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Examining Financial Analyst Herding Behavior in Collectivistic versus Individualistic Countries

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Abstract

Research Question: Does national culture influence financial analysts' herding behavior and does firm-level uncertainty intensify this relationship?
Motivation: Analyst herding can reduce the information quality of analysts' forecasts and impair market efficiency. Prior research has examined the effects of the information environment on analyst herding behavior, but limited research has examined how the national culture where analysts are located impacts the propensity to engage in herding behavior.
Idea: The study examines the impact of the collectivism-individualism dimension of national culture on analyst herding behavior. We argue that analysts in collectivistic cultures face stronger pressures to conform to consensus forecasts, especially when there exists greater uncertainty in the firm information environment.
Data: The sample consists of 28,588 firm-year observations from 2010-2020 across multiple international stock exchanges using analyst forecast data from I/B/E/S and firm information from Compustat.
Tools: Analyst herding is measured using the S-statistic. National culture is proxied using Hofstede's individualism index (inverted to measure collectivism), and regression models include firm and year fixed effects.
Findings: Analyst herding is significantly more prevalent in collectivistic countries than in individualistic countries. Furthermore, the relation between collectivism and herding is stronger when firms operate in information environments characterized by greater information uncertainty.
Contribution: The study provides international evidence that national culture impacts analyst behavior. By showing that collectivistic national cultures are associated with greater analyst

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herding, the study highlights the impact that cultural norms can have on financial market inputs, given the role of financial analysts as important information intermediaries.

Keywords: national culture, analyst herding behavior, collectivism–individualism, financial analyst forecasting, information environment uncertainty, S-statistic forecast bias.

JEL codes: G14

1. Introduction

In a world that is becoming increasingly globalized, different national cultures intersect and interact with greater frequency. In capital markets research, investigators are beginning to scrutinize the influence culture can have on market participants. For example, researchers are examining the influence national culture can have on how a nation organizes their financial system (Kwok & Tadesse, 2006). Researchers are also studying the impact of culture on accounting quality, which has implications for market efficiency (Han *et al.,* 2010). Additionally, there is growing research which is evaluating the impact of national culture on financial analyst behavior (Chen *et al.,* 2020; Qi *et al.*, 2014). Exploring the effect of national culture on analyst behavior recognizes that financial analysts provide important inputs to the market. Financial analysts engage in two roles with respect to the firms they cover (1) information production and (2) monitoring (Xu *et al.*, 2017). Analysts play a significant role in producing information and scrutinizing firms. However, the effectiveness of financial analysts in contributing information to the market can be damaged by their tendency to herd (Keskek *et al.,* 2014; Leece & White, 2017). Analyst herding can damage the role analysts play in financial markets if they lean more on the group consensus instead of their own private information gathering. The current study examines the effect of national culture on analyst herding behavior.

Specifically, we examine how the collectivism-individualism dimension of national culture impacts analysts' propensity to herd. Analyst herding is defined as the decision to "bias a forecast away from an analyst's best estimate toward the consensus forecast of earlier analysts" (Bernhardt *et al.,* 2006, p. 660). Analysts herd for a variety of reasons including career concerns (Hong *et al.,* 2000a) as well as the complexity of the firm being analyzed (Segara *et al.,* 2023). Individual analyst characteristics can also exacerbate or mitigate the propensity to herd. Research has found that more experienced analysts and analysts with a higher risk tolerance herd less (Clement & Tse, 2005; Christoffersen & Stæhr, 2019). While many different analyst characteristics have been scrutinized thoroughly, the effects of national culture on analyst herding behavior has not been studied extensively.

Understanding the effects of national culture on analyst herding is important because analyst herding can have detrimental effects on market efficiency and herding has even been found to be associated with greater stock price crash risk (Arya *et al.,* 2005; Xu *et al.,* 2017). Furthermore, analyst forecasts are an important information source to investors (Bernhardt *et al.,* 2006). Therefore, it is important to examine cultural considerations that could introduce bias into analyst forecasts.

One recent study by Cao *et al.* (2024) does examine the effects of U.S. financial analysts' culture of origin on analyst herding behavior. The authors find that U.S. analysts whose ethnic background is from a collectivistic culture demonstrate a greater propensity to herd. The theoretical underpinning of the study is that individualistic analysts are more confident of their private information therefore they overweight their private information. Collectivistic analysts, on the other hand, feel a greater pressure to conform to the consensus. The Cao *et al*. (2024) study represents an important step forward in examining the effects of culture on analyst herding. The setting of the study is limited, however, because it focuses solely on U.S. analysts. While U.S. analysts may have different cultures of origins, it is important to recognize these original cultures are likely to assimilate into the national culture of the U.S. through the process of acculturation. Therefore, it is difficult to disentangle the assimilated culture of the immigrant population in the U.S. and identify the true cultural reasons for the decision-making of the immigrant financial analysts. To overcome this limitation, our study focuses on the differences in analyst herding in collectivistic versus individualistic countries. Our study examines how analysts immersed in culturally distinct societies, where tasks, decisions, rewards and incentives are informed by that culture, engage in herding behavior. Despite the differences in setting, we expect that collectivism (individualism) will continue to be associated with greater herding (anti-herding) behavior.

To test our primary hypothesis regarding the effects of individualism-collectivism on analyst herding, we utilize the S-statistic, a common herding measure. This measure of herding was developed by Bernhardt *et al*. (2006) and it analyzes the degree to which analysts bias their forecasts toward the consensus (i.e. exhibit herding behavior). To measure the degree of collectivism in a given country, we formulate a collectivism score by inverting Hofstede's (2001) individualism score (collectivism is equal to 100 minus the individualism score). Tests of the association between analyst herding and collectivism demonstrate that collectivism is related with greater herding behavior. Our study provides further support of the existing literature that states individualistic analysts overweight their private information compared to collectivistic analysts, who tend to herd toward the group consensus, to gain loyalty of their networks.

To further examine the effect of collectivism on analyst herding behavior, we examine how this relationship is moderated by uncertainty in the firm's information

environment. Our proxy for firm uncertainty is the average forecast error. Prior research (Segara *et al*., 2023; Leece & White, 2017) demonstrates that analysts are more likely to herd when firm uncertainty is higher. Firm uncertainty increases the pressure to conform in a collectivistic culture because the reputational consequences of deviating from the pack may be more severe when there is greater uncertainty surrounding the firm. We predict greater firm uncertainty will intensify the relation between collectivism and analyst herding. We find that the relation between firm uncertainty and analyst herding is stronger in collectivistic countries. This is consistent with our hypothesis that firm uncertainty increases reputational concerns in collectivistic cultures.

To our knowledge, this study is the first that has extensively compared analyst herding behavior across nations to examine the effect of culture on analyst herding. Our study shows that distinct national cultures can exhibit a different tendency in analyst herding behavior based on the degree of individualism/collectivism present in the culture. The current study has implications for how capital markets in different countries may be impacted by analyst herding behavior. Overall, we provide evidence regarding the influence of national culture on analysts' decision to not act fully on their private information and instead choose to conform to the group consensus. Only by adhering to the group consensus are these individuals able to exhibit loyalty to their groups, which in turn, protects their interests.

2. Background and hypotheses development

Analysts have an information set which they use to forecast company earnings. This information set includes publicly available information as well as information they discover through their own research. "The analyst uses all of this information to update and form a posterior distribution of earnings. An analyst's forecast is unbiased if the forecast is equal to his posterior estimate of the median or mean earnings per share" (Bernhardt *et al*., 2006, p. 660). Unbiased forecasts are most useful to investors who depend on analysts as important aggregators and creators of information about the firm they follow. Herding behavior refers to the behavior of analysts issuing biased forecasts as opposed to forecasts which are unbiased. Analyst herding is defined as the decision to "bias a forecast away from an analyst's best estimate towards the consensus of earlier analysts" (Bernhardt *et al*., 2006, p. 660). When herding is present, analysts' forecasts do not convey as much information to the market because analysts are not fully acting on their private information when issuing forecasts.

Analyst herding can have consequences. Herding theory, as presented in Arya *et al*. (2005) predicts that herding has negative consequences on market efficiency. The reason is that herding can be detrimental to investors. This is because analysts do not showcase fully their private information in their forecasts, but instead herd towards the consensus of other analysts (Mensah & Yang, 2008). Empirical studies have

demonstrated that greater analyst herding in a firm is associated with greater risk of the stock price crashing. Xu *et al*. (2017) study a sample of Chinese firms and find that firms in which more analyst herding is present have a higher crash risk. This is because herding behavior among analysts prevents a firm's bad news information from being disclosed in a timely manner to the market. Eventually, however, when this bad news information accumulates beyond a threshold, there is a flood of negative information to the market which leads to a stock price crash.

The study also documents that this effect on information delay caused by analyst herding occurs principally with bad news and not good news. The authors conjecture that this is because bad news has been found to travel slower than good news (Hong *et al*., 2000b). Xu *et al*. (2017) postulate that, when engaging in herding behavior, analysts are not acting in their full capacity as monitors of a firm. Additional studies have demonstrated that when herding is present, the accuracy of forecasts suffers. For example, Fluharty (2020) documented herding behavior around "All Star" analysts and showed that when this type of herding behavior is present, the consensus forecast is less accurate. Clement and Tse (2005) show that herding forecasts are less accurate than bold forecasts.

Furthermore, studies have demonstrated that stock market reactions are greater to forecasts that express analysts' private information to a greater extent (Gleason & Lee, 2003; Clement & Tse, 2005). Along with research showing how analyst herding can be detrimental to market efficiency and forecast accuracy, additional streams of research examine the reasons for analyst herding. One group of studies has identified the career concerns of analysts as an important influence in their decision to herd (Hong *et al*., 2000a; Clement & Tse, 2005). Related to this explanation of career concerns is a study by Frijns and Huynh (2018) which finds that analysts actually herd less when stocks are covered more in the media. The reason given for this effect of media coverage on analyst herding behavior is that when companies are covered more in the media, it enhances an analyst's career prospects by giving them a chance to stand out. Finally, research has shown that less transparent disclosure is associated with analyst herding. Segara *et al*. (2023) find that firms with greater intangible assets experience greater analyst herding around their forecasts. The authors state that the findings highlight the need for more transparent disclosure.

Another stream of literature examines analyst characteristics that affect the analyst's propensity to herd. In a foundational study on analyst characteristics and herding behavior, Clement and Tse (2005) find that analysts herd less (i.e. are more bold) when they have a previous history of accuracy, are affiliated with a larger brokerage, and have more experience. Lin (2018) also finds that experience mitigates herding behavior. In their study, they find that while information uncertainty is associated with greater herding, this effect is less pronounced for more experienced analysts.

Clement and Tse (2005) find that analysts who cover more industries are more prone to herding behavior. Similarly, Kim and Pantzalis (2003) find that greater analyst

herding occurs when an analyst has a more diversified portfolio of companies. This result is consistent with the hypothesis that herding is more likely when forecasting capacity increases. Finally, Christoffersen and Stæhr (2019) examine the effect of an analyst's risk tolerance on their propensity to herd. They find that less risk tolerant individuals are more prone to engage in herding behavior.

In the literature, there are competing theories regarding whether analyst herding behavior is detrimental to market efficiency. For example, under trade-off theory, both analysts forecasting earlier as well as analysts forecasting later would be issuing informative forecasts which contribute to efficient markets. On the other hand, reputational herding theory predicts a negative effect of analyst herding on market efficiency (Arya *et al*., 2005). As outlined in Keskek *et al*. (2014), reputational herding theory predicts that earlier forecasts are more informative and of a higher quality than later forecasts because the best informed, most capable analysts forecast earlier and then later analysts protect their reputation by falling in line with the consensus. Keskek *et al*. (2014) find evidence of reputational herding. Specifically, the results of their study show that earlier forecasts are of a higher quality than later forecasts. The authors posit that in the earlier stage of the forecast period, more capable analysts engage in information discovery and analysis. This explains why earlier forecasts are of a higher quality and is consistent with reputational herding theory.

2.1 Effect of culture on analyst behavior

Recently, a stream of literature has emerged which examines the effect of culture on analyst behavior. Table 1 summarizes recent relevant literature. Liu *et al*. (2025) study the effect on forecasting behavior associated with having ancestry from a country that uses more negative language. The authors find that U.S. analysts who have ancestry from countries with greater language negativity demonstrate a propensity to issue forecasts that are less optimistic. Pursiainen (2022) studies the degree to which cultural biases against other countries affect stock recommendations. The results of the study show that if the analyst's country of origin has a positive cultural trust bias towards the country where the company being followed is headquartered, the analyst is more likely to issue a positive recommendation.

Table 1. Recent literature on the effects of culture on financial analyst behavior

Authors and year	Findings
Liu *et al*. (2025)	U.S. analysts that have ancestry from countries which use more negative language issue forecasts that are less optimistic. The effect of negative language on forecast optimism is stronger (1) during times of financial crisis (2) for firms with greater losses and higher earnings volatility and (3) for analysts who are younger and for those employed by smaller brokerages. The study shows how culturally influenced behavior affects the properties of analyst forecasts.

Authors and year	Findings
Cao *et al*. (2024)	U.S. analysts who have an ethnic background from a collectivistic country are more likely to herd in their forecasts. This arises from greater pressure to conform to the consensus.
Choi *et al*. (2022)	Demonstrates that the greater accuracy of local resident financial analysts over expatriate financial analysts and global financial analysts is due to the forecasts of bold local analysts. Local analysts who herd are among the least accurate type of analysts. The results underscore the importance of controlling for analyst herding when analyzing the accuracy of different types of financial analysts in Asia.
Pursiainen (2022)	Analysts' stock recommendations are significantly more positive towards companies headquartered in countries where there is a positive cultural trust bias extended from the analysts' country of origin. Stock price reactions to recommendations by analysts exhibiting greater bias are weaker and recommendations that are more biased are less predictive of monthly stock returns.
Merkley *et al*. (2020)	Greater ethnic diversity among the set of analysts following a firm leads to a more accurate consensus forecast. Cultural diversity improves accuracy by 1) reducing the forecast error covariance through a more diverse set of analyst forecasting practices and 2) individual analyst accuracy improves via exposure to new and different forecasting practices.

Merkley *et al*. (2020) study the impact having a culturally diverse set of analysts has on the quality of analysts' forecasts. The results of the study demonstrate that an increase in the cultural diversity of analysts following a firm is associated with a higher quality consensus forecast. In other words, having a more ethnically diverse set of analysts following a firm leads to more accurate analyst forecasts. The authors conjecture that cultural diversity positively affects forecasts in two ways. The first way cultural diversity positively affects forecasts accuracy is by reducing the error covariance in analysts' forecasts. The reason for this reduction in forecast error covariance is because having more diverse analysts introduces more diverse analyst forecast practices (i.e. different beliefs, different ways of processing information, etc.). The second way cultural diversity improves forecast accuracy is that having a more culturally diverse set of analysts may improve an individual analyst's accuracy by introducing them to new and different forecasts practices. Choi *et al*. (2022) is one of the few studies that examine the effect of culture specifically on analyst herding behavior. Their study examines forecasting behavior for foreign firms, comparing analysts which are local to that foreign country against analysts who are either not located in that foreign country or who are located in the country but are expatriates. The results show that the forecasts of the local analysts are superior to both analysts not located in that country and expatriate analysts, but these results are solely owed to herding behavior amongst the local analysts.

2.2 Background on Individualism versus Collectivism

While the research analyzing the impact of national culture on analyst herding behavior is limited, there is an abundance of literature that has evaluated the impact of national culture on decision-making behavior in different contexts. Hofstede (1984) defines culture as "the interactive aggregate of common characteristics that influence a human group's response to its environment" (p. 21). Based on the analysis of the IBM data, Hofstede (1984) initially developed the following four dimensions of national culture: individualism (versus collectivism), masculinity (versus femininity), power distance, and uncertainty avoidance. Later, Hofstede and his colleagues added two additional dimensions of national culture. These are long-term orientation and indulgence (versus restraint). While all dimensions are important, research has focused extensively on analyzing the relationship between individualism (versus collectivism) and decision-making behaviors. Hofstede (1984, pp. 2-3) summarizes the difference between individualism - collectivism below:

Individualism on the one side versus its opposite, collectivism, is the degree to which individuals are integrated into groups. On the individualist side, we find societies in which the ties between individuals are loose: everyone is expected to look after him/herself and his/her immediate family. On the collectivist side, we find societies in which people from birth onwards are integrated into strong, cohesive in-groups, often extended families (with uncles, aunts and grandparents) which continue protecting them in exchange for unquestioning loyalty. The word "collectivism" in this sense has no political meaning: it refers to the group, not to the state (Hofstede, 1984, p. 2-3).

As stated above, the individualism (versus collectivism) dimension of Hofstede's national culture has been extensively studied in accounting literature. For example, Rhee *et al*. (2020) examine the effect of the individualism collectivism dynamic on performance theory. When forming aspiration levels, collectivistic decision makers considered social reference points more while individualistic decision makers gave greater weight to historical reference points. Furthermore, when there was a gap between aspiration levels and actual performance, collectivistic decision-makers demonstrated a preference for finding a proximal alternative to what is currently being done while individualistic decision-makers were more willing to look for a distant alternative. Gil *et al*. (2019) examine the influence of individualism/collectivism on the relationship between top management team (TMT) function diversity and firm performance. The authors noted that the relationship between TMT functional diversity and firm performance is positive in collectivistic cultures while it is negative in individualistic cultures. The authors noted that in collectivistic cultures, TMTs allow for consideration of multiple options, but because of the emphasis on group harmony in those cultures, integration and cooperation are maintained.

In another study, Frijns *et al*. (2022) examine the relationship between individualism and corporate risk-taking behavior across the world. With a sample size of 111,697 firm-year observations, the authors found that there is a strong relationship between the individualism (IDV) dimension of national culture and corporate risk-taking behavior. The authors note that "IDV through increased risk-taking incentives, focuses on self-achievement or overconfidence, which leads to increased risk-taking, which is reflected in an increased corporate risk-taking" (p. 6).

Furthermore, Chen *et al*. (2015) examined the relationship between different dimensions of national culture and corporate cash holding in different countries. With respect to the individualism dimension, the authors found an inverse relationship between individualism and corporate cash holdings around the world. Additionally, the authors analyzed the influence of individualism/collectivism at the state level in the U.S. and noted that the firms in individualistic U.S. states hold much less cash than those in collectivist states. Finally, the study also reported a positive relationship between individualism and a firm's capital expenditures, acquisitions, and repurchases.

These studies represent just a sample of the deep stream of literature examining the effect of individualism/collectivism dynamic on decision making.

2.3 Effects of individualism/collectivism on analyst herding behavior

While there are not many studies which have examined the effects of individualism and collectivism on analyst herding, a few studies are emerging which analyze the association between this aspect of culture and analyst herding behavior. Naujoks *et al*. (2009) examine analyst herding behavior in Germany which is traditionally a very individualistic country. They find evidence of anti-herding behavior among analysts. The study finds that the anti-herding behavior of the German analysts is especially pronounced in settings of higher competition among analysts. Cao *et al*. (2024) analyze U.S. financial analysts and find that analysts whose ethnic background is from a collectivistic culture demonstrate a greater propensity to herd. Analysts from individualistic cultures, on the other hand, tend to issue more bold earnings (anti-herding) forecasts. The theory put forth by Cao *et al*. (2024) to explain their findings is that individualistic analysts may exhibit greater trust in the usefulness of their private information than collectivistic analysts. Because of this trust, they put greater weight on their private information when issuing forecasts, causing greater deviation from the consensus. Collectivistic analysts, on the other hand, feel greater pressure to conform to the consensus which they view as a type of implicit agreement among peers.

Our study is similar to the Cao *et al*. (2024) study in that we examine the effects of the individualism/collectivism dynamic on analyst herding behavior, but instead of

looking only at U.S. analysts, we compare analysts across countries. So, while Cao *et al*. (2024) look at the influence of the analysts' cultural origins, our study examines the influence of the national culture in which the analyst is forecasting. For example, Cao *et al*. (2024) describe how, in their setting, the monetary incentives and competitive nature of the U.S. financial industry may counteract the effect of ethnic culture on analyst herding behavior. In our setting, however, we look at how having different risk and reward structures as established by different national cultures affect the propensity to herd. We anticipate that in collectivistic countries, reputational concerns will be greater and herding behavior will be more prevalent due to the collectivistic desire to conform to the group. Moreover, collectivist analysts will be exhibiting loyalties to their groups by engaging in herding behavior as they will be focused on group success compared to individual success. Analysts in individualistic cultures, however, will be less concerned by the reputational consequences of not conforming to the consensus. Therefore, they will weigh their private information more and herd less. This leads to our first hypothesis:
H_1: Financial analysts in collectivistic countries will exhibit greater herding behavior than those in individualistic countries.

2.4 Effects of firm information environment on analyst herding behavior

Within the analyst herding literature, there are a number of studies which demonstrate that herding behavior is more prevalent when there exists greater uncertainty either in the firm's information environment or in the market as a whole. For example, Lin (2018) finds that analysts' tendency to herd increases when aggregate market uncertainty increases. Segara *et al*. (2023) show that the tendency of analysts to herd is higher when firm-level uncertainty is high. Leece and White (2017) find analyst herding is more prevalent in firms with greater short-term institutional ownership. The authors posit that the link between short-term institutional ownership and analyst herding is the lack of transparency in the firm's information environment. Their theory is that short-term institutional investors exploit opportunities in firms with more opaque information environments. This opaque information environment also leads analysts to herd together in their forecasts. Wen and Tikoo (2022) find that corporate strategy uniqueness is positively related to analyst herding. The authors suggest corporate strategy uniqueness causes a higher level of information asymmetry between the insiders of a company versus external stakeholders. In summary, numerous studies demonstrate increased herding behavior in the presence of uncertainty in the firm's information environment.

In collectivistic cultures, the association between analyst herding behavior and information uncertainty is likely to be intensified. Kim and Cohen (2010) demonstrate that respondents from Asian cultures, which are typically very collectivistic, are highly influenced by others' perceptions of their behavior. In cultures with higher levels of collectivism, there is great importance attached to how

you are viewed by others. This cultural consideration is important with respect to analysts because collectivistic analysts may care more about protecting their reputation or credibility in the eyes of others. Research has shown that when financial analysts issue inaccurate forecasts, their credibility can be damaged, especially if they strayed from the pack. Kadous *et al*. (2009) find that when analysts deviate from the herd and issue a bold forecast and are wrong, their credibility will suffer greater damage than if they were wrong but went with the herd. In other words, there is a credibility risk associated with going rogue and being wrong. Because the risk of being wrong is greater in an uncertain information environment, it is expected this type of environment will amplify the relation between collectivism and analyst herding, as losing credibility in the eyes of others is more important in a collectivistic culture. Therefore, we expect the association between collectivistic national culture and analyst herding to be greater in firms with higher information uncertainty.
H_2: The relation between collectivism and analyst herding behavior will be stronger in firms with higher uncertainty in their information environments.

3. Research design

3.1 Does individualism-collectivism impact herding behavior (H_1)? Classifying countries as individualistic or collectivistic

The main hypothesis of our study examines the effects of collectivism/individualism on analyst herding behavior. To classify countries as individualistic or collectivistic, we follow the Hofstede (2001) classifications. Table 2 presents our classification of countries based on their Hofstede individualism scores. In our tests of the influence of individualism-collectivism on analyst herding, we use one model specification where we assign countries to either an individualistic or collectivistic group. We also use another model specification where we utilize a collectivism score, formulated by inverting the country's individualism score (Hofstede, 2001), in place of merely categorizing the country as "collectivistic" or "individualistic". Next, we will introduce our measure of analyst herding, the S-statistic.

Table 2. List of countries included in sample

Panel A: INDIVIDUALISTIC COUNTRIES GROUP		
PStock Exchange	**Country Name**	**Individualism Score**
NYSE/Nasdaq	United States of America	91
Australian Stock Exchange	Australia	90
London Stock Exchange	United Kingdom	89
Amsterdam Stock Exchange	Netherlands	80
Toronto Stock Exchange	Canada	80
New Zealand Stock Exchange	New Zealand	79

Panel A: INDIVIDUALISTIC COUNTRIES GROUP		
PStock Exchange	**Country Name**	**Individualism Score**
Milan Stock Exchange	Italy	76
Euronext Brussels	Belgium	75
Euronext Paris	France	71
Nasdaq Stockholm	Scandinavia	71
Swiss Exchange	Switzerland	68
Frankfurt Stock Exchange	Germany	67
Johannesburg Stock Exchange	South Africa	65

Panel B: COLLECTIVISTIC GROUP		
Stock Exchange	**Country Name**	**Individualism Score**
National Stock Exchange of India	India	48
Tadawul Stock Exchange	Saudi Arabia	48
Tokyo Stock Exchange	Japan	46
Moscow Stock Exchange	Russia	39
Mexican Stock Exchange	Mexico	30
Hong Kong Stock Exchange	Hong Kong	25
Santiago Stock Exchange	Chile	23
Shanghai Stock Exchange	China	20
Korea Stock Exchange	South Korea	18
Taiwan Stock Exchange	Taiwan	17
Indonesian Stock Exchange	Indonesia	14

3.2 S-statistic

We utilize the S-statistic (Bernhardt *et al*., 2006) to examine the relationship between individualism/collectivism and analyst herding. The S-statistic improves upon the methodology used in past studies, specifically because "no assumptions regarding how an analyst forms his posterior [distribution of earnings]" (Bernhardt *et al*., 2006, p. 659).

The S-statistic utilizes conditional probability and assumes that when a forecast is above the consensus, it should be above actual earnings 50% of the time and below actual earnings 50% of the time. In essence, there should be a normal distribution of analyst estimates around the actual earnings number. However, if analysts are regularly biasing their forecasts and herding, then we will see forecasts closer to the consensus. For forecasts above the consensus, this means they will be above the consensus but below actual earnings. Those forecasts are labeled "herding forecasts". The forecasts above the consensus that are also above actual earnings would be labeled as "anti-herding" forecasts because those forecasts are not being skewed towards the consensus. In the exhibit below, herding forecasts are

represented as γ while anti-herding forecasts are represented as δ. Exhibit 1 is adapted from Mensah and Yang (2008, p. 322) and illustrates the calculation of the S-statistic:

	Forecast > Consensus	**Forecast < Consensus**
Forecast > Actual EPS	∑δ+	∑γ- less ∑δ-
Forecast < Actual EPS	∑γ+ less ∑δ+	∑δ-
Column Total	∑γ+	∑γ-

δ+ = 1 if forecast > prior consensus forecast, and forecast > actual earnings; zero otherwise;
δ- = 1 if forecast < prior consensus forecast, and forecast < actual earnings; zero otherwise;
γ+ = 1 if forecast > prior consensus forecast; zero otherwise;
γ- = 1 if forecast < prior consensus forecast; zero otherwise

Exhibit 1: Measurement of the S-statistic (Adapted from Mensah & Yang, 2008, p. 322)

$$\text{S-statistic} = 0.5 * \left[\frac{\sum_{i=1}^{N} \delta_i^+}{\sum_{i=1}^{N} \gamma_i^+} + \frac{\sum_{i=1}^{N} \delta_i^-}{\sum_{i=1}^{N} \gamma_i^-}\right] \quad (1)$$

Essentially, the S-statistic measures the percentage of "anti-herding" forecasts made in the forecast observation period. This is calculated by taking the average of the percentage of forecasts above the consensus that are anti-herding forecasts and the percentage of forecasts below the consensus that are anti-herding forecasts. So, an S-statistic of 1 or 100% indicates perfect "anti-herding" behavior while an S-statistic of 0 indicates perfect "herding" behavior.

Based on the methodology in Mensah and Yang (2008) and Leece and White (2017), we estimate the following regression model:

$$S_i = \alpha_1 + \beta_1 COLLECT\_IND + \beta_2 NANALYST_i + \beta_3 NANALYST\_INT_i + \beta_4 OBS_i + \beta 5 OBS\_INT_i + \beta_6 AGE_i + \beta_7 AGE\_INT_i + \beta_8 CUSIP_i + \beta_9 YEARS_i + \varepsilon_i \quad (2a)$$

S, our measure of analyst herding, is calculated using all annual earnings forecasts made within the calculation period. The S-statistic calculation period includes the period which starts 150 days before annual earnings are announced and extends through the earnings announcement date (Bernhardt *et al*., 2006; Leece & White, 2017). To enhance the readability of our coefficients in all models, we scale S by 100 (perfect herding=0; perfect anti-herding=100). COLLECT_IND is an indicator variable that is equal to 1 if the stock exchange in which the country is traded is domiciled in a collectivist country. Consistent with our first hypothesis, we expect a significant relationship between collectivism and analyst herding. Therefore, the estimated coefficient on β_1 is expected to be negative since a lower S-statistic is associated with greater analyst herding behavior. A negative and statistically significant coefficient on β_1 would provide support for our first hypothesis.

Equation 2a contains additional control variables which could explain differences in analyst herding evidenced in companies. NANALYST is the number of unique analysts forecasting company earnings in the period. The coefficient on this variable is expected to be positive because when there are more analysts, they will seek to stand out from other analysts (Lin & McNichols, 1998).

OBS is equal to the aggregate number of forecasts used to calculate the S-statistic (Mensah and Yang 2008). No prediction is made regarding the sign on this coefficient. AGE is the average age of forecasts issued in days. The age for one forecast is equal to the number of days in between the forecast issue date and the actual earnings announcement date. We expect the coefficient on AGE to be positive because older forecasts should be more diffuse while newer forecasts should be more clustered together. The model also includes three interaction variables (NANALYST_INT, OBS_INT, and AGE_INT), representing COLLECT_IND interacted with each of the control variables (NANALYST, OBS, and AGE, respectively). Finally, the model includes CUSIP which employs the label encoder method to control for firm fixed-effects and a vector of dummy variables (YEARS) representing the year of the forecast period to control for time fixed-effects.

An additional specification of our model uses a continuous variable to measure collectivism (COLLECT_CONT). This variable is calculated by transforming the Hofstede (2001) individualism score in to a collectivism score (by subtracting the individualism score from 100). The collectivism score is from 0 to 100 based on the degree of collectivism in the national culture. This specification of the model is as follows:

$$S_i = \alpha_1 + \beta_1 COLLECT\_CONT + \beta_2 NANALYST_i + \beta_3 NANALYST\_INT_i + \beta 4 OBS_i + \beta_5 OBS\_INT_i + \beta_6 AGE_i + \beta_7 AGE\_INT_i + \beta_8 CUSIP_i + \beta_9 YEARS_i + \varepsilon_i \quad (2b)$$

Our model specification follows Mensah and Yang (2008) and Leece and White (2017). Following those models, we include NANALYST, OBS, and AGE as important control variables. However, for our test of H_1, we do not follow the convention of these prior authors in including forecast error (FE) but instead include this variable in our test of H_2 where we use it as a measure of uncertainty. The reason why we do not include FE in our model to test H_1 is that H_1 is an overall test of the effect of culture on herding. There can be a correlation between culture and FE as cultural norms impact the disclosure environment and other facets of the analyst information environment. Therefore, excluding FE allows for meaningful variation in the cultural effect that may not be present when the result is conditioned on FE. Excluding FE allows a broad-based test of country differences in herding associated with collectivism while including FE examines the cross-country difference conditioned on uncertainty in the information environment as captured by forecast error. Market capitalization or size is also excluded from our model. The firm-fixed effects serve to capture the time-invariant component of firm size. Furthermore, size

is heavily correlated with analyst coverage which is picked up by NANALYST and OBS. Therefore, in order to maximize our sample size when dealing with gaps in data coverage for global market capitalization data, firm size was excluded from our model.

3.3 Is the individualism-collectivism effect on analyst herding exacerbated by firm uncertainty (H_2)?

Our second hypothesis examines how the association between collectivism and analyst herding is moderated by firm uncertainty. Following prior research, we use analysts' forecast error as the proxy for firm information environment (Horton *et al*., 2013; Filip *et al*., 2022). Research has shown that firms with superior disclosure quality have lower analyst forecast errors (Lang & Lundholm, 1996; Hope, 2003). A lower average forecast error implies that analysts have a higher quality of information from which to make their forecast (Barron *et al*., 1998; Filip *et al*., 2022). The variable we utilize to measure forecast error is FE_PERCENTILE. FE_PERCENTILE is the percentile of the firm's forecast error (from 0 to 100), compared against other companies from that country and for that year. It is calculated using the absolute value of the difference between the company's actual earnings and the last available consensus forecasts. So, if company X had an FE_PERCENTILE of 90, that would mean that the size of their forecast error was in the 90th percentile for that country and for that year. Similar to the test of our first hypothesis, we implement two specifications of our model, one utilizing the indicator variable COLLECT_IND and one utilizing the continuous variable COLLECT_CONT. Thus, the two model specifications utilized to test H_2 are as follows:

$$S_i = \alpha_1 + \beta_1 COLLECT_{IND} + \beta_2 FE\_PERCENTILE_i + \beta_3 FE\_PERCENTILE\_INT_i + \beta_4 NANALYST_i + \beta_5 NANALYST\_INT_i + \beta_6 OBS_i + \beta_7 OBS\_INT_i + \beta_8 AGE_i + \beta_9 AGE\_INT_i + \beta_{10} CUSIP_i + \beta_{11} YEARS_i + \varepsilon_i \quad (3a)$$

$$S_I = \alpha_1 + \beta_1 COLLECT\_CONT + \beta_2 FE\_PERCENTILE_i + \beta_3 FE\_PERCENTILE\_INT_i + \beta_4 NANALYST_i + \beta_5 NANALYST\_INT_i + \beta_6 OBS_i + \beta_7 OBS\_INT_i + \beta_8 AGE_i + \beta_9 AGE\_INT_i + \beta_{10} CUSIP_i + \beta_{11} YEARS_i + \varepsilon_i \quad (3b)$$

3.4 Sample selection and descriptive statistics

Sample Selection

Our sample period is from 2010 to 2020. The S-statistic, our measure of analyst herding, is constructed using data from I/B/E/S and I/B/E/S Global. The Compustat data set was used to classify the stock exchange in which the company is traded. Our final sample examining analyst herding behavior across nations has 28,588 firm-year observations.

Table 3. Descriptive statistics for S-Stat measure of analyst herding

Panel A: Individualistic Countries Sample

Country	count	mean	std	min	25%	50%	75%	max
S-Stat	21101	0.613	0.237	0.000	0.500	0.593	0.767	1
NANALYST	21101	9.537	6.900	2.000	4.000	7.000	13.000	55
OBS	21101	17.545	17.171	4.000	6.000	11.000	22.000	268
AGE	21101	87.117	17.551	0.375	76.500	87.200	98.341	147.25

Panel B: Collectivistic Countries Sample

Country	count	mean	std	min	25%	50%	75%	max
S-Stat	7487	0.607	0.254	0.000	0.500	0.591	0.783	1
NANALYST	7487	8.565	6.581	2.000	4.000	6.000	10.000	51
OBS	7487	12.955	12.363	4.000	5.000	9.000	15.000	123
AGE	7487	83.186	18.008	7.500	72.380	82.941	94.000	148.4

Note: See Appendix for variable descriptions.

Table 3 presents the descriptive statistics for all our control variables of interest for both the individualistic and collectivistic samples. The S-stat is our measure of analyst herding. The mean S-Stat for the individualistic sample is 0.613 and the standard deviation is 0.237. In the collectivistic sample, the mean is 0.607 and the standard deviation is 0.254. A mean S-stat of 0.607 means that for the average firm, 60.7% of the forecasts are "anti-herding" forecasts or away from the consensus while a standard deviation of 0.254 suggests that approximately 68% of the firm-year observations have an S-stat between 0.353 and 0.861. NANALYST represents the number of analysts who made forecasts for that firm in that year. The mean value for NANALYST for the individualistic sample is 9.537. For the collectivistic sample, the mean value for NANALYST is slightly lower, 8.565. OBS measures the number of analyst forecast observations for a given firm in a year. For the individualistic sample, the average value for OBS was 17.545 while for the collectivistic sample, the mean value for OBS was lower at 12.955. Finally, AGE captures the average age of all forecasts for that firm-year, measured in days. For the individualistic sample, the mean value for AGE was 87.117 days while for the collectivistic sample, the mean value was 83.186 days.

Table 4 presents the descriptive statistics of our herding measure, the S-stat, by country. The country with the highest mean S-stat is Australia (mean=0.679) while the country with the lowest mean S-stat is Taiwan (mean=0.539). An S-stat of 0.679 means that for Australia, 67.9% of the forecasts are "anti-herding" forecasts or away from the consensus while for Taiwan that number is 53.9% which means 46.1% of Taiwan's forecasts are "herding" forecasts. Taiwan is also the country with the highest standard deviation (std=0.288). The country with the lowest standard deviation in S- stat is France (std=0.209). Table 5 presents descriptive statistics on

the control variables we use in our model, NANALYST, OBS, and AGE by country. Regarding analyst following (NANALYST), the country with the highest average analyst following is South Korea (mean for NANALYST=12.696). New Zealand, on the other hand, is the country with the lowest analyst following (mean for NANALYST=4.255). The country with the highest average analyst observations is South Korea (OBS=24.444) while the country with the lowest mean analyst observations is New Zealand (OBS=7.176). The country with the lowest average age of forecasts is New Zealand with 73.923 days while the United States has the highest average value (AGE=91.414). Table 6 presents Pearson correlations for the main variables utilized in our model. Other than NANALYST and OBS which are mechanically related, no other correlations above 0.30 were observed[2]. This indicates that multicollinearity is unlikely to be a concern.

Table 4. Descriptive statistics for S-Stat measure of analyst herding

Panel A: Individualistic Countries Sample								
Country	**count**	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
United States	12022	0.589	0.239	0.000	0.500	0.563	0.750	1
United Kingdom	3443	0.632	0.239	0.000	0.500	0.625	0.800	1
France	1055	0.668	0.209	0.000	0.500	0.667	0.820	1
Australia	968	0.679	0.224	0.000	0.500	0.667	0.833	1
Scandinavia	724	0.650	0.225	0.000	0.500	0.643	0.812	1
Germany	597	0.640	0.212	0.000	0.500	0.625	0.795	1
Canada	547	0.604	0.258	0.000	0.500	0.563	0.759	1
Italy	493	0.636	0.216	0.000	0.500	0.625	0.778	1
Switzerland	486	0.658	0.214	0.000	0.500	0.649	0.833	1
Netherlands	289	0.670	0.219	0.000	0.500	0.667	0.833	1
South Africa	216	0.650	0.227	0.000	0.500	0.625	0.833	1
Belgium	159	0.662	0.227	0.000	0.500	0.667	0.800	1
New Zealand	102	0.611	0.271	0.000	0.500	0.600	0.833	1

[2] Across all model specifications, variance inflation factors computed for the baseline models excluding interaction terms are below conventional thresholds (maximum VIF < 5), including those for OBS and NANALYST.

Panel B: Collectivistic Countries Sample								
Country	**count**	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
Japan	1524	0.605	0.253	0.000	0.500	0.590	0.750	1
Hong Kong	1398	0.620	0.255	0.000	0.500	0.619	0.800	1
India	1281	0.639	0.243	0.000	0.500	0.635	0.818	1
China	628	0.592	0.268	0.000	0.500	0.577	0.750	1
South Korea	626	0.568	0.218	0.000	0.500	0.511	0.684	1
Taiwan	578	0.539	0.288	0.000	0.500	0.529	0.750	1
Saudi Arabia	358	0.557	0.280	0.000	0.500	0.540	0.750	1
Mexico	356	0.639	0.236	0.000	0.500	0.604	0.817	1
Indonesia	319	0.610	0.239	0.000	0.500	0.600	0.750	1
Russia	261	0.656	0.230	0.000	0.500	0.667	0.833	1
Chile	158	0.658	0.246	0.000	0.500	0.643	0.869	1

Table 5. Descriptive statistics for control variables

Panel A: Individualistic Countries Sample							
Variable:		**NANALYST**		**OBS**		**AGE**	
Country	**count**	**mean**	**std**	**mean**	**std**	**mean**	**std**
United States	12022	10.136	7.192	18.364	18.139	91.414	15.156
United Kingdom	3444	8.956	6.026	16.467	16.253	80.725	18.659
France	1057	9.733	7.339	18.076	16.260	81.224	19.705
Australia	968	6.655	3.792	12.758	11.083	77.243	19.274
Scandinavia	725	7.645	6.656	18.899	18.207	82.343	13.961
Germany	597	11.039	7.603	19.226	15.431	86.723	17.953
Canada	548	7.402	5.606	14.417	13.932	90.168	17.999
Italy	493	8.759	5.993	14.822	13.423	83.598	20.195
Switzerland	486	10.788	8.360	21.426	19.618	77.693	20.880
Netherlands	289	9.972	7.362	17.367	14.995	83.716	17.710
South Africa	216	6.241	2.798	10.296	7.315	76.464	16.460
Belgium	159	9.044	7.219	16.252	16.439	81.430	17.962
New Zealand	102	4.255	1.325	7.176	3.219	73.923	18.471

Panel B: Collectivistic: Collectivistic Countries Sample							
Variable:		**NANALYST**		**OBS**		**AGE**	
Country	**count**	**mean**	**std**	**mean**	**std**	**mean**	**std**
Japan	1524	7.006	4.149	10.323	7.402	78.248	14.351
Hong Kong	1398	9.050	6.121	12.476	10.613	81.589	20.604
India	1281	12.109	9.333	17.426	16.206	89.266	14.170
Country	**count**	**mean**	**std**	**mean**	**std**	**mean**	**std**
China	628	5.629	2.705	7.545	4.314	90.123	22.976
South Korea	626	12.696	9.112	24.444	20.809	81.850	12.800
Taiwan	579	7.469	5.877	12.386	12.269	86.524	20.285
Saudi Arabia	358	5.913	2.578	8.291	3.896	75.774	16.085
Mexico	356	6.983	3.078	10.882	5.236	83.213	15.464
Indonesia	319	7.831	4.084	10.843	7.264	87.162	18.412
Russia	262	5.425	2.448	9.889	6.200	77.826	19.477
Chile	158	6.120	2.638	8.943	4.229	78.730	17.509

Table 6. Pearson Correlation Matrix

	S	**COLLECTIVISM**	**NANALYST**	**OBS**	**AGE**	**FE_Percentile**
S	1.000	0.002	0.096***	0.101***	-0.056***	-0.289***
COLLECTIVISM	0.002	1.000	-0.069***	-0.114***	-0.119***	0.019***
NANALYST	0.096***	-0.069***	1.000	0.883***	-0.015***	-0.003
OBS	0.101***	-0.114***	0.883***	1.000	-0.070***	0.048***
AGE	-0.056***	-0.119***	-0.015***	-0.070***	1.000	-0.017***
FE_Percentile	-0.289***	0.019***	-0.003	0.048***	-0.017***	1.000

Note: This table reports Pearson correlations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

4. Results

4.1 Relation between collectivism-individualism and analyst herding

Table 7 presents the results of estimating Equation 2a, which examines the relationship between analyst herding (S-statistic) and national culture. The coefficient on COLLECT_IND is - 9.4149 and is highly significant (p-value <.0001). This demonstrates that collectivist countries experience higher analyst herding behavior. If we use a rough mean of 0.60, the coefficient represents a 15.69% increase in herding behavior in collectivistic cultures. Next, we examine the control variables.

NANALYST is not significant. However, the interaction of NANALYST with COLLECT_IND, NANALYST_INT is positive and significant. This means that in collectivistic countries, analyst following mitigates herding behavior. This is consistent with prior research showing greater analyst following can cause analysts to want to distinguish themselves from other analysts (Lin & McNichols, 1998). The coefficient on OBS is positive and significant (coeff.=0.1170; p-value<.0001). However, in collectivistic countries, the effect reverses as evidenced by the negative coefficient on the interaction variable, OBS_INT. This means that a large pool of observations in a collectivistic country is associated with more analyst herding. This could be evidence of analyst revising their forecasts to be more in line with the group consensus. AGE is significantly related to herding behavior as evidenced by the negative coefficient. However, the effect is very small. A 10-day increase in the average age of forecasts is only associated with a decrease in the S-stat of -0.685. The coefficient on the interaction of AGE with COLLECTIVE (AGE_INT) is positive and statistically significant (coeff.=0.0536; p-value=0.003). This implies that forecast age is less strongly associated with analyst herding in collectivist countries.

Table 7. Effects of collectivism on analyst herding

Panel A: COLLECTIVE INDICATOR VARIABLE

S = COLLECT_IND + NANALYST + NANALYST_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	**Coefficient**	**P-Value**	**R-Squared**	**N**
COLLECT_IND	-9.4149	<0.0001	0.0187	28,588
NANALYST	0.0656	0.192		
NANALYST_INT	0.7259	<0.0001		
OBS	0.1170	<0.0001		
OBS_INT	-0.3355	<0.0001		
AGE	-0.0685	<0.0001		
AGE_INT	0.0536	0.003		

Panel B: COLLECTIVSIM CONTINUOUS VARIABLE

S = COLLECT_CONT + NANALYST + NANALYST_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	Coefficient	P-Value	R-Squared	N
COLLECT_CONT	-0.1642	<0.0001	0.0180	28,588
NANALYST	-0.1147	0.0762		
NANALYST_INT	0.0129	<0.0001		
OBS	0.1892	<0.0001		
OBS_INT	-0.0054	<0.0001		
AGE	-0.0845	<0.0001		
AGE_INT	0.0010	0 .001		

Note: See Appendix for variable descriptions.

The results of estimating Eq. 2b, which utilizes the variable COLLECT_CONT to capture the collectivism dimension of national culture as a continuous variable, instead of the COLLECT_IND indicator, are presented in Panel B of Table 7. The coefficient on COLLECT_CONT is -0.1642 and is highly significant (p-value <.0001). Since a higher S-stat is associated with anti-herding behavior, this means that collectivism is associated with greater analyst herding. Given the magnitude of the coefficient, a 45-point increase in COLLECT_CONT (moving from the score of Mexico to the score of Belgium, for example) would result in a 12.31% increase in herding behavior (decrease in S-stat of 7.39). This is in line with the results from the previous model. Regarding the control variables, some minor changes can be noticed. First, the coefficient on NANALYST is now negative and significant. However, this significance is only marginal. The coefficient on OBS continues to be positive and significant while the interaction variable OBS_INT is negative. Given the results in the previous model specifications, as well as the fact that the interaction coefficient is positive, it is evident that the relation between greater analyst observations and herding is driven by collectivistic countries. Overall, the results are consistent with increased analyst herding behavior in collectivistic countries.

4.2 Effects of firm uncertainty on the culture-herding relation

The results of estimating the model depicted in Eq. 3a, which includes FE_PERCENTILE as a measure of firm uncertainty, are presented in Table 8. Panel A utilizes the indicator variable COLLECT_IND as a measure of collectivism. The R-square of this model is noticeably higher than in previous model specifications. The R-square increases from 1.87% to 10.94%. In the model, collectivism continues to be associated with greater analyst herding behavior, however, the significance of the effect as well as the magnitude of the effect are diminished. The coefficient on COLLECT_IND is now -5.2132 and the p-value is now 0.001. Some of the statistical significance of COLLECT_IND is now subsumed by FE_PERCENTILE. The coefficient on FE_PERCENTILE is -0.2203 and is highly significant (p-value <.0001). This is consistent with analysts herding more in the presence of greater firm uncertainty (Leece & White, 2017). The coefficient on the interaction of COLLECT_IND and FE_PERCENTILE (FE_PERCENTILE_INT) is negative and highly significant.

This shows that firm uncertainty is more likely to be associated with analyst herding in collectivistic countries. This result suggests that when there is greater uncertainty, analysts in collectivistic cultures perceive potential reputational consequences associated with deviating from the consensus and being wrong as being more severe. As such, analysts will likely herd even more in these situations.

Panel B of Table 8 exhibits the results of estimating Eq. 3b which utilizes COLLECT_CONT as the measure of the collectivism dimension of national culture. The coefficient on COLLECT_CONT is -0.0957 and is statistically significant (p-value=0.001). Collectivism continues to be associated with greater herding behavior. Again, the coefficient on FE_PERCENTILE is negative and significant, demonstrating that higher firm uncertainty is associated with greater herding

behavior (coeff.=-0.1997; p-value<.0001). The magnitude of this coefficient means that a 10% increase in the forecast error percentile is associated with a 1.997 decrease in the S-stat. The coefficient on the interaction between FE_PERCENTILE and COLLECT_CONT (FE_PERCENTILE_INT) is negative. The negative value demonstrates that FE_PERCENTILE is more strongly associated with analyst herding in countries that are more collectivistic. With respect to the control variables, the coefficient on NANALYST is negative and significant (coeff.= -0.3207; p-value<0.0001). OBS continuous to have a positive coefficient while AGE continues to have a negative coefficient. Overall, the results demonstrate that the association between analyst herding and firm uncertainty (as proxied by forecast error) is strong in collectivistic countries.

Table 8. Effects of collectivism on analyst herding (including information uncertainty)

Panel A: COLLECTIVE INDICATOR VARIABLE

S = COLLECT_IND + FE_PERCENTILE + FE_PERCENTILE_INT + NANALYST + NANALYST_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	Coefficient	P-Value	R-Squared	N
COLLECT_IND	-5.2132	0.001	0.1094	28,588
FE_PERCENTILE	-0.2203	<0.0001		
FE_PERCENTILE_INT	-0.1035	<0.0001		
NANALYST	-0.1474	0.002		
NANALYST_INT	0.6061	<0.0001		
OBS	0.2109	<0.0001		
OBS_INT	-0.2277	0.001		
AGE	-0.0709	<0.0001		
AGE_INT	0.0646	0.001		

Panel B: COLLECTIVISM CONTINUOUS VARIABLE

S = COLLECT_CONT + FE_PERCENTILE + FE_PERCENTILE_INT + NANALYST + NANALYST_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	Coefficient	P-Value	R-Squared	N
COLLECT_CONT	**-0.0957**	**0.001**	**0.1086**	**28,588**
FE_PERCENTILE	**-0.1997**	**<0.0001**		
FE_PERCENTILE_INT	**-0.0017**	**<0.0001**		
NANALYST	**-0.3207**	**<0.0001**		
NANALYST_INT	**0.0116**	**<0.0001**		
OBS	**0.2647**	**<0.0001**		
OBS_INT	**-0.0038**	**0.001**		
AGE	**-0.0896**	**<0.0001**		
AGE_INT	**0.0012**	**<0.0001**		

Note: See Appendix for variable descriptions.

4.3 Additional analyses

To test the robustness of our results, we utilize an additional proxy for information uncertainty, FREQ. FREQ is the frequency with which a given company appears in our sample. It is the number of firm-year observations for that company. FREQ measures information uncertainty because firms with greater analyst coverage (frequency) are larger and have more informative levels of disclosure (Bhushan 1989; Lang & Lundholm, 1996). The adjusted model is as follows below:

$$S_i = \alpha_1 + \beta_1 COLLECT\_IND + \beta_2 FREQ_i + \beta_3 FREQ\_INT_i + \beta_4 OBS_i + \beta_5 OBS\_INT_i + \beta_6 AGE_i + \beta_7 AGE\_INT_i + \beta_8 CUSIP_i + \beta_9 YEARS_i + \varepsilon_i \quad (3)$$

If analyst herding in collectivistic cultures is more pronounced in firms with greater information uncertainty, we would expect the coefficient on the interaction between COLLECTIVE_IND and FREQ, FREQ_INT, to be positive and significant. This would show that the association between collectivism and analyst herding is mitigated in companies which possess a rich information environment. Conversely, for companies that are less followed and possess more information uncertainty, there is a strong association between collectivism and analyst herding. The results in Table 9, Panel A support this rationale. The interaction between collectivism and frequency, FREQ_INT is positive and significant (coeff.=0.2369; p-value=0.022). This means that for firms that receive less coverage from analysts, the S-statistic will be lower and this is indicative of greater analyst herding. This result is consistent with the conjecture that greater information uncertainty intensifies the relationship between collectivism and analyst herding. In Panel B of Table 9, we include both of our proxies for information uncertainty, forecast error (FE_Percentile) and frequency (FREQ) together in one model. The variables of interest are the interactions between collectivism and each of the two proxies for information uncertainty. Both interaction variables are highly significant and in a direction consistent with our hypothesis that information uncertainty heightens the relationship between collectivism and analyst herding. The results of Table 9 – Panel B are presented graphically in Figure 1. This figure shows the marginal increase in herding due to moving from the first quartile to the third quartile in collectivism, low analyst following, and average forecast error, respectively.

Given that our proxies for information uncertainty utilize factors pertaining to financial analysts, this could raise concerns of endogeneity. Specifically, the dependent variable analyzed is analyst herding and the measures of information uncertainty also pertain to analysts' decisions and behavior. Is it possible that analyst herding causes information uncertainty? While we do not test specifically for endogeneity, there are two important factors to consider. First, our study follows a long line of research which documents financial analysts reacting to the information environment of the firm (Leece & White, 2017; Segara *et al*., 2023; Wen & Tikoo,

2022). It is a generally accepted paradigm of research to scrutinize analyst behavior and assume it is the information environment of the firm affecting analyst behavior and not vice versa. Second, with respect to the behavior of analysts in collectivistic countries, it does not really matter whether the uncertain information environment is caused by factors internal to the firm or to poor analyst coverage. Whether the information environment is poor due to lack of analyst coverage or whether there is some other issue causing uncertainty like more opaque financial reporting and disclosures, the fact remains that in these uncertain environments, analysts from more collectivistic cultures exhibit a greater likelihood to protect their reputation by going with the herd.

Table 9. Using Alternative Measures of Information Uncertainty

Panel A: Including only FREQ

S = COLLECT_IND + FREQ + FREQ_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	Coefficient	P-Value	R-Squared	N
COLLECT_IND	-10.3016	<0.0001	0.0182	28,588
FREQ	0.1584	0.003		
FREQ_INT	0.2369	0.022		
OBS	0.1299	<0.0001		
OBS_INT	0.107	0.679		
AGE	-0.0666	<0.0001		
AGE_INT	0.0663	0.001		

Panel B: Including both FREQ and FE

S = COLLECT_IND + FREQ + FREQ_INT + FE_PERCENTILE + FE_PERCENTILE_INT + OBS + OBS_INT + AGE + AGE_INT + CUSIP + YEARS + ε

Variable Name	Coefficient	P-Value	R-Squared	N
COLLECT_CONT	-6.9058	0.001	0.1095	28,588
FREQ	0.0582	0.257		
FREQ_INT	0.3915	<0.0001		
FE_PERCENTILE	-0.2181	<0.0001		
FE_PERCENTILE_INT	-0.1093	<0.0001		
OBS	0.1548	<0.0001		
OBS_INT	0.0170	0.492		
AGE	-0.0736	<0.0001		
AGE_INT	0.0783	<0.0001		

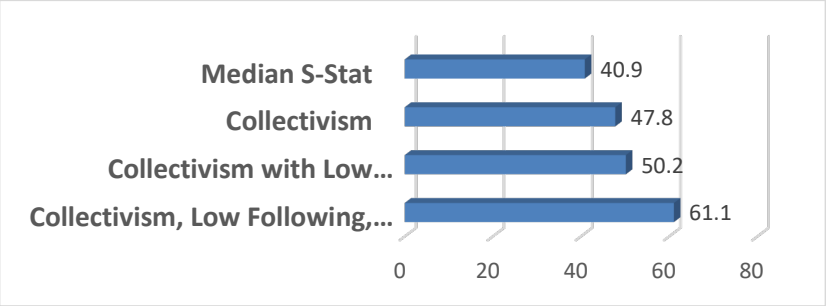

Figure 1. Expected Percentage of Herding Forecasts Under Different Conditions

5. Conclusions

The extant literature contains a few studies on the effects of culture on analyst herding behavior. The Cao *et al*. (2024) study represents an important step forward by examining the impact of cultural descendancy and upbringing on herding behavior. The current study extends the literature by examining the effects of individualism/collectivism on analyst herding behavior across nations.

The measure of individualism/collectivism employed in our study is the Hofstede (2001) individualism score for each nation. Analyst herding behavior is measured by using the S-statistic, a measure developed by Bernhardt *et al*. (2006). The results of our study show that analyst herding behavior is greater in countries with greater collectivism. As a second test, we incorporate firm uncertainty in our model. Results drawn from this model show that firm uncertainty exacerbates the association between collectivism and analyst herding behavior. We believe this demonstrates that when there exists greater firm uncertainty in a collectivist culture, reputational concerns and pressure to conform to the consensus is heightened, resulting in greater herding behavior. This is likely to happen because in the environment of uncertainty, there is greater perception of risks associated with not conforming to the group consensus. Therefore, exhibiting loyalty to the group becomes even more important in firms which are marked by information asymmetry.

As discussed previously, financial analysts' forecasts represent valuable information to markets. Analyst herding hinders market efficiency because analysts do not fully reveal their private information, instead biasing their forecasts toward the consensus (Arya *et al*., 2005). Therefore, if analyst herding is more prevalent in collectivistic countries, this could mean market efficiency is damaged by this type of running towards the consensus. Other negative consequences of financial analyst herding on capital markets include less accurate forecasts (Fluharty, 2020) and even an increased risk of stock price crash (Xu *et al*., 2017). In addition, analyst herding can detrimentally affect corporate governance due to

the important role analysts have in monitoring companies. This monitoring role could be affected if forecasts are biased. A final area impacted by analyst herding pertains to the corporate financing decisions of companies. Companies which experience greater analyst herding behavior surrounding their earnings forecasts are less likely to seek external financing (Wu & Tikoo, 2022). For these reasons, the existence of financial analyst herding in a country's capital markets is undesirable. Since research has found that disclosure regulations can impact analysts' herding behavior (Mensah & Yang, 2008), these types of regulations may be considered by countries looking to deter the existence of herding.

The current study represents an important contribution to the analyst herding literature by examining the effects of national culture on analyst herding behavior. By demonstrating that nations with greater collectivism (individualism) experience greater herding (anti-herding) behavior, the analysis advances literature examining the effect of national culture on analyst decision-making. The study also contributes to literature examining how the interaction of market participants such as investors, analysts and firm management vary across nations. Finally, by introducing the interactive effects of firm uncertainty and collectivism on analyst herding, the study puts forth one potential mediating factor, namely the firm's information environment, which impacts the association between collectivism and analyst herding. Future research can continue to explore how firm information environments in different national cultures impact analyst decision-making.

5.1 Limitations and future research directions

We now note limitations of our research and provide directions for future research. First, we only utilize the individualism-collectivism dimension of national culture in our study. While individualism-collectivism dimension is very important, we recognize that there are other dimensions of national culture (e.g., power distance and uncertainty avoidance) that may have different relationships with the analyst herding behavior.

Another limitation relates to the cultural model employed in the study. We utilize Hofstede's national culture scores in our research. However, we also acknowledge that literature is full of other cultural models and frameworks that could be used to explain the behavior of financial analysts in individualistic versus collectivist countries. One such prominent model is Globe Study (House *et al*., 2004) that expanded the universe of culture by adding additional dimensions such as Humane Orientation and Performance Orientation. The Globe study is based on data collected from 17,000 middle-level managers in 62 societies. Additionally, as Lin and Mancik (2020) note, using the World Values survey, Inglehart and Welzel (Inglehart & Baker, 2000; Inglehart, 2006) created a map of cultural values of societies that differ in two dimensions, i.e., traditional versus secular-rational values and survival versus

self-expression values. We suggest that future researchers utilize different cultural frameworks to replicate and expand on our findings.

Future research should also consider incorporating analyst experience into models examining the effects of culture on herding as experience has been found to be an influential factor on herding behavior (Clement & Tse, 2005; Keskek *et al*., 2014). The methodology of the current study did not lend itself to this type of analysis due to the fact that firm-year observations were used. To include analyst experience in firm-year observations some type of aggregate operation would have had to be performed (such as average analyst experience or median analyst experience). Future studies could potentially employ a methodology that disaggregates the data to examine the behavior of individual analysts with varying levels of experience.

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Appendix: Variable List

Variable	Definition
S-Stat	S-stat is our measure of analyst herding. Developed by Bernhardt *et al*. (2006), the S-stat is the percentage of anti-herding forecasts present. An S-stat of 0 is associated with perfect herding while an S-stat of 1 would indicate perfect anti-herding behavior. The S-stat is calculated using annual forecasts from the time period between 150 days before the announcement date and the announcement date (following convention of Bernhard *et al*., 2006, Leece & White, 2017).
COLLECT_IND	COLLECT_IND is an indicator variable that is equal to 1 if the stock exchange on which the company is traded is located in a collectivist country (see Table 2 for our country groupings).
COLLECT_CONT	COLLECT_CONT is a continuous variable that measures collectivism. This collectivism score ranges from 0 to 100 and is calculated by taking 100 and subtracting the Hofstede (2001) individualism score for the country in whose stock exchange the company is traded.
NANALYST	NANALYST represents the number of unique analysts following the firm in that year.
OBS	OBS represents the total number of forecasts used in the S-Stat calculation period.
AGE	AGE represents the average age of the forecasts (in days) in the S-stat calculation period.
FE_PERCENTILE	FE_PERCENTILE represents the percentile of average forecast error for the firm. Average forecast error is calculated as the average of the absolute difference between the last consensus forecast and the firm's actual earnings. Then according to the average forecast error, the firm is assigned to a percentile (0 to 100) based on the distribution of forecast errors for all firms in the same country and in the same year. An FE_PERCENTILE of 100 would indicate that the firm has the highest average forecast error of all firms in that country for that year.
FREQ	FREQ represents the frequency with which a given company appears on the IBES dataset in our sample. It is calculated as the number of times the company's CUSIP appears in our sample (i.e. the number of firm-year observations for that company).