crossland, & Huang, 2014; Huang & Kisgen, 2012). Other studies show how men are better able to exploit network ties for career advancements (Ibarra, 1992; Fang & Huang, 2017). Recently, scholars in finance have also been interested in gender differences among analyst recommendations (Bosquet, de Goeji, & Smedts, 2014), performances (Green, Jegadeesh, & Tang, 2009; Kumar, 2009), and career outcomes (Li, Sullivan, Xu, & Gao, 2013). Other findings reported stronger tendencies of risk averseness among female fund managers and retail investors (Beckmann & Menkhoff, 2008; Barber & Odean, 2001). However, these studies have depicted the behavior of male and female analysts as gender differences, explaining how men and women have dispositional inclinations to act in certain ways. Most of these studies portray gender characteristics as invariantly fixed—ignoring the social contexts of behavior.

From a sociological perspective, research on self-categorization theory reveals how people make sense of their social world by classifying people into different social categories (Turner & Onorato, 1999). Social psychologists have conducted experiments that revealed how people are likely to classify others with minimal information, e.g., visible characteristics such as race and gender (Ashburn-Nardo, Voils, & Monteith, 2001). Festinger (1954) introduced a theory of social comparison and the formation of social identity, focusing on various influence processes in social groups. Social comparison theory states that the perception of the self is dependent
on the specific context the individual is in (Buunk & Mussweiler, 2001; Gardner, Gabriel, & Hochschild, 2002). One of the characteristics that individuals use to choose referents to compare themselves with is the level of ‘similarity’ the individual feels with the group (Hyman, 1942). This theory argues that personal identity is a product of intragroup comparisons by differentiating the contrasts between the self and other in-group members. This phenomenon of referencing similar others has been found in diverse empirical settings, from medical practitioners (Coleman, Katz, and Menzel, 1966), students and housewives (Park and Lessig, 1977), and to alcoholics (Clarke, Beeghley, & Cochran, 1990). Management scholars have incorporated this social psychological perspective by exploring self-categorization and social comparison processes among top managers, examining topics of CEO compensation (O’Reilly et al., 1988), strategic change (Chen, Crossland, & Huang, 2014), interfirm competition (Kilduff, Elfenbein, & Staw, 2010; Kim & Tsai, 2012), and firm performance (Ridge, Aime, & White, 2015). Moreover, some scholars have shown how social comparison based on similarity in attributes can lead to various intergroup biases, such as in-group favoritism among elite executives and other institutional actors (Westphal & Multon, 2000; Park & Westphal, 2013).

Token status and minority conformity: an alternative lens

Alternatively, more contextual factors of demographical proportions or status differences between social categories have also received research attention (Wolman & Frank, 1975; Taylor & Fiske, 1976). Kanter (1977: 966) states how “skewed
groups” in terms of demographic compositions lead to various performance biases. The relative number of actors from a certain social category among “tilted groups” will lead to the “preponderance of one type over another” (Kanter, 1977: 966). Specifically, the author states that when group skewness is high—in a sense that a proportion of social category A dominates that of social category B—tokenism can occur, which denotes a type of status symbol where minorities are perceived as representatives of their social category. Skewness leads to the increase in attention on tokens’ behavior, over-exaggeration of differences between tokens and dominants, and the distortion of tokens’ attributes to fit the preexisting generalizations or prejudices against their social category. Kanter (1977) states that due to the high visibility of their action, tokens avoid showing outstanding performance in tasks and group events in fear of public humiliation when failing. Due to fear of retaliation from dominant groups, token actors face greater pressures to perform but not stand out.

According to this framework, any social category can become tokenized depending on the demographic composition of the group. For example, studies have shown how male actors in nursing, child-care services, and flight attendant services saw a loss in status as they became tokenized (Segal, 1962; Seifert, 1974; Young & James, 2001). Thus, the demographic proportions framework shows how tokenism is a contextual factor that leads to social category stereotyping. Until their presence becomes taken-for-granted and incorporated into the dominant culture of the professional society, minorities with token status will most likely face stereotyping.
Like many other women in the professional society, female analysts are considered the minority in the financial analyst field. In an interesting case report on a star research analyst at Lehman Brothers by Groysberg and Roberts (2005), a woman named Josie Esquivel stated her troubles on the conformity pressures females had to face: “I had always been told that, in order to meet this challenge, I had to think like a woman but act like a man.” Moreover, the differences between female and male analysts are shown in the wide wage gap between the two demographic groups. Although recent studies reveal that female financial analysts with above average abilities usually get self-selected into the field and thus, on average, give more accurate earnings forecast (Kumar, 2009), field professionals have pointed out that not many women are acknowledged for their superior performance. According to the *Institutional Investor* magazine, although female representation has been increasing, nominations for females for the prestigious All-America Research Team award has been stagnant at around 13% for the past decade since 2009.\(^1\) Therefore, in line with Kanter’s (1977) argument of proportion skewness, I argue that as the gender minority in the financial analyst industry, females may face a stronger normative pressure to conform to the majority due to their increase in visibility. Former research has shown that in male-dominated fields where female representation is much lower, and the gender differences are continuously reinforced, female professionals are likely to internalize such stereotypes and show revisions in

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\(^1\) Mary Lowengard, “Where are the women on the All-America Research Team?” *Institutional Investor*, October 2018.
behavior, such as conformity (Epstein, 1970; Cussler, 1958). Therefore,

**H1: Female analysts will be less likely to deviate (i.e., forecast further) from the consensus forecast compared to male analysts.**

**Token actors’ acceptance or deflection of stereotypes**

Although it is more common knowledge that minorities conform to the majority opinion, it is, however, a puzzle whether minority actors try to conform or deviate from their actors within their own category. In her research on social status and the dynamics of envy, Fiske (2011:65) states that “women consistently compare themselves to other women, not to men.” Addressing the wide wage gap between men and women, Fiske points out that professional women tend to disregard this as injustice because they continuously compare their wage to other women in general. Therefore, their social referents tend not to be other men in the same profession, but other women.

According to Kanter (1977:984), a personal consequence of the tokenism phenomena is that token actors face a certain degree of self-distortion because they are aware of their perceived image. A study on women within the workplace showed how certain females believed they were accepting organizational images of stereotypical women due to the dominant organizational culture (Athanassiades, 1974). In the personality literature, scholars state that when individuals internalize given stereotypes and conform to their expected roles, “self-stereotyping” can occur. Self-stereotyping is the outcome of gender groups internalizing stereotypic attributes
of the in-group (Turner et al., 1994). According to socio-psychological research on self-construal, how people define themselves in terms of gender differences is highly context-dependent rather than being inherently fixed (Guimond et al., 2007). Through a series of personality experiments, Guimond and colleagues (2007) found that gender differences in self-construal were highly dependent on the individuals’ environmental context as well as social comparison processes. Specifically, the authors found that gender differences in defining oneself arose only when individuals engaged in between-gender social comparisons (or intergroup social comparisons) and were attenuated during within-gender social comparisons. Thus, this research shows that women are more likely to internalize gender stereotypes when they compare themselves with other men, especially when they are continuously reminded of gender differences. Therefore, in fields where female representation is much lower, and the gender differences are continuously reinforced, it is possible that women are more likely to internalize such stereotypes and show revisions in behavior, such as conformity.

On the other hand, some studies show that token actors may face stereotype threat, or the threat that others’ judgments of their actions will negatively stereotype them in the domain (Steele, 1997). Thus, minority individuals try to contrast themselves from their minority status by deflecting negative stereotype threat (Ambady et al., 2004). For instance, a study on female leaders shows how, since professional roles are generally unassociated with feminine characteristics of emotional warmth, female leaders and professionals try to affirm competency and
assertiveness at the expense of being perceived as warm (Cuddy, Fiske, & Glick, 2008). In line with these results, I propose that female analysts faced with stereotype threat may try to deflect their stereotypes by deviating from their category consensus. Thus, the arguments above lead to the following competing hypotheses on the conformity or deviation behavior of minority actors among themselves.

**H2a:** Female analysts will conform (i.e., forecast closer) to their same-gender consensus more than male analysts will conform to their same-gender consensus.

**H2b:** Female analysts will deviate (i.e., forecast further) from their same-gender consensus more than male analysts will deviate from their same-gender consensus.

**Culture as another contextual factor of minority conformity**

Recently, social psychologists have highlighted how contextual variables, like culture, play as important situational factors that activate conformity and self-stereotyping behavior. Introduced by Festinger (1954), social comparison research shows that the perception of the self is dependent on the specific context the individual is in (Festinger, 1954; Buunk & Mussweiler, 2001; Gardner, Gabriel, & Hochschild, 2002). Since social comparison processes are dependent on the context, discrepancies or tensions between social categories can become situational, rather than individual, factors that affect social comparison. These differences have been referred to as social category fault lines, which become situational standards of social comparison and conformity, such as culture (Garcia, Tor, & Schiff, 2013). Guimond and colleagues (2007) have tried to delineate the universal and culture-specific
consequences of social comparison between genders. The difference in the extent of
gender stereotyping, as well as the tendency to compare oneself with others of the
same social category, may differ across cultures; thus, this difference can be stronger
in some countries compared to others. According to prior research on culture and
self-construal, the individual is viewed as an independent, autonomous entity and
uniqueness is valued in Western cultures (Kim & Markus, 1999). On the other hand,
the interdependent view is exemplified in Asian, Latin-American, and African
cultures (Markus & Kitayama, 1991), where the individual is categorized in
relational concepts to another and conformity is valued (Kim & Markus, 1999). Thus,
the effect of same-category conformity will be stronger in China than in the U.S.

_H3: Female analysts will be less likely to deviate (i.e., forecast further) from their
same-gender consensus when they are working in China._

However, Costa and colleagues (2001) and Guimond et al. (2007) provided
counterintuitive results that showed that gender differences in self-identification
were more strongly pronounced in Western cultures, where traditional gender roles
are comparatively minimized, compared to Eastern cultures. These scholars find that,
contrary to predictions of the social role model, gender differences are magnified in
countries that endorse progressive gender role ideologies because intergroup
comparison is more socially prevalent at a macro-level (Costa et al., 2001). Thus,
women from Western countries tend to identify with feminine attributes more than
women in Eastern countries. Relatedly, studies by Williams and Best (1990) also
showed that gender stereotypes were more distinct and differentiated in Western
cultures. Accordingly, former literature states that although Western countries have more progressive views on gender equality, they also have a starker differentiation between male and female characteristics and personalities (Siddiqi & Shafiq, 2017).

In line with the arguments of prior research, self-stereotyping of female analysts may more strongly occur among male-dominant groups in Western cultures. Aligned with the findings of Guimond and colleagues (2007), I postulate that the differences between male and female characteristics will be stronger in the U.S.; thus, female analysts in the U.S. will have a stronger group identification toward other female analysts. Therefore,

*H4: The same-gender deviation gap between female and male analysts will be greater in the U.S. than in China.*

**METHODS**

**Sample and data collection**

The main source of the data was from the Institutional Brokers Estimate System (I/B/E/S) database, which provided the earnings forecast of analysts. The population for this study included all individual financial analysts who have issued a public forecast on a U.S.-listed Chinese firm from 1998-2012, which consists of a total of 852 unique analysts covering 224 unique firms. For the subsequent target firms, data on firm characteristic and performance data was collected from COMPUSTAT. Analyst background data was obtained through multiple online and secondary sources. This information was collected from web sources and profiles, including
LinkedIn, ZoomInfo, Bloomberg, BrokerCheck by FINRA, Nelson’s directory of Investment Analysts, brokerage profiles, and news articles. Through these data sources, I was able to collect information about the analysts’ demographics—such as gender and ethnicity, educational background, and employment history—and career information such as career starting year and job location.

**Dependent variable**

*Deviation.* The main dependent variable of the analysis was the deviation of analysts from all prior consensus EPS forecasts. The measure was created following the influential work of Hong, Kubik, and Solomon (2000) to find the absolute difference between an analyst’s EPS forecast and the mean EPS forecast of the corresponding target firm’s forecast period. Usually, analysts issue and update multiple forecasts during a forecast period given new information regarding the target firm’s expected performance. In this process, analysts may easily access forecasts issued by other financial analysts regarding the same target firm. Thus, I define $F_{i,j,t}$ as the earnings forecast issued by analyst $i$ on stock $j$ for each target firm’s forecast period $p$. Moreover, for each target firm’s forecast period, I capture the mean forecast as $\bar{F}_{-i,j,p} = 1/n \sum_{m \neq i} F_{m,j,p}$, with $-i$ as all analysts other than analyst $i$ who issued an earnings forecast for stock $j$ at forecast period $p$. Moreover, in order to examine the sequence in which the forecasts were conducted, I coded the analysts’ forecast order based on their announcement date. Using this forecast order, I created the dependent variable that measured the absolute difference between a
focal analysts’ forecast and the mean of all prior forecasts made in the period. The forecast deviation from the consensus is measured as the absolute difference between the analyst $i$’s forecast and the mean forecast:

$$Deviation_{i,j,p} = |F_{i,j,p} - \bar{F}_{-i,j,p}|.$$  

When creating this measure, the first forecast observations that did not have any prior forecasts were omitted for each period. This changed the final observation size to 12,925 observations. Moreover, to check the consistency of the deviation measure, I created another deviation measure using the final revision EPS forecasts only.

**Same-gender deviation.** The second dependent variable was measured in a similar manner as the first dependent variable. To observe which group a focal analyst referenced before issuing her forecast, I calculated the consensus of each gender group prior to the analysts’ forecasts. By measuring the difference between the analysts’ EPS forecast from each gender group’s prior mean forecast, I can examine the within gender deviation of each analyst. Thus, for each forecast period, I coded the forecast order of male and female analysts separately based on the date of their announcement. To illustrate, for female analyst A, I calculated the absolute difference between the forecast of female analyst A and the mean of all prior forecasts made by other female analysts. I did the same for male analyst B’s forecasts deviation from the mean of prior male analysts’ forecasts. Additionally, I omitted the first forecast observations per period for each gender, thus the first male and female forecasters. This changed the final sample size to 12,589 observations.
Independent variables

*Gender.* The main independent variables for the analysis were financial analysts’ gender and career location. In order to obtain the gender of individual analysts, I screened all images, profiles, and news articles found online and hand-coded a dummy variable (0: male, 1: female).

*Analyst location.* For the second independent variable, used various online resources mentioned above to hand-code a dummy variable for whether the analyst was working in the U.S. or China (0: Located in the U.S., 1: Located in China).

Control variables

*Analyst-level controls.* Two sets of control variables were collected and created for the analyses: those regarding analyst characteristics and analysts’ brokerage characteristics. For the control variables related to analyst characteristics, I controlled for analysts’ ethnicity as well as their working experience. *Analyst ethnicity* was a hand-coded dummy variable where Chinese and non-Chinese analysts were differentiated. For working experience, I controlled for *Analyst experience* in cumulative years as well as *Analyst tenure at brokerage* by year. Moreover, I controlled for *Analyst coverage portfolio* by the number of firms covered by analysts in the corresponding year. Analysts’ turnover was controlled by *Analyst experience order* which measures the order of brokerages at which analysts was employed. Additionally, I controlled for the *Analyst status* which was measured by whether the analyst was on the top of the Institutional Investors All-Americans
poll—the most prestigious recognition that financial analysts generally aspire to attain. I created a dummy variable that indicated whether an analyst had ever received an All-Americans award as well as a numerical variable, *Analyst status cumulative*, that measured the cumulative number of awards received over an analyst’s career. Moreover, I controlled for the *Time gap of forecast* between the analyst’s forecasts and the actual EPS announcement date in days. I also controlled for the number of *Forecast revisions* the analysts made for the corresponding forecast period.

**Brokerage-level controls.** For the brokerage variables, I created a measure for the *Total coverage by brokerage* which measures the unique number of target-firms that the analysts’ brokerage covers. *Brokerage size* measures the number of analysts working at the brokerage by year. Moreover, *Total coverage by analyst* measures the number of analysts in the brokerage covering U.S. listed Chinese firms. Lastly, I included industry and year fixed effects in the models. For the industry fixed effects, I followed the SIC classification system obtained from the COMPUSTAT dataset.

**RESULTS**

Table 1 presents the descriptive statistics and correlations for all the variables incorporated into the study. Moreover, Table 2 presents the preliminary t-test analyses, which show that the female and male mean same-gender deviation is significantly different (p<0.01). For the other hypotheses, I find initial support as well. The mean female deviation is slightly lower in China than in the U.S., however,
the difference between the same-gender deviation mean of male and female analysts is greater in the U.S. than in China. Thus, the preliminary analyses show initial support for the third and fourth hypotheses, without incorporating other control variables.

Table 3 presents the result of panel regressions that test the proposed hypotheses. All models include year and industry fixed effects. The effect of control variables is tested in Model 1. Model 2 provides the baseline hypothesis testing gender effects on the likelihood of deviating from the prior mean, within the same target firm-forecast period. This measure was used to measure in order to observe the sequential effect of conformity and deviance. The results show that female analysts tend to deviate less than male analysts ($\beta=-0.1145$, $p<0.01$). The model strongly supports hypothesis 1. A noticeable characteristic of using the Deviation measure is that the time gap between the forecast and actual announcement showed a significant change in direction. This can be explained by the fact that when using the Deviation measure the distance from prior forecasts, it is natural that later forecasts will show a greater discrepancy from the initial forecasts, due to an increase in information. Figure 1 considers this relationship between forecast time gap as well as the deviation from the prior forecast. These figures show that, at first, deviation from the prior consensus is high but then slows down and decreases after a certain point. The second portion
of Figure 1 more clearly shows this non-linear relationship between forecast time and deviation from the prior consensus between male and female analysts. To check for consistency, I used two other measures of deviation in order to check the direction and significance of the gender effect. Along with using the conventional measure of deviation provided by Hong et al. (2000), I also ran regressions using the difference from the consensus forecast and analysts’ last forecast—thus, to see if there is conformity in the analysts' final forecast before the earnings announcement. Regressions using both alternative measures provided consistent results.

Models 3 and 4 are the fixed-effect regressions that test the deviation from the prior same-gender consensus. Model 3 tests the effect of control variables on the likelihood of analysts’ deviating from the prior same-gender consensus. Model 4 tests the female effect on the competing hypotheses of 2a and 2b, which proposed that females may conform to or deviate from the same-gender consensus, respectively. With the control variables, the results show that female analysts are less likely to deviate from the consensus of other female analysts ($\beta=-0.1547$, $p<0.01$). Thus, only hypothesis 2a was strongly supported. The results show that, compared to the sample mean deviation from the prior same-gender consensus (.366), female analysts are 42.3% less likely to deviate from the prior consensus of other females than male analysts are likely to deviate from the prior consensus of other males.
The remaining models present the fixed-effect regressions of location on the likelihood of analysts to deviate from their prior same-gender consensus. Model 5 shows that the same-gender deviation effect is weaker in China than in the U.S (β=-0.0449, p<0.1). In model 6, gender is also incorporated into the model. The results show that females are less likely to deviate from the consensus of other female analysts (β=-0.1551, p<0.01), and that while controlling for the effect of gender, analysts located in China are more less likely to deviate from their same-gender consensus (β=-0.0461, p<0.1). Model 7 tests the third hypothesis. The interaction term between gender and analysts’ location is negative but non-significant. Moreover, even controlling for the interaction effect, the gender coefficient is the only variable that remains significant from the two (β=-0.1322, p<0.01). Thus, although the coefficients show that analysts located in China are less likely to deviate from their same-gender consensus, the results were not statistically significant.

To test hypothesis 4, models 8 and 9 show subsample regressions for the analysts located in China and the analysts located in the U.S, respectively. In model 8, the results show that among analysts located in China, same-gender deviation is lower among female, though, the coefficient size is relatively small and the results are non-significant. However, model 9 reports that among analysts located in the U.S., same-gender deviation is much lower among female analysts, and the results are highly significant (β=-0.1438, p<0.01). Moreover, the coefficient of determination for both models shows that model 5 is more strongly supported than model 6 (R²=0.1152).
Since I used a subsample regression for models 8 and 9, I performed a Chow test to examine whether the regression coefficients of the two models were significantly different. The test results showed that the level of significance for female analysts was statistically different based on their location, which supported hypothesis 4 ($F = 2.770$, $p<0.1$). Thus, my postulation that same-gender deviation among females would be greater in the U.S. than in China was supported. As depicted in Figure 2, although the overall deviation from prior same-gender consensus is lower in China, the gap between male and female in terms of same-gender deviation, is greater in the U.S. Therefore, the results are coherent with the studies of Costa et al. (2001) and Guimond et al. (2007), which showed that self-stereotyping may be greater in Western than in Eastern cultures.

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Insert Figure 2 about here

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DISCUSSION AND CONCLUSION

This study aimed to provide an investigation of minority conformity using an alternative perspective of demographic proportions. The goal of the paper was to examine the conformity behavior of minority actors arising from social comparison processes within minority groups. Overall, the results provided support for the propositions that female analysts are more likely to use other female analysts as their referent groups. Therefore, the findings show that individuals are more likely to
select similar others, or counterparts of their same social category, as their reference group. Using the mechanisms of self-stereotyping, I theorize that this behavior is amplified among token actors. Moreover, regarding the third and fourth hypotheses, the results show that, surprisingly, the level of same-gender referencing among female and male is more strongly contrasted in Western cultures, which is coherent with the findings of former psychology studies (e.g., Costa et al., 2001; Guimond et al., 2007). Thus, the theoretical perspectives of this study focus on the contextual contingencies of minority conformity.

This paper makes both specific and broad contributions to a number of research streams. First, this study attempts to advance research on minority demographic groups in the management and organizational studies. While most former work in both management and finance literature has examined dispositional characteristics found among the general female population (e.g., risk-averseness or conformity), this study suggests that minorities’ behaviors are contingent on their underrepresentation in the field and on the emphasis of cultural stereotypes. Thus, the study highlights that social comparison and gender effects should be examined under its cultural context through cross-country research.

Second, the study adds on to prior literature on social comparison theory in the management field by addressing the need to investigate specific referent groups that focal actors compare their opinions and evaluations with. Extant literature has questioned the extent to which industry mean or median performance when examining social comparison (Shinkle, 2012). Thus, studies on social comparison
must focus on different social or relational groups within an industry to more directly investigate the effect of social influence on performance goals or outcomes. In the current study, I examined differences in group referencing among minority groups.

Third, although the empirical setting focused on female financial analysts, this study is generalizable to other gender and racial minority professionals, such as Asian executives, Jewish managers, black analysts, and female entrepreneurs. Although a growing number of studies on strategic leadership has focused on gender or ethnic effects, they have mostly focused on compensational or strategic outcomes of minority executives. Moreover, there were a number of research that used ethnicity and gender as control or independent variables in their study, but less research has focused specifically on the referencing behavior of minorities. Additionally, while many studies have examined minority conformity in general, this paper examines whether minorities conform to other minorities specifically. This study advances the need for research on group dynamics as well as strategic leadership to review into how minority executives and social elites may be more likely to reference one another when making decisions.

This study is not without limitations and has potential areas of improvement. The demographic background and career information of financial analysts who had issued statements on U.S.-listed Chinese firms were only examined. Future research may examine how the effects of same-gender referencing differ in multiple empirical settings, such as different industries and firms. It would be interesting to see whether same-gender referencing persists or attenuates in industries where female and male
proportions are balanced. As mentioned above, in female-dominated industries such as cosmetics and fashion, the predictions from this study would point toward results moving in the opposite direction, where male executives and leaders conduct greater same-gender social comparison. If these results hold true, then Kanter’s (1977) proposition on proportion skewness would receive greater support.

Another limitation of this study is from the inability to examine social comparison effects among female analysts in more micro-level context, such as within brokerages are teams. Due to data limitations, I was unable to examine the entire analyst background characteristics of all brokerages in the U.S. and China. Therefore, I was unable to examine the proportion of female analysts at the brokerage house or the proportion of female analysts within the focal analyst’s team. I did conduct additional analyses after measuring the proportion of female versus male analysts at the brokerage that forecasted U.S.-listed Chinese firms and the results did not change. This study opens an arena to a more fine-grained investigation of social categories as referent groups. Further research could be conducted on whether other individual or social characteristics override the effect of gender categories. Although ethnicity is examined as one of the key control variables, other visible or relational characteristics could also be of interest. Similarities in hometown, economic background, or prior performance could be examined. Moreover, relational mechanisms, such as affiliations to the same university, prior brokerage, or informal groups may also be of interest to study.
Further research could also examine other social categories, especially ethnic or racial minorities. Will same-ethnicity or same-race referencing be stronger or weaker in culturally diverse countries? As the depiction of gender varies in different cultures, I can predict that stereotypes of different races will vary as well. Therefore, the level of same-ethnicity or same-race categorizing and self-stereotyping may be stronger in some cultures. This would be an interesting and meaningful avenue to research further into.

In sum, this study extends former social comparison literature and takes a step further in trying to delineate gender differences in social comparison processes in a unique empirical setting. Moreover, this study attempts to contribute to the broad stream of research on social processes of decision-making by adding on to former discourse on how evaluation and decision-making is a socially construed process. The paper attempts to argue that institutional actors need to evaluate their opinions and assess their environment by referencing those of others. Moreover, under high uncertainty, actors are more likely to be socially influenced by others when making decisions. Therefore, this study extends past literature related to social processes of firm evaluation and the influence of institutional actors.
REFERENCES


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### Table 1. Descriptive statistics and correlation matrix

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Table 2. Preliminary T-tests

Deviation from (A) entire and (B) same-gender prior forecast consensus

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<th>Fem. (Mean)</th>
<th>dif</th>
<th>St_Err</th>
<th>p_value</th>
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<tr>
<td>All</td>
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<td>.255</td>
<td>.139</td>
<td>.024</td>
<td>.000</td>
<td>11306</td>
<td>2542</td>
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<tr>
<td>All</td>
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<td>.231</td>
<td>.163</td>
<td>.025</td>
<td>.000</td>
<td>11200</td>
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<td>.226</td>
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<td>.179</td>
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Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Figure 1: Deviation and Same-gender deviation among male and female analysts
Figure 2: Same-gender deviation in U.S. and China
본 연구의 목적은 전문가 집단에서 인구 통계적 소수자들의 순응 행위를 분석하는 것이다. 저자는 “도균 지위”로 불리는 소수자 지위 연구에 기반하여 집단 내의 인구 통계적 분포에 따른 순응 행위를 분석한다. 재무 분석가들의 수익예측 데이터를 통해 검증한 결과, 인구 통계적 분포에서 소수자 집단으로 나타나는 여성 재무 분석가의 수익예측이 타 집단의 평균값에 비해 여성 재무 분석가 집단 전체의 평균값에 더욱 가까운 것으로 확인하였다. 또한, 다른 상황적 요인으로 작용할 수 있는 문화적 요인을 확인하기 위해 재무 분석가들이 위치한 국가를 개인주의적 또는 집단주의적 문화권으로 구분하고, 성별과의 상호 작용 효과를 검증하였다. 이를 통해 소수자 집단인 여성 재무 분석가 집단의 순응 행위가 집단주의적 문화권보다 개인주의적 문화권에서 더욱 강하게 나타남을 확인하였다. 본 연구는 순응 행위의 유발 요인으로 단순한 인구통계적 특성에 집중하는 기존 논의에서 벗어나 순응 행위가 인구 통계적 분포 내의 소수자 집단에서 강하게 작용하는 현상임을 보여줌에 의의가 있다. 또한, 본 연구는 전문가 집단에서 나타나는 순응 행위의 문화적 차이를 조명함에 따라 문화에 대한 사회심리학적 논의에 기여한다.

주요어: 순응 행위, 소수자, 도균 지위, 다양성, 문화, 편견, 여성 재무 분석가
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