Cultural Biases in Equity Analysis

Pursiainen, Vesa

The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXVII, NO. 1 • FEBRUARY 2022

Cultural Biases in Equity Analysis

VESA PURSIAINEN

ABSTRACT

A more positive cultural trust bias by an equity analyst's country of origin toward a firm's headquarter country is associated with significantly more positive stock recommendations. The cultural bias effect is stronger for eponymous firms whose names mention their home country and varies over time, increasing with negative sentiment. I find evidence of a negative North-South bias during the European debt crisis and United Kingdom-Europe divergence amid Brexit. Share price reactions to recommendations by more biased analysts are weaker, and more biased recommendations are worse predictors of monthly stock returns. More positively biased analysts also assign higher target prices.

ARE GERMANS MORE TRUSTWORTHY THAN the French? It turns out that the answer varies greatly depending on whom you ask. Based on a Eurobarometer survey, the average European would have said yes, but the average Belgian, Greek, or Portuguese would have disagreed. Such cultural perceptions of the

This article is a revised version of my dissertation at the University of Hong Kong. I am grateful to Stefan Nagel (Editor); the Associate Editor; two anonymous referees; Raj Aggarwal; Farooq Ahmad; Shashwat Alok; Darwin Choi; Claudia Custodio; Francesco D'Acunto; Thuy Duong Dang; Rik Frehen; Mikael Homanen; Mobeen Iqbal; Ivika Jäger; Marcin Kacperczyk; Markku Kaustia; Matti Keloharju; Alan Kwan; Tse-Chun Lin; Xin Liu; Yang Liu; Thomas Maurer; Jordan Nickerson; Steven Ongena; Mikael Paaso; Stefan Pohl; Ronnie Sadka; Thomas Schmid; Armin Schwienbacher; Mingzhu Tai; Dragon Tang; Chi-Yang Tsou; Roger Vicquéry; Hans-Joachim Voth; Alexander Wagner; Baolian Wang; Guosong Xu; conference participants at European Finance Association (EFA) 2019, American Economic Association (AEA) 2020, EEA-ESEM 2019, German Finance Association (DGF) 2019, Econometric Society Winter Meeting 2019, SSES Annual Congress 2019, Helsinki Finance Summit 2018, and Research in Behavioral Finance Conference 2018; as well as the seminar participants at Imperial College London, University of Hong Kong, University of St. Gallen, Bocconi University, University of Amsterdam, HEC Montreal, and SKEMA Business School for the many helpful comments. All remaining errors are my own. Substantial parts of this research were done during my time at University of Hong Kong and during academic visits at Imperial College London and University of Zurich. I am grateful for the financial support from the University of Hong Kong Faculty of Business and Economics. I have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Vesa Pursiainen, University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; e-mail: vesa.pursiainen@unisg.ch.

DOI: 10.1111/jofi.13095

trustworthiness of people from other countries differ substantially by country. Thus, where we come from affects both how we perceive other people and how we are perceived by others. These perceptions can affect economic behavior. Guiso, Sapienza, and Zingales (2009) show evidence that cultural biases affect the volume of trade and investment between countries. Bottazzi, Da Rin, and Hellmann (2016) find that a higher level of bilateral trust between countries positively predicts venture capital firms' investment decisions but is negatively associated with the performance of such investments.

In this paper, I study the role of cultural biases in analysts' stock recommendations in Europe. My analysis can be divided into four parts. First, I construct a survey-based measure of trust bias as a proxy for cultural biases between European nations and study its effect on analyst recommendations. Second, I study the effect on stock recommendations of two short-term shocks to cultural perceptions: the European debt crisis and Brexit.[1] Third, I investigate the effect of trust bias on both the perceived and actual information content in stock recommendations by studying stock price announcement reactions to recommendations as well as recommendations' ability to predict monthly stock returns. Finally, I perform a number of additional analyses to explore the effect of cultural biases on analysts' target prices and earnings estimates as well as cross-sectional differences in the effect of trust bias on stock recommendations.

To quantify general cultural biases, I follow the methodology of Guiso, Sapienza, and Zingales (2009) and Bottazzi, Da Rin, and Hellmann (2016) to construct a bilateral measure of trust between European countries based on Eurobarometer surveys. These surveys ask citizens of different European nations how much they trust citizens of each of the other nations included in the survey. This provides a unique measure of directional generalized trust between countries. Following Guiso, Sapienza, and Zingales (2009), I use regression analysis to separate the general tendency of different nationalities to be trusted by, and to trust, others. I define *Trust bias* as the residual from this regression, that is, the component of trust not explained by the general tendency to trust or the generally perceived level of trustworthiness. To test the effect of trust bias on analyst recommendations, I construct a comprehensive sample of analyst recommendations at a monthly frequency for all publicly listed firms based in the 15 European countries covered by the Eurobarometer trust surveys, by analysts from any of the same 15 countries.[2]

I find that a more positive trust bias by the analyst's country of origin toward the country in which the firm has its headquarters is associated with significantly more positive stock recommendations. I include analyst-month fixed effects and firm-month fixed effects in the regression analysis, which means that the results are *within analyst* and *within firm*, that is, they are not driven by underlying firm-specific factors or the general tendency of the analyst to

[1] In the Internet Appendix, which may be found in the online version of this article, I also include analysis of a third shock, the Iraq war.

[2] I estimate each analyst's country of origin based on their surname using data from Forebears.io, a genealogical online directory of sources for family history research.

assign more or less positive recommendations at that point in time, as both of these effects are captured by the fixed effects. The fixed effects also capture any broker-specific variation. The trust bias effect is economically significant: A one-standard-deviation increase in trust bias is associated with an 8.2% increase in the likelihood of buy recommendation, relative to the sample average.

If analyst recommendations are affected by the analyst's cultural biases, one might expect a stronger effect when the nationality of the firm is more salient. Several factors might affect the salience of firm nationality, but one obvious candidate is the firm's name. I define firms as *Eponymous* if the firm name includes the name of its home country.[3] Nearly 7% of the monthly observations in my data are attributable to eponymous firms. These firms are often what might be called "national champions," large and prominent firms in their home countries. This means they also tend to be larger than average. On the other hand, size alone might be associated with national champion status and hence make the nationalities of these firms more salient. I find that the effect of trust bias on stock recommendations is significantly larger for eponymous firms, as well as for larger firms in general. The estimated trust bias effect on recommendations is 45% to 60% larger for eponymous firms than for other firms and is robust to controlling for the effect of size.

One limitation of my study is that I do not observe possible time-variation in trust bias, as the last Eurobarometer survey to include the bilateral trust question was in 1996, the first year in my sample. The analysis thus implicitly assumes a degree of cross-sectional stability in cultural biases that can be captured with a time-invariant measure. This is not an aggressive assumption, as cultural attitudes, including trust in particular, are quite stable over long periods.[4] At the same time, it seems likely that cultural perceptions and their strength change over time. To explore this, I estimate the effect of trust bias on a monthly basis. This analysis captures the time-variation in the strength of cultural biases, but not changes in their cross-sectional distribution. I find that the effect of trust bias is strongly correlated with sentiment. The bias effect increases with general pessimism in Europe, notably during and around recessions, and decreases with consumer confidence.

To overcome the limitation of not observing short-term cross-sectional changes in trust bias, I study two shocks to cultural perceptions that are specific to certain country pairs and that can be studied without the trust bias measure: the European debt crisis and Brexit.[5] The European debt crisis of 2011 to 2013 was the culmination of a North-South divide in economic performance and represented the second dip of the Eurozone's double-dip recession in the aftermath of the financial crisis of 2008.[6] Response to this crisis

[3] Examples of such eponymous firms include Deutsche Bank, Hellenic Telecommunications Organisation, Telecom Italia, and Bolsas y Mercados Espanoles.

[4] For a discussion of persistent cultural beliefs, see Guiso, Sapienza, and Zingales (2006). Guiso, Sapienza, and Zingales (2009) provide an extensive analysis of the determinants of cultural trust, and nearly all of the significant determinants are time invariant.

[5] In the Internet Appendix, I perform a similar analysis around the Iraq war.

[6] For discussion of the crisis, see Landesmann (2015) and Lane (2012).

involved bailouts of several South European states, with Northern Europe largely perceived to be paying for these bailouts. This dynamic created antipathy between Mediterranean and North European states. For instance, stories invoking stereotypes of lazy Mediterraneans were common in North European media and even in political discourse.[7] I find that North European analysts issue significantly more negative stock recommendations on South European companies during the crisis, consistent with an increase in the level of negative bias induced by the crisis.[8] Economically, Northern analysts are between 10 and 23 percentage points less likely to assign Southern firms a buy recommendation, depending on the model specification, during the crisis.

Turning to Brexit, the United Kingdom's decision to leave the European Union (EU) following the referendum in June 2016 and the subsequent political disarray represented a substantial shock to cultural perceptions about Britain. On March 29, 2017, Prime Minister Theresa May formally triggered Article 50 and began the two-year countdown to the United Kingdom leaving the EU. The ensuing process to negotiate the terms of withdrawal and the future relationship between the EU and the United Kingdom has been characterized by many observers as a "mess" or "shambles."[9] At the same time, Brexit was associated with a rise in economic nationalism and may have been viewed differently by British analysts compared to other analysts.[10] I find a significant divergence of views on U.K. firms between British and other European analysts following Article 50, with other European analysts issuing substantially more negative recommendations on U.K. firms than British analysts. The likelihood of British analysts assigning a buy recommendation to a U.K. firm increases by more than 30 percentage points relative to other analysts. Taken together, the analyses of these two shocks to cultural perceptions suggest that, in addition to persistent long-term biases, short-term shifts in cultural perceptions can be seen in analyst stock recommendations. In Internet Appendix Section VII, I perform a third analysis around the Iraq war and find that French analysts issue more negative recommendations on British firms during the war.

I next study the perceived and actual information content of stock recommendations depending on the level of trust bias. Intuitively, a more positive trust bias should mean that buy recommendations contain less useful information and sell recommendations contain more useful information. This is because the hurdle for issuing a buy recommendation is lower for positively

[7] In 2010, during EU negotiations of a Greek bailout, the Swedish Finance Minister, Anders Borg, said: "Obviously, Swedes and other taxpayers should not have to pay for Greeks who choose to retire in their 40s," while Bild, the German tabloid and the largest newspaper in Europe, declared that "Greece, but also Spain and Portugal have to understand that hard work – meaning ironfisted money-saving – comes before the siesta."

[8] For the purposes of this analysis, I define *Northern Europe* as Germany, the United Kingdom, Netherlands, Austria, Sweden, Denmark, and Finland, and *Southern Europe* as Portugal, Italy, Greece, and Spain.

[9] Martin Wolf, the chief economics commentator at the *Financial Times* wrote: "The UK once had a deserved reputation for pragmatic and stable politics. That will not survive the spectacular mess it is making of Brexit."

[10] See, for example, Born et al. (2019).

biased analysts. The opposite is true for sell recommendations—a more positively biased analyst should be more reluctant to issue a sell recommendation, which means that such sell recommendations should be more negative signals.

First, I provide evidence on the stock market's assessment of the information content in analyst recommendations by analyzing the stock price reactions to recommendation announcements, conditional on the analyst's level of trust bias. Generally, buy recommendations are associated with positive cumulative abnormal returns (CARs) around the announcement date, while sell recommendations are associated with negative abnormal returns. I find that higher trust bias is associated with significantly lower (less positive) announcement returns for buy recommendations. This result is consistent with the stock market judging the information content of more positively biased buy recommendations to be lower. I find the reverse for sell recommendations—more positively biased sell recommendations are associated with more negative announcement returns, consistent with such recommendations containing more information. These results suggest that, at least directionally, the stock market recognizes the bias in analyst recommendations.

Second, I study the actual information content of analyst recommendations. I construct a monthly panel data set of excess stock returns for the stocks in my recommendations sample and calculate the average recommendation as well as average trust bias of the analysts assigning recommendations for each stock at the end of each month. I then divide stocks into quintiles at the beginning of each month based on the previous month's recommendations and perform regression analysis of monthly excess returns conditional on recommendation and trust bias. I find that stock recommendations have predictive power over excess stock returns. The highest recommendation quintile outperforms the lowest quintile by approximately 50 basis points (bps) per month. I also find that the level of trust bias affects the predictive power of recommendations. More positive trust bias is associated with lower subsequent stock returns in the highest recommendation quintile, suggesting that positive recommendations issued by more positively biased analysts are less useful in predicting stock returns. Similarly, in the most negative recommendation quintile, more positive trust bias is associated with significantly lower stock returns, suggesting that sell recommendations by more positively biased analysts are better at predicting lower stock returns. These findings suggest that cultural biases, as captured by the trust bias measure, affect the information content of analyst recommendations in a predictable fashion.

Next, I study the relationship between cultural bias and two other important analyst outputs: target prices and earnings estimates. Similar to my analysis of stock recommendations, I construct a monthly panel of the latest target price for each analyst-firm pair to compare target prices within-firm and within-analyst at all points in time. As with stock recommendations, I find a significant positive relationship between analyst target prices and trust bias. One key difference between target prices and recommendations is that target prices are likely to get outdated faster, as they are intrinsically linked to the current share price. Hence, I perform the analysis using various maximum target price age thresholds. The results remain similar regardless of the maximum age limit applied.

I also study the relationship between trust bias and earnings estimates. I construct a yearly panel of earnings forecast errors at the end of each fiscal year. Interestingly, unlike stock recommendations and target prices, earnings forecast errors do not exhibit a significant positive relationship with trust bias – the relationship between directional earnings forecast error and trust bias is not statistically significant. For absolute forecast error, the relationship with trust bias is significantly negative. In other words, more positively biased analysts generate more accurate earnings estimates. A possible explanation is that earnings estimates are conceptually different from both recommendations and target prices. First, their quality is easily observable ex post, as they can be compared to actual announced numbers. Second, they do not incorporate qualitative judgment the way stock recommendations and target prices do, and hence they are associated with greater accountability.

For additional insight into the determinants of the cultural bias effects that I document, I estimate the effect of trust bias on stock recommendations conditional on various broker, analyst, and firm characteristics. I find that analysts working at larger, higher status, and culturally more diverse brokers exhibit smaller effects of trust bias. These results suggest that a more diverse and more competitive or meritocratic environment may mitigate the effects of cultural biases. I also find that analysts with more experience in general, and in covering a given firm in particular, are more affected by their cultural biases. This finding is consistent with an entrenchment effect, whereby long-tenure analysts have weaker incentives to work hard. I further find that analysts from countries with more negative attitudes toward globalization exhibit stronger trust bias effect, and that larger firms are associated with larger trust bias effect, possibly related to a *national champion* effect similar to the results on eponymous firms. Finally, controlling for other characteristics, I find evidence of higher idiosyncratic volatility (IVOL) being associated with more pronounced trust bias effect, consistent with harder-to-value firms being more affected by the bias.

This study provides novel evidence of cultural biases affecting the judgment of sell-side analysts. While prior studies examine cultural bias, the setting of equity analysis has certain benefits. Most importantly, it allows for cross-sectional comparisons within-analyst and within-firm, which means that I can compare analyst opinions on the same underlying asset, unlike prior settings such as trade (Guiso, Sapienza, and Zingales (2009)) or venture capital investments (Bottazzi, Da Rin, and Hellmann (2016)). The ability to perform the analysis at a monthly frequency also allows for documentation of both persistent long-term biases and possibly transitory short-term shifts, as illustrated by the case studies that I include. Another advantage of the setup in this paper is that comparing stock recommendations with actual subsequent stock returns allows bias to be disentangled from information. In my analysis of monthly stock returns, I show that more biased recommendations tend to be predictably worse in both directions. This means that my results are not driven by trust bias acting as a proxy for information, as more positive trust bias is not associated with universally better recommendations. This point is important, given prior literature suggests that cultural proximity can be associated with an information advantage (e.g., Du, Yu, and Yu (2017), Fisman, Paravisini, and Vig (2017)).

I also contribute to the literature on personal biases affecting sell-side analysts. For example, Jannati et al. (2020) find evidence of in-group favoritism in sell-side analyst forecasts and recommendations as measured by gender, race/ethnicity, or political attitudes. Lai and Teo (2008) find evidence of a home-country bias in equity analyst recommendations in Asia. Related literature on credit rating analysts documents political bias in corporate credit ratings (Kempf and Tsoutsoura (2021)) and a home-country bias in sovereign credit ratings (Fuchs and Gehring (2017)). There is also evidence of biased reactions to analyst recommendations that depend on social connections between analysts and investors (Jia, Wang, and Xiong (2017)) or the favorability of the analyst's surname (Jung et al. (2019)).

My findings are closely related to the literature on home bias in stock market investments (e.g., Coval and Moskowitz (1999), French and Poterba (1991)). Morse and Shive (2011) find that the level of patriotism is positively related to the level of home bias in equity selection. Using data on Finnish firms, Grinblatt and Keloharju (2001) also show that investors are more likely to hold stocks of firms that are located close to the investor, that communicate in the investor's native tongue, and that have chief executives of the same cultural background.

My findings on the effect of short-term shocks to cultural perceptions on stock recommendations are similar in spirit to those of Kumar, Niessen-Ruenzi, and Spalt (2015), who find that fund managers with Middle-Eastern–sounding names experience significantly lower fund flows following the 9/11 terrorist attacks, and of Fouka and Voth (2016), who find that the conflict between Greece and Germany during the sovereign debt crisis resulted in larger declines in the sales of German cars in areas where Germans carried out massacres during World War II. It is also worth noting that the results are found in the context of financial market professionals, who may be less affected by behavioral biases than the general population (e.g., List, Haigh, and Nerlove (2005), Alevy, Haigh, and List (2007)). It is therefore possible that such biases may have larger effects in the general population.

The paper is organized as follows. Section I describes the data sources and methodology. Section II presents the main results on stock recommendations. Section III studies two distinct shocks to cultural biases. Section IV studies announcement returns and the predictive power of analyst recommendations. Section V studies target prices and earnings forecast errors. Section VI explores cross-sectional differences in the effect of trust bias on stock recommendations. Section VII provides a brief discussion of additional analyses presented in the Internet Appendix. Section VIII concludes.

I. Data and Methodology

A. Measuring Cultural Trust Bias

To quantify cultural biases, I construct a bilateral measure of cultural trust bias between different European countries. To do so, I follow the methodology of Guiso, Sapienza, and Zingales (2009) and use a trust measure based on Eurobarometer surveys. These surveys, discussed in detail in Guiso, Sapienza, and Zingales (2009), are sponsored by the European Commission and conducted yearly to measure the social and political attitudes and awareness of citizens within the EU. The trust measure is based on how much citizens of one country say they trust citizens of each other country (including their own). The specific question asked is: "I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all." This question was included in various survey waves, the most recent one being in 1996.[11] Following Bloom, Sadun, and Van Reenen (2012) and Bottazzi, Da Rin, and Hellmann (2016), I define bilateral trust as the proportion of respondents indicating they have a lot of trust toward the country in question.

Of course, the level of trust is not the same as cultural bias. Some nationalities may be more trustworthy than others, and some nationalities may trust people more than others. To account for systematic differences in trustworthiness and the tendency to trust, I follow Guiso, Sapienza, and Zingales (2009) and regress trust on country dummies for origin of trust, country dummies for destination of trust, as well as dummies for the survey year,

$$Trust_{i,j,t} = \lambda_i + \kappa_j + \gamma_t + \epsilon_{i,j,t}, \tag{1}$$

where i, j, and t index origin-of-trust country, destination-of-trust country, and survey year, respectively. I define *Trust bias* as the residual from this regression. By construction, this measure of trust bias represents the component of trust that differs from the consensus level of trust. The trust bias values for each analyst-firm country pair are presented in Internet Appendix Table IA.I. Table IA.II reports the unadjusted original trust values.

The question on bilateral trust was included in several Eurobarometer survey waves from 1970 to 1996. I start my sample in 1996, so the trust bias variable that I use does not change over the sample period. Guiso, Sapienza, and Zingales (2009) provide an extensive analysis of the determinants of bilateral trust using the Eurobarometer data. Their results suggest that factors associated with higher bilateral trust include common language and linguistic roots, religious similarity, genetic and somatic similarity, and similar legal origin. In contrast, geographic distance, history of wars, and differences in wealth level are associated with lower levels of bilateral trust. Notably, essentially all of these variables are time-invariant, suggesting that cultural biases are relatively stable over long periods.

[11] See the Online Appendix of Guiso, Sapienza, and Zingales (2009) for a detailed summary.

B. Recommendations, Target Prices, and Earnings Estimates

I obtain analyst recommendations data from IBES to construct a comprehensive data set of analyst-firm-month observations of stock recommendations for all listed companies based in the 15 West European countries included in the Eurobarometer trust data, namely, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. I obtain company location data from Compustat. To avoid companies headquartered in locations that are not relevant for their operations, I require that the company's location and country of incorporation be the same in Compustat. For each analyst-firm-month, I use the latest available recommendation. Similar to Malmendier and Shanthikumar (2014), I include recommendations that are no older than 180 days from their last revision date.[12] Following Loh and Stulz (2011), I code recommendations on a five-point scale where strong buy is denoted by 5 and strong sell by 1.

I next construct a comprehensive monthly panel data set of analyst target prices from IBES, using the latest target price issued by each analyst. Following the methodology of Bradshaw, Huang, and Tan (2019), I scale each target price by the share price at the beginning of the month and exclude observations for which the target price is above 400% or below 70% of the current stock price (adjusted for currency and split adjustment factors). Given most target prices do not have explicit stopping dates in IBES, I perform the target price analysis using various maximum age limits for target prices. For stock prices, I use data from Compustat. I winsorize scaled target prices at the 1% level.

For earnings estimates, I construct a yearly panel of earnings per share (EPS) estimates. I keep the most recent EPS estimate at the end of each fiscal year for each analyst, conditional on the estimate not being more than 360 days old based on its last revision date. I define forecast bias, FB, as the signed difference between the forecast and the actual EPS,

$$FB_{i,j,t} = EPS\ estimate_{i,j,t} - Actual\ EPS_{j,t}, \tag{2}$$

where i, j, and t index analyst, firm, and year, respectively. Similarly, I define the absolute forecast error, AFE, as the absolute value of FB. I demean these measures using the consensus forecast bias and absolute error, respectively, and similar to Harford et al. (2019) and Horton, Serafeim, and Wu (2017), I follow Clement (1999) and scale them by the (absolute) consensus mean forecast bias and consensus mean absolute forecast error, respectively. I define the proportional mean forecast bias (PMFB), $PMFB$, as[13]

$$PMFB_{i,j,t} = \frac{FB_{i,j,t} - MFB_{j,t}}{|MFB_{j,t}|} \tag{3}$$

[12] In the Internet Appendix, I show that my results are not sensitive to this age limit.

[13] Horton, Serafeim, and Wu (2017) denote this variable by *Rel_DFB*.

and the proportional mean absolute forecast error (PMAFE) as:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - MAFE_{j,t}}{MAFE_{j,t}}, \tag{4}$$

using the same variable names as Clement (1999). Following Horton, Serafeim, and Wu (2017), I winsorize both measures at the 5% level to avoid the effect of extreme outliers.[14]

For measures of firm opacity, I obtain management guidance data from IBES. I calculate IVOLs using monthly stock return data from EUROFIDAI and define IVOL using the residuals from a rolling 36-month regression on the Fama-French four-factor model. I obtain data on institutional ownership from the Factset Stock Ownership Summary database by Ferreira and Matos (2008).

C. Analyst Nationalities and Geography

I obtain analyst surnames and initials from the IBES Recommendations Detail file. I then estimate analysts' nationalities based on their surnames, using data from *Forebears.io*, a genealogical online directory of sources for family history research. This website, launched in 2012, has a dictionary of 11 million surnames, including information on their geographic distribution. I assign an estimated nationality for each analyst based on the country that has the highest frequency of the analyst's surname. For my final sample, I retain analysts whose country of origin is one of the 15 countries included in the Eurobarometer trust data. In all of my regression analyses, I include analyst-month and firm-month fixed effects, which effectively limits the regression sample to analysts who cover at least two stocks in the 15 countries in a given month, and to firms that are covered by at least two analysts from these countries.

To obtain analyst office locations, I use the Capital IQ Persons database. This database includes detailed information on each sell-side analyst, including office address. I match analysts to IBES data based on analyst name, and their contemporary employers based on broker name, on an annual basis. This methodology gives me locations for approximately 90% of the analyst-year observations in the data. For analysts with locations missing, I estimate locations using the following methodology. First, I identify all office locations for the analyst's broker ESTIMID code. If the broker has an office in the analyst's home country, I assume that the analyst is based in that office. This is the case for 8% of the sample. For the remaining 2%, I assume that the analyst is based in the largest office of the broker, measured by the number of analysts included in my sample. For a few cases, Capital IQ location data only include the country, not the city. In such cases I assume that the city is the main financial center of the location country. In most cases this is the capital of the country, but for

[14] The results are qualitatively similar when winsorizing at the 1% level.

Germany and Italy I use Frankfurt and Milan, respectively, as these are more important financial centers than Berlin or Rome. I obtain city coordinate data from the MaxMind WorldCities database.

D. Investment Banking Relationships

To control for brokers' investment banking relationships with the firms they cover, I calculate each broker's share of syndicated loan issuance, underwriting mandates, and financial advisory mandates with each firm in the data. I use Dealscan data for syndicated loans and the Capital IQ Transactions database for equity and bond underwriting mandates as well as financial advisory mandates related to mergers and acquisitions. To do so, I first use a manually updated version of an IBES link table to identify each broker based on the ESTIMID code in the IBES data. As brokers' business relationships with covered firms are likely most relevant at the group level, I manually identify the ultimate owner of each broker, as identified by the ESTIMID code, and adjust these dynamically for mergers and acquisitions during the sample period. I manually match the relevant entities in Dealscan and Capital IQ data to the corresponding ESTIMID codes in the IBES data. To match Dealscan data to my sample, I use the Roberts Dealscan-Compustat Linking Database (Chava and Roberts (2008)).

Similar to Ljungqvist, Marston, and Wilhelm, Jr. (2006), I capture underwriting, advisory, and lending relationships by calculating each broker's share of each firm's mandates and loans during the last five years. I calculate the market shares at the entity level and aggregate them to the top group level, adjusting for mergers and acquisitions during the sample period. For debt and equity underwriting mandates, the market share is based on lead underwriter mandates and for syndicated loans on lead arranger mandates.

I also define four additional dummy variables measuring different aspects of IB relationships. The first, *IB relationship*, is a dummy that takes the value of one if the broker group has acted as lead arranger on a syndicated loan, lead underwriter on a debt or equity issue, or financial advisor on a merger or acquisition (M&A) for the firm in question during the last five years. The second dummy, *Has IB*, takes the value of one if the broker group has acted as lead arranger on a syndicated loan, lead underwriter on a debt or equity issue, or financial advisor on a M&A transaction for any firm in the sample during the last five years. The third dummy, *IB client*, takes the value of one if the firm has done a syndicated loan, debt or equity issue, or M&A transaction with any broker in my sample during the last five years. Finally, *IB potential* is the product of *Has IB* and *IB client*. This variable indicates whether the firm has done IB business with a broker in my sample, the broker group has done IB business with a firm in my sample, and hence whether there may be potential for an IB relationship, even if one may not yet exist.

E. Announcement Returns and Monthly Stock Returns

For analyses of stock returns, I use return data from EUROFIDAI, which also provides factor returns data at the country level. I calculate announcement returns for each analyst recommendation as the CAR over a three-day window including the announcement day as well as the previous and the next trading day (days -1 to $+1$ relative to announcement). I estimate abnormal daily returns based on the Fama-French four-factor model (FF4) using local market factors by country.[15] I estimate factor betas from daily returns during trading days (-252, -42) relative to the event date. Similar to Loh and Stulz (2011), I exclude recommendations announced during the three-day windows around earnings announcement days and management guidance days, as well as all days with multiple stock recommendations, as these days are more likely to be associated with company news announcements. Similarly, I trim the sample at the 1% and 99% levels to avoid including events that are unlikely to be caused by analyst recommendations.

To study longer term stock returns and the information content of analyst recommendations, I construct a monthly stock-level data set of excess returns, using data from EUROFIDAI. I measure excess returns in the local currency, calculated as the monthly stock return less the local risk free rate. To limit the impact of outliers, I winsorize returns at the 1% level. For control variables, I use accounting data from Compustat.

II. Cultural Biases in Analyst Recommendations

A. Description of the Data

Table I reports summary statistics for the recommendations sample at the analyst-firm-month level. The average recommendation, coded from 1 (*Strong sell*) to 5 (*Strong buy*), is 3.53, roughly half-way between *Hold* (3) and *Buy* (4). The median recommendation is *Buy* (4), and half of the monthly observations are buy recommendations. The average *Trust bias* is 0.22. In 74% of the observations, the analyst comes from the same country as the firm. The average distance between the headquarters city of the company and the analyst's office location is 500 km and the median is 194 km, suggesting that many analysts are quite local.

The average number of firms that a given analyst covers is slightly below 12. The average time the analyst has covered a stock is three years, while analysts' average overall experience is nearly six years. The average broker size, measured as the number of active analysts, is 46, while the median size is 25. This reflects the skewed distribution of broker size. The average number of nationalities at a broker is 8.4, and the average Herfindahl-Hirschmann Index (HHI) of nationality concentration at the broker is 0.46. These broker metrics are based on those analysts covering at least one firm headquartered

[15] FF4 refers to the three-factor model of Fama and French (1993) plus the momentum factor of Carhart (1997).

Table I

Summary Statistics

This table presents summary statistics for the analyst-firm-month observations in the sample. The sample period is 1996 to 2018. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Sell recommendation* is a dummy taking the value of one if the recommendation is 1 (*Strong sell*) or 2 (*Sell*). All variables are defined in the Appendix.

	Mean	Std	p10	p50	p90
Recommendations					
Recommendation	3.528	1.151	2.000	4.000	5.000
Buy rec.	0.508	0.500	0.000	1.000	1.000
Sell rec.	0.169	0.375	0.000	0.000	1.000
Trust bias and geography					
Trust bias	0.218	0.148	−0.012	0.246	0.387
Same country	0.738	0.440	0.000	1.000	1.000
Distance ('000 km)	0.502	1.354	0.000	0.194	0.841
Broker					
Broker HHI	0.464	0.234	0.182	0.433	0.792
Broker nationalities	8.382	7.002	2.000	6.000	20.000
Broker size	46.014	51.895	8.000	25.000	112.000
Top 10	0.304	0.460	0.000	0.000	1.000
Analyst					
Analyst *N* firms	11.534	8.275	4.000	10.000	20.000
Years covered	3.008	3.233	0.318	1.912	7.263
Ana. experience (yrs)	5.834	4.769	1.036	4.419	12.934
Anti-globalization	0.441	0.135	0.299	0.393	0.651
Firm					
N recommendations	16.408	11.707	3.000	14.000	33.000
N rec. (in sample)	5.803	4.341	1.000	5.000	12.000
Eponymous	0.066	0.249	0.000	0.000	0.000
Market cap (USDb)	9.155	20.768	0.097	1.493	26.883
Inst. ownership	0.209	0.143	0.034	0.187	0.416
IVOL	0.072	0.034	0.039	0.065	0.113
Mgmt guidance	0.209	0.406	0.000	0.000	1.000
Broker relationship					
IB relationship	0.119	0.324	0.000	0.000	1.000
IB potential	0.281	0.449	0.000	0.000	1.000
Has IB	0.681	0.466	0.000	1.000	1.000
IB client	0.344	0.475	0.000	0.000	1.000
Share - syndicated loans	0.012	0.064	0.000	0.000	0.000
Share - underwriting	0.020	0.107	0.000	0.000	0.000
Share - advisory	0.008	0.076	0.000	0.000	0.000
N	1,269,560				

in the 15 countries included in my sample. Following Harford et al. (2019), I classify a broker as a *Top 10* broker if it is in the top decile of brokers based on the number of analysts.[16] About 30% of the sample is attributable to such

[16] For the purposes of this classification, a broker is defined by its ESTIMID code.

top 10 brokers. This number is lower than in some prior studies focusing on the United States, in part because some of the largest brokers do not provide analyst names in IBES and therefore cannot be included in my sample.

The average number of active recommendations for a firm in a given month is slightly above 16. This number includes recommendations from analysts who do not come from the 15 European countries or whose names are not disclosed in the IBES data. The average number of monthly recommendations for a firm by analysts included in my sample is 5.8. These numbers imply that the analysts whose nationality I can estimate and who are from one of the 15 countries in my sample, represent approximately 35% of the total analyst coverage of the sample firms. Nearly 7% of the observations correspond to firms classified as eponymous, meaning that the firm name mentions the name of its home country.

In approximately 12% of the sample, the broker group and the covered firm have an on-going investment banking relationship, defined as the broker having acted as lead arranger on a syndicated loan, lead underwriter on a debt or equity issue, or financial advisor in a merger or acquisition for the firm during the last five years. The variable *Has IB* indicates whether the broker has had an IB relationship with *any* firm in my sample; this is the case in 68% of the monthly observations. Similarly, *IB client* indicates whether the firm has had an IB relationship with *any* broker in my sample, which holds in 34% of the sample. The interaction between these two, *IB potential*, thus indicates that both the broker and the firm have engaged in IB business with a counterparty in the sample, and hence could potentially have an IB relationship together. This last variable is meant to capture biases arising from seeking IB business in the future. I find that 28% of the sample have such potential for relationship.

B. Trust Bias and Analyst Recommendations

To test for the relationship between analyst recommendations and trust bias, I perform a regression analysis specified as follows:

$$Recommendation_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t}, \tag{5}$$

where i, j, and t index the analyst, firm, and month, respectively. The dependent variable, $Recommendation_{i,j,t}$, is the analyst recommendation for company j by analyst i during month t. Analyst recommendations are coded 1 (*Strong sell*) to 5 (*Strong buy*). The independent variable of interest, $Trust\ bias_{i,j}$, is the estimated trust bias of country-of-origin of analyst j toward the home country of company i. The vector of controls, $X_{i,j,t}$, includes *Same country*, a dummy that takes the value of one if the analyst and firm are from the same country, to control for pure home-country bias (Lai and Teo (2008)), *ln(Distance)* to control for geographic proximity (Malloy (2005)), and *IB relationship* and *IB potential* to control for existing or possible investment banking relationships during the last five years. The controls also include *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*, calculated as rolling five-year market shares of the broker in each firm's syndicated loans, equity and debt underwriting mandates, and M&A advisory mandates, in order to control for potential biases arising from investment banking relationships between the broker and the firm (e.g., Lin and McNichols (1998), Bradley, Jordan, and Ritter (2003), Ljungqvist, Marston, and Wilhelm,Jr. (2006), Ljungqvist et al. (2007).

In all model specifications, I include *firm-month joint fixed effects* and *analyst-month joint fixed effects*. Thus, the estimated effects of trust bias are effectively *within-analyst* and *within-firm* each month, which implies that the bias effect is not driven by certain firms being better or worse or by certain analysts being more positive or negative. Similarly, the estimated effect of trust bias is not affected by any country- or broker-specific characteristic, as such characteristics are absorbed by the fixed effects. The estimates therefore capture only the relative differences in recommendations assigned by each analyst to each firm.

The results are reported in Panel A of Table II. As shown in columns (1) and (2), a higher trust bias is associated with significantly more positive stock recommendations. Column (2) shows that the estimated coefficient on *Same country* is positive but not statistically significant, suggesting that the level of home bias is mostly captured by the trust bias variable. Analysts who are located further away are generally more negative, while the existence of an investment banking relationship is associated with more positive recommendations. Conditional on having an IB relationship, advisory mandates appear to be the strongest predictor of more positive recommendations. In Internet Appendix Section IV, I perform additional analysis on the role of investment banking relationships.

Columns (3) and (4) show similar results using *Buy recommendation* and *Sell recommendation* dummies as the dependent variable. The results are consistent with those using *Recommendation (1-5)* as the dependent variable: a more positive trust bias is associated with a significantly higher likelihood of a buy recommendation and a lower likelihood of a sell recommendation.

In the analysis above, I include a same-country dummy as a control variable to ensure that my results are not driven merely by home-country bias. To further check the robustness of the results, I perform regression analysis of analyst recommendations after excluding all observations where the analyst and the firm are from the same country. Given nearly 74% of observations involve same-country analysts, and identification including analyst-month and firm-month fixed effects requires that the analyst issue recommendations on at least two companies in the month and that the firm receives recommendations by at least two analysts, these filters substantially reduce the sample size and hence the statistical power of the analysis. Notwithstanding, as the results in Panel B of Table II show, the effect of trust bias remains statistically significant even for the foreign-only subsample. The estimated coefficients are of similar magnitude or even slightly larger than for the full sample. This analysis confirms that the results are not driven solely by same-country observations.

Table II

Recommendations and Trust Bias

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Sell recommendation* is a dummy taking the value of one if the recommendation is 1 (*Strong sell*) or 2 (*Sell*). The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: All analysts

	Rec. (1-5)		Buy rec.	Sell rec.
	(1)	(2)	(3)	(4)
Trust bias	0.9583***	0.5916***	0.2802***	−0.1421***
	(0.0873)	(0.1514)	(0.0724)	(0.0468)
Same country		0.0702	0.0244	−0.0151
		(0.0488)	(0.0238)	(0.0141)
ln(Distance)		−0.0158***	−0.0078***	0.0056***
		(0.0053)	(0.0016)	(0.0010)
IB relationship		0.0763***	0.0302***	−0.0323***
		(0.0159)	(0.0060)	(0.0083)
IB potential		0.0310	0.0094	−0.0088
		(0.0273)	(0.0095)	(0.0073)
Share - syndicated loans		−0.0556	−0.0324	0.0331
		(0.0761)	(0.0337)	(0.0207)
Share - underwriting		0.1166	0.0708	−0.0105
		(0.0996)	(0.0447)	(0.0199)
Share - advisory		0.1779***	0.0912**	−0.0299
		(0.0633)	(0.0360)	(0.0185)
Firm-Month FE	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes
N	1,035,166	1,035,166	1,035,166	1,035,166
R^2	0.564	0.565	0.547	0.547

Panel B: Excluding domestic analysts

	Rec. (1-5)		Buy rec.	Sell rec.
	(1)	(2)	(3)	(4)
Trust bias	0.7611**	0.6883*	0.2576*	−0.2086**
	(0.3429)	(0.3496)	(0.1453)	(0.0959)
ln(Distance)		−0.0256***	−0.0115***	0.0103***
		(0.0093)	(0.0044)	(0.0030)
IB relationship		0.1396**	0.0481*	−0.0712***
		(0.0536)	(0.0248)	(0.0168)
IB potential		0.0406	−0.0003	0.0073
		(0.0619)	(0.0280)	(0.0188)
Share - syndicated loans		−0.0712	−0.0295	0.0254
		(0.2391)	(0.0809)	(0.0814)

(*Continued*)

Table II—*Continued*

Panel B: Excluding domestic analysts				
	Rec. (1-5)		Buy rec.	Sell rec.
	(1)	(2)	(3)	(4)
Share - underwriting		0.5384**	0.2787**	0.0055
		(0.2353)	(0.1176)	(0.0595)
Share - advisory		0.2406	0.1491**	−0.0345
		(0.1518)	(0.0710)	(0.0465)
Firm-Month FE	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes
N	173,274	173,274	173,274	173,274
R^2	0.683	0.684	0.685	0.673

C. Eponymous Firms and the Salience of Nationality

If analyst recommendations are affected by the analyst's cultural biases, it seems possible that firms whose nationality is more salient might be more affected. This could be due, in part, to activation of the analyst's cultural biases without the analyst being aware of it, a phenomenon referred to as priming in the experimental psychology literature (e.g., Bargh and Chartrand (2000)). Priming has also been used extensively in experimental economics in recent years.[17]

Several factors are likely to affect the salience of firm nationality, but one obvious candidate is the firm's name. Belenzon, Chatterji, and Daley (2017) show that naming a firm after its owner creates an association between the entrepreneur and her firm that increases the reputational benefits (costs) of successful (unsuccessful) outcomes. Following a similar rationale, I define firms as *Eponymous* if the firm's name includes the name of its home country. Examples of such eponymous firms include Deutsche Bank, Hellenic Telecommunications Organisation, Telecom Italia, and Bolsas y Mercados Espanoles. Nearly 7% of the monthly observations in my data are associated with such eponymous firms. These firms are often what one might call "national champions." As such, they also tend to be larger than average. However, because size alone might be associated with national champion status and hence make the nationalities of these firms more salient, I also include an interaction term between firm size (market capitalization) and trust bias.

Table III reports the results of regressions that include the interaction between trust bias and the eponymous firm indicator. The recommendations for

[17] For example, Cohn, Fehr, and Maréchal (2014) find that bank employees behave more dishonestly when their professional identity as bank employees is rendered salient. Callen et al. (2014) find that asking subjects to recollect fearful experiences reduces risk appetite. Cohn et al. (2015) show that financial professionals primed with a financial bust are more fearful and risk averse than those primed with a boom.

Table III

Eponymous Firms and the Salience of Nationality

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Eponymous* is a dummy taking the value of one if the firm name includes the name of its home country. *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
Eponymous × Trust bias	0.3208**	0.3188**	0.2659*	0.1170**	0.1198**	0.1052*
	(0.1325)	(0.1354)	(0.1475)	(0.0472)	(0.0512)	(0.0552)
ln(Market cap) × Trust bias			0.0983***			0.0271***
			(0.0256)			(0.0104)
Trust bias	0.5384***			0.2608***		
	(0.1480)			(0.0725)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	Yes	No	Yes	Yes
N	1,035,166	1,035,166	1,013,829	1,035,166	1,035,166	1,013,829
R^2	0.565	0.566	0.568	0.547	0.549	0.550

firms classified as eponymous are significantly more affected by analysts' cultural biases. This effect continues to hold even when controlling for the interaction between trust bias and firm size. I also find a strong positive relationship between size and the effect of trust bias. These results suggest that firms whose nationalities are more salient are more affected by cultural biases.

The findings above are consistent with extant research showing that names can modulate the effects of cultural biases. For example, Kumar, Niessen-Ruenzi, and Spalt (2015) find that fund managers with Middle-Eastern–sounding names experience significantly lower fund flows following the 9/11 terrorist attacks, while Jung et al. (2019) find that analysts with more favorable surnames elicit stronger market reactions.

D. Cultural Biases and General Sentiment

One limitation of my study is that I cannot observe possible time-variation in trust bias, as the last Eurobarometer survey to include the bilateral trust question was in 1996, which is the first year in my sample. The analysis thus implicitly assumes that there is a degree of cross-sectional stability in cultural biases that can be captured with a time-invariant measure. This assumption does not appear to be aggressive, as a large literature suggests that many cultural attributes, including trust, are stable over long periods (e.g., Guiso, Sapienza, and Zingales (2006, 2009)). At the same time, it seems likely that cultural perceptions and their strength change over time.

To explore this issue, I estimate the effect of trust bias on a monthly basis—that is, while my measure of cultural bias is time-invariant, I study time-variation in its estimated effect. This analysis can capture time-variation in the strength of cultural biases but not changes in its cross-sectional distribution. For explaining time-variation in the strength of cultural biases, general sentiment appears to be a good candidate. Some prior evidence suggests that the effect of cultural bias is more pronounced during bad times. For instance, Golez and Karapandza (2021) show that home-country media bias in covering domestic automobile companies is significantly larger during difficult periods for the focal companies, including scandals and car recalls, and Fouka and Voth (2016) find that the conflict between Greece and Germany during the sovereign debt crisis resulted in larger declines in the sales of German cars in areas where Germans carried out massacres during World War II. I therefore also include indicators of sentiment in my analysis.

First, I estimate monthly coefficients for the effect of trust bias on analyst recommendations using the specification

$$Recommendation_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Month_t \times Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t}, \quad (6)$$

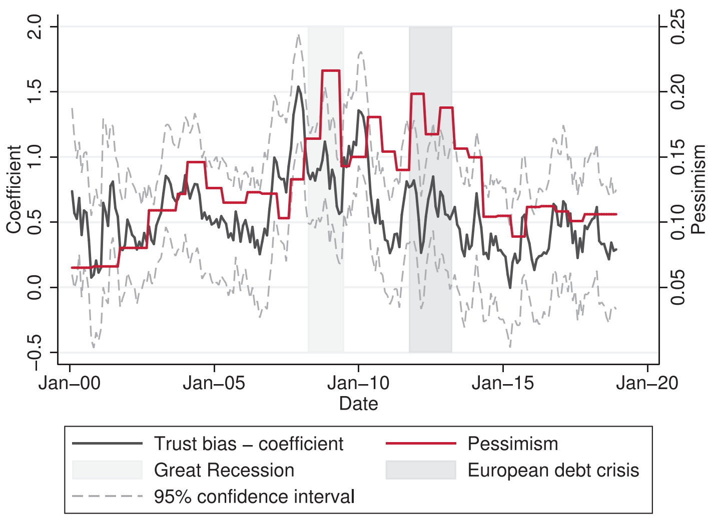
where *Month* is a vector of dummies for each month in the sample period, and the other variables are as described above. Panels (a) and (b) of Figure 1 plot these monthly coefficients against *Pessimism*, a Eurobarometer-based variable measuring the general level of pessimism in Europe, and Consumer Confidence Indicator (*CCI*), a measure of general consumer confidence in Europe. These measures of sentiment are described in more detail in Internet Appendix Section III. The panels suggest a clear positive relationship between the effect of trust bias and the level of pessimism, and a negative relationship between the effect of trust bias and consumer confidence.

To test for these relationships more formally, I perform regression analysis according to

$$Recommendation_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Pessimism_t \times Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t}. \quad (7)$$

Results of these regressions are reported in Panel A of Table IV. Across all specifications, the results suggest a significant positive relationship between the effect of trust bias and the level of pessimism. In other words, during times of negative sentiment, cultural biases have a significantly stronger effect. These results are robust to including country-pair fixed effects and even analyst-firm fixed effects, estimating pure time-variation within an analyst-firm pair. Panel B repeats this analysis using CCI as the sentiment measure. The results are the reverse of those using pessimism, indicating that higher levels of consumer confidence are associated with a significantly weaker effect of trust bias.

Panel (a) Estimated trust bias effect vs. pessimism



Panel (b) Estimated trust bias effect vs. consumer confidence

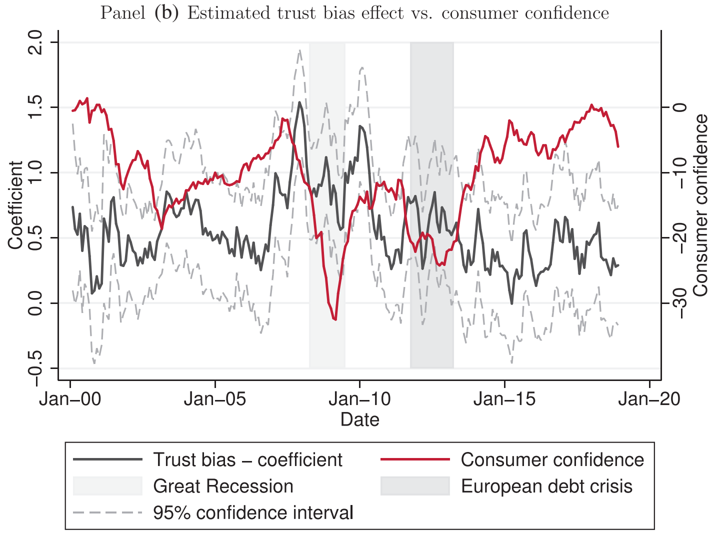


Figure 1. Trust bias versus pessimism and consumer confidence. This figure plots monthly estimates of regression coefficients for *Trust bias* from the regression below against the aggregate level of pessimism and consumer confidence in the European Union. Regression equation:

$$Recommendation\_i, j, t = \alpha_{i,t} + \gamma_{j,t} + \beta Month_t \times Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t},$$

where *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*), *Month* is a vector of dummies for each month in the sample period, X is a vector of controls, including *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*, as well as analyst-month and firm-month fixed effects. *Pessimism* is the proportion of people who expect their life to be worse in the next year, based on Eurobarometer surveys. *Consumer confidence* is the Consumer Confidence Indicator for the EU, published by the European Commission. Variables are defined in the Appendix. Highlighted areas show CEPR recessions. (Color figure can be viewed at wileyonlinelibrary.com)

Table IV

The Effect of Cultural Bias versus Sentiment

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Pessimism* is the proportion of people who expect their life to be worse in the next year, based on Eurobarometer surveys. *Consumer confidence* is the Consumer Confidence Indicator for the EU, published by the European Commission. *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Trust bias vs. pessimism

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
Pessimism × Trust bias	2.9518***	3.4093***	3.3153***	0.8864**	1.1468***	1.3807**
	(0.9387)	(0.9664)	(1.2630)	(0.3977)	(0.4000)	(0.5538)
Trust bias	0.2179			0.1705*		
	(0.2009)			(0.0873)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	No	No	Yes	No
Analyst-Firm FE	No	No	Yes	No	No	Yes
N	1,023,849	1,023,849	1,023,636	1,023,849	1,023,849	1,023,636
R^2	0.565	0.566	0.792	0.546	0.549	0.773

Panel B: Trust bias vs. consumer confidence

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
CCI × Trust bias	−0.0155***	−0.0166***	−0.0164***	−0.0045**	−0.0053***	−0.0053*
	(0.0046)	(0.0046)	(0.0060)	(0.0020)	(0.0019)	(0.0028)
Trust bias	0.4135**			0.2286***		
	(0.1718)			(0.0789)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	No	No	Yes	No
Analyst-Firm FE	No	No	Yes	No	No	Yes
N	1,035,166	1,035,166	1,034,964	1,035,166	1,035,166	1,034,964
R^2	0.565	0.566	0.793	0.547	0.549	0.774

III. Shocks to Cultural Biases

In the analysis above, I find both a persistent long-term effect of cultural biases on stock recommendations and time-variation in the effect. In this section, I explore implications of short-term shocks to cultural perceptions that are specific to certain countries. This allows me to study short-term cross-sectional changes in cultural perceptions without relying on the trust bias measure. I study two such shocks, namely, the European debt crisis and Brexit. In Internet Appendix Section VII, I also perform similar analysis around the Iraq war.

A. European Debt Crisis and North-South Cultural Bias

The European debt crisis of 2011 to 2013 was the culmination of a North-South divide in economic performance (as discussed by, for example, Landesmann (2015) and Lane (2012)), and represented the second dip of the Eurozone's double-dip recession in the aftermath of the 2008 financial crisis. Response to this crisis involved bailouts of several South European states, with Northern Europe largely perceived to be paying for these bailouts. This dynamic created significant antipathy between Mediterranean and Northern states. Stories invoking stereotypes of lazy Mediterraneans were common in the North European media and even in political discourse. In 2010, during EU negotiations of a Greek bailout, the Swedish Finance Minister, Anders Borg, said that "Obviously, Swedes and other taxpayers should not have to pay for Greeks who choose to retire in their 40s," while Bild, the German tabloid and the largest newspaper in Europe by circulation, declared that "Greece, but also Spain and Portugal have to understand that hard work – meaning ironfisted money-saving – comes before the siesta."

Given substantial media attention given to negative stereotypes of South Europeans during the crisis, I study changes in analyst recommendations during the crisis period when the analyst is North European and the firm is domiciled in Southern Europe. For the purposes of this analysis, I define *Northern Europe* as Germany, the United Kingdom, the Netherlands, Austria, Sweden, Denmark, and Finland, and *Southern Europe* as Portugal, Italy, Greece, and Spain.

I define the *Crisis* variable as a dummy taking the value of one during the period Q4 2011 to Q1 2013, which is the Eurozone recession period as classified by CEPR. I then perform regression analysis interacting this variable with dummies indicating analyst-firm pairs for which the analyst is Northern and the firm Southern, as classified above. The regression results are reported in Table V. Panel A shows that North European analysts issue significantly more negative stock recommendations on South European companies during the crisis, consistent with increasingly negative bias introduced by the crisis. This effect is economically large. My regression analysis suggests that during the crisis, Northern analysts are between 11 and 23 percentage points less likely to assign Southern firms a buy recommendation, depending on the model specification. I also estimate monthly coefficients for this interaction variable and plot them in Figure 2, where the increasingly negative bias is clearly visible. I find no statistically significant effect when the analyst is South European and the firm North European, as shown in Panel B, although the estimated coefficients are negative in these cases as well.

Table V

European Debt Crisis and North-South Biases

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Crisis* is a dummy taking the value of one during the Eurozone recession of Q4 2011 to Q1 2013. *Northern analyst* is a dummy taking the value one if the analyst is from Germany, the United Kingdom, Netherlands, Austria, Sweden, Denmark, or Finland. *Southern firm* is a dummy taking the value one if the firm is from Portugal, Italy, Greece, or Spain. *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 2008 to 2014. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Northern analyst and Southern firm

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis × Northern a. × Southern f.	−0.3740***	−0.4259***	−0.2173*	−0.2257***	−0.2466***	−0.1143**
	(0.1179)	(0.1303)	(0.1159)	(0.0589)	(0.0615)	(0.0564)
Northern a. × Southern f.	0.0077			0.0638*		
	(0.1062)			(0.0360)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	No	No	Yes	No
Analyst-Firm FE	No	No	Yes	No	No	Yes
N	362,547	362,547	362,291	362,547	362,547	362,291
R^2	0.565	0.569	0.793	0.544	0.549	0.774

(*Continued*)

Table V—*Continued*

Panel B: Southern analyst and Northern firm

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis × Southern a. × Northern f.	−0.1203	−0.1486	−0.1311	−0.0684	−0.0776	−0.0918**
	(0.1029)	(0.1054)	(0.1031)	(0.0498)	(0.0484)	(0.0447)
Southern a. × Northern f.	−0.0309			−0.0331		
	(0.0847)			(0.0377)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	No	No	Yes	No
Analyst-Firm FE	No	No	Yes	No	No	Yes
N	362,547	362,547	362,291	362,547	362,547	362,291
R^2	0.565	0.569	0.793	0.544	0.549	0.774

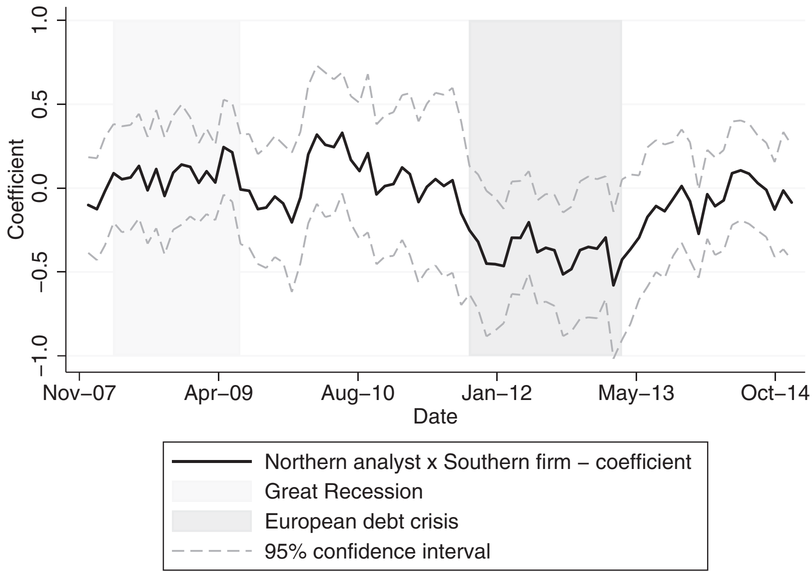


Figure 2. European debt crisis, northern analysts, and southern firms. This figure plots monthly estimates of regression coefficients for *Northern analyst* × *Southern firm* from the regression

$$Recommendation_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Month_t \times Northern\ analyst_i \times Southern\ firm_j + \phi X_{i,j,t} + \epsilon_{i,j,t},$$

where *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*), *Month* is a vector of dummies for each month in the sample period, *X* is a vector of controls, including *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*, as well as analyst-month and firm-month fixed effects. Variables are defined in the Appendix. Highlighted areas show CEPR recessions.

B. Brexit and the United Kingdom versus the Rest of Europe

The United Kingdom's decision to leave the EU following the referendum in June 2016 and the subsequent political disarray represented a substantial shock to cultural perceptions about Britain. On March 29, 2017, Prime Minister Theresa May triggered Article 50 and began the two-year countdown to the United Kingdom formally leaving the EU. The negotiation process between the EU and the United Kingdom that followed Article 50 has been characterized by many observers as a "mess" or "shambles."[18] Martin Wolf, the chief economics commentator at the Financial Times, wrote: "The UK once had a deserved reputation for pragmatic and stable politics. That will not survive the spectacular

[18] See, for example, "Brexit vote "shambles" blows hole in Theresa May's authority" by the *Financial Times* (https://www.ft.com/content/2b9a95f8-307c-11e9-8744-e7016697f225) or "The best way out of the Brexit mess" by the Economist (https://www.economist.com/leaders/2018/12/08/the-best-way-out-of-the-brexit-mess).

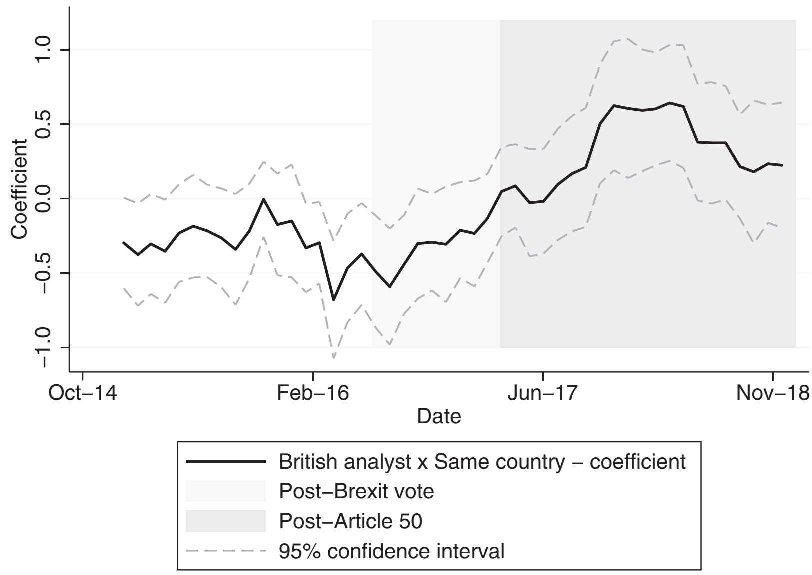


Figure 3. Brexit and United Kingdom versus the rest of Europe. This figure plots monthly estimates of regression coefficients for *British analyst x Same country* from the regression

$$Recommendation_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Month_t \times British\ analyst_i \times Same\ country_{i,j} + \psi Month_t \times Same\ country_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t},$$

where *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*), *Month* is a vector of dummies for each month in the sample period. *X* is a vector of controls, including *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*, as well as analyst-month and firm-month fixed effects. Variables are defined in the Appendix.

mess it is making of Brexit.” At the same time, Brexit was broadly interpreted as a manifestation of rising economic nationalism (Born et al. (2019)) and may have been viewed as a patriotic project by some British analysts, suggesting a possibly more positive view on it (Morse and Shive (2011)).

To study changes in the perceptions of European analysts, relative to U.K. analysts, about U.K. firms, I study the relative home bias exhibited by U.K. analysts over time. In Figure 3, I plot the estimated monthly coefficients for a dummy indicating observations for which both the analyst and the firm are from the United Kingdom. I control for general home bias on a monthly basis, so this coefficient represents the difference in home bias for British analysts versus other analysts. The figure clearly shows that there is a significant divergence of views on U.K. firms between British and other European analysts following Article 50, with other European analysts issuing substantially more negative recommendations on U.K. firms than British analysts.

I test this change more formally in regression analysis that includes an interaction between *British analyst*, a dummy indicating same country, and a dummy that takes the value of one post-Article 50 being triggered. The results, reported in Table VI, show that the divergence between British and other European analysts is statistically significant. Prior to Article 50, the home bias exhibited by British analysts is not significantly different from that exhibited by other analysts. Following Article 50, the difference increases significantly, with the economic magnitude of the shift large. The estimated coefficients suggest that the increase in the likelihood of British analysts assigning a buy recommendation to a U.K. firm increases by more than 30 percentage points relative to other analysts. The results are robust to including country-pair and even analyst-firm fixed effects, although in the latter case the estimated coefficients are somewhat smaller.

IV. Cultural Biases and Stock Returns

A. Stock Recommendation Announcement Returns

If analyst recommendations are systematically biased because of analysts' cultural biases, this should affect the information content of recommendations in a predictable fashion. In particular, one might expect buy recommendations issued by more positively biased analysts to be less useful than buy recommendations issued by more negative analysts. The reverse should be true for sell recommendations—if the analyst is positively biased toward the firm, issuing a sell recommendation signals a more negative assessment than that of a negatively biased analyst. This predicts an inverse U-shaped relationship between stock recommendations and the effect of trust bias on announcement returns: Both buy and sell recommendations should be associated with more negative announcement returns when the analyst is more positively biased. In the case of buy recommendations this would imply a more muted reaction to more positively biased recommendations (less information content), while in the case of sell recommendations it would mean a stronger reaction (more information content).

To test this prediction, I calculate the CAR over a three-day window around each recommendation announcement and regress the announcement CAR on trust bias,

$$CAR_{i,j,t} = \alpha_i + \gamma_j + \lambda_t + \beta Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t}. \tag{8}$$

I include analyst and firm fixed effects, so similar to other analyses in this paper, the estimated trust bias effect is within-analyst and within-firm. I also include time fixed effects and the same analyst-firm control variables as in the stock recommendation analyses above.

The results are reported in Table VII. Panel A shows that buy recommendations are, on average, associated with a positive announcement return of 0.5% while sell recommendations are associated with a negative return of −0.7%. When including all announcement returns regardless of the recommendation, the average is zero, as one might expect when averaging over positive and negative announcements.

Table VI

Brexit and United Kingdom versus the Rest of Europe

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Post* is a dummy taking the value of one after March 29, 2017, which is when the United Kingdom invoked Article 50, formally beginning the Brexit process. *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 2015 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × British × Same country	0.7002***	0.6886***	0.4778***	0.3217***	0.3357***	0.1685**
	(0.1494)	(0.1582)	(0.1235)	(0.0639)	(0.0731)	(0.0640)
Post × Same country	−0.0721**	−0.0895**	0.0270	−0.0115	−0.0284	0.0244
	(0.0357)	(0.0353)	(0.0356)	(0.0173)	(0.0171)	(0.0197)
British × Same country	−0.3638**			−0.0588		
	(0.1480)			(0.0794)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	No	Yes	No	No	Yes	No
Analyst-Firm FE	No	No	Yes	No	No	Yes
N	147,331	147,331	147,259	147,331	147,331	147,259
R^2	0.570	0.578	0.830	0.553	0.562	0.817

Table VII

Recommendation Announcement Returns

This table presents regression results for recommendation announcement returns. The dependent variable in Panels B and C is the three-day cumulative abnormal return over days −1 to 1 relative to the recommendation announcement day. Abnormal returns are estimated based on the Fama-French four-factor model at the country level and factor betas are estimated from daily returns during trading days (−252, −42) relative to the event date. *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and announcement date, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Summary statistics	Mean	Std	p10	p50	p90
CAR	−0.000	0.038	−0.043	−0.001	0.045
CAR - Buy	0.005	0.038	−0.037	0.003	0.052
CAR - Sell	−0.007	0.040	−0.053	−0.006	0.038
CAR - Upgrade to buy	0.009	0.038	−0.032	0.006	0.057
CAR - Downgrade to sell	−0.009	0.041	−0.057	−0.008	0.037
Trust bias	0.218	0.149	−0.018	0.246	0.387
N	92,084				

Panel B: Buy recommendations

	Buy (all)		Buy (active analysts)		Upgrade to buy	
	(1)	(2)	(3)	(4)	(5)	(6)
Trust bias	−0.0135**	−0.0142**	−0.0179**	−0.0167**	−0.0166*	−0.0162
	(0.0055)	(0.0055)	(0.0073)	(0.0076)	(0.0091)	(0.0101)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes	No	Yes
N	42,600	42,600	27,487	27,487	18,269	18,269
R^2	0.182	0.190	0.210	0.223	0.275	0.289

Panel C: Sell recommendations

	Sell (all)		Sell (active analysts)		Downgrade to sell	
	(1)	(2)	(3)	(4)	(5)	(6)
Trust bias	−0.0046	−0.0033	−0.0304*	−0.0292*	−0.0387**	−0.0421**
	(0.0101)	(0.0096)	(0.0159)	(0.0165)	(0.0181)	(0.0201)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes	No	Yes
N	15,239	15,239	10,684	10,684	8,144	8,144
R^2	0.277	0.293	0.315	0.336	0.353	0.386

Columns (1) and (2) in Panel B report the regression estimates for all buy recommendations in the data. Columns (3) and (4) only include recommendations by active analysts, defined as analysts who have issued recommendations on a given firm during the 360 days before the current recommendation. Columns (5) and (6) only include recommendation upgrades to *Buy* or *Strong buy*, with active analysts only included in this subsample. Across all specifications, a more positive trust bias is associated with less positive stock price reactions to buy recommendations. This evidence is consistent with more positively biased recommendations being considered less informative.

In Panel C, I repeat the analysis of Panel B for sell recommendations. Unlike in the case of buy recommendations, here a more negative stock price reaction signals more information content. The estimated coefficients on trust bias are negative across all specifications, although statistically significant only for active analysts and somewhat larger for downgrades than for other sell recommendations. These results suggest that a sell recommendation by a more positively biased analyst is considered more informative.

Taken together, these findings are consistent with the market recognizing analysts' cultural biases and adjusting reactions to analyst recommendations accordingly. In Internet Appendix Section IX, I also analyze medium-term returns following the announcement day, starting from day +2 and for periods of up to days +30, +45, and +60. These results show no significant differences in one- to two-month abnormal returns following recommendation announcements between different levels of trust bias.

The result that the market adjusts for bias is consistent with the findings of Lai and Teo (2008) in the context of home bias in Asian stock recommendations. This result contrasts, however, with Jannati et al. (2020), who find evidence of in-group favoritism in sell-side analyst forecasts and recommendations but show that the market does not adjust for this bias.

B. Monthly Stock Returns

The announcement return results suggest that the market adjusts for perceived cultural biases in analyst recommendations. In this section, I study whether such adjustment fairly reflects the actual information content in analyst recommendations. Prior literature suggests that analyst recommendations contain useful information. Womack (1996) provides early evidence of analysts' market timing and stock picking abilities. Barber et al. (2001) show that portfolios formed from consensus recommendations yield significant abnormal returns, while Jegadeesh et al. (2004) argue that recommendation changes are a robust return predictor. Prior evidence also shows that affiliated analysts issue worse buy recommendations (Michaely and Womack (1999), Barber, Lehavy, and Trueman (2007)).

To study how trust bias affects the information content of analyst recommendations, I construct a monthly panel data set of excess stock returns for the stocks in my recommendation sample and calculate the average recommendation as well as average trust bias of the analysts assigning recommendations for each stock at the end of each month. I then divide stocks into quintiles at the beginning of each month based on the previous month's recommendations, with quintile limits calculated at the country level.

Specifically, I regress monthly excess stock returns on recommendation quintiles and their interactions with trust bias,

$$\begin{aligned} \textit{Excess return}_{i,t} &= \alpha_0 + \beta \textit{Rec. quintile}_{i,t} \times \textit{Trust bias}_{i,t} \\ &\quad + \gamma \textit{Rec. quintile}_{i,t} + \phi X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{9}$$

where i and t index stocks and months, *Excess return* is the monthly stock return less the local risk-free rate, *Rec. quintile* is calculated on a monthly basis based on the average recommendation of all sample analysts covering the stock, where stocks are assigned into quintiles at the beginning of each month based on the recommendation at the end of the previous month (higher quintile means more positive average recommendation, quintile limits are set by firm country), *Trust bias* is the average trust bias of the analysts included in the calculation of the average recommendation, and X is a vector of stock-level controls, including *Market beta*, calculated using monthly returns over the preceding 12 months, *ln(Market cap)* to control for firm size, book-to-market ratio (B/M), return on equity (*RoE*), and stock returns over both the previous month and the previous 12 months. All control variables are lagged by one month to avoid look-ahead bias.

The results are reported in Table VIII. Columns (1) to (3) present results without trust bias and show that analyst stock recommendations have significant predictive power over excess stock returns. The highest recommendation quintile outperforms the lowest quintile by approximately 50 bps per month over the sample period. This difference comes primarily from the lowest recommendation quintile versus the others, but the estimated excess returns increase in a near-monotonic fashion with recommendation quintile in the other quintiles as well. In column (3), I add country-month fixed effects, effectively testing for cross-sectional return differences within-country each month. Given recommendation quintiles are determined within-country on a monthly basis, this specification is the cleanest cross-sectional test of information content across analyst recommendations. In this specification, returns increase monotonically with recommendation quintile, and the difference between high and low quintiles increases to 60 bps. These patterns, as well as the difference between high and low quintile returns, are qualitatively similar to the results of Barber et al. (2001), who find a return spread of 79 bps between high and low portfolios using monthly rebalancing.[19]

More importantly, columns (4) to (6) show that the level of trust bias affects the predictive power of recommendations. A more positive trust bias is associated with lower subsequent stock returns in the highest recommendation

[19] The results are not entirely comparable, as Barber et al. (2001) use fixed, predefined cutoff points for recommendation portfolios rather than percentiles. The markets and time periods studied are also different.

Table VIII
Monthly Stock Returns and Trust Bias

This table presents regression results for monthly stock returns. Panel A presents summary statistics for the monthly stock returns sample. The dependent variable in Panel B is *Excess return*, the monthly stock return less the risk-free rate. *Return* is the monthly raw stock return. *Trust bias* is calculated as the average trust bias across all sample analysts covering the stock, on a monthly basis. *Market beta* is calculated using a rolling 12-month window based on monthly returns. *Recommendation quintile* is calculated based on the average recommendation of the sample analysts, on a monthly basis, with limits set by firm country. The sample period is 1996 to 2018. Heteroskedasticity-consistent standard errors, clustered by firm, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Stock return					
Excess return	0.432	10.516	−11.227	0.180	12.065
Return	0.567	10.505	−11.062	0.300	12.205
Return (LTM)	11.235	43.456	−38.394	8.133	60.056
Trust bias and controls					
Trust bias	0.219	0.124	0.044	0.246	0.387
ln(Market cap.)	6.604	2.052	3.918	6.539	9.386
B/M	0.780	0.838	0.176	0.558	1.539
RoE	0.069	2.200	−0.114	0.102	0.265
Market beta	0.852	0.834	−0.023	0.794	1.804
N	291,839				

Panel B: Monthly excess return regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Rec. quintile 2	0.4370***	0.4142***	0.3865***	0.3453***	0.4239***	0.2960**
	(0.0644)	(0.0712)	(0.0621)	(0.1262)	(0.1396)	(0.1248)
Rec. quintile 3	0.4176***	0.3593***	0.4163***	−0.0208	0.0038	0.0950
	(0.0614)	(0.0693)	(0.0593)	(0.1199)	(0.1348)	(0.1183)
Rec. quintile 4	0.5439***	0.5037***	0.5137***	0.1400	0.1741	0.1052
	(0.0647)	(0.0722)	(0.0626)	(0.1386)	(0.1488)	(0.1327)
Rec. quintile 5	0.5113***	0.4949***	0.5893***	0.4862***	0.3300*	0.3549**
	(0.0762)	(0.0875)	(0.0758)	(0.1629)	(0.1790)	(0.1577)
Rec. quintile 1 ×				−1.4334***	−1.1498***	−0.6634*
Trust bias				(0.3502)	(0.4152)	(0.3921)
Rec. quintile 2 ×				−0.9680**	−1.1277**	−0.2020
Trust bias				(0.4016)	(0.4454)	(0.4220)
Rec. quintile 3 ×				0.6431*	0.5578	0.8728**
Trust bias				(0.3824)	(0.4388)	(0.4098)
Rec. quintile 4 ×				0.4394	0.3822	1.1853***
Trust bias				(0.4210)	(0.4302)	(0.4242)
Rec. quintile 5 ×				−1.1669**	−0.3436	0.4172
Trust bias				(0.5761)	(0.6776)	(0.6304)
Market beta		−0.0162	0.0091		−0.0158	0.0087
		(0.0316)	(0.0291)		(0.0316)	(0.0292)
ln(Market cap.)		−0.0188	0.0275**		−0.0252**	0.0289**
		(0.0119)	(0.0110)		(0.0123)	(0.0115)

(*Continued*)

Table VIII—*Continued*

Panel B: Monthly excess return regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
B/M		0.7363***	0.4033***		0.7359***	0.4049***
		(0.0581)	(0.0517)		(0.0582)	(0.0517)
RoE		0.0239***	0.0188**		0.0234***	0.0184**
		(0.0074)	(0.0088)		(0.0074)	(0.0087)
Return (t-1)		0.0430***	−0.0275***		0.0429***	−0.0276***
		(0.0033)	(0.0036)		(0.0033)	(0.0036)
Return (LTM)		0.0111***	0.0109***		0.0111***	0.0108***
		(0.0006)	(0.0008)		(0.0006)	(0.0008)
Constant	0.0895**	−0.2518**		0.3935***	0.0319	
	(0.0441)	(0.1149)		(0.0824)	(0.1486)	
Country-Month FE	No	No	Yes	No	No	Yes
N	290,872	194,860	194,684	290,872	194,860	194,684
R^2	0.000	0.007	0.283	0.001	0.007	0.283

quintile, suggesting that positive recommendations by more positively biased analysts are less useful in predicting stock returns. Similarly, in the most negative recommendation quintiles, a more positive trust bias is associated with significantly lower stock returns, suggesting that sell recommendations by more positively biased analysts are better at predicting lower stock returns. Given high trust bias in and of itself, that is, not conditional on recommendations, is not associated with significant differences in stock returns the negative correlation between trust bias and both very positive and very negative recommendations must be offset in the middle of the recommendation distribution. This can be seen in the positive coefficients on trust bias in recommendation quintiles 3 and 4. These findings suggest that cultural biases, as captured by the trust bias measure, affect the information content in analyst recommendations in a predictable fashion.

In Internet Appendix Section VIII, I further sort all sample stocks into portfolios based on the average recommendation and trust bias and confirm that a more positive trust bias is associated with less informative buy recommendations (top quintile) and more informative sell recommendations (bottom quintile). An implication is that a hypothetical zero-cost portfolio that is long buy recommendations (top quintile) by low-trust-bias analysts and short sell recommendations (bottom quintile) by high-trust-bias analysts generates an average monthly return of 70 to 80 bps over the sample period, depending on the currency the returns are measured in. Adjusting for Fama-French four-factor model (FF4), the long-short spread measured in EUR generates an average monthly alpha of 55 bps over the sample period. When measured in USD, this spread decreases to 38 bps and is not statistically significant.[20] Sorting only on recommendations, without considering trust bias, generates an

[20] The available sample period is slightly longer in USD, as EUR did not exist prior to 1999.

average monthly return of less than 40 bps and a FF4 alpha of 25 bps in EUR (only marginally statistically significant) and 16 bps in USD (not statistically significant). This analysis does not imply that any such trading strategy would be profitable in practice after transaction costs, but rather suggests that adjusting for cultural biases can improve the information content of analysts' stock recommendations.

V. Other Analyst Outputs

A. Target Prices

To study the relationship between cultural bias and analyst target prices, similar to my analysis of stock recommendations, I construct a monthly panel of the latest target price for each analyst-firm pair to compare target prices within-firm and within-analyst at all points in time. I scale the target price by the firm stock price at the beginning of the month. I then run a regression analysis similar to equation (6) after replacing recommendations with analyst target prices. One key difference between target prices and recommendations is that target prices are likely to get obsolete faster, as they are intrinsically linked to the current share price. Hence, I perform the analysis using various maximum target price age thresholds.

The results are reported in Table IX. As with stock recommendations, there is a significant positive relationship between analyst target prices and trust bias. The results remain qualitatively similar regardless of the maximum age limit considered, although the estimated effect of trust bias is largest for very recent target prices. These results are consistent with the relevance of the target price decreasing over time.

B. Earnings Forecast Bias and Errors

To study the relationship between trust bias and earnings estimates, I construct a yearly panel of earnings forecast errors at the end of each fiscal year. I calculate both directional forecast bias, captured by the PMFB, and absolute forecast errors, captured by the PMAFE. PMFB differentiates between under- and overestimating actual earnings, while PMAFE simply measures the absolute difference from actual earnings. Thus, PMFB corresponds to directional bias in estimates, while PMAFE measures accuracy.

I next run a regression of forecast bias and absolute forecast errors,

$$PMFB_{i,j,t} = \alpha_{i,t} + \gamma_{j,t} + \beta Trust\ bias_{i,j} + \phi X_{i,j,t} + \epsilon_{i,j,t}, \tag{10}$$

where i, j, and t index analyst, firm, and year, respectively.

The results are reported in Table X. I find no statistically significant relationship between trust bias and directional earnings forecast bias (PMFB). The estimated coefficients are positive but not statistically significant. For absolute forecast error (PMAFE), there is a significant negative relationship with trust

Table IX

Target Price

This table presents regression results for analyst target prices. The dependent variable in Panel B is *Target price*, the most recent broker target price divided by beginning-of-month stock price. The analysis is performed using monthly observations, for several maximum allowed target price ages, calculated as days from the target price announcement. The sample period is 1999 to 2018 (IBES PTG data begin in 1999 for my sample firms). Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
Target price (360)	1.168	0.313	0.874	1.111	1.485
Target price (30)	1.147	0.255	0.891	1.116	1.399
Trust bias	0.218	0.152	−0.015	0.246	0.387
N	623,833				

Panel B: Target prices and trust bias

	Maximum target price age				
	(1) 360	(2) 180	(3) 90	(4) 60	(5) 30
Trust bias	0.0825**	0.1043***	0.1300***	0.1425***	0.2368***
	(0.0320)	(0.0306)	(0.0303)	(0.0341)	(0.0752)
Same country	0.0004	−0.0025	−0.0103	−0.0171	−0.0518**
	(0.0092)	(0.0093)	(0.0096)	(0.0112)	(0.0219)
ln(Distance)	−0.0017	−0.0011	−0.0011	−0.0015	−0.0028**
	(0.0011)	(0.0013)	(0.0014)	(0.0015)	(0.0011)
IB relationship	0.0075**	0.0087***	0.0072**	0.0045	0.0035
	(0.0036)	(0.0027)	(0.0032)	(0.0041)	(0.0064)
IB potential	0.0182***	0.171***	0.0176***	0.0204***	0.0093
	(0.0050)	(0.0044)	(0.0052)	(0.0056)	(0.0069)
Share - syndicated loans	0.0028	−0.0075	−0.0005	0.0233	0.0516
	(0.0287)	(0.0241)	(0.0243)	(0.0241)	(0.0357)
Share - underwriting	0.0220	0.0162	0.0011	0.0035	0.0004
	(0.0170)	(0.0209)	(0.0204)	(0.0223)	(0.0232)
Share - advisory	0.0224**	0.0192**	0.0132	0.0223	0.0177
	(0.0102)	(0.0088)	(0.0120)	(0.0137)	(0.0117)
Firm-Month FE	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes
N	496,069	376,915	230,952	144,853	47,723
R^2	0.757	0.778	0.810	0.832	0.874

bias. In other words, more positively biased analysts generate more accurate, but not significantly more optimistic, earnings estimates.

A possible explanation for these findings is that earnings estimates are conceptually different from both recommendations and target prices. Their quality is easy to observe ex post, as they can be (and typically are) compared to actual announced numbers. They also do not incorporate qualitative judgment

Table X

Forecast Bias and Error

This table presents regression results for analyst forecast bias and forecast errors. This analysis is run using a yearly panel of observations with the most recent EPS estimate for each analyst-firm pair at the fiscal year end included. The dependent variable in Panel B is shown above each column. *PMFB* is calculated as the analyst forecast bias (EPS estimate less the actual reported EPS) less the consensus mean forecast bias, scaled by the absolute value of the consensus mean forecast bias. *PMAFE* is calculated as the absolute forecast error (absolute value of EPS estimate less the actual reported EPS) less the consensus mean absolute forecast error, scaled by the consensus mean absolute forecast error. *ln(Days to FY end - ann.)* is the number of days from the announcement day of the earnings forecast to the fiscal year-end. The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and year, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Summary statistics

	Mean	Std	p10	p50	p90
PMFB	−0.019	1.599	−1.835	0.000	1.807
PMAFE	−0.037	0.583	−0.802	−0.022	0.832
Trust bias	0.216	0.150	−0.018	0.246	0.387
N	101,894				

Panel B: Forecast errors and trust bias

	PMFB			PMAFE		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust bias	0.0450	0.0393	0.2247	−0.1308**	−0.1350**	−0.2565**
	(0.1656)	(0.1690)	(0.2069)	(0.0587)	(0.0587)	(0.0917)
Same country	−0.0097	−0.0059	−0.0297	−0.0026	0.0002	0.0087
	(0.0597)	(0.0607)	(0.0779)	(0.0166)	(0.0169)	(0.0257)
ln(Days to FY end - ann.)	0.1153***	0.1117***	0.1271***	0.0869***	0.0866***	0.0930***
	(0.0214)	(0.0212)	(0.0218)	(0.0071)	(0.0072)	(0.0080)
ln(Distance)	0.0052	0.0062	0.0085	0.0005	0.0007	0.0007
	(0.0042)	(0.0040)	(0.0072)	(0.0016)	(0.0017)	(0.0028)
IB relationship	0.0158	0.0041	0.0143	0.0150	0.0134	0.0267
	(0.0441)	(0.0439)	(0.0454)	(0.0121)	(0.0123)	(0.0201)
IB potential	0.0081	−0.0086	−0.0411***	0.0029	−0.0029	−0.0024
	(0.0214)	(0.0216)	(0.0118)	(0.0065)	(0.0061)	(0.0136)
Share - syndicated loans	−0.1575*	−0.1330	−0.0730	−0.0597**	−0.0564**	−0.0893**
	(0.0911)	(0.0928)	(0.1027)	(0.0261)	(0.0269)	(0.0413)
Share - underwriting	−0.0919	−0.0767	−0.0897	−0.0419**	−0.0398**	−0.0995***
	(0.0848)	(0.0835)	(0.1351)	(0.0177)	(0.0188)	(0.0345)
Share - advisory	−0.1467	−0.1314	−0.1904	0.0135	0.0156	0.0636
	(0.1052)	(0.1025)	(0.1624)	(0.0251)	(0.0255)	(0.0441)
Analyst FE	Yes	Yes	No	Yes	Yes	No
Firm FE	Yes	Yes	No	Yes	Yes	No
Year FE	No	Yes	No	No	Yes	No
Analyst-Year FE	No	No	Yes	No	No	Yes
Firm-Year FE	No	No	Yes	No	No	Yes
N	100,880	100,880	86,192	100,928	100,928	86,231
R^2	0.080	0.080	0.334	0.093	0.093	0.333

the way stock recommendations and target prices do, and thus they involve a different level of accountability.[21] This might be one reason that they appear to be less affected by trust bias than recommendations and target prices.

It is also possible that while the difference in earnings estimates between high- and low-trust-bias analysts appears small, these two sets of analysts may apply different judgments in valuing estimated earnings, with positively biased analysts applying a higher valuation to the same earnings stream. This would be consistent with trust bias being positively associated with target prices and recommendations but not with earnings estimates. In Internet Appendix Section XI, I explore this possibility further by studying the price-to-earnings (P/E) ratios implicit in each analyst's target price and EPS estimate for the same firm. The results suggest that there is a positive relationship between trust bias and the implied P/E ratio that analysts assign to firms when valuing them.

VI. Cross-Sectional Differences in the Effect of Trust Bias

A. Broker Characteristics

In this section, I investigate the extent to which broker characteristics affect the strength of cultural biases. First, I construct two measures of broker diversity: the number of analyst nationalities working at the broker, and the HHI of the nationality concentration at the broker. This analysis is motivated by prior research suggesting that cultural diversity among analysts improves the accuracy of consensus forecasts (Merkley, Michaely, and Pacelli (2020)). Second, I use the number of analysts working at the broker as a proxy for broker size. I also define a top 10 indicator dummy that takes the value of one if the broker is among the top decile of brokers in the sample, based on the number of analysts. Prior research suggests that competition can reduce the effects of biases in equity analysis (Hong and Kacperczyk (2010), Merkley, Michaely, and Pacelli (2017)), and thus working at a more competitive and meritocratic environment may mitigate the effect of cultural biases.

These measures suffer from two limitations due to the nature of my data. First, my data only include those analysts who cover firms in my 15 sample countries. Therefore, if a broker has analysts covering firms only in countries outside my sample, those analysts will be excluded from these measures. Second, I can calculate the number of nationalities and HHI only based on those analysts whose nationality I am able to estimate. Analysts whose names are not disclosed in the IBES data, or whose nationalities I cannot estimate based on Forebears data, are excluded from the diversity measures.

[21] Target prices are usually based on estimates of cash flows and risk over long time periods and hence involve more qualitative judgment than (typically short-term) earnings estimates. Unlike earnings estimates, the expected realization period for target prices is often loosely defined, if at all, and target prices are rarely systematically compared with actual realized stock prices.

I perform a regression analysis of stock recommendations including interactions between the broker diversity and size measures and trust bias. The results are reported in Panel A of Table XI. Analysts working at brokers with higher diversity, as captured by both the number of nationalities and HHI, are significantly less affected by cultural biases. Similarly, the effect of trust bias is significantly weaker for analysts working at top 10 brokers or larger brokers in general. These results suggest that being in a more multi-cultural environment may mitigate cultural biases. High-status brokers are also likely to be more attractive employers for analysts, which means that analysts working at them are both better (screening effect) and face more competitive pressure. The latter interpretation is consistent with the findings of Hong and Kacperczyk (2010) and Merkley, Michaely, and Pacelli (2017), who show that increased competition reduces bias in analyst earnings forecasts.

B. Analyst Characteristics

I next study the role of analyst characteristics. Experience may result in learning more about a covered firm itself, as well as in becoming more skilled at analyzing companies. For example, Seru, Shumway, and Stoffman (2010) find evidence of at least some individual investors learning through trading. This would suggest that experience should decrease the effect of cultural biases. Alternatively, analysts may become more entrenched over time and hence have weaker incentives to work hard. This idea is consistent with the findings of Bertrand and Mullainathan (2003) on managers preferring the quiet life when shielded from competition. Similarly, Hong, Kubik, and Solomon (2000) show that analysts with longer tenure are less likely to be fired, particularly in the case of poor performance. More shielded analysts may be less incentivized to work hard and hence be more affected by cultural biases.

To address these questions, I perform regression analysis including the interaction between trust bias and overall analyst experience, as well as experience covering the given firm. The results are reported in Panel B of Table XI. Both measures of experience are associated with a significantly larger effect of trust bias. This result suggests that cultural biases do not decrease over time as the analyst acquires more information about the firm or gains experience. Instead, the result is consistent with an entrenchment effect whereby more experienced analysts have less reason to work hard.

It seems plausible that analysts who are less open to other cultures may be more affected by cultural biases. To test this conjecture, I use a Eurobarometer-based measure of attitudes toward globalization. This variable captures the extent to which people in the analyst's home country perceive globalization as a threat instead of an opportunity. This measure is described in more detail in Internet Appendix Section III. The results, reported in Panel B of Table XI, show that the effect of trust bias is significantly stronger when the analyst is from a country that is more prone to perceive globalization as a threat.

Table XI

Cross-Sectional Differences in the Effect of Trust Bias

This table presents regression results for analyst recommendations. The dependent variable is shown above each column. *Recommendation* is the analyst recommendation, coded from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*). *Buy recommendation* is a dummy taking the value of one if the recommendation is 5 (*Strong buy*) or 4 (*Buy*). *Controls* include *Same country*, *ln(Distance)*, *IB relationship*, *IB potential*, *Share - syndicated loans*, *Share - underwriting*, and *Share - advisory*. The sample period is 1996 to 2018. Variables are defined in the Appendix. Heteroskedasticity-consistent standard errors, double-clustered by analyst-firm country pair and month, are shown in parentheses. Significance levels: *0.1, **0.05, ***0.01.

Panel A: Broker characteristics

	Rec. (1–5)				Buy rec.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Nationalities) × Trust bias	−0.2030***				−0.0574**			
	(0.0670)				(0.0251)			
Broker HHI × Trust bias		1.0506***				0.3024***		
		(0.3076)				(0.0881)		
Top 10 × Trust bias			−0.2032**				−0.0612*	
			(0.0821)				(0.0325)	
ln(Broker size) × Trust bias				−0.1417***				−0.0403**
				(0.0441)				(0.0171)
Trust bias	1.0568***	0.2179	0.6952***	1.1436***	0.4118***	0.1726**	0.3114***	0.4371***
	(0.2433)	(0.1603)	(0.1672)	(0.2596)	(0.0977)	(0.0757)	(0.0755)	(0.1052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,035,166	1,035,166	1,035,166	1,035,166	1,035,166	1,035,166	1,035,166	1,035,166
R^2	0.565	0.565	0.565	0.565	0.547	0.547	0.547	0.547

(*Continued*)

Table XI—*Continued*

Panel B: Analyst characteristics						
	Rec. (1–5)			Buy rec.		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Time covered) × Trust bias	0.0734***			0.0320***		
	(0.0178)			(0.0059)		
ln(Experience) × Trust bias		0.1082*			0.0653***	
		(0.0551)			(0.0239)	
Anti-globalization × Trust bias			1.4488**			1.4539***
			(0.6939)			(0.3576)
Trust bias	0.1294	−0.1829	0.5116	0.0785	−0.1873	−0.0463
	(0.2112)	(0.4534)	(0.3703)	(0.0852)	(0.1879)	(0.1737)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,035,166	1,035,166	420,093	1,035,166	1,035,166	420,093
R^2	0.565	0.565	0.560	0.547	0.547	0.543

(*Continued*)

Table XI—*Continued*

Panel C: Firm characteristics										
	Rec. (1–5)					Buy rec.				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IVOL × Trust bias	0.2207				3.1123**	0.7070				1.7224***
	(1.3794)				(1.5265)	(0.5596)				(0.6270)
Mgmt guidance ×		0.1487**			0.0427		0.0473			0.0185
Trust bias		(0.0721)			(0.0779)		(0.0361)			(0.0353)
IO × Trust bias			0.9428***		0.5613			0.2568*		0.1848
			(0.3604)		(0.3643)			(0.1450)		(0.1510)
ln(Market cap) ×				0.1141***	0.1346***				0.0378***	0.0459***
Trust bias				(0.0223)	(0.0323)				(0.0088)	(0.0127)
Trust bias	0.7178***	0.5224***	0.3097*	−0.5202*	−1.0509**	0.3084***	0.2581***	0.2073***	−0.0923	−0.3077*
	(0.1921)	(0.1487)	(0.1729)	(0.2661)	(0.4288)	(0.0974)	(0.0706)	(0.0750)	(0.1173)	(0.1796)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	721,068	1,035,166	840,576	1,013,829	639,962	721,068	1,035,166	840,576	1,013,829	639,962
R^2	0.574	0.565	0.561	0.566	0.572	0.556	0.547	0.542	0.548	0.554

C. Firm Characteristics

As suggested by the analysis on eponymous firms in Section II.C, firm characteristics may influence the effect of cultural biases. In this section, I study the role of four firm characteristics suggested by Loh and Stulz (2018) as proxies for firm opacity: IVOL, existence of management guidance, institutional ownership, and size.

The results, reported in Panel C of Table XI, are somewhat mixed on opacity. When included as an interaction with trust bias alone, higher IVOL, management guidance dummy, higher institutional ownership, and larger market capitalization are all associated with a larger effect of trust bias, although the result for IVOL is not statistically significant. However, all of these characteristics are correlated with size. When including all of them jointly in the same regression specification, management guidance and institutional ownership become statistically insignificant, while IVOL and market capitalization show a statistically significant positive relationship with the effect of trust bias. The IVOL result is consistent with more opaque (and perhaps harder-to-value) firms being more affected by cultural biases. The size result appears opposite to the opacity argument. The latter result may be related to issues of salience, as discussed in Section II.C, with larger firms possibly having a stronger national identity.

VII. Additional Analysis and Robustness Checks

In the Internet Appendix, I perform a number of additional analyses and robustness checks of my main results. I discuss some of these analyses briefly below.

(i) *Analyst career concerns*. One potential concern is that my results could be affected by trust bias being correlated with analyst career concerns and hence leading to biased recommendations (e.g., Hong, Kubik, and Solomon (2000), Hong and Kubik (2003), Jackson (2005)). In Section V, I show that the results are not likely to be driven by analyst career concerns by controlling for the career concerns measures of Harford et al. (2019) and removing banks from the sample to eliminate the concern of analysts rating prospective employers (Horton, Serafeim, and Wu (2017)).

(ii) *Trust bias at different levels*. In Section VI, I report results comparing trust bias based on analyst home country with trust bias based on analyst office country, broker entity home country, or broker top-group country. I find that all of these trust bias measures exhibit a trust bias effect, but analyst level trust bias dominates trust bias based on office country or broker entity country. In the case of broker top-group home country, the magnitude of the estimated trust bias effect is roughly similar to that of the analyst home country, suggesting that the ultimate cultural identity of the broker group has a significant effect on analyst output.

(iii) *Controlling for information*. In Section X.A, I perform a recommendation analysis controlling for i) forecast errors (both absolute and directional), which capture actual forecast accuracy and hence provide an objective measure of the analyst's information quality, and ii) the extent of social connectedness between the analyst's home and office countries and the firm's country of domicile, as measured by Facebook's Social Connectedness Index (SCI) (e.g., Bailey et al. (2018)). Controlling for these proxies for information quality has virtually no impact on the estimated effect of trust bias, providing further assurance that my results are not driven by differences in information.

(iv) *Currency*. One possible concern is that differences in recommendations may relate to different risk profiles of the stocks for investors based in different currency areas. To ensure that this explanation is not driving my results, in Section X.B, I perform a regression analysis in which I focus on companies and analysts from Eurozone countries, where the currency is the same for all parties, and hence there are no currency-related differences in risk. My results continue to go through. The results are also robust to further excluding Portugal, Italy, Ireland, Greece, and Spain from the sample. These countries experienced particularly difficult recessions during the Great Recession and the European debt crisis, during which time there was some speculation that one or more of them could consider leaving the single currency zone and hence, in a broad sense, they may have been considered as facing potential currency risk. Even excluding these countries, the results remain statistically significant. These results suggest that currency risk cannot explain my results.

(v) *Language*. Another potential concern relates to the role of languages in information acquisition. Analysts with different language skills may have different abilities to follow relevant news for the firms they cover. To mitigate this concern, I perform regression analysis including only analysts from the same language family as the firm's home country. The analysis is reported in Section X.B. The positive relationship between trust bias and stock recommendations remains statistically significant and of similar economic magnitude as for the full sample. This finding mitigates the concern that my results might be driven by differences in information due to language differences.

(vi) *Legal institutions*. A related potential concern is that the analysts may differ in their understanding of the legal environment. I address this concern by performing an analysis using only those observations for which the analyst and the firm come from countries that share the same legal origin. To classify legal systems, I use the categorization of La Porta, de Silanes, and Shleifer (1998) to classify legal systems in my sample into English, French, German, and Scandinavian origin. The results are reported in Section X.B. The estimated positive relationship between trust bias and stock recommendations remains statistically significant and of similar magnitude as or the full sample. This finding suggests that differences in legal institutions do not explain my results.

(vii) *Trust bias by different demographics*. My measure of trust bias is based on a survey for a representative sample of Europeans in each country. However, the typical respondent may not be representative of the average finance professional. To address this concern, in Section X.C, I construct three alternative measures of trust bias, using three subsamples of the Eurobarometer respondents, based on factors along which financial analysts are likely to differ from the average population: income, age, and education. I find that trust bias based on respondents with above-median income, respondents aged 20 to 55, or highly educated respondents yields similar results as my main measure, suggesting that the representativeness of the trust measure is not a substantial concern.

(viii) *Recommendation age and observation frequency*. My recommendation analysis is run at a monthly frequency to account for shifts in recommendations at a relatively high frequency. In Section X.D I show that the main results continue to hold if the same analysis is run at a quarterly or yearly frequency. In my recommendations analysis, I allow recommendations to be at maximum 180 days old from their last revision date, similar to Malmendier and Shanthikumar (2014). In Section X.E, I show that this choice of maximum age does not materially affect my main results.

(ix) *Recommendation scales*. My main *Recommendation* is coded from 1 to 5, following Loh and Stulz (2011). However, one potential concern, as discussed by Kadan et al. (2009), is that changes in broker recommendation scales between five tiers and three tiers may affect results. This concern is mitigated by the fact that I also report all recommendation results for a buy recommendation dummy that is not affected by changes between three- and five-tier scales. However, to further check that this is not an issue for my results, in Section X.F, I replicate my main recommendation analysis using a three-tier recommendation scale and find that the results are similar to those based on a five-tier scale.

VIII. Conclusion

My findings suggest that cultural biases affect analysts' stock recommendations and target prices. Using a Eurobarometer-based measure of bilateral trust bias between European countries, firms based in countries that the analyst is more positively biased toward receive more positive stock recommendations and higher target prices. When the nationality of the firm is more salient, the trust bias effect is stronger. The effect of trust bias is also stronger in times of negative sentiment, notably around recessions. Broadly interpreted, this result might suggest that economic prosperity can help mitigate culture-based prejudices.

The results point to both persistent long-term biases, as captured by the trust bias variable, and more transitory short-term shifts in cultural perceptions driven by current events. During the European debt crisis, North European analysts were significantly more negative toward South European firms, but this shift in recommendations disappeared after the crisis. Similarly, during the Brexit process, there was substantial divergence of views on British firms between British and other European analysts, potentially reflecting rising economic nationalism in the United Kingdom, as suggested by some prior studies.

In additional analysis I show that the cultural bias in recommendations and target prices that I document is not driven by differences in information. Although higher trust bias is associated with lower earnings forecast errors, possibly implying an information advantage, more biased stock recommendations are worse at predicting stock returns. Importantly, this bias effect in the information content of recommendations is symmetric in both directions: more positively biased analysts provide worse buy recommendations but better sell recommendations, while more negatively biased analysts do the opposite. Finally, I find that the market recognizes the effect of cultural bias, with more biased recommendations eliciting weaker stock price reactions.

Initial submission: November 6, 2019; Accepted: January 25, 2021
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

Appendix: Variable Definitions

Variable	Definition
Recommendation	Numeric code for analyst recommendation, ranging from 1 (lowest, *Strong sell*) to 5 (highest, *Strong buy*).
Buy rec.	Dummy taking the value of one if the recommendation is *Strong buy* (5) or *Buy* (4).
Sell rec.	Dummy taking the value of one if the recommendation is *Strong sell* (1) or *Sell* (2).
Trust bias	Residual from a regression of *Trust* on country dummies for origin and recipient of trust, as well as year dummies.
Trust	Eurobarometer-based measure of bilateral trust. Proportion of people in country i that trust a lot people from country j.
Same country	Dummy taking the value of one if the firm is headquartered in the analyst's home country.
Distance	Distance in km between the firm's headquarters city and the analyst's office location.
Broker HHI	Herfindahl-Hirschman Index of nationality concentration at the broker.

(*Continued*)

Variable	Definition
Broker nationalities	Number of nationalities at the broker covering firms in sample countries.
Broker size	Number of analysts providing stock recommendations at the broker.
Top 10	Dummy taking the value of one if the broker is in the top decile of brokers based on the number of analysts covering firms in my sample countries.
Analyst N firms	Number of firms the analyst covers during the month.
Time covered	Time since the first recommendation issued by the analyst on the given firm.
Analyst experience	Time since the first recommendation issued by the analyst on any firm.
Anti-globalization	Eurobarometer-based measure of negative attitude toward globalization in the analyst's country of origin. Defined as the proportion of people in the country who consider globalization a threat to employment and companies.
N recommendations	Number of active analyst recommendations for the firm. Includes all analysts, including those otherwise excluded from the sample (non-European or no name available).
N rec. (in sample)	Number of active analyst recommendations for the firm by analysts in the sample.
Eponymous	Dummy taking the value of one if the firm's name includes its home country.
Market cap	Market capitalization of the firm, measured in USD.
Inst. ownership	The share of the firm held by institutional investors.
IVOL	Idiosyncratic volatility, calculated based on monthly residual returns over the Fama-French four-factor model, using a rolling 36-month window.
Mgmt guidance	Dummy taking the value of one if management has issued earnings guidance during the last 12 months.
IB relationship	Dummy taking the value of one if the broker group has acted as lead arranger on a syndicated loan, lead underwriter on a debt or equity issue, or financial advisor on a M&A transaction for the firm in question during the last five years.
Has IB	Dummy taking the value of one if the broker group has acted as lead arranger on a syndicated loan, lead underwriter on a debt or equity issue, or financial advisor on a M&A transaction for any firm in the sample during the last five years.
IB client	Dummy taking the value of one if the firm has done a syndicated loan, debt or equity issue, or M&A transaction with any advisor in my sample during the last five years.
IB potential	The product of *Has IB* and *IB client*, indicating whether the firm has done IB business with a broker in my sample, and that the broker group has done IB business with a firm in my sample (i.e., whether there is potential for an IB relationship, even if one may not yet exist).
Share - synd. loans	The broker group's market share as lead arranger of the firm's syndicated loans during the last five years.
Share - underwriting	The broker group's market share as lead underwriter of the firm's debt and equity issues during the last five years.
Share - underwriting	The broker group's market share as financial advisor of the firm's M&A transactions during the last five years.

REFERENCES

Alevy, Jonathan E., Michael S. Haigh, and John A. List, 2007, Information cascades: Evidence from a field experiment with financial market professionals, *Journal of Finance* 62, 151–180.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, 2018, Social connectedness: Measurement, determinants, and effects, *Journal of Economic Perspectives* 32, 259–280.
Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531–563.
Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490–517.
Bargh, John A., and Tanya L. Chartrand, 2000, The mind in the middle: A practical guide to priming and automaticity research, in Harry T. Reis and Charles M. Judd, eds.: *Handbook of Research Methods in Social and Personality Psychology* (Cambridge University Press, Cambridge, MA).
Belenzon, Sharon, Aaron K. Chatterji, and Brendan Daley, 2017, Eponymous entrepreneurs, *American Economic Review* 107, 1638–1655.
Bertrand, Marianne, and Sendhil Mullainathan, 2003, Enjoying the quiet life? Corporate governance and managerial preferences, *Journal of Political Economy* 111, 1043–1075.
Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, 2012, The organization of firms across countries, *Quarterly Journal of Economics* 127, 1663–1705.
Born, Benjamin, Gernot J. Müller, Moritz Schularick, and Petr Sedlácek, 2019, The costs of economic nationalism: Evidence from the Brexit experiment, *Economic Journal* 129, 2722–2744.
Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann, 2016, The importance of trust for investment: Evidence from venture capital, *Review of Financial Studies* 29, 2283–2318.
Bradley, Daniel J., Bradford D. Jordan, and Jay R. Ritter, 2003, The quiet period goes out with a bang, *Journal of Finance* 58, 1–36.
Bradshaw, Mark T., Alan G. Huang, and Hongping Tan, 2019, The effects of analyst-country institutions on biased research: Evidence from target prices, *Journal of Accounting Research* 57, 85–120.
Callen, Michael, Mohammad Isaqzadeh, James D. Long, and Charles Sprenger, 2014, Violence and risk preference: Experimental evidence from Afghanistan, *American Economic Review* 104, 123–148.
Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
Chava, Sudheer, and Michael R. Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085–2121.
Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, *Journal of Accounting and Economics* 27, 285–303.
Cohn, Alain, Jan Engelmann, Ernst Fehr, and Michel André Maréchal, 2015, Evidence for countercyclical risk aversion: An experiment with financial professionals, *American Economic Review* 105, 860–885.
Cohn, Alain, Ernst Fehr, and Michel André Maréchal, 2014, Business culture and dishonesty in the banking industry, *Nature* 516, 86–89.
Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.
Du, Qianqian, Frank Yu, and Xiaoyun Yu, 2017, Cultural proximity and the processing of financial information, *Journal of Financial and Quantitative Analysis* 52, 2703–2726.
Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
Ferreira, Miguel A., and Pedro Matos, 2008, The colors of investors' money: The role of institutional investors around the world, *Journal of Financial Economics* 88, 499–533.
Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, 2017, Cultural proximity and loan outcomes, *American Economic Review* 107, 457–492.
Fouka, Vasiliki, and Hans-Joachim Voth, 2016, Reprisals remembered: German-Greek conflict and car sales during the euro crisis, Working paper, Stanford University and University of Zurich.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–226.

Fuchs, Andreas, and Kai Gehring, 2017, The home bias in sovereign ratings, *Journal of the European Economic Association* 15, 1386–1423.

Golez, Benjamin, and Rasa Karapandza, 2021, Home-country media slant and equity prices, Working paper, University of Notre Dame and European Business School.

Grinblatt, Mark, and Matti Keloharju, 2001, How distance, language, and culture influence stockholdings and trades, *Journal of Finance* 56, 1053–1073.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2006, Does culture affect economic outcomes?, *Journal of Economic Perspectives* 20, 23–48.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2009, Cultural biases in economic exchange?, *Quarterly Journal of Economics* 124, 1095–1131.

Harford, Jarrad, Feng Jiang, Rong Wang, and Fei Xie, 2019, Analyst career concerns, effort allocation, and firms' information environment, *Review of Financial Studies* 32, 2179–2224.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313–351.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *RAND Journal of Economics* 31, 121–144.

Horton, Joanne, George Serafeim, and Shan Wu, 2017, Career concerns of banking analysts, *Journal of Accounting and Economics* 63, 231–252.

Jackson, Andrew R., 2005, Trade generation, reputation, and sell-side analysts, *Journal of Finance* 60, 673–717.

Jannati, Sima, Alok Kumar, Alexandra Niessen-Ruenzi, and Justin Wolfers, 2020, In-group bias in financial markets, Working paper, University of Miami.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083–1124.

Jia, Chunxin, Yaping Wang, and Wei Xiong, 2017, Market segmentation and differential reactions of local and foreign investors to analyst recommendations, *Review of Financial Studies* 30, 2972–3008.

Heon Jung, Jay, Alok Kumar, Sonya S. Lim, and Choong-Yuel Yoo, 2019, An analyst by any other surname: Surname favorability and market reaction to analyst forecasts, *Journal of Accounting and Economics* 67, 306–335.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2009, Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations, *Review of Financial Studies* 22, 4189–4217.

Kempf, Elisabeth, and Margarita Tsoutsoura, 2021, Partisan professionals: Evidence from credit rating analysts, *Journal of Finance* 76, 2805–2856.

Kumar, Alok, Alexandra Niessen-Ruenzi, and Oliver G. Spalt, 2015, What's in a name? Mutual fund flows when managers have foreign-sounding names, *Review of Financial Studies* 28, 2281–2321.

La Porta, Rafael, Florencio Lopez de Silanes, and Andrei Shleifer, 1998, Law and finance, *Journal of Political Economy* 106, 1113–1155.

Lai, Sandy, and Melvyn Teo, 2008, Home-biased analysts in emerging markets, *Journal of Financial and Quantitative Analysis* 43, 685–716.

Landesmann, Michael A., 2015, The new North–South divide in Europe: Can the European convergence model be resuscitated? In Jan Fagerberg, Staffan Laestadius, and Ben R. Martin, eds.: *The Triple Challenge for Europe: Economic Development, Climate Change, and Governance* (Oxford Scholarship Online).

Lane, Philip R., 2012, The European sovereign debt crisis, *Journal of Economic Perspectives* 26, 49–68.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

List, John A., Michael S. Haigh, and Marc Nerlove, 2005, A simple test of expected utility theory using professional traders, *Proceedings of the National Academy of Sciences of the United States of America* 102, 945–948.

Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei, and Hong Yan, 2007, Conflicts of interest in sell-side research and the moderating role of institutional investors, *Journal of Financial Economics* 85, 420–456.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, Jr, 2006, Competing for securities underwriting mandates: Banking relationships and analyst recommendations, *Journal of Finance* 61, 301–340.

Loh, Roger K., and René M. Stulz, 2011, When are analyst recommendation changes influential?, *Review of Financial Studies* 24, 593–627.

Loh, Roger K., and René M. Stulz, 2018, Is sell-side research more valuable in bad times?, *Journal of Finance* 73, 959–1013.

Malloy, Christopher J., 2005, The geography of equity analysis, *Journal of Finance* 60, 719–755.

Malmendier, Ulrike, and Devin Shanthikumar, 2014, Do security analysts speak in two tongues?, *Review of Financial Studies* 27, 1287–1322.

Merkley, Kenneth, Roni Michaely, and Joseph Pacelli, 2017, Does the scope of the sell-side analyst industry matter? An examination of bias, accuracy, and information content of analyst reports, *Journal of Finance* 72, 1285–1334.

Merkley, Kenneth, Roni Michaely, and Joseph Pacelli, 2020, Cultural diversity on Wall Street: Evidence from consensus earnings forecasts, *Journal of Accounting and Economics* 70, 1–24.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Morse, Adair, and Sophie Shive, 2011, Patriotism in your portfolio, *Journal of Financial Markets* 14, 411–440.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705–739.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.