Disclosure Standards and the Sensitivity of Returns to Mood

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Abstract: We provide evidence that higher-quality disclosure standards are associated with stock returns that are less sensitive to noise driven by investors' moods. We identify return-mood sensitivity (RMS) based on the association between index returns and urban cloudiness, a source of short-term variation in mood. Based on a stylized model, we predict and find evidence consistent with higher-quality disclosure standards reducing RMS by tilting susceptible investors' trades toward information and by facilitating sophisticated investors' arbitrage. Our findings suggest that disclosure standards play an important role in enhancing price efficiency by reducing noise in returns, particularly noise related to investors' short-term moods. (*JEL* G14, G15, M48)

Introduction

This study investigates the relation between disclosure standards and the sensitivity of stock returns to investors' short-term moods. We posit that noise from investors' short-term moods enters returns through the trades of "susceptible" investors. These investors are generally rational and use any available public or private information. However, they are prone to misinterpreting signals; for example, they underweight informative signals or overweight noninformative signals like personal mood. If susceptible investors have access to informative corporate disclosures, underpinned by high-quality disclosure standards, we expect that they will be more likely to base investment decisions on such disclosures and less likely to rely on misattributed feelings, like mood (Schwarz and Clore 2007). We provide evidence on whether high-quality disclosure standards are negatively associated with return-mood sensitivity (RMS). We also examine how the effect of disclosure standards on RMS predictably varies based on proxies for relative levels of sophisticated and susceptible investors.

We interpret RMS as reflecting noise in returns because short-term moods are unlikely to convey fundamental information. There is a significant identification problem in isolating the effect of disclosure standards on stock return noise. Several existing proxies for noise are plausibly contaminated by capturing information in addition to noninformative factors like sentiment (e.g., abnormal price volume and variance; closed-end fund discounts). Our identification strategy involves using urban cloudiness as a source of short-term, mood-based return noise. Prior studies have found a significant negative relation between urban cloud cover and index returns, argued by the studies to reflect the influence of short-term uninformative moods on returns due to an attribution bias (e.g., Hirshleifer and Shumway 2003). Although urban cloudiness is a salient noninformative signal that investors should disregard, cloudiness has a negative influence on mood. Susceptible investors may view their mood as an informative signal relevant to trading decisions. With higher-quality disclosures, susceptible traders will have more precise information about firm fundamentals, lessening the influence of mood on subjective valuations and trading decisions (Hirshleifer and Shumway 2003; Clore, Schwarz, and Conway 1994; Forgas 1995). High-quality disclosures also provide information that facilitates arbitrage, further reducing noise driven by shocks to short-term mood.

We investigate the relation between disclosure standards and return-mood sensitivity using a panel of 46 countries from 1995 through 2009. Using daily data, we estimate RMS for each country-year as the association between market returns and deseasonalized cloudiness in the city that hosts a country's stock exchange. We standardize this association to correct for differences in estimation precision across country-years. We find that the average degree of RMS varies greatly across countries, suggesting that there are country-level factors, such as disclosure standards, that mitigate or exacerbate the effect of mood on market returns.

We create country-year measures of disclosure standard quality using the World Economic Forum's Global Competitiveness Report and the disclosure index from the Center for International Financial Analysis and Research (CIFAR). We isolate the impact of disclosure standards by controlling for economic development and the fraction of Internet users, both of which proxy for the level of susceptible-investor participation (and hence independently suggest higher levels of return-mood sensitivity). We also control for each country's climate, legal tradition, and level of investor protection and estimate specifications using country and year fixed effects. We find consistent evidence that higher-quality disclosure standards are significantly associated with less return-mood sensitivity. These findings are consistent with higher-quality disclosures reducing the noise in returns induced by susceptible investor trading.

We provide additional insight into the relation between disclosure standards and RMS by examining cross-sectional variation in this relation. First, if disclosure standards affect the likelihood that susceptible investors trade based on information, rather than on cloudiness-induced mood, then countries with a higher level of susceptible investor participation should experience larger reductions in return noise from higher-quality disclosure standards. We allow the coefficient on disclosure standard quality to vary based on three proxies for susceptible investor participation: GDP, Internet usage, and the fraction of the market that is closely held. We find that the coefficient on disclosure quality is only significant in high-participation countries. However, it is not consistently significantly larger than the coefficient in low-participant countries, likely due to low power. Thus, there is weak evidence that disclosure standards have a greater effect on return noise when susceptible investor participation is greater.

Second, higher-quality disclosure standards can facilitate sophisticated investors' information gathering and processing, increasing the likelihood that they can arbitrage away mood-based noise in stock prices. For this mechanism to affect return-mood sensitivity, there must be a sufficient mix of both sophisticated and susceptible investors in the country, that is, enough susceptible investor participation to impound noise and enough sophisticated investor participation to effect arbitrage. To identify countries with a sufficient amount of both sophisticated and susceptible investors, we partition the sample sequentially based on the average fraction of the market that is closely held and then on the fraction held by mutual funds. Consistent with the arbitrage-facilitation mechanism, we find that high-quality disclosure standards have the biggest effect in reducing RMS in countries with relatively high mutual fund holdings and a low fraction of closely held shares.

A concern is that the results are driven by a correlated omitted variable related to foreign investor participation. Foreign investors are immune to the mood effects of local cloudiness and tend to invest in countries with better disclosure standards (Leuz, Lins, and Warnock 2009). These effects would cause a negative relation between disclosure standards and RMS independent of the susceptible investor effect. We address this concern by including two additional controls for foreign investor participation: an indicator for nonresident equity purchase restrictions (*NREPR*) and the fraction of the local market held by foreign mutual funds. Our findings are robust to the inclusion of these controls.

To ensure that our results are not an artifact of the international setting, we also test our hypotheses in a sample of U.S. firms. We estimate RMS and disclosure quality at the firm-year level and find that high-quality disclosure is negatively associated with RMS in firms with high individual (i.e., susceptible) investor participation. The negative association is most pronounced when sophisticated investor participation is also high. We also find that firms with higher recent idiosyncratic volatility, that is, those firms likely to be more susceptible to sentiment (Baker and Wurgler 2006), tend to have higher RMS and larger negative associations between disclosure quality and RMS. Thus, the U.S. evidence is consistent with our international results.

We contribute to the literature by providing empirical evidence on the relation between information provided by public disclosures and return noise in capital markets. Previous studies find that high-quality disclosure standards are associated with higher liquidity, lower transaction costs, and lower costs of capital (e.g., Bloomfield and Wilks 2000; Daske et al. 2008; Francis, Khurana, and Pereira 2005; Hail, Leuz, and Wysocki 2010; Healy and Palepu 2001; Leuz and Verrecchia 2000). While these are important facets of market efficiency, return noise remains relatively unexamined despite its theoretical prominence (e.g., Admati 1985; Black 1986; Kyle

1989; Verrecchia 1982) and its significant implications for price informativeness, capital allocation, systematic risk, and asset bubbles (De Long et al. 1989, 1990; Dichev, Huang, and Zhou 2010; Kyle 1985; Zhang 2010). Our study provides evidence on the role of disclosure standards in attenuating noise in returns that can impair market efficiency.

We also contribute to the debate over the efficacy of regulation in improving price efficiency. We focus on return noise resulting from mood-susceptible traders, who are exactly the types of traders that securities regulators like the SEC implicitly target when enacting regulation. For example, disclosure standards are frequently motivated as a policy tool to protect relatively uninformed retail investors. Langevoort (2009, 1043) notes "The SEC's habitual use of the disclosure remedy for purposes of retail investor protection, for instance, rests on the unexamined (and often dubious) premise that investors who fall sufficiently short of the rational actor model to require paternalistic intervention will necessarily process the information rationally once it is delivered to them."

To the extent that higher-quality disclosures help susceptible investors calibrate their sensitivities to various signals, and tilt away such traders from trades based on noninformative signals, our study suggests that disclosure regulation can effectively reduce noise in prices.

1. Hypothesis Development

1.1 A theory of susceptible traders

We hypothesize that there is a potentially large class of investors who use information but who are susceptible to influence from noninformative signals. These traders are largely absent from the microstructure literature that features noise traders, although they are frequently implied by the exposition surrounding the model. For example, Lee (2001) presents a model in which he defines noise traders as investors trading on information that ex post is either value irrelevant or wrong. Rather than suggesting that market participants are either purely noise traders or purely rational, we posit that market participants fall on a spectrum of susceptibility, with noise (sophisticated) traders falling on the more (less) susceptible end of the spectrum.[1] For comparison to prior models that include only noise and purely rational traders, we treat susceptible traders as a separate group.

To build hypotheses on how mood might affect stock prices, we adopt the "feelings-as-information" perspective (Schwarz and Clore 2007). The primary idea is that feelings can inform decisions in the same way that traditional sources of information can. When evaluating a decision, such as whether to buy a stock, a susceptible investor might ask herself, "How do I feel about stocks?" Such a question may elicit integral feelings (i.e., feelings related to the decision target) like "they seem too risky for me" or "I feel good about the risk." In this paper, we exploit the effects of incidental feelings (i.e., feelings unrelated to the decision target), such as mood caused by the weather. The feelings-as-information perspective implies that "mood-congruent judgments arise because people misread incidental moods as part of their apparent affective reaction to the target" (Schwarz and Clore 2007, 389). This perspective also supports the idea that the influence of mood on decisions is weaker when the decision maker has more decision-relevant information or is more familiar with the decision context (e.g., Ottati and Isbell 1996).

We incorporate these features into a simple asset-pricing model to show how disclosure standards and investor characteristics can influence the sensitivity of returns to mood (see the Appendix for full model). The model includes susceptible and rational traders in a competitive market with a single risky asset. A public disclosure provides information about the risky asset

[1] Heuristic traders (e.g., in Fischer and Verrecchia 1999) can be considered a special case of susceptible traders, for which a noninformative factor like overconfidence affects the impact of information on trading strategies.

that both types of traders use. Susceptible investors receive an additional signal—their mood—which they incorrectly interpret as informative about the risky asset's value. The setup is similar in spirit to that of De Long et al. (1990)—whose setup features noise traders but no informational signal—and to Daniel, Hirshleifer, and Subrahmanyam (2001), whose setup features overconfident traders who overweight an informative signal. In contrast, the susceptible traders in our model put positive decision weight on a noninformative signal, while underweighting the informative disclosure. The model generates the following observations:

1. Returns are positively associated with susceptible investors' mood.
2. For a risk-free asset, mood plays no role.
3. Higher-quality disclosures reduce the mood-return association in (1).
4. The impact of higher-quality disclosures on the mood-return association in (3) is stronger when there are more investors who are susceptible to mood.
5. As long as there are a sufficient number of susceptible investors in the market, the effect described in (4) is stronger when there are more nonsusceptible investors.

The extant literature has focused on market reactions to salient noninformative signals by examining the trading behavior of individual investors, who are assumed to be relatively unsophisticated and whose trades lose money on average (Barber and Odean 2000; Barber, Odean, and Zhu 2009; Hirshleifer et al. 2008). While the susceptible investor label plausibly applies well to individual investors, susceptible investors can encompass any class of investor that is influenced by mood. For example, Goetzmann et al. (2015) finds that weather-induced moods can influence institutional investors' trading decisions, suggesting that institutional investors display susceptibility as well.[2] However, we expect sophisticated investors to be generally less susceptible to noninformative signals than are individual investors.

Prior research on stock market reactions to salient noninformative signals includes that by Greene and Smart (1999), who provide evidence that the appearance of a stock in the "dartboard" section of the *Wall Street Journal* is associated with higher liquidity and lower adverse selection components of bid-ask spreads. Edmans, Garcia, and Norli (2007) find that international soccer results are significantly associated with subsequent abnormal stock returns. Although these studies focus on potential noise traders, they generally do not consider susceptibility or address the degree to which noise trades are priced or arbitraged away. Our measure of return-mood sensitivity allows us to directly examine the degree of return noise due to susceptible investors and how this noise is affected by disclosure standards.

1.2 Investor mood as a noninformative signal

Consistent with the "feelings-as-information" paradigm, current mood can influence evaluative judgments about specific targets (Schwarz and Clore 2003), including financial assets (Hirshleifer 2001). Recent work shows that measures of investor sentiment or mood are associated with stock market outcomes. Baker and Wurgler (2006, 1655) find an association between future returns and an index for the annual level of investor sentiment in the United States "based on the common variation in six underlying proxies for sentiment: the closed-end

[2] Goetzmann et al. (2015) find evidence that cloudiness in the prior 14 days is associated with more institutional investor selling relative to buying and with survey-elicited perceptions of both overpricing and mispricing. However, they find that one-day cloudiness, which is the measure we use, is not associated with institutional investor mispricing. Goetzmann and Zhu (2005) find an absence of evidence for relations between individual investors' trade imbalances and cloudiness in the city in which the investors reside, concluding that there is no evidence for cloudiness influencing retail investor trading activity. The retail-institutional investor dichotomy is not central to our theory; although we do use mutual fund holdings as a proxy for less mood-susceptible investors. Our empirical results on the effects of disclosure standards on RMS could be driven in part by mutual funds making better use of disclosures, rather than mutual funds being less susceptible to mood-influenced affect. In other words, their investment-mood sensitivity could decrease faster when the decision context becomes less uncertain.

fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium." Lemmon and Portniaguina (2006) find that sentiment is associated with returns of small, neglected firms using the University of Michigan's Index of Consumer Sentiment and the Conference Board's Index of Consumer Confidence. Each of these measures of sentiment is plausibly confounded by capturing information in addition to noninformative sentiment (Sibley, Xing, and Zhang 2013). Moreover, these measures likely reflect longer-term trends in investor sentiment, which affect the economy and stock market by influencing fundamentals and informed trade (e.g., Mishkin 1978), whereas short-term mood is more likely to influence only noise in returns.

In this study, we focus on a salient, noninformative signal—cloudiness—that is likely to be both short-term in nature and unaffected by disclosure standards. Weather affects individuals' moods, and moods potentially influence cognition and behavior related to stock trading decisions through misattribution of weather-related feelings to feelings about the economy (Isen 2001) or changes in risk attitudes (Bassi, Colacito, and Fulghieri 2013). Hirshleifer and Shumway (2003) show that cloudiness has a negative relationship with stock market returns, arguing that this relationship can be attributed to cognitive limitations and biases of traders, as it is not easily reconcilable with rational price discovery.[3] Furthermore, short-term mood shocks based on weather are likely to be systematic and hence not diversifiable. Thus, we use the association between cloudiness and stock returns as a basis for measuring return-mood sensitivity.

[3] Linnainmaa and Rosu (2009) provide an explanation for why rational agents' trading behavior may be influenced by weather through variation in the opportunity cost of trading. Whether or not the association arises due to mood effects, it reflects a degree of nonfundamental information being impounded into prices and returns.

1.3 Disclosure quality and information

While there is little direct evidence that high-quality disclosure tilts trades toward information and away from sentiment, prior work finds that disclosure quality is positively associated with measures related to liquidity, transaction costs, and the cost of capital (e.g., Bhattacharya, Daouk, and Welker 2003; Bloomfield and Wilks 2000; Diamond and Verrecchia 1991; Healy and Palepu 2001; Kim and Verrecchia 1994; Lambert, Leuz, and Verrecchia 2007). At the country level, prior research suggests that high-quality disclosure standards reduce information asymmetry across investors and improve comparability across firms (see Hail, Leuz, and Wysocki 2010 for a review of this literature).[4] Furthermore, mandatory disclosures like earnings announcements provide not only firm-specific information but also macroeconomic information through information transfers and spillovers (Foster 1981; Savor and Wilson 2013).

The psychological literature suggests that the influence of mood is stronger in less-certain decision contexts (e.g., Forgas 1995). Hirshleifer (2001) notes that "people are likely to be more prone to bias in valuing securities for which information is sparse," (1537) and that "Mood states tend to affect relatively abstract judgments more than specific ones about which people have concrete information." (1551). By providing susceptible and sophisticated investors with a greater amount of information, high-quality disclosure standards should reduce the sensitivity of returns to mood, consistent with observation 3 from the model, leading to Hypothesis 1.

H1: Disclosure standard quality is negatively associated with return-mood sensitivity.

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[4] Morck, Yeung, and Yu (2000) and Jin and Myers (2006) also examine links between information availability and properties of stock returns. However, they focus on synchronicity and crash risk, while we focus on the sensitivity of returns to short-term mood. Our finding that disclosure is associated with RMS is consistent with the interpretation in Morck, Yeung, and Yu (2000) that informed arbitrageurs reduce noise by more when they take larger positions, either due to greater ability to retain their profits (property rights protections) or due to greater availability of information (disclosure standards). Our finding does not speak as directly to Jin and Myers (2006), who argue that transparency increases firm-specific return variation by impairing insiders' ability to divert cash flows. The theory underlying our analysis implies that better disclosures would allow more firm-specific information to be capitalized into price by rational outsiders, while reducing noise capitalized by outsiders susceptible to mood-based trading.

We provide additional insight into the relation between disclosure standards and return-mood sensitivity by examining whether cross-sectional variation in this relation is driven by better-informed susceptible investors, better-informed sophisticated investors, or both. Prior work suggests that individual investors use firms' disclosures to guide their trades. Bushee, Matsumoto, and Miller (2004) find a significant increase in small trades during conference calls when individual investors are provided access to calls after Regulation FD. Brüggemann et al. (2009) show that firm-level IFRS adoption is associated with individual investment on the German Open Market. Lawrence (2013) finds that individual investors tend to invest in firms with more readable, transparent, and concise financial statements. Taylor (2010) finds increases in individual investor trading around earnings announcements, though the trades on average result in losses.[5] Together, these studies suggest that individual investors, on average, use firms' disclosures but are relatively unsophisticated (i.e., they are susceptible investors). If disclosure standards reduce return-mood sensitivity by improving susceptible investors' information set, then settings with a higher level of susceptible investor participation should experience larger reductions in return-mood sensitivity due to higher-quality disclosure standards. This argument, consistent with observation 4, leads to Hypotheses 2.

H2: The effect of disclosure standard quality on return-mood sensitivity is stronger when there is more susceptible investor participation.

Disclosure standards can also facilitate sophisticated investors' information gathering and processing, increasing the likelihood that they can arbitrage away any return-mood sensitivity due to susceptible investor trading. Prior studies find that sophisticated investors use information

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[5] These investor losses are higher around more informative earnings announcements, suggesting that the investors in Taylor's (2010) sample pay attention to, but misinterpret, the information in earnings announcements.

from public disclosures to mitigate mispricing (e.g., Bartov, Radhakrishnan, and Krinsky 2000; Collins, Gong, and Hribar 2003) or to improve forecasts (Ashbaugh and Pincus 2001). However, for this arbitrage mechanism to affect return-mood sensitivity, there must be a sufficient mix of both sophisticated and susceptible investors in the country. Given a sufficiently large pool of unsophisticated investors, disclosure standards should have a stronger effect when there are relatively more sophisticated investors who can use the information for arbitrage. These arguments, consistent with observation 5, lead to Hypotheses 3.

H3: Given a sufficient level of susceptible investor participation, the effect of disclosure standard quality on sentiment-based return noise is stronger when there are more sophisticated investors.

2. Empirical Methodology

2.1 Return-mood sensitivity

We construct our measure of return-mood sensitivity based on the sensitivity of local market stock returns to deseasonalized cloudiness. For 26 cities and the period 1982 through 1997, Hirshleifer and Shumway (2003) examine the relation between daily stock market index returns and cloud cover in the city in which the stock market is located . In our first stage, we extend their sample to 46 countries between 1995 and 2009. As in Hirshleifer and Shumway (2003), we estimate regressions of daily local index returns (*RET*) on "sky coverage" (*SKC*), which is a measure of deseasonalized cloudiness. We also control for the world portfolio index return (*WR)*, which reflects macroeconomic information. The model is

$$RET_{i,d} = \alpha_i + \beta_{SKC,i} * SKC_{i,d} + \beta_{WR,i} * WR_{i,d} + \varepsilon_{i,d} , \qquad (1)$$

where *i* denotes country-year and *d* denotes day. $\beta_{SKC,i}$ in Equation (1) is an estimate of the sensitivity of price to *SKC*, a noninformative signal.

We estimate this regression separately for each country-year. We define return-mood sensitivity (*RMS*) as the negative *t*-statistic of the coefficient on $SKC_{i,d}$, which is the coefficient divided by its standard error. The *t*-statistic is a measure of the strength of the relationship deflated by the noise in the estimation of the relationship, both of which vary across country-years. Regression (1) also can be interpreted as the first stage of a two-stage least-squares regression, where $SKC_{i,d}$ is used as an instrument for $RET_{i,d}$. In this interpretation, $SKC_{i,d}$ is a stronger instrument when *RMS* is higher.

We collect index returns data from Datastream and cloud coverage data from the International Surface Weather Observations dataset.[6] Sky coverage is calculated using the average cloud cover between 6 a.m. and 4 p.m. for cities in which the country's primary stock exchange resides. Cloud cover is measured on a scale of zero to eight, representing the number of eighths of the sky that are covered by clouds.[7] Since cloudiness is seasonal, the average daily cloud cover measure is deseasonalized by subtracting the week's average cloudiness over the entire time series from the daily cloudiness measure, consistent with Hirshleifer and Shumway's (2003) methodology. This adjusted sky coverage measure ($SKC_{i,\mathrm{d}}$) controls for geographic and seasonal factors that may influence returns independent of cloudiness (e.g., Keim 1983).

2.2 Disclosure standards

We measure disclosure standard quality using the World Economic Forum's Global Competitiveness Report (GCR) and the CIFAR index. The GCR is published annually and, since 1999, includes data on either the quality of disclosure or the accounting standards based on the

[6] These data are provided by the U.S. National Oceanic and Atmospheric Administration.

[7] For some observations, the range is different but is scaled to the [0,8] interval. The city must have at least three observations during this ten-hour period for the city-day cloudiness observation to be nonblank.

World Economic Forum's extensive Executive Opinion Survey.[8] In 1999 and 2000, the GCR reported average country-level responses to "The level of financial disclosure required is extensive and detailed. (1=strongly disagree; 7=strongly agree)." These measures are used in Gelos and Wei (2005) and Jin and Myers (2006) to measure country-level opacity related to disclosure standards. From 2002 through 2009, the GCR reported average country-level responses to "In your country, how would you assess financial auditing and reporting standards regarding company financial performance? (1 = extremely weak; 7 = extremely strong)."[9] For disclosure quality prior to 1998, we use values for the 1995 CIFAR, as reported in Bushman, Piotroski, and Smith (2004). It is constructed as the sum of indicators for specific disclosure items in companies' annual reports, averaged at the country level, based on annual report disclosures from the early 1990s. Values of all *GCR* and *CIFAR* variables are standardized so that each year is mean zero and unit variance. This allows for better comparison across years, especially when comparing the CIFAR score to the GCR-based scores.[10]

We use these standardized proxies to construct a country-year-level disclosure score (*DISC*). We use the individual GCR score as *DISC* for 1999, 2000, and 2002–2009. There is no GCR score for 2001; we define *DISC* as mean of the 2000 and 2002 *GCR* scores. We use the 1999 GCR score for the 1998 value of *DISC*. For 1995–1997, we use the CIFAR score. The country-level standardized proxies are all positively and significantly correlated ($p < 0.001$), with

[8] For example, the 2009 Executive Opinion Survey had 12,614 respondents in 133 countries.

[9] The wording of the strength of accounting and auditing question in the GCR changes slightly from year to year but always asks the respondent to rate the country's auditing and reporting standards on a 1 to 7 scale.

[10] An additional benefit of the survey-based GCR measures is that they also capture the enforcement of disclosure standards because survey respondents are likely to consider enforcement when evaluating the quality of the standards. Hope (2003) constructs a country-level measure of accounting enforcement based on audit spending, insider trading, judicial efficiency, rule of law, and antidirector rights. In an unreported country-level regression using values reported by Hope (2003) for 22 countries, we find that the judicial efficiency, rule of law, and antidirector rights scales help explain over 90% of the variation in Hope's enforcement measure ($R^2 = 0.909$). Since these variables are included separately as controls or captured by country-level fixed-effects, we do not utilize Hope's enforcement measure.

correlations ranging from 0.57 (between the 1995 CIFAR score and the 2009 GCR score) to 0.98 (between the 2007 and 2008 GCR scores). In subsequent regressions, standard errors are clustered at the country level, and country-level fixed effects are employed to mitigate concerns related to the persistence of within-country measures like *DISC*.

2.3 Control variables

We include a number of control variables to account for the fact that disclosure standards do not exist independently of a country's broader market environment. We limit the main set of control variables to those that are plausibly exogenous with respect to disclosure standards; for example, we omit controls such as average returns, cost of capital, and liquidity.

High-quality disclosure standards could be associated with high return-mood sensitivity because susceptible traders provide an incentive for regulators to impose tougher standards. Recent research on the relation between financial institutions and market development suggests that stock market development can encourage participation, which creates political support for shareholder protections like disclosure standards (e.g., Bebchuk and Neeman 2010; Pagano and Volpin 2006). We use three main controls for susceptible investor participation: country fixed effects, wealth, and Internet use. Country fixed effects will absorb variation in *RMS* caused by average participation at the country-level over the sample period. Wealth is a necessary condition for market participation; thus, wealthier societies are prone to have a greater number of small, relatively uninformed noise traders (Guiso, Sapienza, and Zingales 2008a).[11] We control for country wealth using the natural logarithm of per capita gross domestic product (*GDP*), measured at purchasing power parity based on data reported by Euromonitor International.

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[11] However, wealth might also increase the benefits to information acquisition. Fund managers are often rewarded based on a percentage of assets or returns. Thus, managers of larger funds, made possible by wealthier societies, have a greater incentive to engage in informed arbitrage.

Finally, countries with a high fraction of Internet users will likely have relatively more trades by susceptible investors, since Internet access provides a low-cost trading method. We control for the fraction of the population that uses the Internet (*INTERNET*), calculated as the number of Internet users divided by the population, both reported by Euromonitor International.

We also include controls related to the institutional environment. These measures are generally expected to favor uninformed investors and thus be positively related to return noise, although they could also favor information-based arbitrageurs. These factors also may be related to disclosure standards and market efficiency within a comprehensive legal framework (e.g., Li 2010; Pincus, Rajgopal, and Venkatachalam 2007). We include an indicator variable, *COMMON*, that is equal to one if the country's legal origin is common law and zero otherwise (as classified in La Porta et al. 1998). We also include a country-year index of country risk constructed from three indices from the International Country Risk Guide, each scaled to the [0,1] interval with high values indicating low country risk. Our composite index, *ICRG*, is the average of (1) Investment Profile, which represents risk related to contract viability, expropriation, profit repatriation, and payment delays, (2) Rule of Law, which represents the impartiality and strength of the legal system and the legal observance by the general population of the country, and (3) Corruption, which measures corruption in the political system that is relevant to the business environment, like the prevalence of bribery or extortion related to business transactions.

We include an indicator variable for tropical climates because the affective impact of cloudiness can vary by climate. Morrissey et al. (1996) reports that excessive heat and humidity are the two most influential environmental factors affecting negative mood in the tropics, suggesting that abnormal cloudiness has a positive effect on mood in tropical countries by reducing excess heat. In addition, Easterly and Levine (2003) find that tropical countries have lower rates of development than do temperate countries due to differences in institutional structures, which could be correlated with disclosure practices. We include an indicator variable, *TROPICAL*, that is equal to one for countries with latitudes between the Tropic of Cancer and Tropic of Capricorn (i.e., absolute latitude less than 23.4 degrees), and zero otherwise.[12]

Finally, in our additional analyses, we include a number of variables to measure investor composition and participation in each country. We proxy for investor participation using the fraction of the market that is closely held (*CH*), as reported by Dahlquist et al. (2003). We proxy for the concentration of sophisticated investors using the average fraction of the market capitalization held by mutual funds (*MF*) based on data from Thomson Financial S12, SP7, and Datastream. We compute the same measure for foreign mutual funds (*Foreign MF*) to proxy for the presence of foreign investors that may be less susceptible to the weather in the local market.[13] As an additional proxy for foreign investor participation, we include an indicator variable, *NREPR*, equal to one for countries with nonresident equity purchase restrictions and zero otherwise, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions.

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[12] The latitudes are reported in La Porta et al. (1999), who uses the latitude measure from the CIA World Factbook, representing "rounded latitude and longitude figures for the centroid or center point of a country."
[13] Foreign investors still may be susceptible to weather-induced mood if they rely on the analysis and decisions of local analysts. Bae, Stulz, and Tan (2008) find that 44.8% of analysts provide at least one forecast of a firm as a local expatriate analyst (i.e., an analyst local to the firm but employed by a foreign research firm).

3. Sample Description and Results

3.1 Sample and descriptive statistics

We chose our initial list of countries based on those used by La Porta et al. (1998). Starting from their list of 49 countries, we collected market index data from Datastream. We chose to start the sample in 1995 because *INTERNET* tends to be zero for years before 1995 due to technological constraints. We eliminated Sri Lanka, Uruguay, and Zimbabwe due to a lack of available data. The final sample consists of 46 countries and between 350 and 644 country-year observations, depending on the variables included in the tests.

Table 1 provides descriptive statistics for the key variables for each of the countries. The first two columns show the range of years with data availability and the number of years with nonmissing *RMS* and *DISC* data. Missing country-years are generally due to a lack of weather data necessary to calculate the measure of return-mood sensitivity. The table shows that 34 (12) countries exhibit a positive (negative) average value for *RMS*, representing a negative (positive) relation between local market returns and sky coverage (*SKC*). Thus, while the overall sample mean value of *RMS* is positive, suggesting weather-induced moods negatively impact market returns, there is a great deal of cross-sectional variation.

Table 2 presents descriptive statistics for the main regression variables. The mean and median values of *RMS* are positive and significantly different from zero ($p < 0.01$), consistent with the overall negative association between sky coverage and returns in Hirshleifer and Shumway (2003). However, the magnitude of mean RMS is small, largely due to the small sample sizes in the country-year regressions (n ≈ 250).[14] *RMS* has a standard deviation of 0.993, with a range of -3.308 to +3.905, suggesting considerable variation in *RMS* across country-years.

The mean and median of *DISC* are close to zero by construction, but different from zero because of slight differences in the sample for the earlier years. Taking exponents of the reported *GDP* value, the geometric average real per capita wealth is $14,443, and real GDP ranges from $1,150 to $53,316. The mean fraction of Internet users (*INTERNET*) is 29.5%, but ranges from zero to 92.3%. About 34% of the country-years are for common-law countries (*COMMON*) and about 33% are for tropical (*TROPICAL*) countries. The average percentage of the market is that is closely held is 45.3%, with 12% (9%) of the market held by mutual funds (foreign mutual funds) on average. About 12% of the country-years had nonresident equity purchase restrictions (*NREPR*).

3.2 Correlations

Table 3 reports univariate correlations among the main variables. *RMS* is positively and significantly correlated with *GDP*, *INTERNET*, and *ICRG*, suggesting that wealth, technology, and investor protections are associated with unsophisticated investor participation and greater return-mood sensitivity. Although wealthier, more-developed economies tend to have many favorable market characteristics that could facilitate arbitrage by informed traders, such as high market capitalization, low costs of capital, and low illiquidity (e.g., Hail and Leuz 2006; La Porta et al. 1998), the correlation evidence suggests that at least a portion of the additional mood-based return noise is not corrected by informed trades.

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[14] For example, the mean *RMS* for Austria based on 15 country-year regressions is 0.324. If we estimate *RMS* for Austria using a regression with all 15 years pooled (n = 3,817), *RMS* is 1.672. Thus, as a *t*-statistic, the value of *RMS* is highly sensitive to sample size. But the sample sizes are almost identical across country-year regressions, and the variation in *RMS* is sufficient to provide enough power to find a relation between disclosure standards and *RMS*.

Perhaps surprisingly, *DISC* and *RMS* are not significantly correlated. However, note that *DISC* and *GDP* are highly positively correlated (r = 0.609). In general, more advanced economies, represented by higher *GDP*, have both more *RMS* and higher-quality disclosure standards. This positive relation between *DISC* and *GDP* provides a suppressor effect that masks the hypothesized negative relation between *DISC* and *RMS*. The regression results in the next section corroborate this suppressor effect. In fact, *GDP* is significantly correlated with all other variables, indicating that controlling for *GDP* in the later regressions is necessary to detect underlying relations between the other variables and *RMS*, independent of wealth.

3.3 Tests of Hypothesis 1

Table 4 reports the results of the regressions related to Hypothesis 1. Each regression is a least-squares estimate of the following equation:

$$RMS_i = \alpha + \beta * DISC_i + \Gamma' X_i + \varepsilon_i, \quad (2)$$

where *X* is a vector of controls and *i* denotes country-year. Standard errors are clustered at the country level to adjust for within-country correlation across years.

Model (1) of Table 4 includes only year fixed effects and *TROPICAL* as controls. The coefficient on *DISC* is negative but insignificantly different from zero, consistent with the insignificant univariate correlation between *RMS* and *DISC* shown in Table 3. Model (2) includes *GDP* as an additional control and the coefficient on *DISC* is negative and significant, ($\beta = -0.112,\ p < 0.05$), supporting Hypothesis 1, in that disclosure standard quality is negatively associated with *RMS*. The coefficient on *GDP* in model (2) is positive and significant ($\Gamma_{GDP} = 0.141,$, $p < 0.001$), consistent with wealth increasing susceptible investor participation and hence *RMS*. Model (3) includes *INTERNET* as an alternative proxy for investor participation and provides results similar to model (2). A comparison of models (2) and (3) to model (1) suggests that disclosure standards are positively related to susceptible investor participation, which in turn is positively related to *RMS*, biasing the coefficient on *DISC* upward in model (1). Controlling for participation mitigates this correlated omitted variable issue, allowing the negative relation between disclosure standards and *RMS* to become apparent.

Models (4), (5), and (6) include varying controls, but generally confirm the inferences from models (2) and (3). Model (4) includes both *GDP* and *INTERNET* as controls. The coefficient on *DISC* remains negative and significant $(\beta = -0.126,\ p < 0.001)$, but the coefficients on *GDP* and *INTERNET*, while still positive, are no longer statistically significant. This insignificance likely results from multicollinearity, as the correlation between *GDP* and *INTERNET* is 0.7. Model (5) drops *INTERNET* but adds *COMMON* and *ICRG*, which capture the legal and institutional environment. The inferences from model (5) are similar to those from model (2), although the coefficient on *COMMON* is positive and significant $(\Gamma_{CommonLaw} = 0.163,$ $p < 0.10)$, suggesting that countries with common law backgrounds tend to have higher levels of *RMS*, on average, than countries with code law backgrounds, which is likely related to a susceptible investor participation effect.

Model (6) includes country-level fixed effects and drops the country-level indicators *COMMON* and *TROPICAL*. Explanatory power increases dramatically, as the R^2 in model (6) is 0.124, while the highest R^2 from the other models is 0.071. This suggests that much of the variation in *RMS* can be explained by country-level features. The coefficient on *DISC* in model (6) remains negative and significant $(\beta = -0.213,\ p = 0.029)$, consistent with models (2) through (5). Model (6) provides strong evidence in support of Hypothesis 1 as it is the least susceptible to a correlated omitted variable problem.

To shed some light on economic effects, we interpret the coefficient magnitudes from the perspective of a researcher trying to infer whether mood is associated with returns, using Bayesian updating and starting with diffuse priors. From Table 2, the mean of RMS is 0.132, which suggests that the average probability of inferring sentiment-based noise is approximately 55.2%, based on the *t*-distribution for 644 observations. The coefficient estimate from Model (6) of Table 4 suggests that increasing *DISC* from one-standard-deviation below the mean to one-standard-deviation above is associated with a 35% reduction in the probability of inferring RMS.[15] Thus, the coefficient magnitudes suggest that the results reflect a meaningful economic effect.

3.4 Tests of Hypotheses 2 and 3

Next, we provide evidence related to Hypothesis 2 (disclosure standards reduce *RMS* more when investor participation is broader) and Hypothesis 3 (conditional on broad participation, disclosure standards reduce *RMS* more when there are more sophisticated investors) using the following regression model:

$$RMS_i = \alpha + \sum \beta_{Split} * DISC_i * Split + \Gamma' X_i + \varepsilon_i, \tag{3}$$

which is similar to Equation (2), except that the coefficient on *DISC* varies across different partitions of the data, based on *Split*.

To test Hypothesis 2, we allow the coefficient on disclosure (*DISC*) to vary based on susceptible investor participation. We split countries into high and low participation groups based on *GDP*. Countries with above-median (below-median) *GDP* in 2002, the middle of our

[15] The mean and standard deviation of *DISC* are 0 and 1, respectively. The coefficient on *DISC* in Model (6) of Table 4 is 0.212. From the mean value of *RMS*, a *DISC* value of -1 (1) is associated with an expected *RMS* of -0.080 (0.344), which corresponds to a 46.8% (63.4%) probability of inferring mood-based returns based on a t-distribution for 644 observations. The 35% reduction is calculated as $-0.35 = (46.8 - 63.4) / 46.8$.

sample, are considered high (low) investor participation countries. We also partition countries using a similar median split based on *INTERNET*. As an additional proxy for investor participation, we use the fraction of the market that is closely held (*CH*). Countries with a high (low) fraction of stocks closely held should have relatively low (high) investor participation.

Models (1) and (2) of Table 5 present evidence supporting Hypothesis 2. In model (1), the coefficient on *DISC* is negative and significant for countries with high participation, proxied for by high *GDP* ($\beta_{HighGDP} = -0.325,\ \text{p} < 0.01$). The coefficient on *DISC* is negative, but not significantly different from zero, for low participation countries ($\beta_{LowGDP} = -0.095,\ \text{p} > 0.10$). This result suggests that the effects of disclosure are strongest where there is broad investor participation; however, it is important to note that the two *DISC* coefficients in model (1) are not significantly different from each other (p = 0.17). Results are similar when *INTERNET* is used as the partition variable. The coefficient on *DISC* for the high participation countries is significantly negative ($\beta_{HighInternet} = -0.331,\ \text{p} < 0.01$), while the coefficient on *DISC* for the low participation countries is negative but insignificant ($\beta_{LowInternet} = -0.088,\ \text{p} > 0.10$). As with *GDP* as the partition variable, the *DISC**Low *INTERNET* and *DISC**High *INTERNET* coefficients are only marginally significantly different from each other (p = 0.14). In model (3), the coefficient on *DISC* varies depending on the value of *CH*, which we expect to be inversely related to investor participation. Consistent with the results for *GDP* and *INTERNET*, the coefficient on *DISC* for the high participation countries is significantly negative, ($\beta_{LowCH} = -0.345,\ \text{p} < 0.01$), while the coefficient on *DISC* for the low participation countries is negative but insignificant ($\beta_{HighCH} = -0.077, \text{p} > 0.10$). These coefficients are nearly significantly different from each other (p = 0.12). Overall models (1), (2), and (3) of Table 5 present evidence that the disclosure effect is concentrated in high participation countries, but we do not have sufficient power to find a significant difference between high and low participation countries using a two-tailed test.

To test Hypothesis 3, we split the sample hierarchically in model (5) of Table 5. We first use the same median split as in model (3), based on the fraction of the market that is closely held. Next, within each *CH* group, we split the countries into those with above- and below-median mutual fund holdings (*MF*). This approach yields four groups. Within each *CH* group, countries with higher *MF* values tend to have lower *CH* values. Across *CH* groups, countries with higher *CH* tend to have lower *MF*.

MF is a proxy for the concentration of sophisticated investors who should be able to use disclosures to facilitate arbitrage and reduce *RMS*. We also split on *CH* because Hypothesis 3 suggests disclosures will help sophisticated investors reduce *RMS* specifically when a sufficient amount of susceptible traders are already in the market. If most of the market is held by insiders, we would not expect disclosures to help sophisticated investors arbitrage away mood-based noise. Also, insiders would tend not to find disclosures informative because they plausibly already possess the information.

Column (5) of Table 5 presents an estimated regression in which the coefficient on *DISC* varies for each of the four country groups. The coefficient on *DISC* is negative and significant only when *CH* is low but *MF* is high ($\beta_{LowCH,HiMF} = -0.531$, $p < 0.01$). The coefficient on *DISC* when *CH* and *MF* are both low is negative but insignificant ($\beta_{LowCH,LowMF} = -0.203$, $p > 0.10$). For the remaining country groups with high *CH*, the coefficients are insignificantly different from zero.[16] Column (4) of Table 5 presents a model in which the coefficient on *DISC* is

[16] An F-test rejects the null that the *DISC* coefficients are equal across all groups ($F = 2.30$, $p = 0.09$).

partitioned based on only the average fraction of mutual fund holdings in each country. The coefficients on *DISC* are negative but significantly different from zero only for countries high average mutual fund holdings ($\beta_{HighMF} = -0.216$, $p < 0.10$), consistent with the logic in Hypothesis 3 that disclosure standards reduce *RMS* by facilitating arbitrage primarily when there is a sufficient amount of noise in the market, which is generated by relatively unsophisticated investor participation. Overall, these coefficients suggest that disclosure standards facilitate the largest reduction in *RMS* when there are low insider holdings and high mutual fund holdings, consistent with Hypothesis 3. Together with the evidence for Hypothesis 2, the results imply that disclosure standards help reduce *RMS*, both by facilitating arbitrage and by tilting unsophisticated investors' trades away from *RMS*.

3.5 Additional analyses

3.5.1 Controlling for foreign investor participation. A possible alternative explanation for the significant association between *DISC* and *RMS* is that high-quality disclosure standards attract foreign investors, who are less susceptible to weather-induced mood in the local market. Leuz, Lins, and Warnock (2009) and Aggarwal, Klapper, and Wysocki (2005) find that foreign investors prefer to invest in firms with better disclosure quality. Thus, if better disclosure standards significantly increase the participation of investors located outside of the area, this would provide a mechanism to reduce the amount of *RMS*. Finding a relation between *DISC* and *RMS* after explicitly controlling for foreign investor participation would help dismiss this alternative explanation.

In Table 6, panel A, we control for the participation of foreign investors with two proxies. In columns (1) and (2), we include an indicator variable (*NREPR*) for any nonresident equity purchase restrictions in the county-year. The coefficient on *NREPR* is positive and significant, indicating that *RMS* is higher when foreign investors are limited from participating in the market, consistent with foreign investors reducing *RMS* by not being susceptible to local weather. The coefficient on *DISC* remains negative and significant at the 0.05 level, both in the main specification and in the specification in which *DISC* is interacted with *Low CH* to capture high investor-participation country-years. In Columns (3) and (4), we include the percent of the market held by foreign mutual funds (*Foreign MF*). These data are only available after 2001, reducing the sample size to 350. The coefficient on *Foreign MF* is not significant. The coefficient on *DISC* remains negative and significant at the 0.10 level in both specifications.[17] This evidence is consistent with disclosure standards having an impact on *RMS* through effects on local investors, and not solely through the attraction of greater foreign investors.

3.5.2 Country-level regressions. Because standard error clustering may not effectively control for repeated country-level observations, we also estimate regressions at the country-level using the mean values of the variables for each country (as reported in Table 1). Table 6, panel B, presents the results of these regressions. In Columns (1) and (2), we include the variables used in Table 4—*DISC*, *GDP*, *COMMON*, and *TROPICAL*—but drop *INTERNET* and *ICRG* due to high multicollinearity.[18] In Column (1), we use all 46 countries in Table 1 for which we have nonmissing *DISC* and *RMS* measures and the coefficient on *DISC* is negative and significant at the 0.10 level. In Column (2), we estimate the same regression using only the 40 countries that also have nonmissing data for closely held and mutual fund ownership. The coefficient on *DISC* is negative and significant at the 0.05 level. The higher significance level on *DISC* is consistent

[17] We estimated the regressions in Columns (3) and (4) using the same sample size, but dropping the *Foreign MF* variable, and the coefficient on *DISC* was still significant at the 0.10 level. This suggests that the lower power from the smaller sample, not the control for foreign investor participation, influences the significance of *DISC*.

[18] The Variance Inflation Factors for *INTERNET* and for *ICRG* both exceed ten, which is the benchmark for harmful mulicollinearity given in Kennedy (1998). The VIFs for the other variables do not exceed three.

with the result in Table 5 that disclosure quality has a large impact on *RMS* in countries with high *GDP*; the six countries dropped in Column (2) due to missing holdings data are all in the lowest quartile of *GDP*.

In the remaining columns of panel B, we include the variables used in our additional analyses: closely held (*CH*), mutual fund ownership (*MF*), nonresident equity purchase restrictions (*NREPR*), and foreign mutual fund ownership (*Foreign MF*). In each case, the coefficient on *DISC* remains negative and significant at the 0.05 level. Thus, our finding that disclosure quality affects *RMS* holds when we use country-level means.

The coefficients on *GDP* are consistently positive and significant at the 0.05 level in Table 6, panel B, consistent with the coefficient estimates from regressions in Table 4 when estimated without country fixed effects. Thus, *RMS* is positively associated with macroeconomic development in the cross-section, implying that, as an economy develops, its markets become more sensitive to behavioral biases. This result is consistent with evidence on the association between macroeconomic development and stock market participation (e.g., Guiso, Sapienza, and Zingales 2008b). In more-developed economies, more-susceptible investors own and trade shares and thereby generate greater return-mood sensitivity. Overall, however, results from regressions with country fixed effects (e.g., Table 4, model (6)) suggest that the associations between *GDP* and *RMS* might be attributable to other sources of cross-sectional variation.[19]

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[19] The consistently negative relation between *TROPICS* and *RMS* raises the possibility that the sign of the association between *DISC* and *RMS* differs between tropical and nontropical countries. Table IA.4 (IA.5) in the Internet Appendix presents replications of the regressions reported in Table 4 (Table 6, panel B), but with all coefficients estimated separately for tropical and nontropical countries. The negative significant associations between *DISC* and *RMS* are present only for the nontropical countries, consistent with (1) cloudier days having a weaker or ambiguous effect on mood in tropical countries, (2) tropical countries being less developed and having lower stock market participation (see also results in Section 4.4), and (3) greater noise in the estimation of *RMS* for tropical countries (i.e., standard error on β_{SKC} estimated from Equation (1) is three times higher, on average, for tropical-country regressions compared to non-tropical-country regressions).

3.5.3 Robustness. The negative association between *DISC* and *RMS* is robust to several alternative specifications (all tabled in an Internet Appendix). First, negative values of *RMS*, which would indicate positive effects of cloudiness on price, could reflect noisy measures of situations in which cloudiness has no effect on prices (i.e., *RMS* equals zero). We defined the variable *RMSpos* to equal *RMS* when *RMS* is positive and zero otherwise. Table IA.1, model (1) shows that our inference from our main regression (model (6) in Table 4) is the same when we use *RMSpos* as the dependent variable. Second, the *DISC* proxy is based on measures from both CIFAR and the GCR, and differences between these two sources may influence our results. Table IA.1, model (2), shows that the inference from the main regression is the same if it is estimated only during years in which the GCR measures are available (1998–2009). Third, since the effects of *GDP* on *DISC* and *RMS* may be nonlinear, we include indicators for *GDP* quintile in our main regression. The coefficient on *DISC* remains negative and significant at the 0.05 level (Table IA.1, model (3)). Fourth, last year's returns may encourage susceptible investor participation, enhance investor confidence, and/or influence the responses to the World Economic Forums' opinion surveys. We add a control for stock market returns in the previous year to our main regression and the coefficient on *DISC* remains negative and significant at the 0.05 level (Table IA.1, model (4)).

Fifth, a levels regression may inadequately control for unobservable variables, so we estimate a regression of the change in *RMS* on the changes in *DISC* and *INTERNET*, with fixed effects for country and year and country-level clustering. Table IA.2 shows that the coefficient on the change in *DISC* is negative and significant ($p < 0.10$). When the change in *GDP* is included as an additional control, the coefficient on the change in *DISC* remains negative, but the *p*-value rises to 0.13, suggesting a weak result in changes, likely due to the low level of dispersion in the annual changes variables. Sixth, *RMS* is based on *t*-statistics from estimations of Equation (1), so variation in market-level return volatility could cause variation in *RMS*. If *DISC* is also associated with return volatility (e.g., if investors in more volatile markets demand higher *DISC*), then our results could be driven by underlying variation in return volatility. We estimate the regressions in Table 4 with an additional control for return volatility. The results in Table IA.3 confirm that our main results are not driven by underlying variation in return volatility.

Overall, these additional tests provide support for our main finding that disclosure standards are negatively related to return-mood sensitivity.

3.5.4 Evidence from a U.S. sample. We also test our hypotheses using firm-level data in the United States to ensure that our results are not an artifact of the international setting. Within the United States, we estimate the following regression for each firm-calendar year *j* using daily observations:

$$RET_{j,d} = \alpha_j + \beta_{SKC,j} * SKC_{j,d} + \varepsilon_{j,d}, \tag{4}$$

where *RMS* is the negative *t*-statistic for the $\beta_{SKC,j}$ coefficient, and *SKC* is deseasonalized cloud cover in New York City. Our measure of disclosure standards is *ITEMS*, the number of nonmissing items (in thousands) reported in the Compustat database entry related to the firm's annual report from the prior fiscal year (i.e., in the fiscal year that ended in the prior calendar year) minus the average number of items (in thousands) for all firms with available data in the firm's industry (Fama-French 48-industry classification) in the same year. The adjustment for industry-year means corrects for variation in reporting standards and necessary disclosures across industries. We focus on the number of Compustat items to be consistent with our CIFAR-based measure of disclosure standards at the country level, while retaining a large sample of firm-year observations.[20]

We proxy for the breadth of ownership and unsophisticated investor participation using the number of shareholders (#*SHAREHOLDERS*) reported in the 10-K in the prior year. Grullon, Kanatas, and Weston (2004) use #*SHAREHOLDERS* as a proxy for individual investor ownership. In each year, we split firms into above-median and below-median groups based on the number of shareholders. Within each number-of-shareholders group, we split firms again in each year based on the institutional ownership ratio (IOR), calculated with quarterly 13-F data from Thomson Reuters. Institutional ownership is a common proxy for sophisticated investor presence. We calculate IOR as the fraction of institutional ownership in each quarter and average over quarters in a calendar year to form an annualized measure.

To test the hypotheses, we regress *RMS* on *ITEMS*. We also allow the coefficient on *ITEMS* to be different across groups of firms based on #*SHAREHOLDERS* and *IOR*. We control for several observable features that are expected to be associated with disclosure standards and also may be predictive of noise in returns, including log market value, squared log market value, log number of shareholders, market-to-book ratio, log firm age, share price, and fixed effects for industry, year, and stock exchange. Market value is the average daily market value based on closing price and shares outstanding from CRSP. The market-to-book ratio is based on Compustat-reported values and is measured in the prior year. Firm age is defined as the current year minus the first year the firm appeared in CRSP. Share price is the price at the beginning of

[20] Recall that the CIFAR scores, which are used extensively in research on disclosure standards, are based on counts of nonmissing data in annual reports. Alternative measures for disclosure quality at the firm level are either restricted in sample (e.g., AIMR scores), require assumptions about earnings and accruals (e.g., abnormal accruals), or would be based on returns (e.g., value relevance), which is problematic because RMS would mechanically affect estimates of returns-based disclosure quality proxies.

the calendar year. Industry is defined by the 48 Fama-French industries, based on Compustat-reported SIC codes.

Table 7 presents results from the regressions. Standard errors are clustered by firm to account for correlated errors within-firm. In model (1), the coefficient on *ITEMS* is negative but is not significantly different from zero, which fails to provide support for Hypothesis 1. However, this result could be attributable to weak effects of disclosure on *RMS* in firms with low participation, as we found in the international sample. Model (2) allows the coefficient on *ITEMS* to be different for firms with low and high participation, as captured by the within-year median split based on the number of shareholders. In model (2), the coefficient on *ITEMS* is negative and significantly different from zero $(\beta_{High\#} = -0.635,$ $p < 0.01$) for firms with high participation, but is not significantly different from zero for firms with low participation. The coefficients on *ITEMS* for high and low *#SHAREHOLDERS* are also significantly different from each other at the 5% level. This result supports Hypothesis 2, which states that disclosure has a negative effect on *RMS* when there is broad investor participation. Model (3) allows the coefficient on *ITEMS* to vary by participation and sophisticated ownership, *IOR*. The coefficient on *ITEMS* is negative and significant $(\beta_{High\#,HighIOR} = -0.752,$ $p < 0.01$) for the high participation, high *IOR* group, as predicted by Hypothesis 3. The coefficient on *ITEMS* for the high participation, low *IOR* group is negative, but not significantly different from zero. Overall, results from the within-U.S. sample corroborate the results from the international sample that disclosure can help reduce noise, particularly for firms with broad investor participation and high sophisticated ownership.

In Table 8, we examine whether the relation between *ITEMS* and *RMS* within the U.S. sample is stronger for firms more susceptible to mood-based mispricing. Baker and Wurgler (2007) use high stock return volatility as a measure of stocks that have "strong speculative appeal" and greater limits to arbitrage, both of which make the stock more susceptible to mood-influenced mispricing. We measure stock return volatility in the prior year using both daily raw returns (*Ret. Vol.*) and daily idiosyncratic returns based on a market-model (*Idio. Ret. Vol.*). Consistent with Baker and Wurgler (2007), Table 8 shows that stocks with higher return volatility in the prior year have significantly higher *RMS* in the current year. In Columns (1) and (3), we show that the coefficient on *ITEMS* remains negative and significant when controls for return volatility are included in the model. In Columns (2) and (4), we find that the coefficient on the interaction between *ITEMS* and return volatility is negative and significant at the 0.10 level. This finding is consistent with a stronger effect of disclosure quality on return-mood sensitivity in firms that are more susceptible to mood-based mispricing.

As an additional robustness check, we examine the relation between *DISC* and *RMS* for firm-years in which we ex ante expect returns to be particularly sensitive to mood. To identify these firm-years, we use advertising expense, as Grullon, Kanatas, and Weston (2004) find that advertising expense is associated with investor breadth and Lou (2014) finds that advertising expense is associated with retail investors' purchasing. In Table IA.6 in the Internet Appendix, we present three regressions involving advertising expense. In these regressions, we find that (1) advertising expense is positively associated with *RMS* once we control for size, (2) *ITEMS* remains negatively associated with *RMS* ($p < 0.001$), and (3) the negative association between *ITEMS* and *RMS* is concentrated (i.e., significant) only for firm-years with high advertising expense (i.e., above the annual median). Since this is a setting with greater expected susceptible investor participation and hence a setting in which return-mood sensitivity should be high, these results provide further support for our conclusion that susceptible investor participation and disclosure quality jointly influence return-mood sensitivity.

4. Conclusions

We examine how disclosure standard quality relates to return-mood sensitivity through the participation of susceptible investors. We develop a measure of return-mood sensitivity (*RMS*) using the previously documented relationship between urban cloudiness and market returns. We find that higher-quality disclosure standards are significantly negatively associated with *RMS* after controlling for various country-level factors, including investor participation and investor protections. We find evidence that disclosure standards have a greater effect on *RMS* in countries with a higher level of investor participation, as proxied by GDP and Internet usage. Additionally, using mutual fund and insider ownership data, we find evidence that disclosure standards have the greatest effect on *RMS* when there are low levels of insider ownership and a mix of noninsider sophisticated and susceptible investors in the market. Together, these results suggest that high-quality disclosure standards discourage susceptible investors' mood-based trading and facilitate sophisticated investors' noise-eliminating arbitrage.

This study is one of the first to focus on how disclosure standards relate to stock return noise, particularly short-term mood-based noise in daily market-level returns. While we find consistent evidence of a negative effect of disclosure standard quality on mood-based noise in our sample, these results are limited to only one of many types of noise and cannot necessarily be extended to broader statements about market efficiency. Despite these limitations, the evidence suggests an interesting mitigating effect of disclosure standards on return noise that is relevant to future work on the consequences of disclosure regulation and market efficiency.

Appendix. Susceptible Investor Model

There is a continuum of investors of two types. Susceptible investors are influenced by nonfundamental mood, *M*, while rational investors are not. A mass *r* is rational and a mass *s* is susceptible, so the mass of all investors is $s + r$. All investors are assumed to have constant absolute risk aversion (CARA) utility with risk-aversion parameter *p*.

There is a single risky asset with random per-share fundamental value *V*, which is normally distributed with mean *U* and precision (inverse-variance) *v*. There is also a single riskless asset with a constant value of one. There is a fixed supply of one share of the risky asset per capita (i.e., a mass of $r + s$ shares) and no restrictions on the supply of the riskless asset. The value of the risky asset, *V*, is realized at the end of the game, at which time investors consume.

There is a public disclosure, *D*, that captures the fundamental value of the risky asset with noise. Specifically, *D* is defined as $V + Q$, with $Q \sim N(0, 1/q)$. Disclosure quality is captured by the precision of the disclosure, *q*. The limiting case of $q \rightarrow 0$ implies a completely uninformative disclosure, while $q \rightarrow \infty$ implies a perfectly informative disclosure.

The random mood of the susceptible investors is *M*, which can have any well-defined nontrivial stochastic distribution. *M* is independent of *V* and *D* (i.e., they are stochastically orthogonal). Susceptible investors misattribute their mood as informative about firm value, meaning that they treat their mood as an additional signal about *V*.[21] Susceptible investors treat their mood *M* as if it is a noisy signal about fundamental value with precision *m*. Strictly speaking, the precision *m* determines the susceptible investors' decision weight on mood and should not be interpreted directly as the variance of the mood signal.

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[21] See Schwarz and Clore (2007, 2003) for a review of the psychological literature on individuals' use of mood as an informative signal.

There are three periods. First, investors trade to take initial positions in the risky and risk-free assets. All investors begin with wealth W and choose demand for shares $x_{1,i}$ to maximize expected utility

$$E\left[-\exp\left\{-p\left(x_{1,i}V+W-x_{1,i}P_1\right)\right\}\right],$$

where P_t is the price of the risky asset in period t and $W - x_{1,i}P_1$ is the amount of wealth held in the risk-free asset in period 1. After taking initial positions, V, D, and M are realized. V is private, but D and M are observed by all investors prior to the second round of trading. In the second round of trading, each investor trades to a holding of $x_{2,i}$ in the risky asset and the market-clearing price is P_2. Disagreement between susceptible and rational investors driven by mood causes positive volume in the second round of trading. Finally, in the third period, the terminal value, V, is revealed.

The model is similar in spirit to De Long et al. (1990), who feature rational traders and noise traders. The noise traders are characterized by having an exogenous, randomly biased belief about the risky asset's expected price. In the model here, the susceptible traders have a biased belief about the risky asset's fundamental value. Different from De Long et al. (1990), this model features an additional signal about fundamentals that provides value-relevant information and is used by both rational and susceptible traders.

Let $w_{t,i}$ be the wealth of investor i maintained in the risk-free asset in period t. In period 1 investors choose demand $x_{1,i}$ as a solution to

$$\begin{aligned}\hat{x}_{1,i} &= \arg\max_{x_{1,i}} E\left[-\exp\left\{-p\left(x_{1,i}V + w_{1,i}\right)\right\}\right] \text{ s.t. } W = x_{1,i}P_1 + w_{1,i} \\ &= \arg\max_{x_{1,i}} E\left[x_{1,i}\left(V - P_1\right) + W\right] - \frac{1}{2}pVar\left[x_{1,i}\left(V - P_1\right) + W\right] \\ &= \arg\max_{x_{1,i}} x_{1,i}\left(E\left[V\right] - P_1\right) - \frac{1}{2}x_{1,i}^2 pVar\left[V\right] \\ &= \arg\max_{x_{1,i}} x_{1,i}\left(U - P_1\right) - \frac{x_{1,i}^2 p}{2v}\end{aligned}.$$

Since all investors are identical in the first round, we can drop the i subscript on $x_{1,i}$ and solve for investor demand as given by the first-order condition, which implies $\hat{x}_1 = v\left(U - P_1\right)/p$. P_1 is set to equate supply and demand such that $\hat{x}_1 = 1$. This market-clearing condition implies $P_1 = U - p/v$, which has a natural interpretation as the expected value of the asset net of the risk premium. We assume $U > p/v$ so prices are positive.

The realizations of D and M cause the investors to update their beliefs about fundamental value. The updated conditional distributions are

$$V_r \mid D \sim N\left(\frac{Uv + Dq}{v+q}, \frac{1}{v+q}\right), \text{ and}$$
$$V_s \mid D, M \sim N\left(\frac{Uv + Dq + Mm}{v+q+m}, \frac{1}{v+q+m}\right)$$

for the rational and susceptible investors, respectively. Investors choose demands $x_{2,i}$ again to maximize expected utility. Going into the second period, the budget constraint is $x_{1,i}P_2 + w_1 = x_{2,i}P_2 + w_2$. The rational investors choose demand $x_{2,r}$ as

$$\begin{aligned}\hat{x}_{2,r} &= \arg\max_{x_{2,r}} E\left[-\exp\left\{-p\left(x_{2,r}V + w_{2,r}\right)\right\}\right] \text{ s.t. } x_1P_2 + w_1 = x_{2,r}P_2 + w_{2,r} \\ &= \arg\max_{x_{2,r}} x_{2,r}\left(\frac{Uv + Dq}{v+q} - P_2\right) - \frac{px_{2,r}^2}{2\left(v+q\right)}\end{aligned},$$

which, by the first-order condition, implies rational trader demand in period 2 of

$$\hat{x}_{2,r} = \frac{v+q}{p}\left(\frac{Uv+Dq}{v+q} - P_2\right).$$

For the susceptible investors, a similar analysis implies

$$\hat{x}_{2,s} = \frac{v+q+m}{p}\left(\frac{Uv+Dq+Mm}{v+q+m} - P_2\right).$$

The market-clearing condition is $r + s = rx_{2,r} + sx_{2,s}$, which implies

$$P_2 = \frac{MG+Uv+qD-p}{G+v+q},$$

where $G = ms/(r-s)$. The risky asset's return from period 1 to period 2 is $R = P_2/P_1 - 1$.

Substituting, returns can be written as

$$R = \frac{Uv+qD-p}{(G+q+v)(U-p/v)} - 1 + \frac{MG}{(G+q+v)(U-p/v)},$$

which can be interpreted as returns based on fundamentals (the first two terms) plus mood-based noise in returns (the third term). Let β be the sensitivity of returns to mood, that is,

$$\beta = \frac{dR}{dM} = \frac{1}{P_1}\frac{dP_2}{dM} = \frac{vG}{(Uv-p)(G+q+v)} > 0.$$

Observation 1: *Returns are positively associated with susceptible investors' mood.*

Note that $\lim_{v\to\infty}\beta = 0$, implying no sensitivity of returns to mood for a risk-free asset.

Similarly, as disclosure quality becomes high, mood also plays no role, since $\lim_{q\to\infty}\beta = 0$.

Observation 2: *For a risk-free asset, mood plays no role.*

Let γ be the sensitivity of β to disclosure quality, that is,

$$\gamma = \frac{d\beta}{dq} = -\frac{vG}{(Uv-p)(G+q+v)^2} < 0.$$

Observation 3: *Higher-quality disclosures reduce the mood-return association noted in Observation 1.*

We have the following limits of γ as the mass of susceptible investors goes to zero or becomes dominant in the market, respectively, with

$$\lim_{s\to 0}\gamma = 0, \text{ and}$$
$$\lim_{s\to\infty}\gamma = \lim_{G\to m}\gamma = -\frac{mv}{(Uv-p)(m+q+v)^2}.$$

These limits imply that the negative effect of disclosure quality on the sensitivity of returns to mood (i.e., γ) is stronger with high susceptible investor participation than with low or no participation. An increase in the mass of susceptible investors has the following effect given by the derivative of γ with respect to s:

$$\frac{d\gamma}{ds} = \frac{d\gamma}{dG}\frac{dG}{ds} = \frac{d}{dG}\left(-\frac{vG}{(Uv-p)(G+q+v)^2}\right)\frac{rm}{(r+s)^2}$$
$$= -\frac{(q-G+v)vrm}{(Uv-p)(G+q+v)^3(r+s)^2} < 0.$$

Negative $d\gamma/ds$ means that more susceptible investors implies a stronger impact of changes in disclosure standards on the sensitivity of returns to mood.

Observation 4: *The impact of higher-quality disclosures on the mood-return association in Observation 3 is stronger when there are more investors who are susceptible to mood.*

Additionally, we can show that $d\gamma/dr > 0$, since more rational traders reduce the susceptibility of price to mood.

Next, we turn to $\frac{d^2\gamma}{dsdr}$ to examine how a change in the mass of rational investors, *r*, impacts the effects of changes in the mass of susceptible investors, *s*, on γ:

$$\frac{d^2\gamma}{drds}=\frac{d}{dr}\left(\frac{d\gamma}{dG}\frac{dG}{ds}\right)=\frac{d^2\gamma}{dG}\frac{dG}{dr}\frac{dG}{ds}+\frac{d\gamma}{dG}\frac{d^2G}{drds}$$

$$=\frac{d}{dG}\left(-\frac{(q-G+v)v}{(Uv-p)(G+q+v)^3}\right)\left(-\frac{sm}{(r+s)^2}\right)\left(\frac{rm}{(r+s)^2}\right)+\left(-\frac{(q-G+v)v}{(Uv-p)(G+q+v)^3}\right)\left(\frac{(s-r)m}{(r+s)^3}\right)$$

$$=-\frac{2(2q+2v-G)v}{(Uv-p)(G+q+v)^4}\left(\frac{srm^2}{(r+s)^4}\right)-\frac{(q+v-G)}{(Uv-p)(G+q+v)^3}\left(\frac{(s-r)m}{(r+s)^3}\right). \qquad \text{(A.1)}$$

For $s > r$ or s not too much smaller than r, we have $\frac{d^2\gamma}{dsdr}<0$. For s << r, the second term in (A.1) will be positive and can overwhelm the first.

Observation 5: *As long as there are a sufficient number of susceptible investors in the market, the effect described in Observation 4 is stronger when there are more nonsusceptible, rational investors.*

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Table 1
Sample description

Country	Years	N	RMS	DISC	GDP	INTERNET	ICRG	COMM.	TROP.	CH	MF	Foreign MF	NREPR
Argentina	1995–2008	14	0.298	-1.109	9.185	0.109	0.523	0	0	0.527	0.015	0.006	0.214
Australia	1995–2009	15	0.176	1.135	10.302	0.475	0.869	1	0	0.249	0.109	0.071	0.933
Austria	1995–2009	15	0.324	0.502	10.325	0.401	0.885	0	0	0.549	0.136	0.117	0.000
Belgium	1995–2009	15	0.325	0.430	10.265	0.386	0.778	0	0	0.471	0.116	0.097	0.000
Brazil	1995–2009	15	-0.457	-0.777	8.987	0.141	0.462	0	1	0.671	0.208	0.088	0.800
Canada	1995–2009	15	0.142	0.938	10.326	0.509	0.914	1	0	0.488	0.050	0.015	0.000
Chile	1995–2009	15	-0.221	0.482	9.261	0.201	0.777	0	0	0.649	0.019	0.011	0.400
Colombia	1995–2009	15	0.517	-1.135	8.817	0.115	0.421	0	1		0.003	0.003	1.000
Denmark	1995–2009	15	0.498	0.859	10.306	0.536	0.926	0	0	0.251	0.125	0.107	0.000
Ecuador	1998–2009	12	-0.184	-2.282	8.714	0.070	0.464	0	1				0.000
Egypt	1998–2001, 2003–2009	11	0.210	-0.933	8.418	0.092	0.529	0	0	0.406			0.000
Finland	1995–2009	15	-0.547	1.289	10.179	0.529	0.958	0	0	0.235	0.209	0.193	0.000
France	1995–2009	15	0.082	0.793	10.217	0.313	0.775	0	0	0.380	0.181	0.142	0.200
Germany	1995–2009	15	0.258	0.527	10.236	0.431	0.851	0	0	0.447	0.198	0.116	0.000
Greece	1995–2009	15	-0.045	-0.682	9.975	0.177	0.695	0	0	0.752	0.129	0.086	0.000
Hong Kong	1995–2009	15	0.142	0.495	10.317	0.396	0.769	1	1	0.427	0.062	0.049	0.000
India	1995–2009	15	0.134	-0.293	7.527	0.017	0.570	1	1	0.403	0.133	0.089	1.000
Indonesia	1998–2009	12	-0.134	-1.791	8.004	0.035	0.422	0	1	0.690	0.095	0.095	0.000
Ireland	1995–2009	15	0.223	0.701	10.336	0.307	0.815	1	0	0.471	0.273	0.299	0.000
Israel	1995–2009	15	0.246	0.450	9.968	0.228	0.709	1	0	0.580	0.043	0.043	0.000
Italy	1995–2009	15	0.460	-0.778	10.148	0.248	0.708	0	0	0.375	0.128	0.103	0.000
Japan	1996–2009	14	0.222	-0.177	10.229	0.454	0.750	0	0	0.384	0.221	0.147	0.000
Jordan	1998–2009	12	0.256	-0.233	8.263	0.111	0.667	0	0	0.656			0.000
Kenya	2003–2009	7	-0.248	-0.896	7.266	0.062	0.455	1	1				0.000
Korea	1995–2009	15	0.313	-0.559	9.832	0.480	0.670	0	0	0.392	0.153	0.153	0.200
Malaysia	1995–2009	15	0.031	0.316	9.215	0.294	0.611	1	1	0.522	0.085	0.062	0.000

Table 1 (Continued)
Sample description

Country	Years	N	RMS	DISC	GDP	INTERNET	ICRG	COMM.	TROP.	CH	MF	Foreign MF	NREPR
Mexico	1996–2009	14	-0.448	-0.574	9.333	0.121	0.537	0	1	0.282	0.061	0.044	0.000
Netherlands	1995–2009	15	0.565	0.747	10.355	0.541	0.932	0	0	0.237	0.194	0.178	0.000
New Zealand	1996–2009	14	0.111	1.104	10.007	0.520	0.913	1	0	0.775	0.084	0.084	0.000
Nigeria	2001–2009	9	0.030	-1.420	7.440	0.069	0.322	1	1				0.000
Norway	1995–2009	15	0.381	0.753	10.646	0.543	0.893	0	0	0.411	0.145	0.123	0.000
Pakistan	1995–1997, 2003–2009	10	-0.002	-0.549	7.567	0.057	0.455	1	0	0.774	0.010	0.010	0.100
Peru	1998–2009	12	-0.146	-0.776	8.719	0.146	0.542	0	1	0.688	0.011	0.011	0.000
Philippines	1995–2001, 2004–2009	13	-0.362	-0.676	7.864	0.035	0.539	0	1	0.511	0.067	0.066	0.462
Portugal	1997–2009	13	0.007	-0.249	9.882	0.272	0.828	0	0	0.350	0.085	0.071	0.000
Singapore	1995–2009	15	0.150	0.772	10.508	0.415	0.844	1	1	0.571	0.110	0.092	0.000
South Africa	1995–2009	15	0.039	0.826	8.913	0.056	0.577	1	0	0.529	0.130	0.079	0.000
Spain	1995–2009	15	0.716	0.021	10.080	0.284	0.786	0	0	0.421	0.151	0.125	0.000
Sweden	1995–2009	15	0.094	1.212	10.260	0.587	0.918	0	0	0.210	0.221	0.104	0.133
Switzerland	1995–2009	15	0.122	0.625	10.404	0.506	0.838	0	0	0.257	0.185	0.152	0.000
Taiwan	1995–2009	15	0.372	-0.430	10.020	0.392	0.701	0	1	0.223	0.145	0.116	
Thailand	1995–2009	15	0.178	-0.650	8.709	0.099	0.537	1	1	0.578	0.136	0.125	0.000
Turkey	1995–2009	15	0.057	-1.118	9.112	0.128	0.578	0	0	0.709	0.082	0.082	0.000
United Kingdom	1995–2009	15	0.217	1.386	10.233	0.449	0.877	1	0	0.099	0.278	0.162	0.000
United States	1995–2009	15	0.283	0.866	10.525	0.515	0.836	1	0	0.079	0.239	0.008	0.000
Venezuela	1998–2009	12	0.153	-1.883	9.161	0.116	0.364	0	1	0.615	0.006	0.006	0.000

Country-level mean values for the primary variables of interest. *Years* indicate the range of years with nonmissing values for *RMS* and *DISC* inclusive. *N* indicates the number of country-year observations with nonmissing *DISC* and *RMS*. *RMS* is the average country-year value for *RMS*, which is the negative *t*-statistic on deseasonalized cloud cover (*SKC*) in a regression of daily index returns on the world return and *SKC*. *DISC* is the average country-year disclosure score based on CIFAR's disclosure index and disclosure and accounting ratings from the World Economic Forum's Global Competitiveness Report. *GDP* is the average of the natural logarithm of *GDP* per capita measured at purchasing power parity, provided by Euromonitor International. *INTERNET* is the average fraction of the population who are Internet users, as reported by Euromonitor International. *ICRG* is an index based on the Investment Profile, Rule of Law, and Corruption scores from the International Country Risk Guide. *COMM.* is an indicator for whether the country has a common-law legal background, as reported by La Porta et al. (1999). *TROP.* is an indicator for tropical countries, based on latitudes reported by La Porta et al. (1999). *CH* is the fraction of the market that is closely held from Dahlquist et al. (2003). *(Foreign) MF* is the average fraction of the market capitalization held by (foreign) mutual funds based on data from Thomson Financial S12, SP7, and Datastream. *NREPR* is an indicator for nonresident equity purchase restrictions, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions.

Table 2
Descriptive statistics

Variable	No. Obs.	Mean	SD	Min	Max	Median
RMS	644	0.132	0.993	-3.308	3.905	0.062
DISC	644	0.007	0.993	-2.830	1.668	0.083
GDP	644	9.578	0.924	7.048	10.884	9.965
INTERNET	644	0.295	0.271	0.000	0.923	0.209
ICRG	644	0.705	0.181	0.188	1.000	0.733
COMMON	644	0.342	0.475	0.000	1.000	0.000
TROPICAL	644	0.328	0.470	0.000	1.000	0.000
CH	601	0.453	0.179	0.079	0.775	0.447
MF	361	0.124	0.094	0.000	0.869	0.119
Foreign MF	359	0.091	0.072	0.000	0.572	0.085
NREPR	624	0.122	0.327	0.000	1.000	0.000

Sample descriptive statistics for the primary variables of interest. *N* indicates the number of country-year observations with nonmissing *DISC* and *RMS*. *RMS* is the average country-year value for *RMS*, which is the negative *t*-statistic on deseasonalized cloud cover (*SKC*) in a regression of daily index returns on the world return and *SKC*. *DISC* is the average country-year disclosure score based on CIFAR's disclosure index and disclosure and accounting ratings from the World Economic Forum's Global Competitiveness Report. *GDP* is the average of the natural logarithm of *GDP* per capita measured at purchasing power parity, provided by Euromonitor International. *INTERNET* is the average fraction of the population who are Internet users, as reported by Euromonitor International. *ICRG* is an index based on the Investment Profile, Rule of Law, and Corruption scores from the International Country Risk Guide. *COMMMON* is an indicator for whether the country has a common-law legal background, as reported by La Porta et al. (1999). *TROPICAL* is an indicator for tropical countries, based on latitudes reported by La Porta et al. (1999). *CH* is the fraction of the market that is closely held from Dahlquist et al. (2003). *(Foreign) MF* is the average fraction of the market capitalization held by (foreign) mutual funds based on data from Thomson Financial S12, SP7, and Datastream. *NREPR* is an indicator for nonresident equity purchase restrictions, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions.

Table 3
Pearson correlation coefficients

Variable	RMS	DISC	GDP	INTERNET	ICRG	COMM.	TROP.	CH	MF	For. MF	NREPR
RMS	**1.000**										
DISC	0.005	**1.000**									
GDP	**0.098**	**0.609**	**1.000**								
INTERNET	0.057	**0.505**	**0.686**	**1.000**							
ICRG	0.068	**0.782**	**0.789**	**0.633**	**1.000**						
COMM.	0.002	**0.309**	-0.072	0.006	0.041	**1.000**					
TROP.	**-0.093**	**-0.479**	**-0.514**	**-0.324**	**-0.604**	**0.132**	**1.000**				
CH	-0.070	**-0.421**	**-0.473**	**-0.374**	**-0.476**	0.022	**0.193**	**1.000**			
MF	0.069	**0.381**	**0.397**	**0.450**	**0.379**	0.021	**-0.269**	**-0.443**	**1.000**		
For. MF	**0.105**	**0.307**	**0.358**	**0.411**	**0.369**	-0.065	**-0.246**	**-0.277**	**0.835**	**1.000**	
NREPR	0.013	-0.061	**-0.249**	**-0.158**	**-0.192**	0.033	**0.219**	-0.005	**-0.133**	**-0.160**	**1.000**

Bold coefficients are significant at the 0.05 level (two-sided). *RMS* is the average country-year value for *RMS*, which is the negative *t*-statistic on deseasonalized cloud cover (*SKC*) in a regression of daily index returns on the world return and *SKC*. *DISC* is the average country-year disclosure score based on CIFAR's disclosure index and disclosure and accounting ratings from the World Economic Forum's Global Competitiveness Report. *GDP* is the average of the natural logarithm of *GDP* per capita measured at purchasing power parity, provided by Euromonitor International. *INTERNET* is the average fraction of the population who are Internet users, as reported by Euromonitor International. *ICRG* is an index based on the Investment Profile, Rule of Law, and Corruption scores from the International Country Risk Guide. *COMM.* is an indicator for whether the country has a common-law legal background, as reported by La Porta et al. (1999). *TROP.* is an indicator for tropical countries, based on latitudes reported by La Porta et al. (1999). *CH* is the fraction of the market that is closely held from Dahlquist et al. (2003). *(Foreign) MF* is the average fraction of the market capitalization held by (foreign) mutual funds based on data from Thomson Financial S12, SP7, and Datastream. *NREPR* is an indicator for nonresident equity purchase restrictions, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions.

Table 4
Main regression results

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
DISC	-0.050	-0.112 **	-0.114 ***	-0.126 ***	-0.185 ***	-0.213 **
	(0.038)	(0.046)	(0.040)	(0.043)	(0.057)	(0.094)
GDP		0.141 ***		0.100	0.142 **	0.016
		(0.045)		(0.061)	(0.065)	(0.739)
INTERNET			0.541 ***	0.274		
			(0.168)	(0.236)		
ICRG					0.305	0.129
					(0.460)	(0.755)
COMMON					0.163 **	
					(0.078)	
TROPICAL	-0.245 **	-0.163 *	-0.199 **	-0.163 *	-0.188 **	
	(0.091)	(0.086)	(0.087)	(0.084)	(0.086)	
Country FE	no	no	no	no	no	yes
Year FE	yes	yes	yes	yes	yes	yes
Cluster	country	country	country	country	country	country
R-square	0.057	0.066	0.064	0.067	0.071	0.124
No. Obs.	644	644	644	644	644	644

Results of regressions of the form, $RMS_i = \alpha + \beta * DISC_i + \Gamma' X_i + \varepsilon_i$, where *RMS* is a measure of return-mood sensitivity, *DISC* is a measure of disclosure standards, and *X* is a vector of controls. *GDP* is the natural logarithm of per capita *GDP* measured at purchasing power parity, and *INTERNET* is the fraction of the population who are Internet users, both provided by Euromonitor International. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). *TROPICAL* is an indicator for tropical countries, using latitudes reported by La Porta et al. (1999). FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. N. Obs is the number of observations used in the regression. White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) level.

Table 5
Tests of participation and sophistication hypotheses

	Partition variable				Hierarchical partition
	GDP	*INTERNET*	*CH*	*MF*	*MF* by *CH*
Parameter	(1)	(2)	(3)	(4)	(5)
*DISC**Low Partition Var.	-0.095	-0.088	-0.345 ***	-0.174	
	(0.134)	(0.134)	(0.099)	(0.172)	
*DISC**High Partition Var.	-0.325 ***	-0.331 ***	-0.077	-0.216 *	
	(0.111)	(0.108)	(0.153)	(0.117)	
*DISC**Low *CH**Low *MF*					-0.203
					(0.153)
*DISC**Low *CH**High *MF*					-0.531 ***
					(0.183)
*DISC**High *CH**Low *MF*					0.214
					(0.216)
*DISC**High *CH**High *MF*					-0.190
					(0.206)
GDP	-0.069	-0.064	0.438	-0.123	-0.167
	(0.775)	(0.781)	(0.767)	(0.825)	(0.962)
ICRG	0.154	0.224	-0.036	-0.199	-0.822
	(0.721)	(0.728)	(0.760)	(0.930)	(0.852)
Country and year FE	yes	yes	yes	yes	yes
Cluster	country	country	country	country	country
R-square	0.127	0.127	0.123	0.140	0.142
Number of observations	644	644	601	556	541

Results of regressions of the form, $RMS_i = \alpha + \sum \beta_{Split} * DISC_i * Split + \Gamma' X_i + \varepsilon_i$, where the dependent variable, *RMS*, is a measure of return-mood sensitivity. *DISC* is the disclosure standards score based on the CIFAR index and the Global Competitiveness Report. *GDP* is the natural logarithm of per capita *GDP* measured at purchasing power parity, and Internet is the fraction of the population who are Internet users, both provided by Euromonitor International. Low and High *GDP* (*INTERNET*) are indicators based on a median split at the country level based on 2002 *GDP* (*INTERNET*). High (Low) *CH* is an indicator for countries where the fraction of the market that is closely held is above (below) the median, based on closely held data from Dahlquist et al. (2003). High (low) *MF* is an indicator for countries for which the average fraction of the market capitalization held by mutual funds is above (below) the median, based on data from Thomson Financial S12, SP7, and Datastream. In Column (4), the median split on *MF* is taken based on the entire sample. In Column (5), the median split on *MF* is taken within each *CH* group. FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption, and investment profile indices compiled by the International Country Risk Guide. All models include country- and year-level fixed effects (FE). White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) level.

Table 6
Additional international-sample regressions

Panel A: Controlling for foreign participation

Extra control parameter	NREPR (1)	NREPR (2)	Foreign MF (3)	Foreign MF (4)
DISC	-0.213**		-0.353*	
	(0.102)		(0.188)	
*DISC*Low CH*		-0.356***		-0.365*
		(0.105)		(0.187)
*DISC*High CH*		-0.096		-0.341
		(0.152)		(0.303)
Extra Control	0.429**		2.196	
	(0.190)		(1.457)	
*Extra Control * Low CH*		0.053		2.517
		(0.271)		(1.742)
*Extra Control * High CH*		0.651***		1.447
		(0.225)		(2.759)
GDP	0.337	0.377	-0.249	-0.229
	(0.882)	(0.813)	(1.692)	(1.682)
ICRG	0.204	0.257	1.381	1.408
	(0.779)	(0.790)	(1.514)	(1.566)
Year FE	yes	yes	yes	yes
Country FE	yes	yes	yes	yes
Country-clustered SE	yes	yes	yes	yes
R-square	0.126	0.132	0.140	0.140
Number of observations	585	585	350	350

Panel B: Cross-sectional country-level regressions

Parameter	(1)	(2)	(3)	(4)	(5)
Intercept	-1.278**	-1.781***	-1.408**	-1.226	-1.343*
	(0.562)	(0.629)	(0.687)	(0.777)	(0.689)
DISC	-0.123*	-0.154**	-0.187**	-0.173**	-0.191**
	(0.068)	(0.070)	(0.076)	(0.079)	(0.076)
GDP	0.149**	0.198***	0.179**	0.158**	0.175**
	(0.057)	(0.063)	(0.066)	(0.074)	(0.065)
COMMON	0.130	0.181*	0.209**	0.212**	0.226**
	(0.093)	(0.094)	(0.097)	(0.098)	(0.098)
TROPICAL	-0.198**	-0.193*	-0.220**	-0.249**	-0.223**
	(0.097)	(0.099)	(0.101)	(0.106)	(0.101)
CH			-0.367	-0.311	-0.442
			(0.276)	(0.288)	(0.284)
MF			-0.182	-0.143	-0.945
			(0.660)	(0.668)	(0.972)
NREPR				-0.052	
				(0.169)	
Foreign MF					1.086
					(1.019)
Adj. R-square	0.195	0.268	0.264	0.252	0.268
N	46	40	40	39	40

Panel A presents results of additional regressions at the country-year level. Panel B presents results of additional regressions at the country level based on averages of country-year values. *RMS* is the dependent variable and is a measure of return-mood sensitivity. *DISC* is the disclosure standards score based on the CIFAR index and the Global Competitiveness Report. High (Low) *CH* is an indicator for countries where the *CH*, the fraction of the market that is closely held is above (below) the median, based on data from Dahlquist et al. (2003). (*Foreign) MF* is the fraction of local market capitalization held by (foreign) mutual funds based on data from Thomson Financial S12, SP7, and Datastream. *NREPR* is an indicator for nonresident equity purchase restrictions, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions. *GDP* is the natural logarithm of per capita *GDP* measured at purchasing power parity. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). *TROPICAL* is an indicator for tropical countries, using latitudes reported by La Porta et al. (1999). FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls, and SE is shorthand for Standard Errors. Standard errors are listed in parentheses below each coefficient estimate. In panel A, standard errors are clustered at the country level and adjusted for heteroscedasticity following White (1980). Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) level.

Table 7
Firm-level RMS regression results within the United States

Parameter\Model	**(1)**	**(2)**	**(3)**
ITEMS	-0.2909		
	(0.182)		
*ITEMS * Low # Shareholders*		0.1188	
		(0.276)	
*ITEMS * Low # Shareholders * Low Inst. Ownership*			0.4643
			(0.455)
*ITEMS * Low # Shareholders * Hi Inst. Ownership*			-0.0278
			(0.344)
*ITEMS * Hi # Shareholders*		-0.6346 ***	
		(0.244)	
*ITEMS * Hi # Shareholders * Low Inst. Ownership*			-0.5243
			(0.514)
*ITEMS * Hi # Shareholders * Hi Inst. Ownership*			-0.7519 ***
			(0.283)
Log(# Shareholders)	-0.0010	-0.0030	-0.0033
	(0.004)	(0.005)	(0.005)
Log(MV)	0.0373 ***	0.0372 ***	0.0360 ***
	(0.002)	(0.002)	(0.003)
*Log(MV)*Log(MV)*	-0.0040 ***	-0.0038 ***	-0.0038 ***
	(0.001)	(0.001)	(0.001)
Market-to-Book Ratio	-0.0001	-0.0001	-0.0001
	(0.000)	(0.000)	(0.000)
Log(Firm Age)	0.0301 ***	0.0299 ***	0.0291 ***
	(0.004)	(0.004)	(0.004)
Share Price	0.0000 ***	0.0000 ***	0.0000 ***
	(0.000)	(0.000)	(0.000)
Low # Shareholders		-0.0073	
		(0.010)	
*Low # Shareholders * Low Inst. Ownership*			-0.0138
			(0.014)
*Low # Shareholders * Hi Inst. Ownership*			-0.0188 *
			(0.011)
Hi # Shareholders		absorbed	
*Hi # Shareholders * Low Inst. Ownership*			-0.0275 **
			(0.013)
*Hi # Shareholders * Hi Inst. Ownership*			absorbed
Fama-French 48 industry FE	yes	yes	yes
Year FE	yes	yes	yes
Firm-clustered standard errors	yes	yes	yes
R-square	0.089	0.089	0.089
N	80,823	80,823	80,823

Results of regressions of the form, $RMS_j = \alpha + \beta * ITEMS_j + \Gamma' X_j + \varepsilon_j$ and $RMS_j = \alpha + \sum \beta_{Split} * ITEMS_j * Split + \Gamma' X_j + \varepsilon_j$, where *j* denotes firm-year. *RMS* a measure of sentiment-based noise in returns, *ITEMS* is a measure of reporting quality, and *X* is a vector of controls. Nonmissing Compustat Items (*ITEMS*) is the industry-year adjusted (observation minus average) number of nonmissing Compustat items for the firm's 10K (in thousands). All regressions include the following controls: Log(Market Value), Log(Market Value) squared, log(# of shareholders), Market-to-Book ratio, Log(Firm Age), Share price, Fama-French 48-industry indicators, calendar year indicators, and indicators for split variables. White (1980) heteroscedasticity-consistent standard errors clustered at the firm level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) level.

Table 8
Additional U.S. firm-level RMS regression results with return volatility interactions

Parameter\Model	(1)	(2)	(3)	(4)
ITEMS	-0.318*	-0.317*	-0.315*	-0.321*
	(0.185)	(0.185)	(0.185)	(0.185)
Ret. Vol.	0.014***	0.013***		
	(0.005)	(0.005)		
*ITEMS * Ret. Vol.*		-0.386*		
		(0.206)		
Idio. Ret. Vol.			0.012**	0.012**
			(0.005)	(0.005)
*ITEMS * Idio. Ret. Vol.*				-0.344*
				(0.208)
Controls included	yes	yes	yes	yes
Firm-clustered standard errors	yes	yes	yes	yes
N	79,581	79,581	79,581	79,581
R-square	0.080	0.080	0.080	0.080

Results of regressions of the form, $RMS_{j,t} = \alpha + \beta * ITEMS_{j,t} + \gamma * volatility_{j,t-1} + \Gamma' X_{j,t} + \varepsilon_{j,t}$, where *j* denotes firm and *t* denotes year. *RMS* a measure of return-mood sensitivity, *ITEMS* is a measure of reporting quality, *volatility* is a measure of stock return volatility, and *X* is a vector of controls. *ITEMS* is the industry-year adjusted (observation minus average) number of nonmissing Compustat items for the firm's annual report (in thousands). *Ret. Vol*. is the standard deviation of daily returns, taken from the prior calendar year. *Idio. Ret. Vol*. is the standard deviation of idiosyncratic returns based on a daily market-model regression estimated for the firm in the prior calendar year using the value-weighted market return. Both *Ret. Vol*. and *Idio. Ret. Vol*. are standardized to be mean-0 and unit-variance. All regressions include the following controls: Log(Market Value), Log(Market Value) squared, log(# of shareholders), Market-to-Book ratio, Log(Firm Age), Share price, Fama-French 48-industry indicators, calendar year indicators, indicators for split variables. White (1980) heteroscedasticity-consistent standard errors clustered at the firm level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) level.

Internet Appendix Tables

Table IA.1
Additional robustness checks

Model:	*RMSpos*	1998-2009	GDP Quintiles	Lag Returns
Parameter\Model variant:	(1)	(2)	(3)	(4)
DISC	-0.152**	-0.240**	-0.163**	-0.147**
	(0.059)	(0.116)	(0.063)	(0.059)
GDP	0.037	0.248	0.043	0.026
	(0.484)	(1.038)	(0.505)	(0.497)
GDP Q1			-0.196	
			(4.706)	
GDP Q2			-0.184	
			(4.741)	
GDP Q3			-0.362	
			(4.743)	
GDP Q4			-0.283	
			(4.787)	
GDP Q5			-0.348	
			(4.807)	
ICRG	-0.052	-0.019	-0.050	0.083
	(0.472)	(0.847)	(0.491)	(0.487)
Lag(Market Returns)				0.074
				(0.151)
Country FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Cluster	Country	Country	Country	
R-square	0.404	0.118	0.406	0.412
N. Obs	644	535	644	592

Results of regressions of the form, $RMS_i = \alpha + \beta * DISC_i + \Gamma ' X_i + \varepsilon_i$ where *RMS* is a measure of return-mood sensitivity, *DISC* is a measure of disclosure standards, and *X* is a vector of controls. In Model 1, the dependent variable is *RMSpos*=max(0,*RMS*) instead of *RMS*. In Model 2, the sample is restricted to 1998-2009, years for which the *DISC* proxy is based on values reported in the World Economic Forum's Global Competitiveness Reports. Model (3) includes *GDP* quintiles as additional controls. Model 4 includes an additional control for last year's index returns, *Lag(Market Returns). GDP* is the natural logarithm of per-capita *GDP* measured at purchasing power parity, and *INTERNET* is the fraction of the population who are Internet users, both provided by Euromonitor International. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). *TROPICAL* is an indicator for tropical countries, using latitudes reported by La Porta et al. (1999). FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. N. Obs is the number of observations used in the regression. White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table IA.2
Main regression results in changes

Parameter	(1)	(2)	(3)	(4)	(5)
$\Delta DISC$	-0.292*	-0.268^{++}	-0.299*	-0.278^{++}	-0.257^{+}
	(0.170)	(0.179)	(0.170)	(0.180)	(0.184)
ΔGDP		-1.903		-1.598	-1.212
		(1.758)		(1.792)	(1.830)
$\Delta INTERNET$			-1.616^{+}	-1.450	-1.306
			(1.238)	(1.264)	(1.292)
$\Delta ICRG$					-1.446
					(1.560)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Country	Country	Country	Country	Country
R-square	0.041	0.042	0.043	0.044	0.045
N. Obs	595	595	595	595	595

Results of regressions of the form, $\Delta RMS_i = \alpha + \beta * \Delta DISC_i + \Gamma ' \Delta X_i + \varepsilon_i$ where Δ indicates changes, *RMS* is a measure of return-mood sensitivity, *DISC* is a measure of disclosure standards, and *X* is a vector of controls. *GDP* is the natural logarithm of per-capita *GDP* measured at purchasing power parity, and *INTERNET* is the fraction of the population who are Internet users, both provided by Euromonitor International. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. N. Obs is the number of observations used in the regression. White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks and plus-signs denote significance at the 10% (*), 15% ($^{++}$), and 20% ($^{+}$)levels.

Table IA.3
Main regression results with return volatility control

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
DISC	-0.076 *	-0.132 ***	-0.143 ***	-0.151 ***	-0.196 ***	-0.206 **
	(0.042)	(0.049)	(0.044)	(0.047)	(0.057)	(0.093)
Ret. Vol.	-14.608 **	-13.616 *	-15.140 **	-14.340 **	-13.090 *	-11.735
	(7.075)	(7.086)	(7.029)	(6.972)	(7.115)	(8.785)
GDP		0.133 ***		0.080	0.140 **	-0.204
		(0.046)		(0.058)	(0.065)	(0.748)
INTERNET			0.562 ***	0.348		
			(0.175)	(0.223)		
ICRG					0.219	0.168
					(0.465)	(0.746)
COMMON					0.155 **	
					(0.075)	
TROPICAL	-0.246 ***	-0.169 *	-0.198 **	-0.170 **	-0.197 **	
	(0.090)	(0.084)	(0.084)	(0.081)	(0.085)	
Country FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Country	Country	Country	Country	Country	Country
R-square	0.065	0.073	0.073	0.075	0.077	0.128
N. Obs	644	644	644	644	644	644

Results of regressions of the form, $RMS_i = \alpha + \beta * DISC_i + \Gamma' X_i + \varepsilon_i$ where *RMS* is a measure of return-mood sensitivity, *DISC* is a measure of disclosure standards, and *X* is a vector of controls. *Ret. Vol.* is return volatility measured as the standard deviation of daily index returns, *GDP* is the natural logarithm of per-capita *GDP* measured at purchasing power parity, and *INTERNET* is the fraction of the population who are Internet users, both provided by Euromonitor International. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). *TROPICAL* is an indicator for tropical countries, using latitudes reported by La Porta et al. (1999). FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. N. Obs is the number of observations used in the regression. White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table IA.4
Main regression results with Tropical interactions

Parameter\Model	(1)	(2)	(3)	(4)	(5)	(6)
*DISC * Not Tropical*	-0.084	-0.148 **	-0.149 ***	-0.164 ***	-0.206 ***	-0.239 **
	(0.051)	(0.057)	(0.048)	(0.052)	(0.069)	(0.106)
*DISC * Tropical*	0.007	-0.049	-0.079	-0.076	-0.152	-0.217
	(0.047)	(0.068)	(0.074)	(0.077)	(0.094)	(0.198)
*GDP * Not Tropical*		0.164 ***		0.119 *	0.132	-0.289
		(0.046)		(0.065)	(0.082)	(0.881)
*GDP * Tropical*		0.110		0.030	0.175 **	0.105
		(0.076)		(0.099)	(0.075)	(0.827)
*INTERNET * Not Tropical*			0.510 ***	0.268		
			(0.161)	(0.235)		
*INTERNET * Tropical*			0.825 **	0.645		
			(0.381)	(0.519)		
*ICRG * Not Tropical*					0.446	0.832
					(0.572)	(0.930)
*ICRG * Tropical*					-0.190	-0.413
					(0.697)	(1.178)
*COMMON * Not Tropical*					0.099	Absorbed
					(0.075)	
*COMMON * Tropical*					0.322 **	Absorbed
					(0.135)	
Not Tropical	0.218 **	-0.372	0.245 *	-0.605	0.274	Absorbed
	(0.085)	(0.848)	(0.146)	(1.004)	(0.820)	
Country FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Country	Country	Country	Country	Country	Country
N	644	644	644	644	644	644
R-Square	0.05818	0.06738	0.0672	0.06939	0.07386	0.1264

Results of regressions of the form, $\Delta RMS_i = \alpha + \beta * \Delta DISC_i + \Gamma' \Delta X_i + \varepsilon_i$ where Δ indicates changes, *RMS* is a measure of return-mood sensitivity, *DISC* is a measure of disclosure standards, and *X* is a vector of controls. *GDP* is the natural logarithm of per-capita *GDP* measured at purchasing power parity, and *INTERNET* is the fraction of the population who are Internet users, both provided by Euromonitor International. *ICRG* is a proxy for the institutional environment, based on the rule of law, corruption and investment profile indices compiled by the International Country Risk Guide. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). (*Not*) *Tropical* is an indicator for (non-)tropical countries, using latitudes reported by La Porta et al. (1999). FE is shorthand for fixed effects, meaning a vector of indicator variables being included as additional controls. N. Obs is the number of observations used in the regression. White (1980) heteroscedasticity-consistent standard errors clustered at the country level are listed in parentheses below each coefficient estimate. Asterisks and plus-signs denote significance at the 10% (*), 15% ($^{+}$), and 20% ($^{++}$) percent levels.

Table IA.5
Cross-sectional country-level regressions with Tropical interactions

Parameter	(1)	(2)	(3)	(4)	(5)
Intercept	-1.338*	-2.095**	-1.737	-1.612	-1.690
	(0.784)	(0.887)	(1.058)	(0.991)	(1.086)
*DISC * Not Tropical*	-0.139	-0.165*	-0.183**	-0.176**	-0.185**
	(0.085)	(0.081)	(0.088)	(0.082)	(0.090)
*DISC * Tropical*	-0.125	-0.231	-0.295*	-0.245	-0.253
	(0.120)	(0.149)	(0.166)	(0.166)	(0.175)
*GDP * Not Tropical*	0.158*	0.232**	0.215**	0.211**	0.213*
	(0.080)	(0.089)	(0.104)	(0.096)	(0.106)
*GDP * Tropical*	0.153*	0.158*	0.152	0.100	0.154
	(0.086)	(0.091)	(0.095)	(0.123)	(0.097)
*COMMON * Not Tropical*	0.055	0.106	0.118	0.124	0.129
	(0.114)	(0.112)	(0.116)	(0.107)	(0.122)
*COMMON * Tropical*	0.271	0.469**	0.531**	0.713***	0.447*
	(0.170)	(0.200)	(0.213)	(0.215)	(0.235)
*CH * Not Tropical*			-0.003	-0.004	-0.004
			(0.003)	(0.003)	(0.004)
*CH * Tropical*			-0.006	0.005	-0.004
			(0.005)	(0.006)	(0.006)
*MF * Not Tropical*			-0.386	-0.641	-0.728
			(0.866)	(0.866)	(1.303)
*MF * Tropical*			-0.147	-2.433	-2.044
			(1.271)	(1.715)	(2.416)
*NREPR * Not Tropical*				-0.185	
				(0.239)	
*NREPR * Tropical*				0.215	
				(0.319)	
*Foreign MF * Not Tropical*					0.422
					(1.184)
*Foreign MF * Tropical*					3.594
					(3.865)
TROPICAL	-0.239	0.323	0.272	0.095	0.113
	(1.162)	(1.265)	(1.456)	(1.577)	(1.493)
Adj R-Sq	0.176	0.291	0.247	0.360	0.219
N	46	40	40	39	40

This Table presents results of additional regressions at the country level based on averages of country-year values. *RMS* is the dependent variable and is a measure of return-mood sensitivity. *DISC* is the disclosure standards score based on the CIFAR index and the Global Competitiveness Report. High (Low) *CH* is an indicator for countries where the *CH*, the fraction of the market that is closely held is above (below) the median, based on data from Dahlquist et al. (2003). (*Foreign) MF* is the fraction of local market capitalization held by (foreign) mutual funds based on data from Thomson Financial S12, SP7 and Datastream. *NREPR* is an indicator for non-resident equity purchase restrictions, taken from Schindler (2009) and the International Monetary Fund's Annual Reports on Exchange Arrangements and Exchange Restrictions. *GDP* is the natural logarithm of per-capita *GDP* measured at purchasing power parity. *COMMON* is an indicator variable for whether the country has a common-law legal background, as reported by La Porta et al. (1998). (*Not*) *Tropical* is an indicator for (non-)tropical countries, using latitudes reported by La Porta et al. (1999). Standard errors are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table IA.6
Firm-level RMS regression results within the US – including Advertising expense

Parameter\Model	(1)	(2)	(3)
ITEMS	-0.9153***	-1.0305***	
	(0.342)	(0.342)	
*ITEMS * Low Ad. Expense*			-0.8098
			(0.524)
*ITEMS * Hi Ad. Expense*			-1.2196***
			(0.448)
Low Ad. Expense			-0.0026
			(0.019)
Ad. Expense	0.0095	0.0189***	0.0187**
	(0.006)	(0.007)	(0.008)
Log(AT)		0.0301*	0.0306*
		(0.015)	(0.016)
*Log(AT)*Log(AT)*		-0.0048***	-0.0049***
		(0.001)	(0.001)
Log(MV)	0.0348***	0.0438***	0.0437***
	(0.005)	(0.007)	(0.007)
*Log(MV)*Log(MV)*	-0.0060***	-0.0026**	-0.0025**
	(0.001)	(0.001)	(0.001)
Market to Book Ratio	0.0001	0.0001	0.0001
	(0.000)	(0.000)	(0.000)
Log(Firm Age)	0.0243***	0.0290***	0.0290***
	(0.008)	(0.008)	(0.008)
Share Price	0.0002***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)
Fama-French 48 Industry and Year FE	Yes	Yes	Yes
Firm-clustered standard errors	Yes	Yes	Yes
R-Square	0.093	0.094	0.094
N	25,483	25,483	25,483

Results of regressions of the form, $RMS_j = \alpha + \beta * ITEMS_j + \Gamma ' X_j + \varepsilon_j$ and $RMS_j = \alpha + \sum \beta_{Split} * ITEMS_j * Split + \Gamma ' X_j + \varepsilon_j$ where *j* denotes firm-year. *RMS* a measure of sentiment-based noise in returns, *ITEMS* is a measure of reporting quality, and *X* is a vector of controls. Non-missing Compustat Items (*ITEMS*) is the industry-year adjusted (observation wminus average) number of non-missing Compustat items for the firm's 10K (in thousands). Ad. Expense is the log of 1+Advertising Expense in dollars. Hi/Low advertising expense are based on annual median-splits. AT is total assets in dollars. All regressions include the following controls: Log(Market Value), Log(Market Value) squared, log(# of shareholders), Market to Book ratio, Log(Firm Age), Share price, Fama-French 48-industry indicators, calendar year indicators, and indicators for split variables. White (1980) heteroscedasticity-consistent standard errors clustered at the firm level are listed in parentheses below each coefficient estimate. Asterisks denote significance at the 10% (*), 5% (**), 1% (***) levels.