

Gender, Competition, and Performance: International Evidence*

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Abstract

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Keywords: gender; competition; equity analysts; forecast error; individualism; international evidence

JEL classification: G14; G15; G24

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Abstract

We study whether and how gender differences in performance under competition vary across countries using a hand-collected sample of 18,269 equity analysts from 42 countries over the period 2004–2019. We first show that female analysts exhibit worse forecast accuracy than male analysts. However, in individualistic countries, there is no gender difference in forecast accuracy. We further show that female analysts are more skilled upon entry and are more likely to drop out when underperforming than male analysts in individualistic countries compared to peers in collectivistic countries. We conclude that gender differences in performance under competition are attenuated in individualistic countries.

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1. Introduction

There are well-documented gender differences in preference for competition – men are more competitively inclined than women – and in performance under competition – there is a gender performance gap in favor of men – based on laboratory studies and/or relying on participants and samples largely from western industrialized countries (see, for example, Gneezy, Niederle, and Rustichini 2003; Niederle and Vesterlund 2007; Croson and Gneezy 2009; Niederle and Vesterlund 2011). There is, however, a scarcity of research on the role of gender differences in preference for competition in women’s career choices and job performance in an international setting. This paper fills a gap in current research related to our understanding of gender, competition, and performance by assembling an international sample of equity analysts with data on gender. Equity research is known to be a highly competitive and largely male-dominated profession, in which performance is precisely measured (Clement 1999; Hong, Kubik, and Solomon 2000; Kumar 2010; Fang and Huang 2017).¹ We address two research questions: Are there cross-country differences in the gender performance gap under competition? And if there are, why do they exist?

National cultural values define what constitutes appropriate decisions and behaviors in a society (North 1990). Our main measure of country-level differences is the individualism dimension in Hofstede’s (1980, 2001) national cultural framework—the most important driver of cultural differences across countries (Triandis 1995). Individualistic societies emphasize independence and equality (Hofstede 2011, p. 11), whereas collectivistic societies emphasize in-groups’ interests and harmony (Trompenaars 1993; Hofstede 2001, 2011).

¹ To help establish that equity research is also a highly competitive profession in our sample countries, we obtain crowd-sourced pay information for equity analysts and an average job in each country, and compute pay ratios of average equity analyst pay to GDP per capita (average pay in a country). Using pay ratios in the U.S. as benchmarks, we show that in many countries around the world, equity analysts are paid significantly more than those in the U.S., supporting our premise that equity research is a highly competitive profession in our sample countries.

Because women are less inclined to compete in male-dominated professions, they need to be incentivized to work in a competitive profession such as equity research. We hypothesize that such incentives would vary between individualistic and collectivistic countries. In collectivistic countries, women are expected to prioritize the interests of in-groups (i.e., their own families, such as their economic benefits or recognition) when choosing to enter a competitive profession such as equity research, irrespective of their own aversions to competition. In contrast, in individualistic countries, women are given more latitude to make decisions according to their own preferences and pursuits of individual success (Hofstede 2011, p. 11; Griffin et al. 2017). Based on laboratory and field studies largely from highly individualistic countries, Niederle and Vesterlund (2011) find that beliefs about one's relative performance play an important role in women's entry into competition, suggesting that women who believe they will succeed are more willing to compete. Gervais, Heaton, and Odean (2011) further note that people who believe in themselves exert more effort because they find the marginal cost of effort to be lower than those who do not have such beliefs. We thus expect that in individualistic countries, only women who believe they can excel in competition choose to become equity analysts. Moreover, because of those beliefs, we expect that female analysts in individualistic countries will make more effort than their counterparts in collectivistic countries. Finally, because in individualistic countries women's choices to become equity analysts are driven by their beliefs that they can excel, they are more likely to switch jobs when their beliefs change compared to their counterparts in collectivistic countries. We expect there will be a higher turnover-to-performance sensitivity for female analysts in individualistic countries compared to their peers in collectivistic countries.

In summary, we identify two potential channels through which individualism helps narrow the gender performance gap under competition: 1) in individualistic countries, only

women who believe they can excel in competition choose to enter a competitive profession; and 2) turnover-to-performance sensitivities for women in high individualistic countries are higher than those for women in low individualistic countries.

Using a hand-collected sample of 18,269 equity analysts for whom we have determined gender based on their biographies from 42 countries over the period 2004–2019, we examine whether and how women’s on-the-job performance relative to men’s under competition varies across countries using a difference-in-differences specification. To account for time-varying unobservable firm characteristics that could potentially drive analysts’ coverage decision and their performance, we include firm times year fixed effects (Clement 1999; Hong and Kacperczyk 2010; Hilary and Shen 2013).

We first show that in low individualistic countries, female analysts exhibit worse forecast accuracy than male analysts, consistent with experimental evidence on the gender performance gap in favor of men under competition (see, for example, Gneezy, Niederle, and Rustichini 2003). We further show that in high individualistic countries, there is no significant difference in forecast accuracy between the genders. This finding is consistent with our hypothesis in which a country’s individualism score helps mitigate the gender performance gap under competition.

To address the concern that our main findings are not specific to analysts based in the U.S. and the U.K., which are the two countries with the highest individualism scores as well as the largest number of analysts in our international sample, we repeat our analysis above removing analysts based in those two countries. We show that our main findings remain, suggesting that our main findings are not driven by analysts based in the U.S. and the U.K.

To help establish the causal effect of individualism on narrowing the gender performance gap, we employ a multi-pronged approach. We first employ the instrumental variables approach to isolate the exogenous component of our measure of culture: a linguistic

variable based on pronoun drop (Kashima and Kashima 1998; Davis and Abdurazokzoda 2016). It is worth noting that our main findings remain. One may argue that the effect of our instrument, pronoun-drop, on the gender performance gap is not exclusively through its effect on individualism. Following Leary and Roberts (2014), we next employ a double sort of the average gender performance gap on the instrumental variable (pronoun drop or not) and on a country's individualism score (high versus low). We find that after controlling for individualism, there is no difference in the average gender performance gap between countries permitting pronoun drop and those that do not. In contrast, after controlling for the linguistic rule, the average gender performance gap in high individualistic countries is significantly smaller than that in low individualistic countries. This analysis suggests that the instrument affects the gender performance gap only through the cultural value of individualism. To rule out alternative explanations for our main findings, we also sort women's on-the-job performance relative to men's on a number of social and economic variables: gender equality policies and GDP per capita, and on the three other national cultural values of Hofstede (1980, 2001): masculinity, power distance, and uncertainty avoidance. In all cases, we do not see the gender performance gap varying with the above variables in any meaningful way.

In terms of the channels underlying our main finding, we show that in high individualistic countries, female analysts entering the profession, compared to their peers in low individualistic countries, are more likely to work for more prestigious brokerage houses and cover more important stocks than male analysts at the same point in their careers. Moreover, we show that female analysts in high individualistic countries, compared to their peers in low individualistic countries, work harder, as measured by their forecasting output and frequency of earnings forecasts, than male analysts. Finally, we show that female analysts in high individualistic countries are more likely to drop out when underperforming

than male analysts compared to their peers in low individualistic countries. All these findings suggest that individualism attenuates the negative association between competition and women's on-the-job performance through its effect on women's entry into competition – in high individualistic countries, only women who believe they can excel in competition choose to become equity analysts – and through its effect on higher female analyst turnover-to-performance sensitivities in high individualistic countries compared to their counterparts in low individualistic countries.

We conduct a number of robustness checks of our main findings. First, we employ an updated version of the individualism score using the World Values Survey and European Values Survey. Second, we employ standard errors clustered at different levels: analyst country times year, brokerage times year, analyst, or firm. Third, we include high-dimensional fixed effects such as firm times year times month fixed effects and/or additional fixed effects such as brokerage fixed effects. Finally, we remove individuals from our sample if the individualism ranking of an analyst's country of origin as determined by their name differs from that of their place of work. Our main findings continue to hold across all these additional analyses.

We conclude that there are important cross-country variations in gender differences in performance under competition, and that these differences are shaped by national cultures.

Our paper is among the first in the economics, finance, and accounting literature, as far as we are aware, to assemble an international data set on equity analysts with gender data and to study the role of country-level factors in attenuating the gender performance gap under competition. We contribute to the literature in two ways.

First, our evidence on the important role of national culture in narrowing the gender gap in performance under competition is new to the literature on gender and competition (see the review articles by Croson and Gneezy (2009) and Niederle and Vesterlund (2011)). Prior

work in a laboratory setting typically takes great care in randomly allocating participants (of both genders) to the various treatments, while failing to recognize that in the real world, labor market choices and outcomes are not random, and some social-cultural factors might influence the competitive orientations of men and women (see, for example, Gneezy, Leonard, and List (2009)). As opposed to samples of individuals largely from western industrialized countries in laboratory settings, our global sample of finance professionals allows us to examine the role of individualism in shaping women's choices to enter competitive professions, which in turn narrows the gender performance gap under competition. Moreover, using a global sample of equity analysts with additional data on job performance and job market outcome allows us to delineate the channels through which country-level factors help narrow the gender performance gap under competition.

Second, our paper contributes to the large literature on gender differences in labor market outcomes (see, for example, Goldin and Rouse (2000) and a survey by Blau and Kahn (2000)). Using U.S. data, Benson, Li, and Shue (2022) and Huang, Mayer, and Miller (2022) show a significant gender promotion gap in retail and finance industries, respectively. Egan, Matvos, and Seru (2022) document a gender punishment gap in the financial advisory industry. In one of the first studies on female analysts in the U.S., Kumar (2010) finds female analysts outperform their male counterparts. He attributes the performance difference to workplace discrimination whereby only more capable women are able to enter and stay in the analyst profession compared to men. Relatedly, Fang and Huang (2017) show that male analysts benefit more than female analysts from alumni ties with corporate boards and hence from access to proprietary information. In contrast to prior work, we show that gender differences in job separation are shaped by national culture: *ceteris paribus*, female analysts in high individualistic countries are more likely to drop out than male analysts compared to their peers in low individualistic countries.

Given the ongoing debate among regulators, policy makers, and institutional investors around the world on the role of female business leaders (i.e., women in another highly competitive profession) in creating shareholder value and societal impact, our findings will inform government policies and business practices.

2. Literature Review and Hypothesis Development

2.1. Literature review on gender, competition, and performance

Economists have long documented gender differences in consumption, investment, trading, and labor market outcomes (see, for example, Sundén and Surette 1998; Goldin and Rouse 2000; Barber and Odean 2001). In a survey of gender differences in economic experiments, Croson and Gneezy (2009) identify robust differences in risk preferences, altruism, and competitive preferences. Observing participants in a laboratory setting solving an actual task, Niederle and Vesterlund (2007) find that women are generally less keen on being exposed to competition. Running a field experiment on job-entry decisions, Flory, Leibbrandt, and List (2015) show that women disproportionately shy away from competitive work settings as captured by a competitive compensation regime.²

There is some suggestive evidence of a gender performance gap in favor of men under competition based on laboratory studies and/or field evidence. Gneezy, Niederle, and Rustichini (2003) present experimental evidence that men's performance increases in competition whereas women's does not. Schurchkov (2012) finds that while women underperform men in a high-pressure math-based tournament, women greatly increase their willingness to compete and performance levels in a low-pressure verbal environment,

² Based on field evidence, a number of studies further show that social norms/behaviors affect individuals' preferences for competition. For example, Gneezy, Leonard, and List (2009) find that while women in a patriarchal society are less competitively inclined than men, their counterparts in a matrilineal society are more competitive than men. Booth and Nolen (2012) show that girls from single-sex schools behave more like boys in their preferences for competition.

suggesting that in stereotypical-male tasks competition does seem to generate a large gender gap in performance.

In summary, based on laboratory studies and/or field evidence, prior work largely shows that in male-dominated tasks/careers, men are more competitively inclined than women and that there is a gender performance gap in favor of men under competition. As far as we are aware, no prior work explores the role of national culture in attenuating the gender difference in performance under competition using large cross-country samples of finance professionals.

2.2. Why study equity analysts?

There are a number of reasons for us to use equity analysts as our study subject. First and foremost, equity analysts are known to be in a highly competitive profession in the U.S. (Clement 1999; Hong, Kubik, and Solomon 2000). Kaplan and Rauh (2010) find that in the U.S., while top executives' representation in the top income brackets has increased from 1994 to 2004, Wall Street's representation, which includes equity analysts, has increased even more. For our purpose, we need to establish that equity research is also a highly competitive profession outside the U.S. Using the Eurostat Structure of Earnings Survey (SES), the largest source with harmonized data across 16 European countries for 2010, Denk (2015) finds that financial sector workers, including equity analysts, comprise 19% of top 1% earners, despite the fact that the overall employment share of finance is only 4%. Table IA1 in the Internet Appendix provides an overview of equity analyst pay in our sample countries. The data for average analyst pay come from the Global Salary Calculator.³ To properly

³ The Global Salary Calculator (GSC) is an online database maintained by the Economic Research Institute, that supports international salary management, reporting on gross annual salaries in the form of an overall mean and percentiles from their database of occupations and locations. The GSC uses data provided from both employer and employee, salary survey data, government salary data, and other statistics and data sources. The data are collected on an ongoing basis and in local currency. Data can be downloaded at: <https://www.erieri.com/globalsalarycalculator>. We employ exchange rates in 2022 from the World Bank to convert pay in local currency to U.S. dollars.

account for national economic development and labor market conditions, we obtain GDP per capita in 2021 from the World Bank (the latest data available), and average pay in a country from the Trading Economics, an online database with historical information for countries around the world.⁴ Panel A presents average analyst pay, average pay, and ratios of average analyst pay to GDP per capita and to average pay. We show that there are wide variations in equity analyst pay ratios across sample countries, with India (8.13), Pakistan (6.66), and Vietnam (6.28) having the highest analyst pay ratios (relative to GDP per capita), and Vietnam (6.77), Turkey (5.14), and Thailand (5.04) having the highest analyst pay ratios (relative to average pay in a country). It is worth noting that in the three countries with the highest individualism scores, the U.S., Australia, and the U.K., the pay ratios relative to GDP per capita (average pay) are: 1.54 (2.12), 1.61 (1.96), and 1.63 (1.87), respectively. Panel B conducts a univariate comparison of pay ratio differences in high (top quartile) and low individualistic (the remainder) countries. Using both t-test and Wilcoxon test, we find that analyst pay ratio in low individualistic countries seems to be significantly higher than that in high individualistic countries. That is, using analyst pay ratio (relative to average pay) as a crude proxy for how competitive their job might be, our analysis seems to suggest that equity research is highly competitive in our sample countries, and even more so in low individualistic countries.⁵

Second, equity analysts are also known to be in a largely male-dominated profession (Kumar 2010; Fang and Huang 2017). Prior work finds that male-stereotyped tasks could be

⁴ Data can be downloaded at: <https://www.eri.com/globalsalarycalculator>. The Trading Economics provides average pay in a country in local currency. We employ exchange rates in 2022 from the World Bank to convert pay in local currency to U.S. dollars.

⁵ Prior work such as Hong and Kacperczyk (2010) and Merkley, Michaely, and Pacelli (2017) examine competition among U.S. analysts at the (covered) firm- and industry-level. In an international setting such as ours, we could also argue that there is a global market competing for analyst talent. In this paper, we have opted to capture exposure to competition by an individual entering the equity research profession without exploring any potential cross-sectional variations in the intensity of such exposure; our findings should be interpreted accordingly.

important confounding factors that help explain gender differences in selection into competition and performance under competition (see, for example, Schurchkov 2012; Flory, Leibbrandt, and List 2015). Based on laboratory and field studies from mostly western countries that score highly on individualism, Niederle and Vesterlund (2011) find that beliefs about one's relative performance play an important role in women's entry into competition, and call for further research. Our global sample of analysts serves as a natural setting for exploring the extent to which individualism fosters free expression of women's beliefs about their abilities, with implications for their on-the-job performance relative to men's across countries.

Last but not least, analyst performance, as captured by earnings forecast accuracy using data from the Institutional Brokers Estimates System (I/B/E/S) international files, is precisely measured.⁶

Taken together, our global sample of equity analysts is an important addition to the literature examining the complex relationships between gender, competition, and performance, and is complementary to existing laboratory evidence (see the survey by Niederle and Vesterlund 2011).

2.3. Hypothesis development

Prior work shows that in male-stereotyped tasks, women are less competitively inclined and underperform compared to men (e.g., Gneezy, Niederle, and Rustichini 2003; Niederle and Vesterlund 2007; Schurchkov 2012), which suggests that working in a competitive profession such as equity research would be less appealing to women than to

⁶ In the U.S., Brown, Call, Clement, and Sharp (2015) show that equity analysts compete on multiple dimensions such as industry knowledge, generating underwriting business and/or trading commissions, broker votes, and accurate earnings forecasts. Hong and Kubik (2003) find that both forecast accuracy and optimism are rewarded in the analyst labor market. Given the international setting of our research, we opted to focus on one objective measure of analyst performance – earnings forecast accuracy, which is generally available across countries and is known to be a key determinant of analyst compensation and career advancement (Brown et al. 2015; Hong and Kubik 2003).

men; women would therefore need incentives to enter such professions. We hypothesize that the incentives for women to enter competition vary between individualistic and collectivistic countries.⁷

Collectivistic countries encourage conformity based on in-groups' perspectives. In such countries, women are expected to prioritize the interests of in-groups (i.e., their own families), such as their economic interests or recognition (Hofstede 2011, p. 11). In other words, women in collectivistic countries are motivated primarily by external considerations when they decide to become equity analysts, irrespective of their own aversion to competition.

In contrast, individualistic countries encourage independent opinions. In individualistic countries, women are given more latitude to make decisions according to their own preferences and pursuits of individual success (Hofstede 2011, p. 11; Griffin et al. 2017). Niederle and Vesterlund (2011) further argue that in the western world with high individualism scores, beliefs about one's relative performance play an important role in women's entry to competition. Gervais, Heaton, and Odean (2011) note that people who believe in themselves exert more effort because they find the marginal cost of effort to be lower than those who do not have such beliefs. When pursuing a career, women in individualistic countries put less weight on external considerations and more weight on their potential for individual success in a job. We thus hypothesize that in individualistic countries, only women who believe in their ability to excel in competition choose to become equity analysts.

The above discussions have the following testable implications. As theorized above, in contrast to women in collectivistic countries, women in individualistic countries become

⁷ In contrast, since men are more competitively inclined than women, entering a competitive profession such as equity research is more appealing. We thus hypothesize that incentives for men to enter competition do not vary between individualistic and collectivistic countries.

equity analysts when they believe they can excel in competition. Moreover, because of those beliefs, we expect that female analysts in individualistic countries, in contrast to their counterparts in collectivistic countries, will work harder, more readily update their beliefs, and be more likely to switch jobs when they experience bad performance, leading to higher turnover-to-performance sensitivities.

In summary, we identify two potential channels: in individualistic countries, only women who believe they can excel in competition choose to enter competition, and there are differential turnover-to-performance sensitivities for female analysts across high and low individualistic countries, that may link individualism to a smaller gender gap in performance under competition. Our hypothesis is thus as follows: The gender performance gap under competition is attenuated for female analysts in individualistic countries.

3. Sample Formation and Overview

To test our hypothesis, we assemble a global sample of equity analysts with information on gender, employment location, and performance.

3.1. Sample formation

One way to determine an analyst's gender is to use their full name (see, for example, Kumar (2010) in a U.S. study).^{8, 9} However, the I/B/E/S Detail Recommendations file reports only an analyst's last name and first-name initial, rather than their full name. Regarding an analyst's employment location, one may infer such information from where their brokerage house operates. However, I/B/E/S provides only abbreviated brokerage names.¹⁰ As a result,

⁸ Kumar (2010) relies on a number of sources to obtain the full names of analysts: the Institutional Investor magazine, Nelson's directory of investment research, and analyst directories available at Yahoo Finance and other financial Web sites, supplemented with searches of news articles on Factiva and Google.

⁹ One caveat of our analysis is that analyst gender data is collected only for the lead analyst, whose identity is recorded in the I/B/E/S database.

¹⁰ Before 2006, researchers could get brokerages' full names using the I/B/E/S broker translation file; this translation file is no longer available.

we cannot determine who the analysts are, for which brokerage house they work, and their gender and employment location from I/B/E/S.

To form an international sample of equity analysts for our study, we start with a list of brokerages (with abbreviated names) that provides stock recommendations on global equities in the I/B/E/S Detail Recommendations file over the period 2004–2019. We start our sample period in 2004 because our key data source – Capital IQ’s coverage of analyst biographies – became more comprehensive beginning in 2004.¹¹ We then conduct manual searches in Capital IQ to obtain a brokerage’s full name; its location, which is used to determine affiliated analysts’ country of origin; affiliated analysts’ full names; and those analysts’ gender information, gleaned from reading their biographies.¹² Appendix IA1 in the Internet Appendix provides a detailed description of our manual search and matching process.

Table 1 reports the impact of various matching steps and data filters to arrive at the final sample of 18,269 (unique) equity analysts affiliated with 1,179 brokerages located in 42 countries/regions.¹³ As far as we are aware, ours is one of the largest global samples of equity analysts in the literature (see, for example, Bae, Stulz, and Tan 2008; Bradshaw, Huang, and Tan 2019).

3.2. Key variables

At the firm-analyst-year level, our key variable of interest is *Average forecast error*, constructed as the average of absolute forecast errors that an analyst makes during a year. We use analysts’ annual earnings per share (EPS) forecasts following the extant literature (see,

¹¹ Capital IQ is a market intelligence platform developed by Standard & Poor’s Global. It provides detailed business histories for brokerages and personal information on analysts, including employment history, employment location, and gender. Capital IQ obtains such information directly from Thomson Reuters (Lourie 2019).

¹² Forecasts made by foreign analysts are those covering a firm whose country of primary listing (based on the nation code in Worldscope) differs from the covering analyst’s country of employment.

¹³ One caveat to our sample formation and variable construction is that we keep only analysts whose gender data is available.

for example, Clement 1999; Hong and Kacperczyk 2010; Kumar 2010) and because annual EPS forecasts have the widest coverage, which is important given our international sample. Absolute forecast error is the absolute value of the difference between an analyst's annual EPS forecast and actual EPS normalized by the stock price at the prior fiscal year end after accounting for stock splits. This measure is expressed as a percentage of the prior year's stock price following Hong and Kacperczyk (2010).

As alternative measures of analyst performance, we also introduce the absolute first/last forecast error made by an analyst in their first/last annual EPS forecast, as well as the absolute same week forecast error made by an analyst in their forecast that is within five days after the prior fiscal year's annual earnings announcement.

The data for individualism scores are obtained from the Hofstede Culture Dimension website.¹⁴ A higher value indicates higher individualism (IDV). The indicator variable, *High IDV*, takes the value of one if a country is in the top quartile of the individualism score among the sample countries, and zero otherwise. In this paper, we focus on differences in the gender performance gap between high IDV and low IDV subgroups (as defined above) because countries in the top quartile of the individualism score are relatively more homogenous in terms of gender equality policies and economic development compared to those outside the top quartile (for example, both China and Vietnam in the low IDV subgroup are Communist countries, which are shown to have little gender differences in willingness to compete (Booth, Fan, Meng, and Zhang 2019)). These differences between high and low IDV groups allow us to capture the role of national culture, as opposed to social norms, in shaping women's decisions to enter competitive professions. The Appendix provides detailed variable definitions.

¹⁴ Data can be downloaded at: <https://geerthofstede.com/research-and-vsm/dimension-data-matrix/>.

3.3. Sample overview

Table 2 Panel A presents an overview of our global analyst sample by country. We note that across 42 sample countries, the average share of female analysts is 19.6%, consistent with our premise that equity research is a largely male-dominated profession. The top three countries with the highest female analyst share (in descending order) are: Vietnam (43.1%), Thailand (37.9%), and Portugal (36.8%), and the top three countries with the lowest female analyst share are: Norway (4.2%), Denmark (7.8%), and New Zealand (9.7%). The top three countries with the largest number of earnings forecasts are: the U.S. (1,276,283 observations, representing 48.5% of the sample); the U.K. (243,251 observations; 9.2%); and Canada (194,929 observations; 7.4%).

Table 2 Panel B presents an overview of country-level variables. The top three countries in terms of individualism are: the U.S., Australia, and the U.K.; and the bottom three are: Indonesia, Pakistan, and South Korea. Using the Global Gender Gap Index (GGGI) from the World Economic Forum (WEF) as a marker for gender equality, we show that the top three countries in terms of gender equality are: Norway, Finland, and Sweden; and the bottom three are: Pakistan, Turkey, and the United Arab Emirates. The top three countries in terms of economic development as measured by GDP per capita are: Norway, Switzerland, and Denmark; and the bottom three are: India, Vietnam, and Pakistan.

Table IA2 Panel A in the Internet Appendix presents the correlation matrix of country-level variables. We show that there is a negative and significant association between the female share of equity analysts and the indicator variable *High IDV*, between the female share of equity analysts and a country's GGGI, and between the female share of equity analysts and a country's GDP per capita. Moreover, we show that there are positive and significant associations between *High IDV* and GGGI, and between *High IDV* and GDP per

capita, suggesting that highly individualistic countries introduce more gender equality policies and enjoy high levels of economic development.

Figure 1 plots the average female share of equity analysts in a country in relation to its individualism score. We show a negative association between a country's individualism score and its share of female equity analysts. As far as we are aware, we are the first to show that in the most developed western countries with the most generous gender equality policies in which women are on par or exceed men in higher education and many other dimensions, women have the lowest presence in equity research. Why is that? In a *Science* article, Falk and Hermle (2018) find that higher levels of gender equality and economic development accentuate gender differences in preferences (e.g., risk-taking, patience, and trust) across countries. Our finding of a negative association between a country's individualism score and its share of female analysts is consistent with their finding, which also serves as univariate evidence in support of our premise that equity research is a competitive profession and women in individualistic countries have more freedom in making career choices.

Table 3 Panel A presents the summary statistics for key country-level variables. The sample comprises 704 country-year observations over the period 2004–2019. We show that the average female share of equity analysts across the 42 sample countries is 16.5%. We further show that the sample average individualism score is 0.51, the sample average GGGI is 0.71, and the sample average GDP per capita is 30.97 thousands.

Panel B presents the summary statistics for key analyst-level variables. The sample comprises 610,847 firm-analyst-year observations over the period 2005–2020. We show that the mean (median) *Average forecast error* (in percentage points) across the 42 sample countries is 2.90% (0.74%). Using a sample of stocks covered by I/B/E/S over the period

1980–2005, Hong and Kacperczyk (2010) show that the mean absolute forecast error is 3.31%. Our summary statistics for *Average forecast error* are largely consistent with theirs.¹⁵

At the firm-analyst-year level, the average female share of equity analysts in the international sample is 11.0%. Compared to the statistics at the country-year level in Panel A, the lower share at the firm-analyst-year level suggests that female analysts cover fewer firms than male analysts.

Table IA2 Panel B in the Internet Appendix presents the correlation matrix of analyst-firm-level variables. We show that there is no significant association between the indicator variable *Female* and three of the four performance measures: *Average forecast error*, *First forecast error*, and *Same week forecast error*, whereas there is a positive and significant association between the indicator variable *Female* and *Last forecast error*. We further show that the indicator variable *High IDV* is negatively and significantly correlated with all four different measures of analyst performance, suggesting that, in general, analysts in individualistic countries perform better compared to their peers in collectivistic countries. Gray and Vint (1995) argue that in collectivistic societies, managers' preference for in-group harmony may reduce the amount of information collected and the breadth of its dissemination to market participants, hence reducing their firms' incentives to invest in transparent reporting. In contrast, in individualistic societies, managers value accountability and transparency (Gray 1988; Hofstede 2011). Consistent with the above arguments, Eun, Wang, and Xiao (2015) show that firms' information environments are more transparent in

¹⁵ It is informative to compare our international sample to the U.S. sample, which is well studied in the analyst literature (see, for example, Clement 1999; Hong, Kubik, and Solomon 2000; Hong and Kacperczyk 2010; Clement and Tse 2005). Table IA3 in the Internet Appendix presents the summary statistics for key analyst-level variables for only the U.S. sample. We show that across all four analyst performance measures, the U.S. sample exhibits smaller values than those in the international sample, consistent with our conjecture that a firm's being located in the country with the highest individualism score—the U.S.—will have information environments that are more transparent than those of firms outside the U.S.; our conjecture is also consistent with the findings in Eun, Wang, and Xiao (2015).

individualistic societies, and we show that such transparency helps equity analysts in individualistic countries outperform their peers in collectivistic countries.

Table 3 Panel C presents the univariate difference-in-differences (DID) analysis of gender differences in performance under competition in the high IDV and low IDV subsamples. We present the average gender difference in performance in the high and low IDV subsamples and conduct the t-test for the difference between the two subsamples.¹⁶ We show that in three out of the four analyst performance measures (with the exception when the measure is *Last forecast error*), the gender performance gap in favor of men is significantly attenuated in high IDV countries. Given that omitted variable bias in univariate comparisons can mask true relations between the variables, we next turn to multiple regressions to properly test our hypothesis.

4. Main Findings

In this section, we examine whether there is any cross-country gender difference in performance under competition using the following panel data regression specification:

$$\begin{aligned} \text{Forecast performance}_{c,i,j,t} = & \alpha + \beta_1 \text{Female}_j + \beta_2 \text{Female}_j \times \text{High IDV}_c + \\ & \beta_3 \text{Country characteristics}_{c,t-1} + \beta_4 \text{Analyst characteristics}_{j,t-1} + \\ & \beta_5 \text{Brokerage characteristics}_{j,t-1} + \text{Firm}_i \times \text{Year}_t \text{ FE} + e_{c,i,j,t} \end{aligned} \quad (1)$$

where the dependent variable is analyst forecast performance. Our main measure, *Average forecast error*, is the average of absolute forecast errors made by analyst j residing in country c on firm i when making the current year t EPS forecasts. For robustness checks, we also use three other performance measures: *First forecast error*, *Last forecast error*, and *Same week forecast error*. *Female* is an indicator variable that takes the value of one if analyst j is a female, and zero otherwise. Our control variables largely follow prior literature, such as Clement (1999), Bae, Stulz, and Tan (2008), Hong and Kacperczyk (2010), Kumar (2010),

¹⁶ To facilitate comparison across analysts following different firms, we demean analyst forecast errors at the firm-year level.

and Bradshaw, Huang, and Tan (2019). Firm times year fixed effects are included to control for time-varying unobservables that might drive an analyst's coverage decisions as well as their performance (Clement 1999; Hong and Kacperczyk 2010; Hilary and Shen 2013). The sample consists of firm-analyst-year observations.

4.1. Using an average performance measure

Table 4 presents the regression results when the dependent variables are different measures of analyst forecast performance. Our variables of interest are the indicator variable, *Female*, and the interaction term: *Female* \times *High IDV*. Column (1) presents the results when the dependent variable is *Average forecast error*. We first show that in low IDV countries, there is a positive and significant association between female analysts and *Average forecast error*, i.e., there is a significant underperformance of female analysts compared to their male counterparts, consistent with findings in controlled experiments that under competition females perform worse than their male counterparts (see, for example, Gneezy, Niederle, and Rustichini 2003). In terms of economic significance, we show that *ceteris paribus*, female analysts in low IDV countries on average produce *Average forecast error* that is 0.043% larger than their male counterparts. Given that the sample average for *Average forecast error* is 2.902%, the performance gap is economically significant.¹⁷

Next, we show that the coefficient on the interaction term *Female* \times *High IDV* is negative and significant, suggesting that female analysts in high IDV countries (for example, the U.K.) tend to perform better than their male counterparts compared to their peers in low IDV countries (for example, Japan) – a difference-in-differences interpretation. In terms of

¹⁷ The mean (median) value of sample firms' market capitalization is USD 1.14 billion (USD 0.29 billion). The mean (median) value of sample firms' P/E ratio is 28.44 (17.92). In terms of economic significance, when using mean values, a difference of 0.043% in forecast error corresponds to a difference of USD 0.49 million in earnings, and a difference of USD 13.94 million in market value; when using median values, a difference of 0.043% in forecast error corresponds to a difference of USD 0.13 million in earnings, and a difference of USD 2.24 million in market value.

economic significance, we show that *ceteris paribus*, female analysts in high IDV countries on average produce *Average forecast error* relative to their male counterparts that is 0.059% smaller than their female peers in low IDV countries. Given that the sample average for *Average forecast error* is 2.902%, the performance gap is economically significant.¹⁸

To test our hypothesis, we employ the F-test of the null that the sum of the coefficients on *Female* and *Female* \times *High IDV* is zero, i.e., there is no gender performance gap under competition in high IDV countries. The p-value shows that we fail to reject the null, suggesting that female analysts in high IDV countries perform the same as their male counterparts, supporting our main hypothesis.

In addition to the main findings above, we show that the coefficient on *High IDV* is negative and significant. Given our inclusion of firm times year fixed effects, this coefficient captures the effect of a home country's individualism score on a foreign analyst's forecast performance of domestic stocks (e.g., a British analyst forecasting the performance of German stocks). We show that for these foreign analysts, *Average forecast error* is on average smaller if they are from high IDV countries than if they are from low IDV countries.¹⁹ We also show that the coefficient on *GGGI* is positive and significant. Given our inclusion of firm times year fixed effects, this coefficient captures the effect of a home country's gender equality politics and practices on a foreign analyst's forecast performance of domestic stocks (e.g., a Norwegian analyst forecasting the performance of French stocks.)

¹⁸ In terms of economic significance, when using mean values, a difference of 0.059% in forecast error corresponds to a difference of USD 0.67 million in earnings, and a difference of USD 19.13 million in market value; when using median values, a difference of 0.059% in forecast error corresponds to a difference of USD 0.17 million in earnings, and a difference of USD 3.07 million in market value.

¹⁹ The social psychology literature establishes that people in high IDV countries are more overconfident and exert more effort (Markus and Kitayama 1991; Heine, Lehman, Markus, and Kitayama 1999; Chui, Titman, and Wei 2010; Gervais, Heaton, and Odean 2011) and have analytical thinking styles (Nisbett, Peng, Choi, and Norenzayan 2001). The negative coefficient on *High IDV* in column (1) is consistent with these interpretations. Our channel analyses in Section 6 provide further supporting evidence for some of those interpretations.

Finally, we show that the indicator variable *Foreign analyst* and *Forecast horizon* (i.e., the average number of months between an analyst's forecast date and the date of the annual earnings announcement) are both positively and significantly, whereas firm-specific and general experiences, and brokerage size (proxying for resources) are negatively and significantly, associated with *Average forecast error*. All these findings are consistent with prior work (see, for example, Clement 1999; Clement and Tse 2005; Bae, Stulz, and Tan 2008).

4.2. Controlling for the timing of analyst forecasts

As is well-established, the timing of forecasts matters for assessing analyst performance (Hong, Kubik, and Solomon 2000; Clement and Tse 2005). For example, when an analyst is making their very first forecast, the role of their private information generated by effort and skill is more prominent than when an analyst is making subsequent forecasts. When an analyst is making their last forecast, more information is available, and the role of their private information diminishes, likely resulting in herding among analysts. We thus expect that if any gender difference in performance will ever appear, it will do so during the first forecast and not in the last.

In columns (2)-(3), we employ two alternative measures of performance: *First forecast error* and *Last forecast error*. We show that when the performance measure is *First forecast error*, the F-test of the null that the sum of the coefficients on *Female* and *Female* \times *High IDV* is zero rejects the null, suggesting that female analysts in high IDV countries significantly outperform their male counterparts when making their first forecasts. When the performance measure is *Last forecast error*, the F-test of the null fails to reject the null, suggesting that female analysts in high IDV countries perform the same as their male counterparts when making their last forecasts. The difference in findings using different measures of forecast performance is consistent with the intuition that the timing of forecasts

matters in assessing gender difference in performance under competition: *ceteris paribus*, earlier forecasts better capture ability and skill (and/or effort), whereas later forecasts are more about information being available and/or herding due to career concerns (Hong, Kubik, and Solomon 2000).

Although we control for the timing of each forecast using *Forecast horizon* in the above analyses, the first/last forecasts do not properly control for the exact timing of those forecasts, especially if female analysts might consistently make their forecasts later than their male counterparts, resulting in our findings above. To level the playing field when assessing gender difference in performance, we focus on a subsample of forecasts made within five days after the prior fiscal year's earnings announcement. We expect this subsample analysis will give us a clean test of the gender difference in performance after requiring the same timing of those forecasts.

Column (4) presents the results when the dependent variable is *Same week forecast error*. We show that the coefficient on the interaction term *Female × High IDV* is negative and significant, suggesting that female analysts in high IDV countries tend to outperform their male peers compared to female analysts in low IDV countries. In terms of economic significance, we show that *ceteris paribus*, female analysts in high IDV countries produce *Same week forecast error* relative to their male counterparts that is 0.122% lower than their female peers in low IDV countries. Given that the sample average for *Same week forecast error* is 3.322%, the performance gap is economically significant.

The F-test of the null that the sum of the coefficients on *Female* and *Female × High IDV* is zero fails to reject the null, suggesting that female analysts in high IDV countries perform the same as their male counterparts, supporting our main hypothesis that a country's individualism score mitigates gender differences in performance under competition.

4.3. Removing analysts based in the U.S. and the U.K.

To address the concern that our main findings are not specific to analysts based in the U.S. and the U.K., which are the two countries with the highest individualism scores as well as the largest number of analysts in our international sample, we repeat our analysis above removing analysts based in these two countries.²⁰ Table IA4 in the Internet Appendix presents the results.²¹ We show that in three out of the four specifications, the F-test of the null that the sum of the coefficients on *Female* and *Female* \times *High IDV* is zero fails to reject the null, suggesting that female analysts in high IDV countries perform the same as their male counterparts, supporting our main hypothesis.

In summary, our results in Table 4 highlight the importance of national culture in attenuating or even reversing gender differences in performance under competition, supporting our hypothesis.

5. Identification

Informal institutions such as culture change sufficiently slowly that they are not likely to be caused by analyst performance over the time horizon in our study. Further, the individualism scores that we use to moderate analyst performance over the period 2005–2020 were measured in the 1960s and 1970s, which also works against endogeneity or reverse causality. However, the association between individualism and the gender performance gap

²⁰ Kumar (2010) finds that female analysts outperform male analysts in the U.S. over the sample period 1983–2005. Using a sample of U.S. equity analysts with LinkedIn profile photos over the period 1990–2017, Peng, Teoh, Wang, and Yan (2022) find that female analysts in general are more accurate than male analysts. In untabulated analysis, using either our sample that overlaps with that of Kumar (2010) over the period 2004–2005, or our sample that backfills analyst gender information in 2004 up to 1996 and hence overlaps with that of Kumar (2010) over the period 1996–2005, we find that female analysts indeed outperform male analysts over those sample periods. However, we find no gender difference in performance for equity analysts based in the U.S. over the more recent sample period 2006–2019. We attribute the difference in findings to the different sample periods employed.

²¹ In untabulated analyses, we repeat Table 4 regressions, removing countries with five or fewer female analysts: Argentina, Denmark, Hungary, Israel, and New Zealand, resulting in a drop in sample size by 3,698 observations (representing 0.6% of the sample). To ensure our premise holds that equity analysts are in a competitive profession with high pay, we also repeat Table 4 regressions, removing the top five countries with the highest personal income tax rates: Austria, Belgium, Denmark, Israel, and the Netherlands, resulting in a drop in sample size by 10,123 observations (representing 1.7% of the sample). In both cases, our main findings remain.

under competition could be affected by omitted variables (such as the cultural value of masculinity) or some confounding factors (such as economic development). We employ a multi-pronged approach to address those concerns.

5.1. The instrumental variables approach

To address the concern that both analyst performance and individualistic values may be determined by a third factor that we fail to control in Equation (1), we employ an instrumental variables approach to isolate the exogenous component of our measure of culture. Following Licht, Goldschmidt, and Schwartz (2007) and Griffin et al. (2018), we use a linguistic variable based on pronoun drop (Kashima and Kashima 1998; Davis and Abdurazokzoda 2016). The instrument is a somatic rule: the license to drop pronouns (*Pronoun drop*). This grammatical rule reflects whether a country's primary language permits speakers to drop a personal pronoun when used as the subject of a sentence. For example, pronoun drop is not permitted in English, as the pronoun "I" is required to make sense of the sentence "I speak". As Kashima and Kashima (1998, p. 465) argue, "An explicit use of 'I' ...signals that the person is highlighted as a figure against the speech context that constitutes the ground; its absence reduces the prominence of the speaker's person, thus reducing figure-ground differentiation." The emphasis on the pronominal subject (especially "I" or "you") in languages in which pronoun drop is not permitted is expected to be associated with the cultural dimension of individualism. In contrast, the greater contextualization of the subject in languages that permit pronoun drop is expected to be associated with more collectivistic cultures.

Table 5 presents the results from the instrumental variables analysis. Panel A presents the first-stage regression results where individualism is projected onto the instrumental variable: *Pronoun drop*, as well as all the controls used in Table 4. The adjusted R^2 from the first-stage model is 0.866, which shows that our instrumental variable and the control

variables have significant explanatory power. Panel B presents the second-stage regression results. We show that the coefficients on the interaction term *Female* × *High IDV (instrumented)* are negative and significant in three out of the four specifications. Importantly, we fail to reject the null that there is a gender difference in performance in high IDV countries in three out of the four specifications.

5.2. Establishing the cultural channel

To establish that our instrumental variable exerts its effect on narrowing the gender performance gap under competition only through the channel of individualism, we follow Leary and Roberts (2014) to perform a double sort of the data based on the instrumental variable (*Pronoun drop* or not) and a country's individualism score (*High IDV* or not). The intuition for this analysis is as follows. If our instrument (*Pronoun drop*) might affect the gender performance gap through channels other than individualism, we would observe that the gender performance gap varies with our instrument within each high (low) IDV subgroup. If instead, we show the gender performance gap does not vary with our instrument within each IDV subgroup, but only varies between the high and low IDV subgroups after controlling for our instrument, it is unlikely that our instrument affects the gender performance gap via channels other than individualism.

Table 5 Panel C presents the double sort results. Within each two by two combination, we compute the average gender performance gap across firm-analyst-year observations and conduct a t-test of whether this average is significantly different from zero. The row labeled "Yes – No" presents the t-test for the difference in the average gender performance gap between countries with pronoun drop and those without. We show that after controlling for individualism, there is no difference in the gender performance gap between countries permitting pronoun drop and those that do not. The column labeled "High – Low" presents the t-test for the difference in the average gender performance gap between high IDV and low

IDV subgroups. We show that, after controlling for the linguistic rule, the gender performance gap in high IDV countries is significantly smaller than that in low IDV countries. In other words, holding the linguistic rule constant, the gender performance gap is negatively and significantly correlated with the individualism score. The converse is not true. The gender performance gap is largely uncorrelated with the linguistic rule, holding the individualism score constant. This analysis suggests that our instrument affects the gender performance gap only through the channel of individualism.

5.3. Addressing alternative explanations

Our main hypothesis is that the national cultural value of individualism helps attenuate the gender performance gap under competition because in individualistic countries, women are given more latitude to make decisions according to their own preferences. One may argue that a country's gender equality policies and practices and/or economic development could also help level the playing field by providing more economic/educational resources to women, resulting in more women in the labor force and possibly more women in the finance profession, including as equity analysts. It is worth noting that both the social and economic channels above do not speak to whether there are meaningful variations in the gender performance gap under competition across countries. Nonetheless, it is important to rule out alternative explanations; for example, does the level of a country's economic development underlie our main findings? To allow for this possibility, we repeat our analysis in Table 4 by replacing individualism with social and economic variables (one at a time): gender equality policies (*High GGGI*) and level of economic development (*High GDP per capita*). Table 6 Panel A presents the results.

We show that across all specifications, the coefficient on the interaction term *Female* \times *High GGGI* (*Female* \times *High GDP per capita*) is not significantly different from zero,

suggesting that neither social policies promoting gender equality nor economic development plays any significant role in narrowing the gender performance gap under competition.

Under the national cultural framework of Hofstede (1980, 2001), in addition to individualism, there are three other national cultural values: masculinity (MAS), power distance (PDI), and uncertainty avoidance (UAI). Conceptually, as delineated in Section 2, we hypothesize that the value of individualism, as opposed to the other three values, narrows the gender performance gap under competition. One may still argue that these other values could drive our main findings, given that all these national cultural values are positively correlated.

Panel B presents the results when we repeat our analysis in Table 4 by replacing individualism with the three other national cultural values of Hofstede (1980, 2001) (one at a time). In all cases, we do not see that the gender performance gap varies with the above variables in any meaningful way, suggesting that any measure of national culture other than individualism does not explain our main findings.²²

In summary, we conclude that the effect of individualism on narrowing the gender performance gap under competition is likely to be causal.

6. The Channels

In Section 2, we hypothesize that there are two possible channels: in individualistic countries, only women who believe they can excel in competition choose to enter competition, and there are differential turnover-to-performance sensitivities for female analysts across high and low individualistic countries, that may link individualism to a

²² The negative and significant coefficient on *Female* \times *High UAI* in three out of four specifications suggests that female analysts in high UAI countries tend to perform worse than their male counterparts compared to their peers in low UAI countries. Parboteeah, Hoegl, and Cullen (2008) posit and find support that in high uncertainty avoidant countries, traditional gender roles are promoted. Our findings that *High UAI* accentuates the gender performance gap under competition are consistent with their proposition. Importantly, when we add *High UAI* and its interaction term with *Female* to our main specification in Equation (1), our main findings remain.

smaller gender gap in performance under competition. In this section, we conduct analyses examining these two channels.

6.1. Analyst skills

To explore the first channel, we need to introduce proxies for analyst skills. We employ two proxies: the prestige of the brokerage house with which an analyst is affiliated, and the economic significance of an analyst's stock portfolio when starting out (first-time analysts are identified by their first appearance in the I/B/E/S database).²³ We zoom in on the brokerage and stock portfolio characteristics of analysts at the start of their professional careers to help separate out (innate) skills from experience (accrued from working as analysts).

We employ a univariate DID comparison by first sorting our first-time analysts into high and low IDV country subsamples, then comparing gender differences in brokerage/stock portfolio characteristics within each subsample, and lastly comparing the gender difference in the same characteristic between the two IDV subsamples. Brokerage reputation is based on an annual global ranking using a broker's number of analysts employed. Top stocks are based on a country-year ranking using either total assets or market capitalization. Essentially, we want to explore whether brokerage/stock portfolio characteristics are consistent with our first channel, that female analysts in high IDV countries are more skilled than their male counterparts compared to their peers in low IDV countries.

Table 7 Panel A presents the results. We first show that in high IDV countries, 40% of new female analysts work for the top ten brokerage houses compared to 27% of new male analysts. In low IDV countries, 22% of new female analysts work for the top ten brokerage

²³ I/B/E/S has been anonymizing the names of contributing brokers and their analysts since 2006, which makes it almost impossible to study inter-brokerage moves, such as an analyst moving to a more prestigious brokerage as a marker for superior analyst skills (Hong and Kubik 2003). As a result, we have to resort to alternative measures in this paper to proxy for analyst skills.

houses compared to 15% of new male analysts. The DID t-test in column (13) shows that the gender gap in women's favor for working at the most prestigious brokerage houses in high IDV countries is significantly larger than that in low IDV countries, suggesting that female analysts are more skilled (based on the prestige of brokerages) in high IDV countries compared to their peers in low IDV countries. Using an alternative measure of prestigious brokerages (i.e., top 20 brokerages) does not change our main finding.

Panel A further shows, through our use of top stocks based on total assets in the top quintile to capture economically important stocks in an analyst's stock portfolio, that in high IDV countries, 42% of the stock portfolios of new female analysts are important stocks compared to 38% of the stock portfolios of new male analysts. In low IDV countries, 40% of the stock portfolios of new female analysts are important stocks compared to 41% of the stock portfolios of new male analysts. The DID test in column (13) shows that the gender gap in women's favor for covering more important stocks in high IDV countries is significantly larger than that in low IDV countries, suggesting that female analysts are more skilled (using the importance of stock portfolios) in high IDV countries compared to their peers in low IDV countries.²⁴

Taken together, the results in Table 7 Panel A provide support for our first channel, that in individualistic countries, only women who are capable choose to become equity analysts, resulting in no gender difference in performance.

6.2. Analyst effort

To further explore the first channel, i.e., only women who believe they can excel in competition choose to enter the equity analyst profession, we introduce two direct measures

²⁴ Using top stocks based on total assets in the top decile to capture the economic significance of analysts' stock portfolios gives weaker but consistent results. Relatedly, using top stocks based on market capitalization gives similar findings.

of effort: # *alternative forecasts*, defined as the number of other forecasts, such as book value per share and dividend per share made by an analyst; and *Forecast frequency*, defined as the number of annual EPS forecasts an analyst makes in a year. Gervais, Heaton, and Odean (2011) show that people who believe in themselves exert more effort than those without such beliefs. We employ the same regression specification as Equation (1). Table 7 Panel B presents the results.

We first show that in low IDV countries, there is a negative association between the indicator variable *Female* and $\ln(\# \text{ alternative forecasts})$, and a positive association between the indicator variable *Female* and *Forecast frequency*. Importantly, the coefficient on the interaction term $\text{Female} \times \text{High IDV}$ is positive and significant in both columns, and the F-test rejects the null that the sum of the coefficients on *Female* and $\text{Female} \times \text{High IDV}$ is zero, i.e., female analysts in high IDV countries exert the same effort as their male counterparts.

Taken together, the results in Table 7 provide support for our first channel, that in individualistic countries, only women who are capable and willing to work hard choose to become equity analysts, reducing gender performance gap under competition.

6.3. Analyst turnover-to-performance sensitivity

In this section, we conduct our analysis on the gender difference in analyst turnover-to-performance sensitivity (TPS) between the high and low IDV country subsamples. The indicator variable, *Turnover*, for analyst j in year t takes the value of one if this is the year in which analyst j makes their last forecasts (i.e., there are no further forecasts after year t according to I/B/E/S).²⁵ The indicator variable, *Bad performance*, takes the value of one if the

²⁵ Our analysis above does not differentiate between voluntary turnover and forced turnover (i.e., firings) due to data limitations. It is worth noting that even if some turnovers are forced, as long as they do not vary systematically in high and low IDV countries, the analysis in this section is still consistent with our conceptual framework: in individualistic countries, women are more likely to switch jobs if they experience bad

average of an analyst's adjusted forecast accuracy in year t and $t-1$ is in the bottom quartile, and zero otherwise. Then, for the sample of analysts (sorted by gender and the individualism score of each analyst's country), we compute the turnover rate in year $t+1$ based on the information that a female analyst has left the profession. Our univariate comparison of the turnover rate conditional on performance can thus serve as a crude proxy for analyst TPS. Table 8 presents the results.

We show that female analysts experience a significantly higher turnover rate when underperforming (as measured by their past performance being in the bottom quartile) relative to male analysts in high IDV countries (column (5)): 10% of underperforming female analysts are gone compared to 7% of underperforming male analysts in high IDV countries. In contrast, female analysts experience a similar turnover rate when underperforming relative to male analysts in low IDV countries (column (10)): 12% of underperforming female analysts are gone compared to the same 12% of underperforming male analysts in low IDV countries. The DID test in column (11) suggests that there is a significant gender gap in TPS between high and low IDV countries.

We conclude that individualism attenuates the negative association between competition and women's on-the-job performance through its effects on women's entry into competition and on greater female analyst turnover-to-performance sensitivity in high IDV countries compared to that in low IDV countries.

7. Additional Investigation

We conduct a number of robustness checks of our main findings.

7.1. Employing an updated version of Hofstede's individualism score

performance and update their beliefs (that they are not good at equity research) compared to women in collectivistic countries, thereby narrowing the gender performance gap in individualistic countries.

Hofstede's (1980, 2001) individualism score was constructed from answers to a survey of 117,000 IBM employees across the company's subsidiaries in 70 countries between 1967 and 1973 (see the Appendix for the list of survey questions). Although Hofstede's score is based on survey data from the late 1960s and early 1970s, as noted earlier, Beugelsdijk, Maseland, and van Hoorn (2015) find that cultural change is absolute rather than relative, i.e., countries' scores on the Hofstede dimensions relative to the scores of other countries have changed little over time, which is important to our empirical analysis.

As a robustness check, we employ an updated version of the individualism score derived from survey data from the World Values Survey (WVS) and its equivalent, the European Values Study (EVS), over the period 1981–2002 (see the Appendix for detailed description). *High IDV_WVS* is an indicator variable that takes the value of one if a country is in the top quartile of updated individualism scores, and zero otherwise. Table IA5 in the Internet Appendix replicates the analysis in Table 4 using the updated individualism score.

We show that in low IDV countries, across all four forecast performance measures, female analysts significantly underperform their male counterparts. However, in high IDV countries, there is no significant difference in performance between the genders.

7.2. Using standard errors clustered at different levels

Our main regression specifications in Table 4 employ standard errors clustered at the firm times year level to account for cross-firm and time-series dependence in the residuals of a given analyst's forecast errors (Petersen 2009). One could argue that the residuals of analyst forecast errors may also be correlated across observations within a country-year, across observations within a brokerage-year, across observations by an individual analyst, or across observations by a firm. As robustness checks, we employ standard errors clustered at the analyst country times year, brokerage times year, analyst, or firm level to account for possible

cross-sectional or temporal correlation at those levels. Table IA6 in the Internet Appendix presents the results. We show that our main findings remain.

7.3. Using forecast-level observations and including high-dimensional fixed effects

As a robustness check, we include high-dimensional fixed effects using firm-forecast-analyst-year observations. We include firm times year times month fixed effects because of known gender differences that might result in female analysts' forecasts being later than those made by their male counterparts. Using more granular fixed effects allows us to compare forecasts made by the different genders within a short window (in this case monthly) to help control for forecast timing differences. Table IA7 Panel A in the Internet Appendix presents the results. We show that our main findings remain unchanged when including different fixed effects and using more granular performance measures at the forecast level.

As a further robustness check, we add brokerage fixed effects to the specification in Equation (1) using firm-analyst-year observations to account for time-invariant brokerage characteristics, including differences in competitive pressure associated with different brokers (Bradley, Gokkaya, and Liu 2017). Table IA7 Panel B presents the results. We show that our main findings remain.

7.4. Removing potentially misclassified analysts

Thus far in our analysis, we have determined an analyst's country of origin by the location of their office. It is possible that using an analyst's office location might potentially misclassify their country of origin; for example, an analyst from the U.S. (based on their name, a high IDV country) might be working in Japan (based on their place of work, a low IDV country), which would create noise in our analysis.

As a final robustness check, we resort to a proprietary database provided by Origins Info Ltd. based on sources such as the American Dictionary of Family Names and

international telephone directories, to identify the most likely ethnic origin for analysts in our sample. Origins Info's classification assigns an ethnicity to each name based first on the family name and, when family names are inadequate for accurate identification (e.g., for family names such as Lee), uses a combination of an individual's family name and given name to identify ethnicity (Hegde and Tumlinson 2014).

Our full sample consists of 18,269 equity analysts from 42 countries. We are able to determine ethnicity using names for 16,318 analysts. Among those, we keep 11,444 equity analysts from 42 countries for whom the individualism ranking of an analyst's country of origin as determined by their name is the same as that of their place of work.

Table IA7 Panel C presents the regression results. Consistent with our intuition, we show that our main findings become stronger when we employ a subsample of analysts with cross-validated information on their respective countries of origin.

We conclude that cross-country differences in cultural values attenuate gender differences in performance under competition.

8. Conclusions

This paper, as far as we are aware, is the first in the literature to study whether and how gender differences in performance under competition vary across countries. Our main measure of country-level differences is the individualism dimension in Hofstede's (1980, 2001) national cultural framework. Individualistic societies emphasize independence and equality (Hofstede 2011), whereas collectivistic societies emphasize in-groups' interests and harmony (Trompenaars 1993; Hofstede 2001, 2011). We expect that individualism helps narrow the gender performance gap under competition through its effects on women's entry into competition, as well as on differential turnover-to-performance sensitivities for female analysts between high and low individualistic countries.

Using a hand-collected sample of 18,269 equity analysts from 42 countries over the period 2004–2019 and firm times year fixed effects to account for time-varying unobservables that could potentially drive analysts’ coverage decisions and performance, we first show that in low individualistic countries, female analysts exhibit worse forecast accuracy than their male counterparts. However, in high individualistic countries, we show that there is no significant difference in forecast accuracy between the genders. In terms of the channel analysis, we first show that female analysts appear to be more skilled upon entry in high individualistic countries compared to their peers in low individualistic countries, and that female analysts are more likely to drop out when underperforming in high individualistic countries compared to their peers in low individualistic countries. We conclude that there are important cross-country variations in gender differences in performance under competition; specifically, such differences are attenuated in high individualistic countries.

Appendix Variable definitions

All continuous variables are winsorized at the 1st and 99th percentiles. All values are reported in 2010 constant US dollars (USD).

Variable	Definition	Source												
<i>Country-level variables</i>														
Individualism	<p>The index is a weighted sum of the following four statements:</p> <ol style="list-style-type: none"> 1) Have sufficient time for your personal or family life 2) Have good physical working conditions (good ventilation and lighting, adequate work space, etc.) 3) Have security of employment 4) Have an element of variety and adventure in the job <p>High individualism is indicated by ratings of “of very little or no importance” to items (2) and (3), and of “of utmost importance” to items (1) and (4).</p> <p>In individualistic cultures, the ties between individuals are loose: Everyone is expected to look after him/herself and his/her immediate family. In collectivistic cultures, people from birth onwards are integrated into strong, cohesive in-groups, often extended families that continue protecting them in exchange for unquestioning loyalty, and oppose other in-groups (Hofstede 1980, 2001, 2011).</p> <p>In a general review of his cultural dimensions, Hofstede (2011) provides 10 contrasts between individualism (IDV) and collectivism. Here are the first five contrasts, which are the most relevant to organizational/individual behaviors:</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="text-align: left;"><i>Individualism</i></th> <th style="text-align: left;"><i>Collectivism</i></th> </tr> </thead> <tbody> <tr> <td>“I” – consciousness</td> <td>“We” – consciousness</td> </tr> <tr> <td>Right of privacy</td> <td>Stress on belonging</td> </tr> <tr> <td>Speaking one’s mind is healthy</td> <td>Harmony should always be maintained</td> </tr> <tr> <td>Others classified as individuals</td> <td>Others classified as in-group or out-group</td> </tr> <tr> <td>Personal opinion expected: one person, one vote</td> <td>Opinions and votes predetermined by in-group</td> </tr> </tbody> </table>	<i>Individualism</i>	<i>Collectivism</i>	“I” – consciousness	“We” – consciousness	Right of privacy	Stress on belonging	Speaking one’s mind is healthy	Harmony should always be maintained	Others classified as individuals	Others classified as in-group or out-group	Personal opinion expected: one person, one vote	Opinions and votes predetermined by in-group	Hofstede Culture Dimension website
<i>Individualism</i>	<i>Collectivism</i>													
“I” – consciousness	“We” – consciousness													
Right of privacy	Stress on belonging													
Speaking one’s mind is healthy	Harmony should always be maintained													
Others classified as individuals	Others classified as in-group or out-group													
Personal opinion expected: one person, one vote	Opinions and votes predetermined by in-group													
High IDV	Indicator equals one if a country is in the top quartile of individualism among sample countries, and zero otherwise.	Hofstede Culture Dimension website												

High IDV_WVS	<p>Indicator equals one if a country is in the top quartile of updated individualism scores, and zero otherwise.</p> <p>Prior work including Schwartz (1994), Triandis (1995), and Beugelsdijk, Maseland, and van Hoorn (2015) associates the following questions in the WVS and EVS with individualism.</p> <p>Based on questions in the WVS, an individual is considered to be individualistic if he/she strongly agrees with: 1) one of my main goals in life is to make my parents proud: 1. strongly agree... 4. strongly disagree; 2) private versus government ownership of business: 1. private ownership should be increased...10. government ownership should be increased; 3) justifiability; homosexuality: 1. never justifiable... 10. always justifiable; and 4) justifiability; abortion: 1. never justifiable... 10. always justifiable.</p> <p>When coding these four items, the response to item 2 corresponding to a high individualism score is the lowest order option (i.e., option 1), whereas for all other three items, the responses are the highest order options (i.e., either option 4 or option 10).</p> <p>To obtain an updated version of the individualism score, we take the following steps. First, for each WVS variable listed above, we compute a country-mean of that variable over the period 1981–2002. Second, we regress Hofstede’s individualism score on the country means of the four survey responses to obtain the coefficients on those four countries means. Third, we multiply the estimated coefficients with the corresponding country-means of the same four survey questions over the period 2003–2015 to obtain an updated score for individualism.</p>	World Values Survey (WVS); European Values Survey (EVS)
Global Gender Gap Index	The Global Gender Gap Index (GGGI) was first introduced by the World Economic Forum (WEF) in 2006 to benchmark progress towards gender parity and compare countries’ gender gaps across four dimensions: economic opportunities, education, health, and political leadership (WEF 2021). We fill the missing values before 2006 with applicable values in 2006.	World Economic Forum
GDP per capita	GDP per capita (in thousands of dollars).	World Bank
Ln(GDP per capita)	Natural logarithm of GDP per capita (in thousands of dollars).	World Bank
Female ratio	Number of unique female analysts divided by the total number of unique analysts in a country-year. We determine whether an I/B/E/S analyst is a female or not based on hand-collected biographic information from Capital IQ, Bloomberg, and online search. Please see Appendix IA1 in the Internet Appendix for details.	I/B/E/S; Capital IQ; Bloomberg
Pronoun drop	Indicator equals one if a country’s population speaks a language in which pronoun drop is permitted, and zero otherwise.	Kashima and Kashima (1998)

Analyst-level variables

Average forecast error	Average of absolute forecast errors that an analyst makes during a year. Absolute forecast error is the absolute value of the difference between an analyst's annual EPS forecast and actual EPS normalized by the stock price at the prior fiscal year end, expressed as a percentage of the prior year's stock price following Hong and Kacperczyk (2010).	I/B/E/S
First forecast error	Absolute value of the forecast error made in an analyst's first forecast during a year.	I/B/E/S
Last forecast error	Absolute value of the forecast error made in an analyst's last forecast during a year.	I/B/E/S
Same week forecast error	Absolute value of the forecast error made in an analyst's forecast that is within five days after the prior fiscal year's annual earnings announcement.	I/B/E/S
Bad performance	Indicator equals one if the average of an analyst's adjusted forecast accuracy in year t and $t-1$ is in the bottom quartile, and zero otherwise. Adjusted forecast accuracy is the difference between an analyst's average forecast error and the mean of the same variable across analysts following the same firm in the same year.	I/B/E/S
Top10 brokerage	Indicator equals one if a brokerage's size is in the global top decile in a year, and zero otherwise.	I/B/E/S
Top20 brokerage	Indicator equals one if a brokerage's size is in the global top quintile in a year, and zero otherwise.	I/B/E/S
%Top10 stock_assets	The share of prestigious stocks in an analyst's stock portfolio in a year. Prestigious stocks are those stocks in the top decile by total assets across firms covered by both Worldscope and I/B/E/S in a country-year.	I/B/E/S; Worldscope
%Top20 stock_assets	The share of prestigious stocks in an analyst's stock portfolio in a year. Prestigious stocks are those stocks in the top quintile by total assets across firms covered by both Worldscope and I/B/E/S in a country-year.	I/B/E/S; Worldscope
%Top10 stock_mkt cap	The share of prestigious stocks in an analyst's stock portfolio in a year. Prestigious stocks are those stocks in the top decile by market capitalization across firms covered by both Worldscope and I/B/E/S in a country-year.	I/B/E/S; Worldscope
%Top20 stock_mkt cap	The share of prestigious stocks in an analyst's stock portfolio in a year. Prestigious stocks are those stocks in the top quintile by market capitalization across firms covered by both Worldscope and I/B/E/S in a country-year.	I/B/E/S; Worldscope

# alternative forecasts	Number of other types of forecasts, excluding EPS, such as book value per share (BPS), dividend per share (DPS), and capital expenditures (CAPX) issued by an analyst during the year.	I/B/E/S
Female	Indicator equals one if an analyst is a female, and zero otherwise.	I/B/E/S; Capital IQ; Bloomberg
Foreign analyst	Indicator equals one if an analyst's affiliated brokerage is in a country different from the country of primary listing of the firm she follows, and zero otherwise.	Capital IQ; Worldscope
Forecast horizon	Average number of months between the forecast date of an analyst during a year to the date of the annual earnings announcement.	I/B/E/S
Forecast frequency	Number of annual EPS forecasts made by an analyst during a year.	I/B/E/S
# firms followed	Number of firms for which an analyst makes at least one forecast during a year.	I/B/E/S
# industries followed	Number of two-digit SIC industries for which an analyst makes at least one forecast during a year.	I/B/E/S
Firm experience	Number of years for which an analyst makes at least one forecast of the focal firm during a year.	I/B/E/S
General experience	Number of years for which an analyst makes at least one forecast of any firm during a year.	I/B/E/S
Brokerage size	Number of analysts making at least one forecast at the focal brokerage during a year.	I/B/E/S
Ln(Brokerage size)	Natural logarithm of the brokerage size in a brokerage-year.	I/B/E/S

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Figure 1
Scatterplot of individualism and country-level female share of equity analysts

This figure plots individualism (IDV) and country-means of the female share of equity analysts. Our sample consists of 18,269 equity analysts from 42 countries over the period 2004–2019 for which we have analyst forecast data from I/B/E/S, firm-level data from Worldscope, and country-level data from the World Economic Forum (WEF), World Bank, and Hofstede Culture Dimension website.

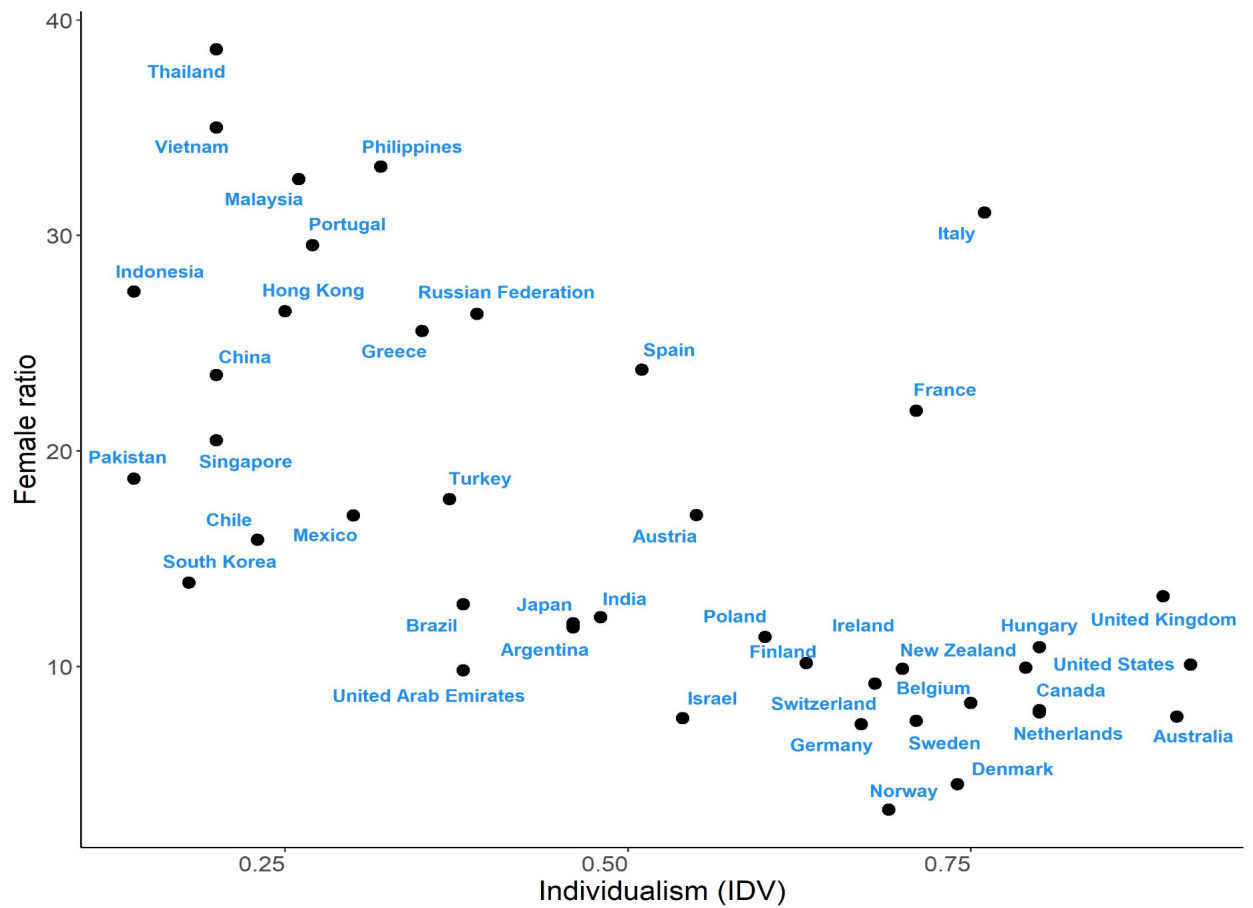


Table 1
Sample formation

This table reports the impact of various matching steps and data filters on the initial sample of analysts covered in the I/B/E/S Detail Recommendations file over the period 2004–2019.

	# analysts	# analysts removed	# brokerage	# brokerage removed	# countries	# countries removed
Obtain unique abbreviated brokerage names and analyst names in the I/B/E/S Detail Recommendations file from 2004 to 2019.	43,193	5,734	1,687	25		
Match abbreviated brokerage names to full brokerage names in Capital IQ.	29,285		1,557		83	
Remove observations with missing information on analyst gender and employment address, and analysts with multiple employment addresses in a year in Capital IQ.	26,841	2,444	1,535	22	80	3
Match I/B/E/S Detail Recommendations file with I/B/E/S EPS files.	23,932	2,909	1,448	87	80	0
Match with Worldscope; remove observations with missing Worldscope unique identifier (<i>ws_id</i>).	19,769	4,163	1,316	132	77	3
Remove firms with stock price less than one unit of local currency and market capitalization less than USD \$10 million at the end of the fiscal year.	19,539	230	1,307	9	77	0
Remove countries with fewer than 10 firms over the sample period.	19,472	67	1,288	19	71	6
Remove countries with fewer than 10 analysts or fewer than 10 firm-female analyst-year observations over the sample period.	19,397	75	1,270	18	55	16
Remove countries with missing information on GGGI or Hofstede's individualism measure.	18,583	814	1,191	79	42	13
Remove observations with missing analyst forecast variables.	18,269	314	1,179	12	42	0

Table 2
Sample overview

This table provides an overview of our sample. Our sample consists of 18,269 equity analysts from 42 countries over the period 2004–2019 for which we have analyst forecast data from I/B/E/S, firm-level data from Worldscope, and country-level data from the World Economic Forum (WEF), World Bank, and Hofstede Culture Dimension website. Panel A presents an overview of our global analyst sample by country. Panel B presents an overview of country-level variables. Definitions of the variables are provided in the Appendix.

Panel A. Overview of our global analyst sample

Country	# firm-year obs.	# firms	# analysts	# female analysts	% female analysts	# forecasts	# forecasts made by female analysts	% forecasts made by female analysts
Argentina	328	68	19	5	26.32%	1,204	78	6.48%
Australia	4,619	1,163	597	63	10.55%	62,358	3,814	6.12%
Austria	929	155	53	8	15.09%	3,847	487	12.66%
Belgium	1,648	401	112	19	16.96%	9,582	1,082	11.29%
Brazil	2,521	402	211	35	16.59%	18,894	2,315	12.25%
Canada	9,681	1,840	910	94	10.33%	194,929	12,616	6.47%
Chile	234	63	49	7	14.29%	525	56	10.67%
China	10,266	2,474	1,062	209	19.68%	38,501	8,311	21.59%
Denmark	846	161	64	5	7.81%	8,197	242	2.95%
Finland	1,617	265	148	26	17.57%	22,516	1,873	8.32%
France	8,307	1,323	528	123	23.30%	64,854	15,057	23.22%
Germany	7,964	1,500	668	70	10.48%	76,984	3,822	4.96%
Greece	477	85	88	20	22.73%	3,771	840	22.28%
Hong Kong	8,671	1,879	878	245	27.90%	56,274	13,002	23.10%
Hungary	218	44	20	3	15.00%	995	65	6.53%
India	5,406	1,079	1,057	149	14.10%	94,214	8,681	9.21%
Indonesia	1,085	174	176	48	27.27%	7,747	2,070	26.72%
Ireland	609	151	78	12	15.38%	2,688	134	4.99%
Israel	349	77	34	5	14.71%	1,567	44	2.81%
Italy	2,486	479	145	44	30.34%	22,416	6,451	28.78%
Japan	15,015	2,048	797	113	14.18%	158,187	14,301	9.04%

Malaysia	2,041	424	224	71	31.70%	15,750	5,433	34.50%
Mexico	857	171	48	11	22.92%	4,930	626	12.70%
Netherlands	2,921	852	234	36	15.38%	15,274	592	3.88%
New Zealand	665	91	31	3	9.68%	4,406	349	7.92%
Norway	2,638	498	265	11	4.15%	32,338	582	1.80%
Pakistan	199	56	89	15	16.85%	738	122	16.53%
Philippines	654	88	69	23	33.33%	3,747	1,289	34.40%
Poland	927	200	103	13	12.62%	3,944	241	6.11%
Portugal	616	115	57	21	36.84%	2,430	535	22.02%
Russian Federation	1,140	289	161	44	27.33%	7,716	2,474	32.06%
Singapore	3,353	831	251	61	24.30%	19,497	3,659	18.77%
South Korea	2,677	602	526	84	15.97%	44,430	7,501	16.88%
Spain	1,618	285	127	30	23.62%	10,557	2,937	27.82%
Sweden	2,964	525	263	27	10.27%	35,129	1,660	4.73%
Switzerland	4,663	1,277	293	43	14.68%	27,990	2,148	7.67%
Thailand	2,100	357	198	75	37.88%	20,810	8,816	42.36%
Turkey	810	125	116	28	24.14%	5,439	476	8.75%
United Arab Emirates	1,051	232	37	7	18.92%	4,410	606	13.74%
United Kingdom	20,553	3,862	1,985	338	17.03%	243,251	29,017	11.93%
United States	56,816	9,248	5,426	704	12.97%	1,276,283	103,229	8.09%
Vietnam	240	79	72	31	43.06%	628	293	46.66%
Total	192,779	36,038	18,269	2,979		2,629,947	267,926	

Panel B. Overview of country-level variables

Country	Female ratio (%)	IDV	GGGI	GDP per capita (\$000)	Ln(GDP per capita)
Argentina	11.81	0.46	0.71	9.64	9.17
Australia	7.67	0.90	0.73	52.00	10.86
Austria	17.02	0.55	0.71	46.83	10.75
Belgium	8.30	0.75	0.73	44.02	10.69
Brazil	12.89	0.38	0.67	10.67	9.27
Canada	7.97	0.80	0.73	47.53	10.77
Chile	15.87	0.23	0.68	12.90	9.47
China	23.52	0.20	0.67	4.66	8.45
Denmark	4.54	0.74	0.76	59.52	10.99
Finland	10.16	0.63	0.82	46.27	10.74
France	21.87	0.71	0.71	41.08	10.62
Germany	7.31	0.67	0.76	42.45	10.66
Greece	25.56	0.35	0.67	25.30	10.14
Hong Kong	26.49	0.25	0.67	32.04	10.37
Hungary	10.89	0.80	0.67	13.79	9.53
India	12.29	0.48	0.63	1.39	7.24
Indonesia	27.39	0.14	0.66	3.18	8.06
Ireland	9.89	0.70	0.77	54.89	10.91
Israel	7.59	0.54	0.70	30.63	10.33
Italy	31.06	0.76	0.68	35.99	10.49
Japan	12.00	0.46	0.65	45.32	10.72
Malaysia	32.62	0.26	0.65	9.37	9.14
Mexico	17.01	0.30	0.67	9.59	9.17
Netherlands	7.86	0.80	0.74	50.78	10.84
New Zealand	9.94	0.79	0.77	34.66	10.45
Norway	3.36	0.69	0.82	88.72	11.39
Pakistan	18.71	0.14	0.55	1.01	6.92
Philippines	33.20	0.32	0.77	2.31	7.74
Poland	11.36	0.60	0.70	12.71	9.45
Portugal	29.54	0.27	0.71	22.24	10.01
Russian Federation	26.36	0.39	0.69	10.39	9.25
Singapore	20.49	0.20	0.68	46.96	10.76
South Korea	13.89	0.18	0.63	22.77	10.03
Spain	23.77	0.51	0.74	30.79	10.33
Sweden	7.47	0.71	0.81	52.90	10.88
Switzerland	9.21	0.68	0.74	76.53	11.25
Thailand	38.63	0.20	0.69	5.06	8.53
Turkey	17.77	0.37	0.60	11.55	9.35
United Arab Emirates	9.81	0.38	0.62	44.62	10.71
United Kingdom	13.26	0.89	0.75	40.57	10.61
United States	10.09	0.91	0.72	49.69	10.81
Vietnam	35.01	0.20	0.69	1.54	7.34

Table 3
Summary statistics

This table provides the summary statistics for our global analyst sample. Panel A provides the summary statistics of country-level variables. The sample consists of 704 country-year observations over the period 2004–2019. Panel B provides the summary statistics of analyst-level variables. The sample consists of 610,847 firm-analyst-year observations over the period 2005–2020 (the sample size for *Same week forecast error* is 318,622 because we require those forecasts are made within five days after the prior fiscal year’s annual earnings announcement). Panel C presents the univariate difference-in-differences (DID) analysis of gender differences in performance under competition in the high IDV (top quartile) and low IDV (the remainder) country subsamples. We use four different measures of analyst forecast performance as the dependent variables: *Average forecast error*, *First forecast error*, *Last forecast error*, and *Same week forecast error*. *Female* is an indicator variable that takes the value one if an analyst is a female, and zero otherwise. The row labeled “High – Low” presents the t-test for the difference in the average gender performance gap between the high IDV and low IDV subsamples. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Country-level variables

	Mean	Median	STD	P25	P75
	(1)	(2)	(3)	(4)	(5)
Female ratio (%)	0.165	0.142	0.121	0.077	0.245
Individualism (IDV)	0.511	0.510	0.238	0.270	0.710
High IDV	0.276	0.000	0.447	0.000	1.000
GGGI	0.705	0.700	0.059	0.664	0.744
GDP per capita	30.968	32.598	21.728	10.530	47.017
Ln(GDP per capita)	3.005	3.484	1.130	2.354	3.851
N	704				

Panel B. Analyst-level variables

	Mean	Median	STD	P25	P75
	(1)	(2)	(3)	(4)	(5)
Average forecast error	2.902	0.740	7.798	0.276	2.073
First forecast error	3.684	0.912	9.627	0.300	2.729
Last forecast error	1.988	0.370	5.867	0.107	1.240
Same week forecast error	3.322	0.881	8.109	0.301	2.603
Female	0.110	0.000	0.313	0.000	0.000
Individualism (IDV)	0.724	0.890	0.246	0.480	0.910
High IDV	0.654	1.000	0.476	0.000	1.000
GGGI	0.714	0.718	0.040	0.691	0.740
GDP per capita	41.893	47.403	15.643	40.059	49.856
Ln(GDP per capita)	3.533	3.859	0.870	3.690	3.909
Foreign analyst	0.185	0.000	0.388	0.000	0.000
Forecast horizon	7.559	7.400	1.983	6.367	8.483
Forecast frequency	4.197	4.000	2.518	2.000	5.000
# firms followed	15.313	14.000	8.299	10.000	19.000
# industries followed	4.262	4.000	2.792	2.000	6.000
Firm experience	4.029	3.000	3.269	2.000	6.000
General experience	7.927	7.000	4.778	4.000	11.000

Brokerage size	105.481	43.000	118.575	18.000	173.000
Ln(Brokerage size)	3.902	3.761	1.328	2.890	5.153
<hr/>					
N	610,847				
<hr/>					

Panel C. The gender difference in performance under competition between high and low IDV countries: Univariate analysis

	Average forecast error			First forecast error			Last forecast error			Same week forecast error		
	Female	Male	Female – Male	Female	Male	Female – Male	Female	Male	Female – Male	Female	Male	Female – Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High IDV	-0.011	-0.002	-0.009	-0.749***	-0.770***	0.021	0.826***	0.852***	-0.026	-0.688***	-0.739***	0.051***
Low IDV	0.029**	0.002	0.028**	-0.684***	-0.830***	0.146***	0.948***	1.052***	-0.104***	-0.678***	-0.783***	0.105***
High – Low			-0.037**			-0.125***			0.078**			-0.054*

Table 4
Cross-country gender differences in performance under competition

This table examines cross-country gender differences in performance under competition using OLS regression with firm times year fixed effects. The sample consists of 610,847 firm-analyst-year observations over the period 2005–2020 (the sample size for *Same week forecast error* is 318,622 because we require those forecasts are made within five days after the prior fiscal year’s annual earnings announcement). We use four different measures of analyst forecast performance as the dependent variables: *Average forecast error*, *First forecast error*, *Last forecast error*, and *Same week forecast error*. *Female* is an indicator variable that takes the value one if an analyst is a female, and zero otherwise. *High IDV* is an indicator variable that takes the value of one if a country is in the top quartile of individualism, and zero otherwise. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043** (0.021)	0.040 (0.025)	0.051** (0.024)	0.114*** (0.038)
Female × High IDV	-0.059** (0.026)	-0.089*** (0.030)	-0.030 (0.029)	-0.122*** (0.041)
High IDV	-0.073*** (0.026)	-0.045 (0.029)	-0.058** (0.028)	-0.061** (0.030)
GGGI	0.770** (0.352)	0.882** (0.408)	1.537*** (0.396)	0.891* (0.461)
Ln(GDP per capita)	-0.012 (0.017)	-0.008 (0.021)	-0.011 (0.018)	-0.060*** (0.022)
Foreign analyst	0.054*** (0.019)	0.005 (0.022)	0.076*** (0.019)	0.020 (0.021)
Forecast horizon	0.156*** (0.003)	0.081*** (0.003)	0.215*** (0.003)	0.011*** (0.003)
Forecast frequency	-0.001 (0.002)	0.016*** (0.003)	-0.028*** (0.002)	-0.001 (0.002)
# firms followed	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)
# industries followed	-0.002 (0.002)	-0.005* (0.002)	0.001 (0.002)	-0.000 (0.002)
Firm experience	-0.003** (0.001)	-0.004** (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003*** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.008*** (0.003)	-0.003 (0.004)	-0.012*** (0.003)	-0.011*** (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.25	8.6	1.59	0.22
P-value	0.26	0.00	0.21	0.64
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.910	0.915	0.782	0.943

Table 5
Cross-country gender differences in performance under competition: identification

This table examines cross-country gender differences in performance under competition using 2SLS regressions and double sort. Panel A reports the first-stage regression results where *High IDV* is instrumented with a linguistic variable *Pronoun drop*. *High IDV* is an indicator variable that takes the value of one if a country is in the top quartile of individualism and zero otherwise. Panel B reports the second-stage regression results where the instrumented *High IDV* from the first stage are used. We use four different measures of analyst forecast performance as the dependent variables: *Average forecast error*, *First forecast error*, *Last forecast error*, and *Same week forecast error*. *Female* is an indicator variable that takes the value one if an analyst is a female, and zero otherwise. Panel C presents average gender differences in performance for four groups of firm-analyst-year observations. The groups are formed based on (1) whether a firm-analyst-year observation is from a high IDV or low IDV country; and (2) whether a firm-analyst-year observation is from a country with pronoun drop permitted or not. The row labeled “Yes – No” presents the t-test for the difference in the average gender performance gap between the countries with pronoun drop permitted and those without. The column labeled “High – Low” presents the t-test for the difference in the average gender performance gap between the high IDV and low IDV subgroups. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. First-stage regression: Instrumenting high IDV

	High IDV (1)
Pronoun drop	-0.839*** (0.008)
Female	0.011*** (0.001)
GGGI	-3.996*** (0.081)
Ln(GDP per capita)	-0.023*** (0.003)
Foreign analyst	0.086*** (0.004)
Forecast horizon	-0.001*** (0.000)
Forecast frequency	0.002*** (0.000)
# firms followed	0.002*** (0.000)
# industries followed	-0.004*** (0.000)
Firm experience	-0.000*** (0.000)
General experience	-0.001*** (0.000)
Ln(Brokerage size)	0.008*** (0.000)
Firm × Year Fixed Effects	Yes
Intercept	Yes
Obs.	559,905
<i>adj-R</i> ²	0.866

Panel B. Second-stage regression: Cross-country gender differences in performance

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.063*** (0.024)	0.048* (0.028)	0.074*** (0.028)	0.113*** (0.042)
Female × High IDV (instrumented)	-0.076** (0.031)	-0.097*** (0.037)	-0.046 (0.036)	-0.121** (0.047)
High IDV (instrumented)	-0.287*** (0.059)	-0.182*** (0.070)	-0.292*** (0.060)	-0.207** (0.098)
GGGI	0.741** (0.354)	0.780* (0.411)	1.555*** (0.403)	0.616 (0.493)
Ln(GDP per capita)	0.000 (0.018)	0.003 (0.022)	-0.002 (0.019)	-0.035 (0.022)
Foreign analyst	0.086*** (0.021)	0.025 (0.024)	0.110*** (0.022)	0.030 (0.023)
Forecast horizon	0.155*** (0.003)	0.079*** (0.003)	0.215*** (0.004)	0.011*** (0.003)
Forecast frequency	-0.001 (0.002)	0.016*** (0.003)	-0.026*** (0.002)	-0.000 (0.003)
# firms followed	0.001 (0.001)	0.002** (0.001)	0.001 (0.001)	0.000 (0.001)
# industries followed	-0.004* (0.002)	-0.006** (0.002)	-0.000 (0.002)	-0.001 (0.002)
Firm experience	-0.003** (0.001)	-0.004** (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003*** (0.001)	-0.001 (0.001)	-0.006*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.004 (0.003)	-0.001 (0.004)	-0.009** (0.004)	-0.010*** (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV (instrumented) = 0				
F value	0.78	4.19	1.18	0.13
P-value	0.38	0.04	0.28	0.72
Obs.	559,905	559,905	559,905	302,904
adj-R ²	0.911	0.916	0.782	0.943

Panel C. Gender difference in performance sorted by pronoun drop and individualism

Panel C.1. Gender difference in average analyst forecast error

Pronoun drop	High IDV			Low IDV			High – Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female	Male	Female – Male	Female	Male	Female – Male	
Yes	-0.062*	0.011	-0.073	0.039	-0.001	0.040***	-0.113*
No	-0.009	-0.003	-0.006	0.071*	0.007	0.064	-0.070*
Yes – No			-0.067			-0.024	

Panel C.2. Gender difference in first analyst forecast error

Pronoun drop	High IDV			Low IDV			High – Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female	Male	Female – Male	Female	Male	Female – Male	
Yes	-0.681***	-0.677***	-0.004	-0.616***	-0.797***	0.181***	-0.185*
No	-0.752***	-0.771***	0.019	-0.684***	-0.913***	0.229***	-0.210***
Yes – No			-0.023			-0.048	

Panel C.3. Gender difference in last analyst forecast error

Pronoun drop	High IDV			Low IDV			High – Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female	Male	Female – Male	Female	Male	Female – Male	
Yes	0.575***	0.791***	-0.216**	0.882***	1.043***	-0.161***	-0.055
No	0.837***	0.853***	-0.016	1.039***	1.065***	-0.026	0.010
Yes – No			-0.200*			-0.135*	

Panel C.4. Gender difference in same week analyst forecast error

Pronoun drop	High IDV			Low IDV			High – Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female	Male	Female – Male	Female	Male	Female – Male	
Yes	-0.740***	-0.537***	-0.203	-0.609***	-0.768***	0.159***	-0.362***
No	-0.685***	-0.741***	0.056***	-0.507***	-0.777***	0.270***	-0.214***
Yes – No			-0.259**			-0.111	

Table 6
Cross-country gender differences in performance under competition: alternative explanations

This table examines alternative explanations for cross-country gender differences in performance under competition. Panel A examines whether there is any gender difference in performance under competition when sorting countries by their gender equality policies or by their GDP per capita. *High GGGI* is an indicator variable that takes the value of one if a country is in the top quartile of the gender equality index, and zero otherwise. *High GDP per capita* is an indicator variable that takes the value of one if a country is in the top quartile of Ln(GDP per capita), and zero otherwise. Panel B examines whether there is any gender difference in performance under competition when sorting countries by the three other cultural values of Hofstede (1980, 2001): masculinity (MAS), power distance (PDI), and uncertainty avoidance (UAI). *High MAS* is an indicator variable that takes the value of one if a country is in the top quartile of masculinity, and zero otherwise. *High PDI* is an indicator variable that takes the value of one if a country is in the top quartile of power distance, and zero otherwise. *High UAI* is an indicator variable that takes the value of one if a country is in the top quartile of uncertainty avoidance, and zero otherwise. We use four different measures of analyst forecast performance as the dependent variables: *Average forecast error*, *First forecast error*, *Last forecast error*, and *Same week forecast error*. *Female* is an indicator variable that takes the value one if an analyst is a female, and zero otherwise. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Confounding social and economic factors

	Average forecast error		First forecast error		Last forecast error		Same week forecast error	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.002 (0.012)	0.019 (0.020)	-0.013 (0.014)	0.000 (0.023)	0.024 (0.014)	0.032 (0.022)	0.017 (0.016)	0.083*** (0.032)
Female × High GGGI	0.030 (0.048)		-0.001 (0.055)		0.052 (0.045)		0.037 (0.070)	
Female × High GDP per capita		-0.024 (0.024)		-0.027 (0.029)		-0.001 (0.027)		-0.090** (0.037)
High GGGI	0.071*** (0.024)		0.044 (0.027)		0.121*** (0.027)		0.034 (0.031)	
High GDP per capita		-0.029 (0.022)		-0.033 (0.025)		-0.065*** (0.024)		-0.049* (0.025)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tests if Female + Female × High GGGI (High GDP per capita) = 0								
F value	0.48	0.15	0.08	2.86	3.22	3.55	0.67	0.16
P-value	0.49	0.70	0.78	0.09	0.07	0.06	0.41	0.69
Obs.	610,847	610,847	610,847	610,847	610,847	610,847	318,622	318,622
adj-R ²	0.910	0.910	0.915	0.915	0.782	0.782	0.943	0.943

Panel B. Confounding cultural factors

	Average forecast error			First forecast error			Last forecast error			Same week forecast error		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	0.020 (0.013)	0.010 (0.013)	-0.011 (0.012)	0.001 (0.016)	-0.021 (0.016)	-0.027* (0.015)	0.036** (0.015)	0.040*** (0.015)	0.018 (0.014)	0.031* (0.017)	0.016 (0.016)	0.007 (0.015)
Female × High MAS	-0.050 (0.033)			-0.052 (0.039)			-0.016 (0.034)			-0.060 (0.058)		
Female × High PDI		-0.021 (0.034)			0.051 (0.040)			-0.051 (0.037)			0.060 (0.049)	
Female × High UAI			0.113*** (0.039)			0.079 (0.049)			0.088* (0.047)			0.235** (0.110)
High MAS	-0.032 (0.022)			-0.038 (0.026)			-0.015 (0.024)			-0.047* (0.027)		
High PDI		0.096** (0.044)			-0.020 (0.051)			0.073 (0.045)			-0.042 (0.091)	
High UAI			0.157*** (0.033)			0.171*** (0.041)			0.121*** (0.038)			0.153*** (0.046)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0												
F value	1.09	0.12	7.79	2.33	0.69	1.28	0.46	0.11	5.56	0.28	2.7	5.11
P-value	0.30	0.72	0.01	0.13	0.41	0.26	0.50	0.74	0.02	0.59	0.10	0.02
Obs.	610,847	610,847	610,847	610,847	610,847	610,847	610,847	610,847	610,847	318,622	318,622	318,622
adj-R ²	0.910	0.910	0.910	0.915	0.915	0.915	0.782	0.782	0.782	0.943	0.943	0.943

Table 7
Cross-country gender differences in analyst skills

This table presents the univariate DID analysis to help explain female analysts' performance. In Panel A, we compare gender differences in analysts' brokerage affiliations and stock portfolios in the high versus low IDV countries for first-time analysts. First-time analysts are identified by their first appearance in the I/B/E/S database. We sort analyst-year observations (in their first year) into the high IDV (top quartile) and low IDV (the remainder) country subsamples. Within each subsample, we compare the female and male differences in their brokerage affiliations and the characteristics of the stocks that they first cover. We further conduct DID analysis of the female and male differences between the high IDV and low IDV subsamples. Columns (5) and (6) report the female and male differences in the high IDV subsample. Columns (11) and (12) report the female and male differences in the low IDV subsample. We conduct both the t-test and Wilcoxon test for the gender differences. We report the DID analysis comparing columns (5) and (11) in column (13). Panel B examines cross-country gender differences in analysts' other output under competition using OLS regression with firm times year fixed effects. The sample consists of 610,847 firm-analyst-year observations over the period 2005–2020. We use two analyst output measures as the dependent variables: *# alternative forecasts* and *Forecast frequency*. *Female* is an indicator variable that takes the value one if an analyst is a female, and zero otherwise. *High IDV* is an indicator variable that takes the value of one if a country is in the top quartile of individualism, and zero otherwise. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Difference-in-differences analysis of an analyst's brokerage affiliation and stock portfolio when first becoming an analyst

	High IDV						Low IDV						DID test	
	Female		Male		Difference between female and male analysts in		Female		Male		Difference between female and male analysts in			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)		(13)
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median		Mean
Top10 brokerage	0.398	0.000	0.268	0.000	0.130***	0.000***	0.217	0.000	0.151	0.000	0.066***	0.000***	0.064***	
Top20 brokerage	0.471	0.000	0.366	0.000	0.105***	0.000***	0.284	0.000	0.219	0.000	0.066***	0.000***	0.039*	
%Top10 stock_assets	0.188	0.000	0.200	0.000	-0.011	0.000	0.216	0.000	0.229	0.000	-0.013	0.000	0.001	
%Top20 stock_assets	0.420	0.211	0.384	0.182	0.036**	0.029	0.397	0.222	0.409	0.231	-0.012	-0.009	0.048**	
%Top10 stock_mkt cap	0.243	0.000	0.227	0.000	0.016	0.000	0.251	0.000	0.260	0.000	-0.009	0.000	0.025	
%Top20 stock_mkt cap	0.482	0.333	0.431	0.286	0.051***	0.048**	0.459	0.333	0.457	0.333	0.002	0.000	0.049**	

Panel B. Cross-country gender differences in analysts' other output under competition

	Ln(# alternative forecasts)	Forecast frequency
	(1)	(2)
Female	-0.009*** (0.003)	0.051*** (0.014)
Female × High IDV	0.031*** (0.004)	0.044** (0.020)
Forecast frequency	0.010*** (0.000)	
High IDV	-0.158*** (0.003)	0.229*** (0.018)
GGGI	-0.252*** (0.052)	3.094*** (0.306)
Ln(GDP per capita)	0.050*** (0.003)	0.154*** (0.011)
Foreign analyst	-0.091*** (0.003)	-0.532*** (0.015)
Forecast horizon	-0.033*** (0.000)	-0.007*** (0.002)
# firms followed	-0.002*** (0.000)	0.016*** (0.001)
# industries followed	-0.008*** (0.000)	-0.042*** (0.002)
Firm experience	-0.000 (0.000)	0.118*** (0.001)
General experience	0.006*** (0.000)	-0.015*** (0.001)
Ln(Brokerage size)	0.086*** (0.001)	0.213*** (0.003)
Firm × Year Fixed Effects	Yes	Yes
Intercept	Yes	Yes
Tests if Female + Female × High IDV = 0		
F value	59.13	50.20
P-value	0.00	0.00
Obs.	610,847	610,847
adj-R ²	0.369	0.350

Table 8
Cross-country gender differences in analyst turnover

This table presents DID analysis to help explain female analysts' performance. We compare the female and male differences in analyst turnover-to-performance sensitivity in the high (low) IDV country subsample. The indicator variable, *Turnover*, takes the value of one for the year when it is the last year that an analyst makes their last forecasts. The indicator variable, *Bad performance*, takes the value of one if an analyst's average relative performance in years t and $t-1$ is in the bottom quartile, and zero otherwise. For the sample of analysts (sorted by gender and their country's individualism score), we compute the turnover rate in year $t+1$ based on the information that she is no longer working as an analyst. We report the gender difference in turnover rates in column (5) for the high IDV subsample and that in column (10) for the low IDV subsample, and the DID test in column (11). Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the analyst and year levels. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	High IDV					Low IDV					DID test
	Female		Male		Difference between female and male analysts in	Female		Male		Difference between female and male analysts in	
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)		
Obs.	Mean	Obs.	Mean	Mean	Obs.	Mean	Obs.	Mean	Mean	Mean	
Bad performance	1,184	0.104	10,786	0.071	0.033***	1,268	0.121	6,412	0.122	-0.001	0.035***

For Online Publication

Appendix IA1

Unmasking brokerage name, analyst name, and analyst gender via Capital IQ

From the I/B/E/S Detail Recommendations file, we obtain a list of 1,687 unique brokerages (both in and outside the U.S.) providing recommendations on global equities over the period 2004–2019. I/B/E/S provides an abbreviated brokerage name in the variable *ESTIMID*, a unique brokerage identifier in the variable *EMASKCD*, the last name and first name initial of each analyst in the variable *ANALYST*, and a unique analyst identifier in the variable *AMASKCD*.

To unmask abbreviated brokerage names and analyst names from I/B/E/S, we manually search each brokerage’s full name and its analysts from Capital IQ. Our matching process takes three steps. First, we match abbreviated brokerage names in I/B/E/S (*ESTIMID*) to full brokerage names in Capital IQ by resemblance. For example, the abbreviated brokerage name “ZACKSINV” in I/B/E/S resembles Zacks Investment Research, Inc. in Capital IQ. Second, we ascertain that this match is correct by matching analyst names in I/B/E/S (*ANALYST*) with those in Capital IQ using the last name and first name initial.²⁶ For example, we are able to match 27 out of the 28 analysts affiliated with Zacks Investment Research in I/B/E/S with those in Capital IQ (more on this later). Third and finally, we supplement the above two steps by checking whether Capital IQ analysts’ stock coverage is the same as that by matched I/B/E/S analysts. To do so, we search through Bloomberg’s “*PEOP*” function. Of the 1,687 brokerages in I/B/E/S, we are able to unmask full brokerage names for 1,557 observations (a 92.3% matching rate).

²⁶ We keep observations with perfect match on brokerage name and analyst name. In cases in which multiple analysts have identical last names and first name initials in a brokerage, we drop those analysts. We also drop analysts with the name “RESEARCH TEAM” (referring to team coverage) or “PERMDENIED” (referring to those permanently denied).

We then obtain individual analyst information, including biography, prefix (Mr. vs. Ms.), and office address from their employment history in Capital IQ. Using Zacks Investment Research, Inc. as an example, Figures IA1-IA4 illustrate how we obtain such information.

We start by searching “Zacks Investment Research, Inc.” in Capital IQ. Figure IA1 shows that each brokerage is assigned a unique *companyId* by Capital IQ that we use as the brokerage identifier. Figure 1A1 also shows that we can search employment history for analysts affiliated with Zacks by navigating to the “*Professionals*” page under the “*People*” tab. Figure IA2 shows that we can identify both former and current analysts affiliated with the brokerage, with each analyst having a unique personal ID (*personId*). By clicking on an analyst, we get to their personal profile in Capital IQ, shown in Figure IA3. We rely on the biography (i.e., “he” vs. “she” is used when referring to an analyst) and the prefix(es) to determine an analyst’s gender. We use the office address as the location of employment and to proxy for an analyst’ residential address, as analysts often reside in countries where they are employed. Figure IA4 shows that in the case of Zacks Investment Research, Inc., we are able to match all 28 unique analysts in I/B/E/S to those in Capital IQ. However, we note one analyst, “BECKER M”, has two I/B/E/S analyst IDs (*AMASKCD*) pointing to the same analyst in Capital IQ. Out of precaution, we remove this analyst from our sample.²⁷

In the end, we are able to unmask 29,285 out of the 37,459 unique analysts in the I/B/E/S Detail Recommendations file (a 78.2% matching rate).

²⁷ *BROKER_NAME* in Figure 4 is the full brokerage name identified via Capital IQ. For analyst “BERCKER M”, we are able to match their prior brokerage affiliations in four out of the seven employers, suggesting that Capital IQ have broader coverage in terms of analyst employment history than I/B/E/S.

Figure IA1
Zacks Investment Research, Inc. main page in Capital IQ

capitaliq.com/CIQDotNet/company.aspx?companyId=4439707

S&P Capital IQ Search Companies, People, Funds, and More...

My Capital IQ Companies Markets Screening Charting Coverage Projects Alpha Factors Structured M

Zacks Investment Research, Inc. Private Company Profile

MARKET INTELLIGENCE Profile Customize Tearsheet Quick Report Tearsheet Report CIQ Report Dun & Bradstreet Create

Website:	Add www.zacks.com
Global Number of Employees (Latest):	262
Ticker:	-
Current Professionals Profiled:	25
Year Founded:	1978
Total Amount Raised (\$ mm)†:	-
Latest Post-Money Valuation (\$ mm)	-

Business Description [Add](#)

Zacks Investment Research, Inc. is an equity research firm. The firm focuses its research on staples; finance; industrial products; medical; multi-sector conglomerates; oils and energy; indicator, estimate analytics, market summary, rank stocks, portfolio tracker, exchange trade Research, Inc. was founded in 1978 and is based in Chicago, Illinois.

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Proprietary Data

Peer Analysis
 Quick Comps
 Comparable M&A Transactions

Transactions
 M&A/Private Placements

Business Relationships
 Customers

Figure IA2
Analysts affiliated with Zack Investment Research, Inc. as recorded by Capital IQ

Professionals	
Copy to List	Add...
Name	Title Sort By Rank ▼
Zacks Ph.D., L	Founder, Chief Executive Officer, President and Chairman
Zacks, B	Executive Vice President
Mian, S	Director of Research
Gregg, T	Director of Communications
Hantke, R	https://www.capitaliq.com/CIQDotNet/Person.aspx?personId=99713945
Marckx CFA, B	Director of Research and Senior Medical Technology, Medical Device & Diagnostics Analyst
Haycock, G	Managing Director and SCR Manager
Bartosiak, D	Technical and Momentum Strategist
Bautz Ph.D., D	Senior Biotechnology Analyst
Blank Ph.D., J	Chief Equity Strategist
Bolan, B	Aggressive Growth Stock Strategist
Borun, D	Stock Strategist
Cohen CFA, A	Senior Vice President Quantitative Consulting
Cook, K	Senior Stock Strategist
Gilson Ph.D., CFA, I	Senior Special Situations Analyst
Heffron C.F.A., CPA, CFA, CPA, A	Senior Bank and Finance Analyst
Marin, M	Senior Technology Analyst
Matras, K	Vice President
Mishra CFA, N	ETF Research Director
Ralston C.F.A., CFA, S	Senior Special Situations Analyst
Ryniec J.D., T	Equity Strategist
Senko CFA, E	Senior Analyst
Shah, K	Analyst
Thompson, L	Senior Technology Analyst
Vandermosten CFA, J	Senior Biotechnology Research Analyst

Figure IA3
Analyst personal information in Capital IQ

B Marckx Professional Summary



Edit Person

Overview	
Mr. B	Marckx, CFA
Director of Research and Senior Medical Technology, Medical Device & Diagnostics Analyst Add	
Zacks Investment Research, Inc. Add Professional Affiliation	
Nickname:	---
Office:	Map 10 South Riverside Plaza Chicago, Illinois 60606 United States Edit Add
Email:	@zacks.com Add
Main:	312-630-
Fax:	312-630-
Mobile:	-
Other Phone:	---

Personal Information

Mr. B Marckx, CFA is a Director of Research and Senior Medical Technology, Medical Device, and Diagnostics An on development-stage companies with novel and emerging technologies, as well as already established names still fly High-Yield Bond Analyst at Wachovia Securities' institutional trading desks where **he** specialized in the healthcare and Wall Street Journal, Barron's, Bloomberg-Businessweek and Kilpinger. **His** work has also been cited in various market Financial Analyst. **He** received Master's Degree in Business Administration from University and a grad [Add](#)

Figure IA4

An example of two different I/B/E/S analyst IDs pointing to the same analyst in Capital IQ

I/B/E/S file for analyst "BACKER M"

	ANALYST	AMASKCD	ESTIMID	EMASKCD	BROKER_NAME
BACKER	M	171815	ZACKSINV	7654	Zacks Investment Research, Inc.
BACKER	M	79164	RESASSOC	5797	Research Associates, LLC
BACKER	M	79164	HUDSONSQ	7844	Hudson Square Research, Inc.
BACKER	M	79164	ASCENDIA	41105	Ascendant Capital Markets LLC, Research Division

Capital IQ file for analyst "BACKER M"

personId	ANALYST	companyId	BROKER_NAME
24165186	BACKER	M 129926045	Ascendant Capital Markets LLC, Research Division
24165186	BACKER	M 12765513	Hudson Square Research, Inc.
24165186	BACKER	M 24165184	Research Associates, LLC
24165186	BACKER	M 7923367	Sidoti & Company, LLC
24165186	BACKER	M 4891357	Soleil Securities Corporation
24165186	BACKER	M 34211035	Wm Smith & Co.
24165186	BACKER	M 4439707	Zacks Investment Research, Inc.

Two I/B/E/S analyst IDs point to the same analyst in Capital IQ

Table IA1
Equity analyst pay around the world

This table provides an overview of equity analyst pay (in U.S. dollars) in our sample countries. The data for average analyst pay in a country come from the Global Salary Calculator (updated to the most recent month as of February 2023), an online database maintained by the Economic Research Institute. The data for average pay in a country come from the Trading Economics (updated as of the end of 2022). Panel A presents average analyst pay, the ratio of average analyst pay to GDP per capita, average pay, and the ratio of average analyst pay to average pay in each country. High IDV is an indicator variable that takes the value of one if a country is in the top quartile of individualism, and zero otherwise. N/A indicates pay data is unavailable. Panel B presents the univariate comparison of pay ratio differences in high IDV (top quartile) and low DIV (the reminder) country subsamples. The row labeled “High – Low” presents the t-test/Wilcoxon test for the difference in pay ratio between the high IDV and low IDV subsamples. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Analyst pay across countries

Country	High IDV	Average analyst pay	GDP per capita	Average analyst pay/GDP per capita	Average pay	Average analyst pay/Average pay
Argentina	0	30,767.34	10,636.12	2.89	18,709.69	1.64
Australia	1	97,535.71	60,443.11	1.61	49,721.26	1.96
Austria	0	85,849.63	53,637.71	1.60	31,810.73	2.70
Belgium	1	90,239.75	51,247.01	1.76	N/A	N/A
Brazil	0	29,794.53	7,507.16	3.97	6,392.45	4.66
Canada	1	87,389.97	51,987.94	1.68	40,803.08	2.14
Chile	0	36,288.59	16,265.10	2.23	12,584.85	2.88
China	0	46,766.62	12,556.33	3.72	15,859.19	2.95
Denmark	1	99,520.61	68,007.76	1.46	74,128.02	1.34
Finland	0	79,864.35	53,654.75	1.49	47,873.82	1.67
France	1	77,176.66	43,658.98	1.77	41,905.36	1.84
Germany	0	88,515.25	51,203.55	1.73	51,747.63	1.71
Greece	0	49,279.71	20,192.60	2.44	N/A	N/A
Hong Kong	0	84,943.24	49,800.54	1.71	26,774.62	3.17
Hungary	1	27,062.16	18,728.12	1.45	17,289.00	1.57
India	0	18,342.14	2,256.59	8.13	N/A	N/A
Indonesia	0	26,570.45	4,332.71	6.13	N/A	N/A
Ireland	0	83,213.46	100,172.08	0.83	47,242.90	1.76
Israel	0	71,529.32	52,170.71	1.37	43,923.79	1.63
Italy	1	67,092.53	35,657.50	1.88	31,230.28	2.15
Japan	0	66,361.48	39,312.66	1.69	61,239.27	1.08
Malaysia	0	29,586.80	11,109.26	2.66	8,283.10	3.57
Mexico	0	25,239.68	10,045.68	2.51	6,931.37	3.64
Netherlands	1	86,686.65	57,767.88	1.50	38,384.86	2.26
New Zealand	1	81,962.86	48,781.03	1.68	43,800.56	1.87
Norway	0	99,380.93	89,154.28	1.11	63,081.71	1.58
Pakistan	0	10,016.83	1,505.01	6.66	N/A	N/A
Philippines	0	15,220.22	3,460.53	4.40	N/A	N/A

Poland	0	35,503.54	17,999.91	1.97	17,650.30	2.01
Portugal	0	51,048.37	24,567.51	2.08	14,990.54	3.41
Russian Federation	0	24,036.79	12,194.78	1.97	10,826.42	2.22
Singapore	0	77,367.81	72,794.00	1.06	57,636.90	1.34
South Korea	0	61,968.12	34,997.78	1.77	39,612.91	1.56
Spain	0	64,809.67	30,103.51	2.15	25,640.38	2.53
Sweden	1	68,148.28	61,028.74	1.12	33,521.14	2.03
Switzerland	0	131,337.45	91,991.60	1.43	83,602.85	1.57
Thailand	0	25,895.72	7,066.19	3.66	5,134.03	5.04
Turkey	0	14,735.75	9,661.24	1.53	2,866.90	5.14
United Arab Emirates	0	85,385.18	44,315.55	1.93	N/A	N/A
United Kingdom	1	75,617.99	46,510.28	1.63	40,369.69	1.87
United States	1	107,939.00	70,248.63	1.54	50,992.34	2.12
Vietnam	0	23,595.47	3,756.49	6.28	3,485.39	6.77

Panel B. The pay ratio difference between high and low IDV countries: Univariate analysis

	Average analyst pay/GDP per capita		Average analyst pay/Average pay	
	Mean	Median	Mean	Median
High DIV	1.59	1.62	1.92	1.96
Low IDV	2.77	2.03	2.76	2.37
High – Low	-1.18**	-0.41**	-0.84*	-0.41

Table IA2
Correlation matrix

This table presents the correlations matrix for our sample over the period 2005–2020. Panel A provides the correlation matrix of country-level variables. The sample consists of 704 country-year observations over the period 2004–2019. Panel B provides the correlation matrix of analyst-level variables. The sample consists of 610,847 firm-analyst-year observations over the period 2005–2020. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. The correlation matrix of country-level variables

		1	2	3	4
1	Female ratio	1.000			
2	High IDV	-0.253***	1.000		
3	GGGI	-0.272***	0.305***	1.000	
4	Ln(GDP per capita)	-0.415***	0.388***	0.528***	1.000

Panel B. The correlation matrix of analyst-level variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	
1	Average forecast error	1.000																
2	First forecast error	0.950***	1.000															
3	Last forecast error	0.894***	0.794***	1.000														
4	Same day forecast error	0.935***	0.995***	0.758***	1.000													
5	Female	0.001	-0.001	0.005***	0.000	1.000												
6	High IDV	-0.076***	-0.064***	-0.087***	-0.058***	-0.087***	1.000											
7	GGGI	-0.065***	-0.061***	-0.062***	-0.062***	-0.083***	0.507***	1.000										
8	Ln(GDP per capita)	-0.027***	-0.016***	-0.045***	-0.017***	-0.093***	0.528***	0.498***	1.000									
9	Foreign analyst	0.014***	0.008***	0.023***	0.012***	0.043***	0.026***	0.141***	0.099***	1.000								
10	Forecast horizon	0.047***	0.027***	0.079***	0.031***	0.004***	0.002	-0.003***	-0.030***	-0.001	1.000							
11	Forecast frequency	0.002*	0.019***	-0.019***	0.037***	-0.039***	0.237***	0.202***	0.189***	-0.001	-0.054***	1.000						
12	# firms followed	-0.026***	-0.021***	-0.033***	-0.015***	-0.097***	0.108***	-0.038***	0.112***	-0.115***	0.024***	0.047***	1.000					
13	# industries followed	0.003***	0.002*	0.006***	0.003	-0.006***	-0.145***	-0.067***	-0.062***	-0.100***	0.045***	-0.109***	0.403***	1.000				
14	Firm experience	-0.046***	-0.042***	-0.051***	-0.043***	-0.041***	0.062***	0.100***	0.116***	-0.071***	-0.050***	0.209***	0.130***	0.026***	1.000			
15	General experience	-0.045***	-0.041***	-0.051***	-0.039***	-0.069***	0.125***	0.168***	0.179***	-0.056***	-0.025***	0.121***	0.269***	0.108***	0.608***	1.000		
16	Brokerage size	-0.013***	-0.013***	-0.014***	-0.026***	0.051***	0.042***	-0.013***	0.067***	0.204***	-0.046***	0.102***	0.013***	-0.117***	0.030***	0.025***	1.000	
17	Ln(Brokerage size)	-0.021***	-0.020***	-0.024***	-0.030***	0.035***	0.055***	-0.003***	0.080***	0.203***	-0.040***	0.116***	0.013***	-0.152***	0.050***	0.047***	0.891***	1.000

Table IA3
Summary statistics for the U.S. sample

This table provides the summary statistics of analyst-level variables for only the U.S. sample. The sample consists of 263,758 firm-analyst-year observations over the period 2005–2020 (the sample size for *Same week forecast error* is 179,153 because we require those forecasts are made within five days after the prior fiscal year’s annual earnings announcement). Definitions of the variables are provided in the Appendix.

	Mean	Median	STD	P25	P75
	(1)	(2)	(3)	(4)	(5)
Average forecast error	2.244	0.539	6.677	0.210	1.494
First forecast error	3.054	0.714	8.563	0.243	2.142
Last forecast error	1.371	0.214	4.878	0.067	0.702
Same week forecast error	2.962	0.745	7.669	0.261	2.188
Female	0.080	0.000	0.271	0.000	0.000
Individualism (IDV)	0.910	0.910	0.000	0.910	0.910
High IDV	1.000	1.000	0.000	1.000	1.000
GGGI	0.724	0.720	0.016	0.704	0.740
GDP per capita	49.934	49.596	2.351	48.467	51.052
Ln(GDP per capita)	3.910	3.904	0.047	3.881	3.933
Foreign analyst	0.115	0.000	0.319	0.000	0.000
Forecast horizon	7.616	7.500	1.761	6.546	8.292
Forecast frequency	4.665	4.000	2.472	3.000	6.000
# firms followed	17.875	17.000	8.014	13.000	22.000
# industries followed	3.814	3.000	2.489	2.000	5.000
Firm experience	4.222	3.000	3.382	2.000	6.000
General experience	8.578	8.000	4.874	5.000	12.000
Brokerage size	106.813	47.000	119.367	19.000	175.000
Ln(Brokerage size)	3.914	3.850	1.345	2.944	5.165
N	263,758				

Table IA4
Cross-country gender differences in performance under competition: excluding the U.S. and/or the U.K.

This table examines cross-country gender differences in performance under competition using OLS regression with firm times year fixed effects excluding analysts based on certain countries. Panel A reports cross-country gender differences in performance under competition with firm times year fixed effects excluding analysts based in the U.S. Panel B reports cross-country gender differences in performance under competition with firm times year fixed effects excluding analysts based in the U.S. and the U.K. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Cross-country gender differences in performance under competition: excluding the U.S.

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043** (0.021)	0.038 (0.026)	0.054** (0.024)	0.106*** (0.039)
Female × High IDV	-0.086** (0.039)	-0.139*** (0.044)	-0.051 (0.041)	-0.140*** (0.052)
High IDV	-0.034 (0.033)	-0.018 (0.036)	0.021 (0.035)	-0.028 (0.041)
GGGI	0.453 (0.375)	0.793* (0.426)	0.884** (0.422)	0.976** (0.486)
Ln(GDP per capita)	-0.012 (0.019)	-0.007 (0.024)	0.000 (0.021)	-0.050* (0.026)
Foreign analyst	0.074*** (0.028)	0.010 (0.032)	0.092*** (0.027)	0.036 (0.034)
Forecast horizon	0.159*** (0.004)	0.096*** (0.004)	0.210*** (0.005)	0.015*** (0.005)
Forecast frequency	0.002 (0.003)	0.022*** (0.004)	-0.034*** (0.004)	-0.001 (0.005)
# firms followed	-0.001 (0.001)	0.000 (0.001)	-0.002* (0.001)	-0.001 (0.002)
# industries followed	-0.004 (0.003)	-0.007* (0.004)	0.004 (0.004)	-0.006* (0.004)
Firm experience	-0.005* (0.002)	-0.004 (0.003)	-0.006** (0.003)	-0.001 (0.003)
General experience	-0.002 (0.002)	-0.000 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Ln(Brokerage size)	-0.019*** (0.005)	-0.003 (0.006)	-0.039*** (0.006)	-0.025*** (0.007)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.77	8.36	0.01	1.00
P-value	0.18	0.00	0.93	0.32
Obs.	347,089	347,089	347,089	139,469
adj-R ²	0.897	0.902	0.772	0.934

Panel B. Cross-country gender differences in performance under competition: excluding the U.S. and the U.K.

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.032 (0.020)	0.019 (0.025)	0.043* (0.024)	0.092** (0.039)
Female × High IDV	-0.073** (0.034)	-0.104** (0.043)	-0.059 (0.045)	-0.081 (0.054)
High IDV	0.060 (0.038)	0.055 (0.043)	0.107** (0.047)	0.035 (0.046)
GGGI	0.784* (0.468)	1.354*** (0.525)	0.774 (0.546)	1.748*** (0.650)
Ln(GDP per capita)	0.002 (0.019)	-0.014 (0.024)	0.013 (0.021)	-0.057** (0.028)
Foreign analyst	0.030 (0.024)	0.010 (0.028)	0.069** (0.029)	0.040 (0.035)
Forecast horizon	0.168*** (0.004)	0.098*** (0.004)	0.225*** (0.005)	0.012** (0.005)
Forecast frequency	0.001 (0.003)	0.031*** (0.004)	-0.039*** (0.004)	0.002 (0.005)
# firms followed	-0.002** (0.001)	-0.001 (0.001)	-0.003** (0.001)	0.000 (0.002)
# industries followed	-0.000 (0.003)	-0.002 (0.004)	0.005 (0.004)	-0.007 (0.004)
Firm experience	-0.008*** (0.002)	-0.005* (0.003)	-0.008*** (0.003)	-0.001 (0.003)
General experience	0.000 (0.002)	0.001 (0.002)	-0.000 (0.002)	-0.003 (0.002)
Ln(Brokerage size)	-0.015*** (0.005)	0.000 (0.006)	-0.037*** (0.006)	-0.016** (0.007)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	2.13	5.7	0.17	0.08
P-value	0.14	0.02	0.68	0.78
Obs.	291,245	291,245	291,245	118,601
adj-R ²	0.918	0.918	0.787	0.942

Table IA5
Cross-country gender differences in performance under competition: using updated individualism scores

This table examines cross-country gender differences in performance under competition using OLS regression with firm times year fixed effects and updated individualism scores. To create an updated version of Hofstede's individualism score, we follow Schwartz (1994), Triandis (1995), and Beugelsdijk et al. (2015) using survey data from the World Values Survey (WVS) and its equivalent, the European Values Study (EVS), which employs a similar set of survey questions but mostly for European countries, over the period 1981–2002. *High IDV_WVS* is an indicator variable that takes the value of one if a country is in the top quartile of updated individualism scores, and zero otherwise. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.069*** (0.026)	0.061* (0.032)	0.074** (0.031)	0.112** (0.054)
Female × High IDV_WVS	-0.088*** (0.029)	-0.088** (0.036)	-0.064* (0.035)	-0.117** (0.057)
High IDV_WVS	-0.097** (0.045)	-0.173*** (0.055)	0.004 (0.056)	-0.147*** (0.053)
GGGI	1.607** (0.680)	1.770** (0.794)	2.698*** (0.735)	1.349 (0.923)
Ln(GDP per capita)	-0.007 (0.026)	-0.003 (0.032)	-0.045* (0.027)	-0.075* (0.038)
Foreign analyst	0.018 (0.022)	0.006 (0.027)	0.028 (0.027)	0.026 (0.028)
Forecast horizon	0.165*** (0.003)	0.079*** (0.003)	0.233*** (0.004)	0.008*** (0.003)
Forecast frequency	-0.001 (0.002)	0.021*** (0.003)	-0.028*** (0.003)	0.002 (0.002)
# firms followed	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)
# industries followed	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.003)	0.002 (0.003)
Firm experience	-0.004*** (0.001)	-0.004*** (0.002)	-0.003 (0.002)	-0.000 (0.002)
General experience	-0.001 (0.001)	0.002 (0.001)	-0.006*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.002 (0.003)	0.000 (0.004)	-0.007* (0.004)	-0.006* (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV_WVS = 0				
F value	2.37	2.83	0.37	0.07
P-value	0.12	0.09	0.54	0.79
Obs.	482,975	482,975	482,975	272,989
adj-R ²	0.931	0.931	0.801	0.949

Table IA6
Cross-country gender differences in performance under competition: clustering standard errors at different levels

This table examines cross-country gender differences in performance under competition clustering standard errors at different levels. Panel A presents the regression results when standard errors (in parentheses) are clustered at the analyst country times year level. Panel B presents the regression results when standard errors (in parentheses) are clustered at the brokerage times year level. Panel C presents the regression results when standard errors (in parentheses) are clustered at the analyst level. Panel D presents the regression results when standard errors (in parentheses) are clustered at the firm level. Definitions of the variables are provided in the Appendix. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Cross-country gender differences in performance: standard errors clustered at the analyst country times year level

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043* (0.024)	0.040 (0.029)	0.051* (0.030)	0.114*** (0.043)
Female × High IDV	-0.059** (0.028)	-0.089** (0.036)	-0.030 (0.036)	-0.122** (0.047)
High IDV	-0.073** (0.030)	-0.045 (0.032)	-0.058* (0.034)	-0.061** (0.031)
GGGI	0.770** (0.379)	0.882** (0.402)	1.537*** (0.438)	0.891* (0.503)
Ln(GDP per capita)	-0.012 (0.017)	-0.008 (0.021)	-0.011 (0.018)	-0.060*** (0.022)
Foreign analyst	0.054*** (0.020)	0.005 (0.024)	0.076*** (0.022)	0.020 (0.020)
Forecast horizon	0.156*** (0.009)	0.081*** (0.005)	0.215*** (0.013)	0.011*** (0.003)
Forecast frequency	-0.001 (0.003)	0.016*** (0.003)	-0.028*** (0.004)	-0.001 (0.003)
# firms followed	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)
# industries followed	-0.002 (0.002)	-0.005* (0.003)	0.001 (0.003)	-0.000 (0.003)
Firm experience	-0.003** (0.001)	-0.004* (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.008** (0.004)	-0.003 (0.004)	-0.012* (0.007)	-0.011** (0.005)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.06	5.02	1.32	0.12
P-value	0.30	0.03	0.25	0.73
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.910	0.915	0.782	0.943

Panel B. Cross-country gender differences in performance: standard errors clustered at the brokerage times year level

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043* (0.022)	0.040 (0.025)	0.051* (0.026)	0.114*** (0.040)
Female × High IDV	-0.059** (0.027)	-0.089*** (0.031)	-0.030 (0.032)	-0.122*** (0.043)
High IDV	-0.073*** (0.028)	-0.045 (0.032)	-0.058* (0.031)	-0.061* (0.033)
GGGI	0.770** (0.389)	0.882** (0.434)	1.537*** (0.447)	0.891* (0.502)
Ln(GDP per capita)	-0.012 (0.018)	-0.008 (0.022)	-0.011 (0.020)	-0.060** (0.025)
Foreign analyst	0.054*** (0.021)	0.005 (0.023)	0.076*** (0.022)	0.020 (0.023)
Forecast horizon	0.156*** (0.003)	0.081*** (0.003)	0.215*** (0.005)	0.011*** (0.003)
Forecast frequency	-0.001 (0.002)	0.016*** (0.003)	-0.028*** (0.003)	-0.001 (0.003)
# firms followed	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)
# industries followed	-0.002 (0.002)	-0.005* (0.003)	0.001 (0.003)	-0.000 (0.003)
Firm experience	-0.003** (0.001)	-0.004** (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.008** (0.004)	-0.003 (0.004)	-0.012*** (0.005)	-0.011*** (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.06	6.55	1.25	0.17
P-value	0.30	0.01	0.26	0.68
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.910	0.915	0.782	0.943

Panel C. Cross-country gender differences in performance: standard errors clustered at the analyst level

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043* (0.022)	0.040 (0.026)	0.051* (0.027)	0.114*** (0.040)
Female × High IDV	-0.059** (0.027)	-0.089*** (0.032)	-0.030 (0.032)	-0.122*** (0.044)
High IDV	-0.073*** (0.027)	-0.045 (0.030)	-0.058* (0.030)	-0.061* (0.033)
GGGI	0.770** (0.377)	0.882** (0.421)	1.537*** (0.439)	0.891* (0.505)
Ln(GDP per capita)	-0.012 (0.017)	-0.008 (0.022)	-0.011 (0.019)	-0.060** (0.024)
Foreign analyst	0.054*** (0.020)	0.005 (0.023)	0.076*** (0.021)	0.020 (0.023)
Forecast horizon	0.156*** (0.003)	0.081*** (0.003)	0.215*** (0.003)	0.011*** (0.003)
Forecast frequency	-0.001 (0.002)	0.016*** (0.003)	-0.028*** (0.003)	-0.001 (0.003)
# firms followed	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)
# industries followed	-0.002 (0.002)	-0.005* (0.003)	0.001 (0.003)	-0.000 (0.003)
Firm experience	-0.003** (0.001)	-0.004** (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.008** (0.003)	-0.003 (0.004)	-0.012*** (0.004)	-0.011*** (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.10	7.04	1.24	0.17
P-value	0.29	0.01	0.27	0.68
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.910	0.915	0.782	0.943

Panel D. Cross-country gender differences in performance: standard errors clustered at the firm level

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.043* (0.023)	0.040 (0.029)	0.051* (0.027)	0.114** (0.048)
Female × High IDV	-0.059** (0.028)	-0.089*** (0.034)	-0.030 (0.032)	-0.122** (0.051)
High IDV	-0.073** (0.032)	-0.045 (0.032)	-0.058* (0.033)	-0.061* (0.032)
GGGI	0.770** (0.392)	0.882** (0.404)	1.537*** (0.450)	0.891* (0.475)
Ln(GDP per capita)	-0.012 (0.018)	-0.008 (0.024)	-0.011 (0.022)	-0.060** (0.023)
Foreign analyst	0.054** (0.025)	0.005 (0.023)	0.076*** (0.021)	0.020 (0.021)
Forecast horizon	0.156*** (0.004)	0.081*** (0.003)	0.215*** (0.004)	0.011*** (0.003)
Forecast frequency	-0.001 (0.002)	0.016*** (0.003)	-0.028*** (0.003)	-0.001 (0.003)
# firms followed	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)
# industries followed	-0.002 (0.002)	-0.005* (0.002)	0.001 (0.003)	-0.000 (0.002)
Firm experience	-0.003** (0.001)	-0.004** (0.002)	-0.003* (0.002)	-0.001 (0.002)
General experience	-0.003** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002 (0.001)
Ln(Brokerage size)	-0.008** (0.004)	-0.003 (0.004)	-0.012*** (0.004)	-0.011*** (0.004)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	1.1	7.04	1.24	0.17
P-value	0.29	0.01	0.27	0.68
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.910	0.915	0.782	0.943

Table IA7**Cross-country gender differences in performance under competition: additional robustness checks**

This table examines cross-country gender differences in performance under competition using alternative samples or model specifications to Table 4. Panel A presents the regression results using firm-forecast-analyst-level observations. The dependent variable is *Absolute forecast error*, the absolute value of the difference between an analyst's annual EPS forecast and actual EPS normalized by the stock price at the prior fiscal year end. Column (1) presents the results with firm times year fixed effects, and column (2) presents the results with firm times year times month fixed effects. Panel B repeats the analysis in Table 4 adding brokerage fixed effects. Panel C repeats the analysis in Table 4 using an analyst's name to determine their country of origin. The sample consists of 11,444 equity analysts from 42 countries who are from the same high (low) IDV countries based on their last name and first name using the algorithm developed by Origins Info Ltd. as those based on their place of work. Definitions of the variables are provided in the Appendix. Heteroscedasticity-consistent standard errors (in parentheses) are clustered at the firm times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Cross-country gender differences in performance under competition using forecast-level observations

	Absolute forecast error (1)	Absolute forecast error (2)
Female	0.073** (0.035)	0.087* (0.050)
Female × High IDV	-0.088** (0.038)	-0.099* (0.054)
High IDV	-0.062** (0.028)	-0.071** (0.035)
GGGI	0.809*** (0.311)	0.676* (0.405)
Ln(GDP per capita)	-0.035** (0.016)	-0.049** (0.023)
Foreign analyst	0.078*** (0.021)	0.066** (0.027)
Forecast horizon	0.007*** (0.000)	0.006*** (0.000)
Forecast frequency	-0.003 (0.003)	-0.004 (0.003)
# firms followed	0.001 (0.001)	0.000 (0.001)
# industries followed	0.000 (0.002)	0.002 (0.002)
Firm experience	-0.001 (0.001)	-0.000 (0.002)
General experience	-0.004*** (0.001)	-0.004*** (0.001)
Ln(Brokerage size)	-0.007** (0.003)	-0.010*** (0.004)
Firm × Year Fixed Effects	Yes	No
Firm × Year × Month Fixed Effects	No	Yes
Intercept	Yes	Yes
Tests if Female + Female × High IDV = 0		
F value	1.01	0.46
P-value	0.31	0.50
Obs.	2,629,947	2,629,947
adj-R ²	0.807	0.882

Panel B. Cross-country gender differences in performance under competition including brokerage fixed effects

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.029 (0.021)	0.038 (0.026)	0.035 (0.025)	0.131*** (0.038)
Female × High IDV	-0.041 (0.026)	-0.079** (0.031)	-0.014 (0.030)	-0.138*** (0.041)
High IDV	-0.054* (0.029)	0.000 (0.034)	-0.023 (0.034)	-0.047 (0.037)
GGGI	0.823* (0.436)	0.755 (0.521)	1.801*** (0.485)	1.107* (0.588)
Ln(GDP per capita)	-0.017 (0.020)	-0.012 (0.025)	-0.016 (0.021)	-0.059** (0.027)
Foreign analyst	0.063*** (0.022)	0.017 (0.025)	0.080*** (0.022)	0.031 (0.025)
Forecast horizon	0.156*** (0.003)	0.081*** (0.003)	0.214*** (0.003)	0.010*** (0.003)
Forecast frequency	-0.001 (0.002)	0.013*** (0.003)	-0.023*** (0.002)	-0.002 (0.002)
# firms followed	0.001 (0.001)	0.002** (0.001)	-0.000 (0.001)	-0.000 (0.001)
# industries followed	-0.007*** (0.002)	-0.006** (0.003)	-0.004* (0.003)	-0.000 (0.003)
Firm experience	-0.003** (0.001)	-0.003* (0.002)	-0.003* (0.002)	-0.000 (0.002)
General experience	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Ln(Brokerage size)	-0.011 (0.010)	-0.019 (0.013)	0.014 (0.011)	0.008 (0.011)
Brokerage Fixed Effects	Yes	Yes	Yes	Yes
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	0.74	6.10	1.51	0.19
P-value	0.39	0.01	0.22	0.66
Obs.	610,847	610,847	610,847	318,622
adj-R ²	0.911	0.915	0.783	0.944

Panel C. Using an analyst's name to determine their country of origin

	Average forecast error (1)	First forecast error (2)	Last forecast error (3)	Same week forecast error (4)
Female	0.074*** (0.023)	0.055* (0.029)	0.097*** (0.028)	0.140*** (0.046)
Female × High IDV	-0.085** (0.034)	-0.073* (0.039)	-0.065* (0.037)	-0.123** (0.053)
High IDV	-0.049 (0.036)	-0.057 (0.041)	-0.037 (0.039)	-0.124*** (0.041)
GGGI	0.491 (0.442)	0.370 (0.533)	1.256** (0.508)	0.694 (0.540)
Ln(GDP per capita)	-0.021 (0.018)	-0.024 (0.023)	-0.004 (0.021)	-0.066** (0.026)
Foreign analyst	0.067*** (0.024)	0.057** (0.028)	0.078*** (0.026)	0.050* (0.027)
Forecast horizon	0.158*** (0.004)	0.086*** (0.004)	0.214*** (0.004)	0.016*** (0.004)
Forecast frequency	-0.002 (0.003)	0.020*** (0.003)	-0.032*** (0.003)	0.000 (0.003)
# firms followed	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
# industries followed	-0.002 (0.003)	-0.008*** (0.003)	0.005 (0.003)	-0.003 (0.003)
Firm experience	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
General experience	-0.002 (0.001)	0.000 (0.002)	-0.005*** (0.002)	-0.001 (0.002)
Ln(Brokerage size)	-0.009** (0.004)	-0.003 (0.005)	-0.016*** (0.005)	-0.011** (0.005)
Firm × Year Fixed Effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Tests if Female + Female × High IDV = 0				
F value	0.21	0.47	1.81	0.48
P-value	0.65	0.49	0.18	0.49
Obs.	384,739	384,739	384,739	190,805
adj-R ²	0.916	0.921	0.788	0.947