Analysts' Risk Discussions and The Use of Valuation Models: A Content Analysis of Sell-Side Equity Analyst reports

CHANGQIU YU

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Abstract

This dissertation consists of three research studies on sell-side equity analysts based on textual analysis of analyst reports from Investext. In the first study, I examine whether analysts' geographic location is associated with their discussions about risk. Using textual analysis of analysts' reports to extract their risk discussions for firms globally, I find that foreign analysts present more risk discussions than local analysts. Foreign analysts' more extensive risk discussions are associated with their unfamiliarity with the underlying firms. The positive association between foreignness and risk discussions is mitigated for analysts with strong personal ability and firms in countries with a better institutional environment. Analysts' risk discussions are incrementally informative to investors. The informativeness of risk discussions is similar for foreign analysts and local analysts.

The second study examines whether comparability of the underlying firms to their peers affects the informativeness of discounted cash flow (DCF) models and price-to-earnings (PE) models used by analysts. The psychology literature suggests that people often rely on a limited number of heuristic principles to simplify their judgmental opinions, and this may cause anchoring and adjustment bias. A PE model is one type of heuristics. I hypothesize that analysts are more likely to be subject to anchoring and adjustment bias when using PE models compared with using DCF models. The bias is more severe when the underlying firms are not comparable to other firms. Consistent with this argument, I find that market reactions to analysts' investment opinions based on DCF models are stronger than their opinions based on PE models. Furthermore, the incremental effect of DCF models on market reactions to analyst' investment opinions is mainly restricted to firms with less comparability.

In the third study, I use textual analysis to detect analysts' use of valuation models for a large sample of analyst reports on firms around the world. I classify these models into accrual models and cash flow models. Given the fact that accrual models are the default models used in analyst reports, I examine whether the firm country's institutional factors are associated with analysts' choice of cash flow models. I find that analysts are more likely to use cash flow models such as the price-to-cash-flow and DCF models to value firms in countries with stronger investor protection, better information environment, and greater economic freedom. The market reactions to target price changes based on cash flow models are stronger, particularly in countries with a stronger institutional environment. The findings suggest that countries with sound institutions facilitate analysts' use of cash flow models.

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Chapter 1: Geographic Location and Analysts' Risk Discussions

1.1 Introduction

There is a large literature on sell-side analysts' role as information intermediaries. These studies mainly examine the informativeness of analysts' point estimates such as EPS forecasts, stock recommendations, and target prices (Givoly and Lakonishok, 1979; Lys and Sohn, 1990; Womack, 1996; Brav and Lehavy, 2003; DeFond and Hung, 2003, 2007; Givoly, Hayn, and Lehavy, 2009), and analysts' qualitative opinions such as the tone and topics discussed in their reports (Asquith, Mikhail, and Au, 2005; Huang, Zang, and Zheng, 2014; Huan, Lehavy, Zang, and Zheng, 2018). However, only a handful of studies have examined analysts' risk analysis in their reports.[1] Risk information is important as investors need to understand the potential risks of the underlying firms.[2] This study adds to the literature by investigating analysts' textual risk discussions in their reports in an international setting.

Specifically, this study examines the effect of geographic location on analysts' risk discussions. I measure geographic location with a *foreign* indicator which equals one if an analyst's domicile country is distinct from the underlying firm's headquarter country, and zero otherwise (i.e., local). It is well known that local analysts have an information advantage due to their geographic proximity to the underlying firms (Malloy, 2005; Bae, Stulz, and Tan, 2008). To the extent that information advantage leads to reduced cost of information collection, one might expect that local analysts discuss more risk information than foreign analysts. However, foreignness is positively associated with unfamiliarity. According to the psychology literature,

[1] For example, see Lui, Markov, and Tamayo (2007, 2012), Joos, Piotroski, and Srinivasan (2016), and Bochkay and Joos (2020).
[2] In 2002, NYSE Rule 472 and NASD Rule 2210 require analysts to include a discussion of firms' risks in their reports. Analysts may face lawsuits from investors if they fail to warn investors of potential risks.

people impute higher risks to issues they are not familiar with. Foreign analysts may be more sensitive to the risks of the underlying firms, and consequently discuss more risks in their reports. Foreign investors' demand for risk information may also stimulate more risk discussions from foreign analysts. In addition, local analysts might face stronger conflicts of interest with the underlying firms than foreign analysts, and thus may avoid discussing potential risks of their covered local firms. Therefore, the association between geographic location and analysts' risk discussions is not clear.

I examine the effect of geographic location on analysts' risk discussions using a sample of 541,631 analyst reports by 10,544 analysts covering 5,495 firms from 38 countries from 1997 to 2019.[3] I focus on risk discussions on the first page of analyst reports, as analysts may have different writing styles with some being verbose and others being concise.[4] Using a dictionary-based approach, I measure analysts' risk discussions by counting the number of risk-related keywords on the first pages of their reports.[5] To examine whether the relationship between geographic location and risk discussions varies with risk categories, I catalog analysts' risk discussions as forward-looking statement risk, firm-specific risk, industry risk, regulation and litigation risk, and macroeconomic risk. Risk category discussions are measured by the number of sentences that include both risk-related keywords and category-related keywords on the first

[3] I thank Hongping Tan from McGill University for sharing the data on analysts' risk discussions

[4] The findings are qualitatively unchanged if I extract analysts' risk discussions in their full reports. Table 1.4 reports the relevant tests.

[5] Appendix 1.C presents the keywords used to identify risk discussions. I acknowledge that some of the risk-related keywords such as "possible" and "uncertainty" could also capture analysts' ambiguous tone (Loughran and McDonald, 2011). Sherman (1974) points out that risky choices and ambiguous choices are different. Risk occurs when the future is not known, but the probability distribution of possible outcomes is known. Ambiguity occurs when the probability distribution is unknown. I do not make a clear distinction between risk and ambiguity as it is hard to empirically disentangle one from the other. However, in a robustness test, I use an alternative risk dictionary that consists of strong risk indicators to detect analysts' risk discussions. The relevant tests are reported in Panel B of Table 1.4. The major findings are unchanged.

page of analyst reports.[6] In addition to the absolute number of risk discussions, I also measure relative risk discussions with the keyword counts scaled by the number of words on the first page of analyst reports.

I find that foreign analysts discuss more risk information than local analysts after controlling for other predictors of risk discussions such as earnings per share volatility, idiosyncratic risk, beta, stock turnover, market-to-book value, and leverage. Furthermore, foreign analysts discuss more forward-looking and firm-specific risk information than local analysts. There is no significant difference between foreign and local analysts in discussing industry, regulation and litigation, and macroeconomic risk information. The findings are robust when I extract analysts' risk discussions from their full reports instead of the first pages only, when I use an alternative dictionary to identify risk discussions, in the subsample excluding analysts from the United States, and in the subsample in which a firm is followed by both local and foreign analysts in the same year.

Next, I develop and test three possible and not mutually exclusive explanations of why foreign analysts may discuss more risk information than local analysts. First, I examine the foreign analyst unfamiliarity hypothesis. This hypothesis is based on the finding in the psychology literature that people normally impute more risks to issues with which they are not familiar (Heath and Tversky, 1991; French and Porterba, 1991). Foreign analysts may discuss more risk information than local analysts because their unfamiliarity with the underlying firm intensifies their sensitivity to risk information.

If unfamiliarity contributes to the greater risk discussions by foreign analysts, the positive association between foreignness (i.e., the analyst does not live in the same country as the

[6] Appendix 1.C presents the top 50 frequently mentioned phrases under each category in analyst reports.

reported firm) and risk discussions will be mitigated when the level of unfamiliarity is reduced. I measure the level of unfamiliarity with the time span of a foreign analyst's coverage, the presence of local analysts in a foreign analyst team, and a foreign analyst becoming local due to a location change. Consistent with this argument, I find that foreign analysts discuss more risk information than local analysts only in the earlier years of foreignness and when there are no local analysts in the foreign analyst team. I also find weak evidence that an analyst discusses less risk information after she moves from another country to the firm headquarter country.

Furthermore, I test the unfamiliarity hypothesis in cross-sectional settings. Analysts' sensitivity to risk arising from unfamiliarity can be alleviated for analysts with stronger personal ability and for firm countries with a better institutional environment. I measure analysts' ability with their experience of analyzing foreign firms, and their industry expertise. I measure a country's institutional environment with the level of investor protection, information disclosure, and trust. I find that the positive association between foreignness and risk discussions is mitigated when analysts have rich experience of analyzing foreign firms and have industry expertise, and when firm countries have strong investor protection, and a high level of information disclosure, and trust.

The second possible explanation is the foreign institutional investor demand hypothesis. Foreign institutional investors may have a stronger demand for risk information to monitor investee firms compared with domestic investors. If foreign investors are the primary readers of foreign analysts' reports, foreign analysts may discuss more risk information in response to foreign investors' information demand. The cross-sectional implication is that the degree to which foreign analysts discuss more risk information than local analysts is positively associated with the firms' foreign institutional holdings. I find some evidence that the positive association between foreignness and risk discussions is more pronounced for firms with foreign institutional holdings at the top decile rank.

The final possible explanation is the conflicts of interest hypothesis. As local analysts are more likely to have close ties with the management than their foreign counterparts, they may face stronger conflicts of interest than foreign analysts. Local analysts may discuss less risk information to avoid jeopardizing their relationship with the management. Following Bradshaw, Richardson, and Sloan (2006), I use the change of the underlying firm's total debt and shareholder's equity to measure the potential conflicts of interest. I find little support for this hypothesis as the positive association between foreignness and risk discussions is not significantly different for firms with different levels of conflicts of interest.

Finally, I examine whether analysts' risk discussions are informative to investors, and whether the informativeness differentiates foreign and local analysts. Following Lui, Markov, and Tamayo (2007), I use the association between analysts' risk discussions and the subsequent stock return volatility to measure the informativeness of risk discussions. I find that risk discussions are significantly positively associated with the subsequent stock return volatility after controlling for other predictors of future stock volatility. I also use stock turnover ratio to capture the informativeness of risk discussions. I find that risk discussions are significantly positively associated with the subsequent stock turnover. Further, I examine whether risk discussions help to strengthen market reactions to analysts' stock recommendations. I find that the market reacts more positively to a buy recommendation and more negatively to a sell recommendation when the recommendations are accompanied by more risk discussions. Overall, there is strong evidence that analysts' risk discussions are informative to investors. I interact the *foreign* indicator with risk discussions in the above tests to examine whether foreign and local analysts are different in the informativeness of their risk discussions. I find that for the same amount of risk keywords discussed, foreign analysts are similar to local analysts in the informativeness of risk discussions.

This study has two major contributions. First, this study extends existing studies on analysts' ability in risk analysis. Using analyst risk ratings from Salomon Smith Barney and Citigroup, Lui et al. (2007, 2012) find that analysts' risk ratings are largely explained by firm risk traits and are positively related to future stock return volatility. Joos et al. (2016) use the spread in Morgan Stanley analysts' scenario-based valuations to capture analysts' attitudes towards firm risks and find that the spread is positively associated with subsequent analysts' forecast errors. I contribute to the literature by using predefined dictionaries to identify analysts' risk discussions in an international setting and to examine the effect of geographic location on analysts' risk discussions.

Second, this study contributes to the literature on local analysts' information advantage arising from geographic proximity (Malloy, 2005; Bae et al., 2008). Contrary to Bae et al. (2008) who find that local analysts are more accurate in earnings forecasts than foreign analysts, I find that foreign analysts are similar to local analysts in the informativeness of risk discussions. The findings suggest that the effect of geographic proximity on analysts' forecast performance is multidimensional.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and hypotheses. Section 3 describes data and variable definitions. Section 4 presents empirical analyses of the effect of geographic location on analysts' risk discussions. Section 5 presents the tests on the informativeness of analysts' risk discussions, and Section 6 concludes and discusses the limitations of this study.

1.2 Literature Review and Hypotheses Development

1.2.1 Literature review

This study is closely related to the literature on the information content of analyst reports and analysts' examination of firm risk information.

1.2.1.1 The information content of analyst reports

Prior literature uses different approaches to extract the information content of analyst reports. For example, Asquith et al. (2005) are among the first to examine the textual information content of an analyst report by manually cataloging 1,126 analyst reports from 56 Institutional Investor All-American Team members from 1997 to 1999. They find that the written justifications provide incremental information to investors after controlling for analysts' quantitative opinions such as EPS forecasts, stock recommendations, and target prices. Twedt and Rees (2012) use a dictionary-based approach to examine the qualitative attributes of 2,057 analyst initiation reports. They find that the detail and tone of analyst reports provide incremental information to the market beyond analysts' EPS and recommendation forecasts.

Huang et al. (2014) use a machine learning approach to extract analysts' textual opinions in 363,952 reports for S&P 500 firms from 1995 to 2008. They find that after controlling for the quantitative opinions, analysts' favorable textual opinions are significantly positively associated with the two-day cumulative abnormal returns from the report date, and the subsequent five-year earnings growth rate after the analyst report date. A follow-up study by Huang et al. (2018) uses the Latent Dirichlet Allocation (LDA) approach to examine the topical differences between conference call content and the subsequent analyst report content. They find that analysts provide significant and differentiated information beyond the information contained in conference calls.

Overall, prior studies find that the textual analysis in analyst reports provides incremental information to investors. Nevertheless, few researchers examine analysts' risk analyses of the covered firms in their reports.

1.2.1.2 Analysts' examination of firm risk

Previous studies on textual risk analysis have been largely restricted to the 10-K filings, as SEC requires firms to include "risk factor" Item 1A in their annual reports since 2005. Overall, these studies find that discussions of risk information in the 10-K filings are informative (Kravet and Muslu, 2013; Campbell et al., 2014; Hope, Hu, and Lu, 2016; Beatty, Cheng, and Zhang, 2018).

By contrast, only a few studies have examined analysts' risk analysis of the underlying firms in their reports. Lui et al. (2007) are the first to examine analysts' risk assessment by using analyst risk ratings from Salomon Smith Barney (now part of Citigroup) from 1997 to 2003. They find that analysts' risk ratings are largely explained by firm risk traits such as size, book-to-market, leverage, earnings quality, losses, and idiosyncratic risks, and are positively associated with future stock return volatility. Building on these findings, Lui et al. (2012) document that changes in analysts' risk ratings are associated with stock returns, and the subsequent changes in Fama-French factor loadings.

Joos et al. (2016) use the spread between upside and downside valuation forecasts from Morgan Stanley analysts' scenario-based valuations to capture analysts' assessment of firm risks. They find that the spread is positively associated with firm risk measured by beta, small size, financial distress, losses, and idiosyncratic risk. Using a similar approach to capture analysts' risk assessment, Bochkay and Joos (2020) find that analysts rely on quantitative and qualitative information for their risk assessments, but the reliance on qualitative information increases when macroeconomic uncertainty is high.

This study contributes to the prior literature by using the dictionary-based approach to capture analysts' risk analysis of the underlying firms in their reports. Moreover, I examine whether geographic location plays a role in analysts' risk discussions.

1.2.2 Hypotheses development

This study examines the relation between analysts' geographic locations and their risk discussions. I develop one hypothesis predicting why foreign analysts may discuss less risk information than local analysts, and three hypotheses predicting why foreign analysts may discuss more risk information than local analysts.

1.2.2.1 Foreign analyst information disadvantage hypothesis

Prior literature shows that local analysts have an information advantage due to their geographic proximity to the underlying firms. For example, Malloy (2005) finds that in the United States, analysts located closer to the underlying firms issue more accurate earnings forecasts and have a larger impact on stock prices than other analysts. Bae et al. (2008) find that analysts who live in the same country as the underlying firms present more accurate earnings forecasts than foreign analysts. O'Brien and Tan (2015) examine the effect of geographic proximity on analyst coverage decisions for U.S. firms. They find that as local analysts have an information advantage, they are more likely than distant analysts to cover IPO firms. It is reasonable to expect that local analysts' information advantage might extend to their risk analysis of the underlying firms.

Foreign analysts' information disadvantage relative to local analysts could be a barrier to their risk discussions. Houston, Lev, and Tucker (2010) find that analyst coverage decreases for firms that stop providing quarterly earnings guidance, because of the deterioration in the information environment of such firms. Similarly, with the lack of information, foreign analysts may discuss less risk information to avoid making mistakes that might jeopardize their reputation. The foreign analysts' information disadvantage hypothesis predicts a negative association between foreignness and risk discussions.

1.2.2.2 Foreign analyst unfamiliarity hypothesis

People normally impute more risks to issues with which they are not familiar (Heath and Tversky, 1991; French and Porterba, 1991). The unfamiliarity due to geographic location could intensify foreign analysts' sensitivity to the underlying firm's risk information, which further drives foreign analysts to be more proactive in acquiring such information to alleviate their concerns. In addition, familiarity may have a negative impact on local analysts' risk discussions. Chan, Covrig, and Ng (2005) find that investors overweight investment in their home countries and restrict their foreign investment to a few familiar international markets, and therefore inadequately diversified geographically. Their findings offer evidence of irrational familiarity among investors. Accordingly, being familiar with the underlying firm, local analysts may be ignorant of potential risks; thus, they may spend less time and effort in seeking risk information.

The foreign analyst unfamiliarity explanation predicts that foreign analysts present more risk discussions than local analysts.

1.2.2.3 Foreign institutional investor demand hypothesis

Compared with domestic investors, foreign institutional investors normally have diversified portfolios worldwide and thus could have a stronger ability to tolerate the investee firms' risks. Consistent with this argument, Luong et al. (2017) find that foreign institutional holdings have a positive effect on firm innovation. Bena, Ferreira, Matos, and Pires (2017) find that foreign institutional investors facilitate the investee firms' long-term investment in tangible and intangible assets. Moreover, because of the relatively independent positions from local management, foreign institutional investors are more likely to be proactive in monitoring the investee firms around the world (Gillan and Starks, 2003; Aggarwal, Erel, Ferreira, and Matos, 2011).

Foreign institutional investors might have a stronger demand for risk information to monitor investee firms, compared with domestic investors. If foreign investors are the primary readers of foreign analysts' reports, it is likely that foreign analysts discuss more risk information in response to foreign investors' information demand. This is consistent with Brown, Call, Clement, and Sharp (2015) who find that client demand for information is the most important determinant of analysts' coverage decisions.

The foreign institutional investor demand hypothesis predicts that foreign analysts discuss more risk information than local analysts, especially for firms with a higher proportion of foreign institutional holdings.

1.2.2.4 Conflicts of interest hypothesis

Local analysts are likely to face stronger conflicts of interest than foreign analysts. Compared with foreign analysts, local analysts have a geographic advantage to obtain investment banking business if the underlying firm requires access to the capital market; they are more likely to curry favor with the management to obtain private information, and generate trading commissions by issuing favorable comments of the underlying firm. To the extent that local analysts face stronger conflicts of interest than foreign analysts, they are more likely to avoid discussing risk information to avoid jeopardizing their relationship with the management. This hypothesis predicts that foreign analysts discuss more risk information than local analysts, especially for firms with more potential underwriting business.

Overall, the foreign analysts' information disadvantage hypothesis predicts a negative association between foreignness and risk discussions, while the foreign analyst unfamiliarity hypothesis, the foreign institutional investor demand hypothesis, and the conflicts of interest hypothesis predict a positive association between foreignness and risk discussions. Taken together, I make the following prediction of the relation between analysts' geographic location (foreign vs local) and their risk discussions.

Hypothesis: Foreign analysts present more risk discussions than local analysts.

1.3 Data and Measures

1.3.1 Sample selection

Data on analysts' risk discussions is extracted from analyst research reports available on Investext from 1997 to 2019. Analyst reports from Investext are matched to the I/B/E/S international database by brokerages' names, analyst names, and the underlying firms' identifiers. To ensure matching accuracy, I require that analyst forecast dates from Investext fall between the forecast announcement dates and review dates from I/B/E/S. I then match the data with Compustat Global to obtain daily stock return, turnover, and annual financial data. I adjust for the discrepancies in the underlying currencies between I/B/E/S and Investext by using daily exchange rates from Compustat.

I use analysts' telephone numbers disclosed in their reports to detect their calling codes, then match calling codes to country calling codes to identify analysts' domicile countries. Therefore, the sample starts with 871,714 analyst reports that identify analysts' telephone numbers. I restrict the sample to firms that are covered by both local and foreign analysts in the sample period, and therefore I delete 318,683 observations. Finally, I delete 11,400 observations with missing values of control variables used in the main tests. The final sample consists of

541,631 analyst reports issued by 10,544 analysts from 12 brokerage firms covering 5,495 firms from 38 countries around the world. The sample size varies with robustness tests and different hypothesis tests. Appendix 1.B describes the sample selection procedures.

1.3.2 Measures

1.3.2.1 Analysts' risk discussions

Following Kravet and Muslu (2013), I use a dictionary-based approach to count the number of risk-related keywords in analyst reports. As analysts may have different writing styles, some being verbose and the others being more concise, I control this effect by focusing on analysts' risk discussions on the first page of their reports. In a typical research report, analysts often present the most important information such as their quantitative estimates, valuation, and risks on the first page. I apply the following procedures to measure analysts' overall risk discussions and risk discussions in various categories.

The first step is to detect the overall risk discussions on the first page of analyst reports. Appendix 1.C lists risk-related keywords in alphabetical order. The top five frequently discussed phrases are "risk", "could", "may", "potential", and "risks". Appendix 1.D provides samples on the first pages of analyst reports with risk keywords highlighted. I measure overall risk discussions with *Risk*, the number of risk-related keywords discussed on the first page of an analyst report, and *Riskpct*, the number of risk-related keywords discussed scaled by the total number of words on the first page of an analyst report.

The second step is to identify the categories of risk discussions. I divide the risk discussions into five categories.[7] One category is forward-looking statement risk, which

[7] The categories are not fully exclusive. For instance, the keyword "market" belongs to both firm-level and macroeconomic-level dictionaries.

recognizes whether the risk discussion is about the future. Hutton, Lee and Shu (2012) find that analysts' information advantage relative to the management differs with respect to firm-, industry-, and macroeconomic-level information. I further investigate whether geographic location matters for analysts' risk discussions in the firm, industry, and macroeconomic categories. Moreover, as local analysts live in the same country as the firm headquarters, they are expected to know the firm country institutions, especially the regulation and litigation, better than foreign analysts. To test this, I construct the measure of regulation and litigation risk discussion.

Appendix 1.C lists the top 50 keywords used to detect the categories of forward-looking, firm, industry, regulation and litigation, and macroeconomic statements. The top five frequently discussed forward-looking phrases are "will", "estimate", "we expect", "forecast", and "we estimate". The firm-specific keyword list is based on the financial and other idiosyncratic lists from Campbell et al. (2014). The top five frequently discussed firm-related phrases are "market", "eps", "earnings", "sales", and "business". The top five frequently discussed industry-related phrases are "industry", "competition", "competitive", "industrial", and "competitors". The top five frequently discussed regulation and litigation phrases are "regulatory", "contract", "contracts", "legal", and "fda". The top five frequently discussed macroeconomic phrases are "market", "markets", "global", "economic", and "domestic".

To capture the category of risk discussion, I examine whether the sentence with risk discussions, identified from the first step, includes any keywords of the five categories. For example, below is the sentence from the first page of an analyst report by Deutsche Bank on Crown Holdings "*Possible risks to our rating include an unforeseen spike in commodity or energy costs that the company may have difficulty passing through to its customers on a timely* *basis, as well as slower than expected start-up of the company's new assets and expansion plans.*" This sentence includes "possible", "risks" and "may" keywords in the risk dictionary. It also includes "costs" and "assets" keywords in the firm category, and "commodity" and "energy" keywords in the macroeconomic category. Therefore, this sentence is classified as having both firm risk discussion and macroeconomic risk discussion.

The definitions of risk category proxies are as follows. *FLS_risk* is the number of sentences that include both risk and forward-looking statement keywords on the first page of an analyst report. *Firm_risk* is the number of sentences that include both risk and firm keywords on the first page of an analyst report. *Ind_risk* is the number of sentences that include both risk and industry keywords on the first page of an analyst report. *Regu_risk* is the number of sentences that include both risk and regulation and litigation keywords on the first page of an analyst report. *Macro_risk* is the number of sentences that include both risk and macroeconomic keywords on the first page of an analyst report. *FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct*, and *Macro_riskpct* are defined as the corresponding absolute number of risk discussions scaled by the total number of words on the first page of an analyst report.

1.3.2.2 Geographic location

Following O'Brien and Tan (2015), I measure foreign analysts with the *foreign* indicator, which equals one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. Firms' headquarter countries are obtained from Compustat Global. O'Brien and Tan (2015) obtain analyst locations from Nelson's Directory of Investment Research that stops updating analyst locations after 2008. Instead, I use analysts' telephone numbers disclosed in their reports to detect their calling codes, then match calling codes to country calling codes to identify analysts' domicile countries.

1.3.2.3 Control variables

Following Lui et al. (2007) and Joos et al. (2016), I include a set of firm characteristic variables including: *eps_std*, the 12-month standard deviation of EPS before an analyst report date; *beta*, the systematic risk calculated from the CAPM model; *preturnover*, the 12-month stock turnover ratio before an analyst report date; *logmv*, the logarithm of firm market value; *negbv*, an indicator of a negative book value; *mb*, the market value to book value; *leverage*, the leverage ratio of the underlying firm, and *idorisk*, the idiosyncratic risk of a stock calculated from the CAPM model. I also control for analyst characteristics such as the experience of following a specific firm (*firmexp*), the general experience of forecasting firms (*genexp*), and the size of the analyst's brokerage firm (*logbrsize*). In addition, I control for the number of total words in an analyst report (*logwords*). Appendix 1.A describes the definitions of all the variables used in this study.

1.3.3 Descriptive Statistics by Country and Year

Panel A of Table 1.1 presents sample details by firm headquarters country with the number of analyst reports, unique firms and analysts, and the average percentage of foreign analysts and risk discussions for each country. Around 34% of analyst reports are for firms headquartered in the United States. The United States, Japan, and Hong Kong are the countries with the lowest number of foreign analysts following firms. Not surprisingly, for firms headquartered in the United States, only 5% of the following analysts are foreign. This is because many large brokerage firms are in the United States.[8] On average, 28% of analyst reports in the final sample are from foreign analysts. Three countries—Belgium, Ireland, and Luxembourg— have foreign analysts only; I have restricted the sample to firms that are followed by both foreign and local

[8] The robustness tests in Table 1.4 show that the main findings are qualitatively unchanged when I exclude analyst reports written by analysts from the United States.

analysts, but the reason for 100% of foreign analysts in these three countries is that the underlying firms have changed their headquarters countries.

On average, there are eight risk-related keywords discussed on the first page of an analyst report. Analysts discuss more risks for firms from Ireland, Greece, and Poland, with more than ten risk words on the first page of their reports, and discuss fewer risks for firms from Bermuda, Japan, and Canada, with an average number of seven risk words on the first page of their reports. Given the variations of risk discussions across countries, I control for firm-country fixed effect in all the analyses, unless otherwise specified. For risk categories, there are on average four forward-looking statement risk discussions, eight firm-specific risk discussions, only one word for industry and regulation and litigation risk discussion, and four macroeconomic risk discussions on the first page of analyst reports.

Panel B of Table 1.1 describes the final sample by calendar year from 1997 to 2019. The reason for the fewer numbers of reports in earlier years is that many PDF files of analyst reports are saved as pictures, which are not readable by Java codes. The percentage of foreign analysts is relatively stable over the years, except that there are only 16% foreign analysts in 1997. Analysts discuss more risks on the first page of their reports in recent years, increasing from about five risk words in 1997 to more than eight risk words since 2003. I add year fixed effect in all the analyses.

Table 1. 1 Sample description

This table shows the number of observations, unique firms and analysts, and the mean value of main variables by firm country and year. *foreign* is an indicator equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. *Risk* is the number of risk-related keywords discussed on the first page of an analyst report. *FLS_risk* is the number of sentences which include both risk and forward-looking statement keywords on the first page of an analyst report. *Firm_risk* is the number of sentences which include both risk and firm-level keywords on the first page of an analyst report. *Ind_risk* is the number of sentences which include both risk and industry-related keywords on the first page of an analyst report. *Regu_risk* is the number of sentences which include both risk and regulation and litigation keywords on the first page of an analyst report. *Macro_risk* is the number of sentences which include both risk and macroeconomic-related keywords on the first page of an analyst report. The keywords list for risk and categories are in Appendix 1.C.

Panel A Sample description by firm headquarters country

Country	Obs	#Firm	#Analyst	foreign	Risk	FLS_risk	Firm_risk	Ind_risk	Regu_risk	Macro_risk
Australia	24,526	304	841	0.16	9.43	3.94	8.87	1.39	1.59	4.95
Austria	1,673	27	148	0.76	9.75	3.86	9.43	1.52	1.27	5.76
Bermuda	368	2	26	1.00	6.25	2.90	6.01	0.91	0.80	3.89
Brazil	12,090	182	347	0.58	8.02	3.18	7.61	1.36	1.56	4.11
Canada	27,953	445	836	0.71	7.69	3.77	7.24	1.12	1.34	4.24
Chile	121	1	16	0.98	9.61	3.73	9.07	2.22	2.86	5.47
China	4,510	67	291	0.92	8.15	3.43	7.78	1.80	0.78	4.87
Finland	3,401	30	261	0.80	8.70	3.81	8.35	1.61	0.82	5.29
France	17,744	182	1,115	0.83	9.00	3.88	8.53	1.28	1.39	4.50
Germany	18,622	223	1,076	0.71	9.98	4.37	9.52	1.74	1.46	5.16
Greece	1,475	32	146	0.85	10.48	4.38	9.99	1.49	1.79	5.71
Hong Kong	16,014	169	856	0.13	8.84	3.89	8.49	1.43	0.96	4.53
India	22,265	236	437	0.21	8.20	3.17	7.89	1.36	1.18	4.09
Indonesia	5,548	77	197	0.38	7.92	3.31	7.55	1.47	1.26	4.03
Ireland	737	8	57	1.00	10.77	4.72	10.26	3.34	1.80	4.22
Israel	1,154	29	82	0.84	9.34	3.94	9.01	1.79	1.53	4.51
Italy	5,196	66	426	0.74	10.02	4.47	9.45	1.17	1.70	5.17
Japan	51,441	535	656	0.09	6.80	3.67	6.56	1.27	0.63	3.70
Korea	9,412	142	365	0.25	10.11	4.43	9.83	1.90	1.60	5.18
Luxembourg	29	1	6	1.00	9.07	3.52	8.90	0.17	0.14	4.31
Malaysia	5,775	99	265	0.62	8.30	3.45	7.88	1.25	1.21	3.69
Mexico	5,602	79	216	0.66	8.53	3.44	8.11	1.74	1.47	4.54
Netherlands	4,397	56	452	0.88	8.94	4.12	8.46	1.39	1.21	4.60
New Zealand	2,263	49	147	0.44	8.68	3.62	8.08	1.69	1.60	4.30
Philippines	2,846	49	154	0.52	8.07	3.17	7.75	1.50	1.47	3.63
Poland	1,857	40	126	0.62	10.36	4.47	9.91	1.91	1.94	5.40
Russia	3,272	71	171	0.42	10.00	3.94	9.53	1.49	1.89	5.81
Saudi Arabia	565	24	40	0.93	9.66	4.18	9.37	1.50	1.30	4.74
Singapore	9,826	119	450	0.26	8.35	3.28	7.97	1.29	0.97	4.08
South Africa	7,390	107	369	0.26	10.19	4.70	9.71	1.39	1.47	5.64
Spain	6,096	59	455	0.74	9.84	4.14	9.26	1.28	1.92	5.24
Sweden	5,952	57	450	0.89	8.67	3.69	8.24	1.55	0.96	4.53
Switzerland	9,625	98	691	0.75	8.78	3.71	8.29	1.68	1.30	4.49
Taiwan	12,470	172	470	0.34	10.25	4.84	9.98	2.40	0.76	4.79
Thailand	6,330	87	235	0.56	8.45	3.72	8.06	1.22	1.12	4.07
Turkey	981	15	79	0.96	10.08	3.87	9.73	1.25	1.77	5.56
United Kingdom	46,928	460	2,226	0.14	9.55	4.28	9.02	1.42	1.64	4.85
United States	185,177	1,253	3,369	0.05	7.72	3.52	7.33	1.42	1.21	3.61
Total/Mean	541,631	5,495	10,544	0.28	8.37	3.76	7.96	1.43	1.25	4.20

Panel B Sample description by year

Year	Obs	#Firm	#Analyst	foreign	Risk	FLS_risk	Firm_risk	Ind_risk	Regu_risk	Macro_risk
1997	1,608	638	415	0.16	5.07	2.50	4.78	0.82	0.69	2.00
1998	3,948	1,298	926	0.29	5.36	2.62	5.02	0.87	0.77	2.45
1999	5,985	1,669	1,139	0.29	5.25	2.60	4.87	0.81	0.72	2.27
2000	11,080	2,213	1,775	0.31	4.96	2.43	4.58	0.76	0.61	2.20
2001	17,249	2,461	2,206	0.32	5.67	2.72	5.27	0.82	0.73	2.68
2002	19,416	2,600	2,283	0.29	6.78	3.01	6.40	1.08	0.90	3.04
2003	22,090	2,595	2,220	0.28	8.34	3.84	7.89	1.59	1.24	4.07

2004	23,278	2,647	2,187	0.26	8.42	3.92	7.97	1.60	1.26	4.05
2005	23,530	2,765	2,124	0.27	8.50	3.97	8.07	1.60	1.30	4.05
2006	20,678	2,864	1,682	0.27	8.10	3.82	7.69	1.44	1.22	3.97
2007	23,772	3,171	1,995	0.27	8.49	3.86	8.06	1.46	1.26	4.15
2008	26,437	3,296	2,085	0.28	9.02	4.06	8.58	1.45	1.29	5.03
2009	27,489	3,183	1,869	0.29	8.94	4.09	8.57	1.40	1.29	4.74
2010	29,583	3,265	2,050	0.27	8.85	4.04	8.44	1.48	1.36	4.51
2011	34,310	3,454	2,316	0.26	8.93	3.91	8.49	1.55	1.35	4.68
2012	36,014	3,505	2,409	0.27	8.93	3.95	8.52	1.49	1.35	4.58
2013	36,000	3,551	2,254	0.27	9.11	4.09	8.70	1.49	1.36	4.57
2014	37,893	3,605	2,220	0.28	8.73	3.91	8.35	1.45	1.35	4.34
2015	38,058	3,570	2,185	0.30	8.51	3.84	8.14	1.45	1.25	4.35
2016	36,086	3,479	2,124	0.30	8.86	3.83	8.47	1.53	1.35	4.62
2017	34,011	3,307	2,033	0.31	8.59	3.62	8.20	1.54	1.33	4.28
2018	20,936	2,868	1,766	0.28	8.16	3.50	7.78	1.53	1.28	4.00
2019	12,182	924	859	0.20	8.05	3.38	7.68	1.52	1.29	3.87

1.3.4 Summary Statistics, Correlation, and Univariate Analysis

Panel A of Table 1.2 shows the summary statistics of key variables. About 28% of analysts are domiciled in countries different from the underlying firm's headquarters country in their reports. On average, 1.12% of words on the first page of an analyst report are about risk, among which 0.49% are on forward-looking statement risk, 1.06% are about firm-specific risk, 0.19% are about industry risk, 0.16% are about regulation and litigation risk, and 0.55% are about macroeconomic risk. The average volatility of earnings per share and stock turnover ratio 12 months before the issuance of a report are 1.47 and 0.2, respectively. The systematic and idiosyncratic risks are 1.01 and 30.26, respectively. The mean value of *logmv* is 8.64. About 2% of firms have a negative book value. The mean value of *leverage* is 0.58. On average, analysts have firm experience of 4.31 years and a general working experience of 8.48 years. The logarithm of brokerage firm size is 5.64, and the logarithm of total words in an analyst report is 6.67.

Panel B of Table 1.2 presents the Pearson correlations of the foreign analyst indicator and risk discussions. The *foreign* indicator is significantly positively associated with the overall risk discussions (*Risk*) and the percentage of risk discussions among the words on the first pages (*Riskpct*). Moreover, *foreign* is significantly positively associated with risk category discussions such as *FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct* and *Macro_riskpct.*

Panel C of Table 1.2 shows univariate comparisons of risk discussions by foreign and local analysts. On average, local analysts discuss eight risk words (1.098% of first page words), and foreign analysts discuss nine risk words (1.179% of first page words). The difference is significant at the 1% level, suggesting that foreign analysts discuss more risk information than local analysts. In addition to the overall risk, foreign analysts also present more discussions for each risk category relative to local analysts.

Table 1. 2 Summary statistics, correlations, and univariate analysis

Panel A shows the summary statistics of the main variables used in the empirical analyses. *foreign* is an indicator equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. *Risk* is the number of risk-related keywords discussed on the first page of an analyst report. The risk discussion variables such as *FLS_risk*, *Firm_risk*, *Ind_risk, Regu_risk,* and *Macro_risk* are defined as the number of sentences including both risk and the category-related keywords on the first page of an analyst report. *Riskpct, FLS_riskpct, Firm_riskpct, Ind_riskpct, Regu_riskpct,* and *Macro_riskpct* are the absolute number of risk discussions scaled by the total number of words on the first page of an analyst report. Other variables are as defined in Appendix 1.A. Panel B shows the Pearson correlation analysis, and Panel C presents the Univariate analysis of risk discussions by geographic location.

Panel A Summary statistics

Variable	Mean	Std	P10	P25	Median	P75	P90
foreign	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Risk	8.37	7.05	1.00	3.00	7.00	12.00	18.00
FLS_risk	3.76	4.05	0.00	1.00	3.00	6.00	9.00
Firm_risk	7.96	6.81	1.00	3.00	6.00	12.00	18.00
Ind_risk	1.43	2.58	0.00	0.00	0.00	2.00	5.00
Regu_risk	1.25	2.53	0.00	0.00	0.00	1.00	4.00
Macro_risk	4.20	4.75	0.00	0.00	3.00	6.00	11.00
Riskpct	1.12	0.80	0.18	0.52	1.00	1.58	2.22
FLS_riskpct	0.49	0.48	0.00	0.11	0.38	0.74	1.16
Firm_riskpct	1.06	0.77	0.14	0.48	0.94	1.51	2.12
Ind_riskpct	0.19	0.33	0.00	0.00	0.00	0.25	0.64
Regu_riskpct	0.16	0.33	0.00	0.00	0.00	0.19	0.58
Macro_riskpct	0.55	0.57	0.00	0.00	0.39	0.85	1.36
eps_std	1.47	1.80	0.15	0.29	0.66	1.84	4.53
beta	1.01	0.47	0.44	0.69	0.97	1.27	1.60
preturnover	0.20	0.28	0.01	0.01	0.06	0.30	0.56
logmv	8.64	1.53	6.71	7.58	8.59	9.66	10.65
negbv	0.02	0.14	0.00	0.00	0.00	0.00	0.00

mb	2.78	4.79	0.02	0.46	1.63	3.31	6.17
leverage	0.58	0.22	0.28	0.43	0.58	0.74	0.90
idiorisk	30.26	157.06	0.93	1.57	3.14	7.40	21.83
firmexp	4.31	4.06	0.31	1.13	3.03	6.38	10.38
genexp	8.48	5.35	1.84	4.12	7.77	12.23	16.21
logbrsize	5.64	0.56	4.88	5.42	5.88	5.98	6.10
logwords	6.67	0.98	5.67	6.10	6.64	7.26	7.84

Panel B Pearson correlation analysis

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*foreign*	1.000						
(2)	*Risk*	0.051***	1.000					
(3)	*Riskpct*	0.046***	0.792***	1.000				
(4)	*FLS_riskpct*	0.020***	0.560***	0.640***	1.000			
(5)	*Firm_riskpct*	0.045***	0.791***	0.971***	0.642***	1.000		
(6)	*Ind_riskpct*	0.011***	0.356***	0.395***	0.240***	0.408***	1.000	
(7)	*Regu_riskpct*	0.020***	0.351***	0.381***	0.258***	0.374***	0.192***	1.000
(8)	*Macro_riskpct*	0.053***	0.599***	0.698***	0.460***	0.708***	0.369***	0.277***

Panel C Univariate analysis

Variables	Local analysts (Obs. 390,012)	Foreign analysts (Obs. 151,619)	Difference
Risk	8.144	8.945	-0.801***
Riskpct	1.098	1.179	-0.081***
FLS_riskpct	0.487	0.509	-0.022***
Firm_riskpct	1.039	1.115	-0.076***
Ind_riskpct	0.182	0.191	-0.008***
Regu_riskpct	0.158	0.172	-0.015***
Macro_riskpct	0.531	0.599	-0.068***

1.4 Geographic Location and Analysts' Risk Discussions

1.4.1 Baseline tests

Table 1.3 reports the results of OLS regressions estimating the effect of geographic location on analysts' risk discussions. The regression model takes the following general form:

$$\begin{aligned} Risk\ Discussion_{ijqt} = {} & \alpha_1 + \alpha_2 foreign_{jt} + \alpha_3 eps\_std_{it} + \alpha_4 beta_{it} + \alpha_5 preturnover_{it} + \\ & \alpha_6 logmv_{it} + \alpha_7 negbv_{it} + \alpha_8 mb_{it} + \alpha_9 leverage_{it} + \alpha_{10} idiorisk_{it} + \\ & \alpha_{11} firmexp_{ijt} + \alpha_{12} genexp_{jt} + \alpha_{13} logbrsize_{jt} + \alpha_{14} logwords_{ijqt} + \\ & Industry\ FE + Year\ FE + Country\ FE + \varepsilon \end{aligned}$$

where subscript *i* refers to firm, *j* refers to analyst, *q* refers to quarter, and *t* refers to year, respectively.

Panel A shows the tests with overall risk discussions; *Risk* in column (1) and *Riskpct* in column (2) are the dependent variables. I use a *foreign* dummy, which equals one if an analyst's domicile country is different from the underlying firm's headquarters country and zero otherwise, to differentiate foreign and local analysts. In addition to the control variables described in section 3.2.3, I also control for firm country, year, and industry fixed effects. Industry fixed effects use the Fama and French 12-industry classification. The standard errors are adjusted for two-way clustering at the firm and analyst levels to correct for potential error correlations within the groups.

Panel A of Table 1.3 shows that the coefficients on *foreign* are significantly positive, suggesting that foreign analysts present more risk discussions on the first page of their reports compared with local analysts. In addition, it shows that analysts discuss more risks for the underlying firms with higher systematic risk, stock turnover ratio, firm size, leverage ratio, and idiosyncratic risk. The results related to firm characteristics are largely consistent with the findings in Lui et al. (2007). Analysts discuss less risk information when they have more firm experience and general working experience. Analysts also tend to discuss more risks if their reports contain more words.

Panel B of Table 1.3 examines whether the association between foreignness and analysts' risk discussions varies with risk categories. The dependent variables in columns (1) to (5) are *FLS_risk*, *Firm_risk, Ind_risk, Regu_risk,* and *Macro_risk*, defined as the absolute number of sentences including both risk and the category-related keywords on the first page of an analyst report, and in columns (6) to (10) are *FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct* and *Macro_riskpct*, the percentage of words related to risk category discussion.

Foreign is significantly positively associated with *FLS_risk* in column (1) and to *FLS_riskpct* in column (6), suggesting that foreign analysts discuss more forward-looking statement risks compared with local analysts. In columns (2) and (7), *foreign* is significantly positively associated with *Firm_risk* and *Firm_riskpct* respectively, suggesting that foreign analysts discuss more firm-specific risks compared with their local counterparts. The coefficients on *foreign* are positive but insignificant for columns (3) to (5) and columns (8) to (10), suggesting that foreign analysts are not significantly different from local analysts in discussing industry, regulation and litigation, and macroeconomic risks.

Overall, the findings in Table 1.3 suggest that foreign analysts present more risk discussions than local analysts, especially for forward-looking statement risk and firm-specific risk.

Table 1. 3 Geographic location and analysts' risk discussions

Panel A presents the tests on the effect of geographic location on analysts' total risk discussions on the first page of their reports. The independent variable *foreign* is an indicator equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. The dependent variables are *Risk* in column (1), the number of risk keywords discussed on the first page of an analyst report, and *Riskpct* in column (2), *Risk* scaled by the total number of words discussed on the first page of an analyst report. Panel B examines whether the relation between analysts' geographic locations and their risk discussions varies with risk categories. The dependent variables in columns (1) to (5) are *FLS_risk*, *Firm_risk*, *Ind_risk*, *Regu_risk,* and *Macro_risk*, defined as the number of sentences including both risk and the category-related keywords on the first page of an analyst report, and in columns (6) to (10) are *FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct,* and *Macro_riskpct,* the percentage of risk category discussion. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

Panel A Total risk discussions

	(1) *Risk*	(2) *Riskpct*
foreign	**0.204****	**0.029*****
	(2.25)	**(2.59)**
eps_std	0.005	0.001
	(0.43)	(0.64)
beta	0.126**	0.014*

	(2.05)	(1.70)
preturnover	0.463***	0.047***
	(4.35)	(3.54)
logmv	0.051**	0.002
	(2.34)	(0.56)
negbv	0.181	0.019
	(1.16)	(0.94)
mb	-0.001	-0.001
	(-0.30)	(-1.04)
leverage	0.486***	0.040*
	(2.91)	(1.88)
idiorisk	0.000***	0.000
	(2.63)	(1.63)
firmexp	-0.047***	-0.006***
	(-5.24)	(-5.12)
genexp	-0.017	-0.003*
	(-1.48)	(-1.94)
logbrsize	-0.029	0.009
	(-0.31)	(0.77)
logwords	3.889***	0.148***
	(89.47)	(31.97)
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES
Observations	541,631	541,631
Adjusted R^2	0.321	0.076

Panel B Analysts' risk discussions in different categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FLS_risk	*Firm_risk*	*Ind_risk*	*Regu_risk*	*Macro_risk*	*FLS_riskpct*	*Firm_riskpct*	*Ind_riskpct*	*Regu_riskpct*	*Macro_riskpct*
foreign	**0.131*** **	**0.182** **	**0.048**	**0.009**	**0.089**	**0.017*** **	**0.026** **	**0.004**	**0.002**	**0.010**
	(2.75)	**(2.06)**	**(1.47)**	**(0.27)**	**(1.38)**	**(3.08)**	**(2.48)**	**(1.00)**	**(0.36)**	**(1.28)**
eps_std	0.012*	0.000	-0.021***	0.002	0.000	0.002**	0.000	-0.003***	0.001	0.000
	(1.71)	(0.03)	(-4.20)	(0.31)	(0.01)	(2.20)	(0.31)	(-4.03)	(0.82)	(0.35)
beta	0.112***	0.119**	-0.120***	-0.056*	0.284***	0.014***	0.012	-0.014***	-0.009**	0.037***
	(3.25)	(2.00)	(-4.61)	(-1.78)	(6.10)	(3.16)	(1.53)	(-4.19)	(-2.11)	(5.85)
preturnover	0.407***	0.419***	0.087*	0.076	0.161*	0.048***	0.040***	0.005	0.009	0.013
	(6.63)	(4.09)	(1.65)	(1.37)	(1.84)	(6.44)	(3.18)	(0.79)	(1.32)	(1.17)
logmv	0.060***	0.028	0.008	0.016	0.088***	0.005***	-0.002	0.000	0.002	0.009***
	(5.33)	(1.34)	(0.81)	(1.48)	(5.55)	(3.28)	(-0.77)	(0.06)	(1.24)	(4.14)
negbv	0.096	0.026	0.146*	0.000	0.073	0.010	-0.001	0.017*	-0.002	0.010
	(1.14)	(0.17)	(1.86)	(0.00)	(0.58)	(0.93)	(-0.07)	(1.65)	(-0.21)	(0.64)
mb	-0.004	-0.007	0.009***	-0.003	-0.001	-0.001	-0.001**	0.001***	-0.000	-0.000
	(-1.19)	(-1.38)	(3.36)	(-1.22)	(-0.30)	(-1.64)	(-2.37)	(2.92)	(-1.35)	(-0.94)
leverage	0.056	0.682***	0.085	0.446***	-0.155	-0.005	0.064***	0.008	0.056***	-0.034**
	(0.62)	(4.28)	(1.26)	(5.34)	(-1.26)	(-0.48)	(3.17)	(0.88)	(5.22)	(-2.13)
idiorisk	0.000**	0.000**	-0.000	0.000	0.000***	0.000**	0.000	-0.000**	0.000	0.000**
	(2.55)	(2.33)	(-1.30)	(0.89)	(3.20)	(2.16)	(1.19)	(-2.01)	(0.30)	(2.49)
firmexp	-0.016***	-0.045***	-0.015***	-0.009***	-0.038***	-0.002***	-0.005***	-0.002***	-0.001***	-0.004***

	(-3.06)	(-5.14)	(-4.64)	(-2.65)	(-6.31)	(-3.08)	(-4.95)	(-4.10)	(-2.68)	(-5.34)
genexp	-0.015**	-0.014	0.005	-0.004	-0.000	-0.002***	-0.003*	0.001	-0.001	-0.001
	(-2.47)	(-1.29)	(1.39)	(-0.95)	(-0.02)	(-2.78)	(-1.89)	(1.34)	(-1.02)	(-0.58)
logbrsize	-0.097*	-0.027	0.025	-0.074**	-0.072	0.000	0.008	0.001	-0.009**	-0.005
	(-1.90)	(-0.31)	(0.77)	(-2.23)	(-1.12)	(0.08)	(0.72)	(0.30)	(-2.08)	(-0.59)
logwords	1.824***	3.723***	0.701***	0.579***	2.053***	0.084***	0.157***	0.039***	0.029***	0.102***
	(83.97)	(89.10)	(52.01)	(39.90)	(75.60)	(34.53)	(36.09)	(28.78)	(23.04)	(35.87)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631	541,631	541,631	541,631	541,631	541,631	541,631
Adjusted R^2	0.209	0.315	0.102	0.109	0.220	0.052	0.084	0.047	0.069	0.085

1.4.2 Robustness tests

Although foreign analysts face an information disadvantage compared with local analysts, this study shows that foreign analysts discuss more risks than their local counterparts. I conduct the following tests to seek further corroborating evidence.

First, instead of using the first page of analyst reports, I extract analysts' risk discussions from their full research reports. Panel A of Table 1.4 reports the tests. The dependent variables *Risk2pct*, *FLS_risk2pct*, *Firm_risk2pct*, *Ind_risk2pct*, *Regu_risk2pct*, and *Macro_risk2pct* are defined as the absolute number of corresponding risk discussions in full analyst reports scaled by the total number of words in their reports. I find that *foreign* is significantly positively related to *Risk2pct*, *FLS_risk2pct*, and *Firm_risk2pct*, consistent with the findings in Table 1.3.

Second, I use an alternative risk dictionary to detect analysts' risk discussions. The new dictionary consists of strong risk indicators, labeled as the risk key dictionary (rkk), which consists of "risk", "risks", "risking", "risky", "riskier", "upside", "downside", "concern", "concerns", "concerned", "catalysts", "sensitivity", "uncertainty", "uncertain" and "uncertainties"[9]. Panel B of Table 1.4 reports the tests with the risk key dictionary used to

[9] Due to fewer keywords for risk identification, unreported summary statistics show that there are on average four risk-related words discussed on the first page of analyst reports using the "rkk" dictionary.

identify the extent of analysts' risk discussions. The dependent variables are *Rkkpct, FLS_rkkpct, Firm_rkkpct, Ind_rkkpct, Regu_rkkpct,* and *Macro_rkkpct,* defined as the absolute number of corresponding risk discussions based on the "rkk" dictionary scaled by the number of words on the first page of the reports. The results show stronger evidence that foreign analysts present more discussions on overall risk, forward-looking statement risk, and firm-specific risk. Moreover, there is some evidence that foreign analysts also discuss more industry and macroeconomic risks compared with local analysts.

Third, I restrict the analysis to the subsample in which analysts from the United States are excluded. This is to address the concern that it is generally the U.S. analysts, and not foreign analysts, who are discussing more risks. Panel C of Table 1.4 reports the tests. The coefficients on *foreign* are significantly positive, except for column (5) with *Regu_riskpct* being the dependent variable. The findings suggest that non-U.S. foreign analysts present more risk discussions than local analysts.[10]

Finally, I restrict the analysis to the subsample in which a firm is followed by at least one local and one foreign analyst in a given year. For such a firm, if foreign analysts present more risk discussions than local analysts, I expect the major reason is the geographic location. The results are reported in Panel D of Table 1.4. Consistently, I find that foreign analysts present more discussions on overall risk, forward-looking statement risk, and firm-specific risk.

Table 1. 4 Robustness tests

Panel A presents the tests on analysts' risk discussions in their full reports. The dependent variables are *Risk2pct, FLS_risk2pct, Firm_risk2pct, Ind_risk2pct, Regu_risk2pct,* and *Macro_risk2pct* from columns (1) to (6), respectively, defined as the absolute number of corresponding risk discussions in full analyst reports scaled by the number of total words in their reports. In Panel B, I use another list of risk keywords (*rkk*) to detect analysts' risk discussions. From columns (1) to (6), the dependent variables are *Rkkpct, FLS_rkkpct, Firm_rkkpct, Ind_rkkpct, Regu_rkkpct,* and *Macro_rkkpct*, respectively, defined as the absolute number of corresponding risk discussions based on "rkk" dictionary scaled by the number of words on the first page of their reports. Panel C reports the tests in the subsample excluding analysts from the United States. Panel D presents the tests in the subsample in which a firm is followed by at least one local and one foreign analyst in a calendar year. The independent variable *foreign* is

[10] The findings are qualitatively unchanged if I exclude U.S. firms from the final sample.

an indicator, equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. Control variables are the same as in Table 1.3 and are not reported for brevity. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

Panel A Analysts' risk discussions in their full research reports

	(1)	(2)	(3)	(4)	(5)	(6)
		Risk Category				
	Risk2pct	*FLS_risk2pct*	*Firm_risk2pct*	*Ind_risk2pct*	*Regu_risk2pct*	*Macro_risk2pct*
foreign	0.025**	0.014**	0.023**	0.002	-0.002	0.009
	(2.16)	(2.45)	(2.11)	(0.49)	(-0.40)	(1.06)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631	541,631	541,631
Adjusted R^2	0.067	0.044	0.073	0.050	0.080	0.084

Panel B Alternative risk dictionary used to detect analysts' risk discussions

	(1)	(2)	(3)	(4)	(5)	(6)
		Risk Category				
	Rkkpct	*FLS_rkkpct*	*Firm_rkkpct*	*Ind_rkkpct*	*Regu_rkkpct*	*Macro_rkkpct*
foreign	0.032***	0.016***	0.030***	0.005*	0.002	0.011**
	(4.14)	(4.79)	(3.95)	(1.66)	(0.64)	(2.18)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631	541,631	541,631
Adjusted R^2	0.078	0.045	0.081	0.040	0.055	0.073

Panel C Subsample in which analysts from the United States are excluded

	(1)	(2)	(3)	(4)	(5)	(6)
		Risk Category				
	Riskpct	*FLS_riskpct*	*Firm_riskpct*	*Ind_riskpct*	*Regu_riskpct*	*Macro_riskpct*
foreign	0.043***	0.024***	0.038***	0.011*	-0.007	0.018*
	(2.94)	(3.48)	(2.74)	(1.91)	(-1.43)	(1.68)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	315,964	315,964	315,964	315,964	315,964	315,964
Adjusted R^2	0.075	0.056	0.085	0.054	0.068	0.078

Panel D Subsample in which a firm is followed by at least one local and one foreign analyst in one year

	(1)	(2)	(3)	(4)	(5)	(6)
		Risk Category				
	Riskpct	*FLS_riskpct*	*Firm_riskpct*	*Ind_riskpct*	*Regu_riskpct*	*Macro_riskpct*
foreign	0.035***	0.015**	0.032***	0.005	-0.000	0.016*
	(2.94)	(2.47)	(2.85)	(1.16)	(-0.11)	(1.90)

Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	214,552	214,552	214,552	214,552	214,552	214,552
Adjusted R^2	0.077	0.057	0.084	0.059	0.066	0.080

1.4.3 Why do foreign analysts present more risk discussions than local analysts?

So far, there is strong evidence that foreign analysts discuss more risks than local analysts. In this section, I explore possible explanations for these results. Section 2 provides various hypotheses on the associations between foreignness and risk discussions. I find no support for the foreign analyst information disadvantage hypothesis which predicts that foreign analysts discuss less risk information than local analysts. I therefore investigate the hypotheses predicting that foreign analysts discuss more risks than local analysts, namely, the foreign analyst unfamiliarity hypothesis, the foreign institutional investor demand hypothesis, and the conflicts of interest hypothesis.

1.4.3.1 Foreign analyst unfamiliarity hypothesis

This hypothesis predicts that foreign analysts discuss more risks because their unfamiliarity with the underlying firms headquartered in a different country intensifies their sensitivity to the risk information. If so, I predict that the positive relation between foreignness and risk discussions will be mitigated when the level of unfamiliarity is reduced. I capture the level of unfamiliarity in three ways. The first one is the time span of a foreign analyst's coverage. The level of unfamiliarity will be reduced with the increase of time span of a foreign analyst tracking the underlying firm. The second one is the analyst team composition. I expect that the level of unfamiliarity can be reduced if the foreign analyst team has local analyst(s). The last one is analyst location change. The level of unfamiliarity can be reduced after a foreign analyst moves to the country where the underlying firm is headquartered. The relevant tests are reported in Table 1.5. The dependent variables are overall risk discussions proxied by *Riskpct* and *Risk.*[11]

Panel A of Table 1.5 examines whether the time span of a foreign analyst's coverage affects risk discussions. The independent variables are *foreign2yr*, which equals one if the foreign analyst has followed the firm for less than two years, and zero otherwise, and *foreignover2yr*, which equals one if the foreign analyst has followed the firm for more than two years, and zero otherwise. I find that *foreign2yr* is significantly positively associated with *Riskpct* and *Risk,* but *foreignover2yr* is not significantly positively associated with *Riskpct* and *Risk.* Furthermore, the coefficients on *foreign2yr* are larger than the coefficients on *foreignover2yr* in both columns (1) and (2). The findings suggest that foreign analysts discuss more risks than local analysts in the earlier years of their following when the level of unfamiliarity is heightened, but there is no significant difference between foreign and local analysts in risk discussions when the level of unfamiliarity is alleviated with the increase of foreign analysts' tracking experience.

Panel B of Table 1.5 examines analyst team composition and risk discussions. The independent variables are *mixlocfor,* which equals one if a report is written by both local and foreign analysts, and zero otherwise, and *foreignpure,* which equals one if a report is written by foreign analyst(s) only, and zero otherwise. In column (1), the coefficient on *foreignpure* is significantly positive and larger than the coefficient on *mixlocfor* with *Riskpct* being the dependent variable. The finding is consistent with the prediction that the level of unfamiliarity is reduced when foreign analyst teams have local analyst(s), and thus the foreign analysts do not discuss risks significantly differently from local analysts. In column (2), both *mixlocfor* and

[11] For the sake of brevity, I report only the tests with overall risk discussions as dependent variables. The findings are qualitatively similar to the findings in Table 1.3 if I use risk category discussions as dependent variables.

foreignpure are significantly positively related to *Risk*, which seems to suggest that the teamwork between foreign and local analysts does not impact the absolute quantity of overall risk discussions.

Table 1. 5 Foreign analysts' unfamiliarity hypothesis

In Panel A, I estimate whether the time span of a foreign analyst's coverage is related to risk discussions. *foreign2yr* equals one if the foreign analyst has followed the firm for less than two years, and zero otherwise. *foreignover2yr* equals one if the foreign analyst has followed the firm for more than two years, and zero otherwise. In Panel B, I examine whether analysts' team composition affects their risk discussions. *mixlocfor* equals to one if a report is written by both local and foreign analysts, and zero otherwise. *foreignpure* equals to one if a report is written only by foreign analyst(s), and zero otherwise. In Panel C, I examine whether an analyst's location change affects the level of risk discussions. *chgtolocal* equals to one after an analyst becomes a local as a result of her location change, and zero before the location change. The dependent variables are analysts' risk discussions denoted by *Riskpct* and *Risk*, which are the same as those in Table 1.3. Control variables are the same as in Table 1.3 and are not reported for brevity. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

Panel A Time span of foreign coverage and risk discussions

	(1)	(2)
	Riskpct	*Risk*
foreign2yr	0.032***	0.230***
	(3.03)	(2.70)
foreignover2yr	0.024	0.153
	(1.60)	(1.26)
Controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES
Observations	541,631	541,631
Adjusted R^2	0.076	0.321

Panel B Analyst team composition and risk discussions

	(1)	(2)
	Riskpct	*Risk*
mixlocfor	0.022	0.351**
	(1.12)	(2.19)
foreignpure	0.040***	0.253***
	(3.39)	(2.67)
Controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES
Observations	541,631	541,631
Adjusted R^2	0.076	0.321

Panel C Analysts' location change and risk discussions

	(1) *Riskpct*	(2) *Risk*
chgtolocal	-0.017	-0.033
	(-0.68)	(-0.16)
Controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES
Observations	18,868	18,868
Adjusted R^2	0.110	0.327

Panel C of Table 1.5 reports the tests in the subsample in which a foreign analyst becomes a local analyst as a result of her location change. In the subsample, the analyst is required to follow a firm when she is foreign and to continue to follow the firm after she moves and becomes a local analyst. I examine analyst reports that are published up to five years around the location changes. The sample size of 18,868 analyst reports reflects the fact that not many foreign analysts change their country of residence. The independent variable is *chgtolocal,* equal to one after an analyst becomes a local as a result of her location change, and zero before the location change. The coefficients on *chgtolocal* are negative but insignificant in both columns (1) and (2). This provides some weak evidence that a foreign analyst discusses less risk information when the level of unfamiliarity is reduced due to the location change.

Taken together, I find that for most cases, when the level of unfamiliarity is reduced, foreign analysts present less risk discussion. This is consistent with the unfamiliarity hypothesis that foreign analysts discuss more risks because of their unfamiliarity with the underlying firms.

So far, I have tested the foreign analyst unfamiliarity hypothesis with the change of the level of unfamiliarity. Next, I examine the effect of foreignness on risk discussions in cross-sectional analyses by interacting the foreignness dummy with proxies for analysts' ability and firm country institutional environment. Analysts' sensitivity to risk arising from unfamiliarity can be alleviated for analysts with strong personal ability and for firm countries with a better institutional environment. If the unfamiliarity hypothesis works, it would imply that strong analysts' ability and good firm country institutions would mitigate the positive association between foreignness and risk discussions. Table 1.6 reports the tests with dependent variables being the overall risk discussions proxied by *Riskpct* and *Risk*.

Panel A of Table 1.6 examines the impact of analysts' ability on the relation between foreignness and risk discussions. I consider two aspects of an analyst's ability. One is an analyst's ability in analyzing foreign firms, measured with *foreignfirmexp*, the number of foreign firms followed by an analyst in one year. The other is an analyst's industry expertise, measured with *indexp*, the number of firms an analyst has followed for an industry in one year. *AnaTrait* denotes *foreignfirmexp* in columns (1) and (3), and *indexp* in columns (2) and (4). I find that the coefficients on *foreign* are still significantly positive, but coefficients on the interaction of *foreign*AnaTrait* are significantly negative in all regressions. The findings suggest that analysts' experience in analyzing foreign firms and using industrial knowledge mitigate the effect of foreignness on risk discussions, consistent with the argument that analysts' strong personal ability alleviates their sensitivity to risk information arising from unfamiliarity.

Table 1. 6 Cross-sectional analyses on analysts' ability and firm country institutional environment

This table presents the regressions of the effect of geographic location on analysts' risk discussions with analysts' ability interactions in Panel A and firm country characteristics interactions in Panel B. The dependent variables are analysts' risk discussions denoted by *Riskpct* and *Risk*, which are the same as those in Table 1.3. The independent variable *foreign* is an indicator equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. In Panel A, I use *foreignfirmexp*, the number of foreign firms followed by an analyst in one year, to measure an analyst's ability in analyzing foreign firms. I use *indexp*, the number of firms an analyst has followed in an industry in one year, to measure an analyst's industry expertise. *AnaTrait* denotes *foreignfirmexp* or *indexp* from columns (1) to (4) listed in the third row of Panel A. The firm country characteristics are as follows in Panel B. I use anti-director rights index (*antidir*) and anti-self-dealing index (*anti_dealing*) from Djankov et al. (2008) to capture the extent of investor protection in a firm country. I use *cifar*, a country's index of financial disclosures from the Center for International Financial Analysis and Research (CIFAR), and *earnmgmt*, the negative value of the index of earnings management of a country (Leuz et al., 2003), to measure the information environment of a firm country. I use *trust*, the level of trust in a country from the World Value Survey, to measure the informal institutional environment of a firm country. All the firm country variables are dummies that equal one if their values are above the median of the countries in the sample, and zero otherwise. *CtryTrait* denotes *antidir, anti_dealing, cifar, earnmgmt,* and *trust* from columns (1) to (10) listed in the third row of Panel B. Control variables are the same as in Table 1.3 and are not reported for brevity. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

Panel A Analysts' ability interacted with foreign analyst indicator

	(1)	(2)	(3)	(4)
	Dependent variable: Riskpct		*Dependent variable: Risk*	
	foreignfirmexp	*indexp*	*foreignfirmexp*	*indexp*
foreign	0.076***	0.051***	0.529***	0.400***
	(5.29)	(3.52)	(4.51)	(3.47)
AnaTrait	0.007***	-0.001	0.049***	-0.005
	(2.75)	(-0.61)	(2.66)	(-0.51)
*foreign*AnaTrait*	-0.011***	-0.003*	-0.081***	-0.025**
	(-4.19)	(-1.70)	(-3.79)	(-1.97)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631
Adjusted R^2	0.077	0.076	0.321	0.321

Panel B Firm country characteristics interacted with foreign analyst indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Riskpct					*Dependent variable: Risk*				
	antidir	*anti_dealing*	*cifar*	*earnmgmt*	*trust*	*antidir*	*anti_dealing*	*cifar*	*earnmgmt*	*trust*
foreign	0.086***	0.074***	0.074***	0.050***	0.023	0.676***	0.567***	0.596***	0.301***	0.239*
	(5.31)	(5.99)	(5.88)	(3.87)	(1.38)	(5.22)	(5.81)	(5.90)	(3.06)	(1.74)
CtryTrait	0.038**	0.085***	0.073***	-0.100***	0.013	0.370***	0.615***	0.584***	-0.844***	0.166*
	(2.37)	(5.67)	(4.78)	(-6.58)	(1.00)	(3.02)	(5.35)	(4.90)	(-7.19)	(1.69)
*foreign*CtryTrait*	-0.045**	-0.033	-0.055***	-0.002	-0.053**	-0.408**	-0.338*	-0.536***	0.091	-0.608***
	(-2.01)	(-1.41)	(-2.77)	(-0.11)	(-2.42)	(-2.35)	(-1.93)	(-3.47)	(0.59)	(-3.45)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Observations	540,700	540,700	525,484	508,821	411,117	540,700	540,700	525,484	508,821	411,117
Adjusted R^2	0.066	0.067	0.067	0.070	0.081	0.314	0.315	0.314	0.316	0.320

Panel B of Table 1.6 examines the effect of firm country institutional environment on the relation between foreignness and risk discussions. The firm country institutional environment is characterized by investor protection, information disclosure, and level of trust. Following Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2008), I use an anti-director rights index (*antidir*) and an anti-self-dealing index (*anti_dealing*) to measure the extent of investor protection. I use the index of financial disclosures from the Center for International Financial Analysis and Research (*cifar*), and the negative value of the index of earnings management of a country (*earnmgmt*) by Leuz, Nanda, and Wysocki (2003) to measure a country's information environment. I use the percentage of people in each country who answered "Most people can be trusted" from the World Value Survey (*trust*) to measure the informal institutional environment. All the country variables are dummies equal to one if the values are above the sample medians, and zero otherwise.

CtryTrait denotes *antidir, anti_dealing, cifar, earnmgmt,* and *trust* from columns (1) to (5) and (6) to (10). I find that seven out of 10 of the coefficients on *foreign*CtryTrait* are significantly negative, suggesting that the positive association between foreignness and risk discussions is mediated for firm countries with a better institutional environment. The possible reason is that foreign analysts' sensitivity to risk arising from unfamiliarity is alleviated when the firm country has a good institutional environment.

1.4.3.2 Foreign institutional investor demand hypothesis

In this section, I examine the role of the foreign institutional investor as an explanation for why foreign analysts present more risk discussions than local analysts. Brown et al. (2015) find that client demand for information is the most important determinant of analysts' coverage decisions. If foreign investors have a stronger demand for risk information, and if they are the primary readers of foreign analysts' reports, it is likely that foreign analysts discuss more risks in response to such information demand. Table 1.7 presents the relevant tests with overall risk discussions (*Riskpct* or *Risk*) as dependent variables.

Table 1. 7 Foreign institutional investor demand hypothesis

This table presents the tests on the effect of foreign institutional ownership on the positive relation between foreignness and analysts' risk discussions. *avgio_for* is the sum of the holdings of all institutions domiciled in a country different from the firm country divided by the firm's market capitalization. *avgio_fordum* is a dummy equal to one if the foreign institutional ownership is in the top decile in one year, and zero otherwise. *InstTrait* denotes *avgio_for*, and *avgio_fordum* from columns (1) to (4) listed in the third row of the table. The dependent variables are analysts' risk discussions denoted by *Riskpct* and *Risk*. Control variables are the same as in Table 1.3 and are not reported for brevity. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

	(1)	(2)	(3)	(4)
	Dependent variable: Riskpct		*Dependent variable: Risk*	
	avgio_for	*avgio_fordum*	*avgio_for*	*avgio_fordum*
foreign	0.023	0.025**	0.176	0.184*
	(1.64)	(2.14)	(1.61)	(1.94)
InstTrait	-0.006	-0.031**	-0.010	-0.253**
	(-0.11)	(-2.03)	(-0.02)	(-2.10)
Foreign InstTrait*	0.055	0.047**	0.365	0.351**
	(0.81)	(2.23)	(0.68)	(2.11)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	495,297	495,297	495,297	495,297
Adjusted R^2	0.075	0.075	0.322	0.322

I measure foreign institutional investor holdings with *avgio_for*, which is the sum of the holdings of all institutions in a country different from the firm country divided by the firm's market capitalization. The data source is Facet. If the foreign investor information demand hypothesis is correct, then the positive association between foreign analysts and risk discussions would be stronger for firms with a larger proportion of foreign institutional investors. I interact the foreignness dummy with foreign institutional ownership to test whether there is an incremental effect on risk discussions.

InstTrait denotes *avgio_for* in columns (1) and (3). I find that the coefficients on *Foreign* avgio_for* are positive but insignificant, which seems to suggest that foreign ownership does not explain the positive association between foreignness and risk discussions. I then construct an indicator of high foreign institutional holdings, *avgio_fordum* which equals one if the value of *avgio_for* is at the top decile, and zero otherwise. *InstTrait* denotes *avgio_fordum* in columns (2) and (4). The coefficients on *Foreign* avgio_fordum* are significantly positive in columns (2) and (4). The finding suggests that the effect of foreign institutional holdings on foreign analysts' risk discussions is not linear. Overall, there is some weak evidence that foreign institutional investor information demand is part of the reason that foreign analysts discuss more risks than local analysts.

1.4.3.3 Conflicts of interest hypothesis

Another possible explanation for the positive association between foreign analysts and risk discussions is that local analysts avoid discussing risk information in the context of concern about conflicts of interest. Local analysts may face stronger conflicts of interest than foreign analysts, and thus they avoid or spend less time in discussing firm risks.

Following Bradshaw et al. (2006), I use the change of the underlying firm's total debt (*deltadebt*) and shareholder's equity (*deltaequity*) to measure the potential conflicts of interest faced by analysts. If the conflicts of interest hypothesis is correct, then the positive association between foreign analysts and risk discussions will be strengthened for firms with stronger potential conflicts of interest. I interact the foreignness dummy with conflicts of interest measures to test whether there is an incremental effect on risk discussions. The relevant tests are reported in Table 1.8.

Conflict denotes *deltadebt* and *deltaequity* from columns (1) to (4). I find that the coefficients on *foreign*Conflict* are insignificant in all regressions, suggesting that conflicts of interest do not have an incremental effect on the positive association between foreign analysts and risk discussions. In other words, there is no evidence supporting the conflicts of interest hypothesis.

Table 1. 8 Conflicts of interest hypothesis

This table presents the tests on the effect of conflicts of interest on the positive relation between foreignness and analysts' risk discussions. I use *deltadebt*, the change of total debt divided by the firm's total assets, and *deltaequity*, the change of shareholders' equity divided by the firm's total assets, to capture the potential conflicts of interest faced by analysts. *Conflict* denotes *deltadebt*, and *deltaequity* from columns (1) to (4) listed in the third row of the table. The dependent variables are analysts' risk discussions denoted by *Riskpct* and *Risk*. Control variables are the same as in Table 1.3 and are not reported for brevity. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

	(1)	(2)	(3)	(4)
Conflict	*Dependent variable: Riskpct*		*Dependent variable: Risk*	
	deltadebt	*deltaequity*	*deltadebt*	*deltaequity*
foreign	0.030***	0.029**	0.211**	0.197**
	(2.65)	(2.56)	(2.31)	(2.15)
Conflict	0.105***	-0.085	0.931***	-1.014**
	(2.61)	(-1.48)	(2.99)	(-2.14)
*foreign*Conflict*	-0.092	0.054	-0.963	1.099
	(-1.16)	(0.61)	(-1.58)	(1.51)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	539,928	539,928	539,928	539,928
Adjusted R^2	0.076	0.076	0.321	0.321

1.5 The Informativeness of Analysts' Risk Discussions

In this section, I examine whether analysts' risk discussions are informative to investors. I use three ways to measure the informativeness of risk discussions. First, following Lui et al. (2007), I use the predictability of analysts' risk discussions regarding the subsequent stock return volatility to capture the informativeness of risk discussions. If risk discussions help predict the cross-sectional variations in volatility after controlling for other predictors of volatility, then risk discussions are incrementally informative. Similarly, the second way is to use the predictability of analyst risk discussions regarding the subsequent stock turnover ratio to capture the informativeness of risk discussions. Higher subsequent stock turnover suggests more informative risk discussions. Last, I examine whether risk discussions affect market reactions to analysts' stock recommendations. If market reactions to stock recommendations accompanied with more risk discussions are stronger than market reactions to stock recommendations accompanied with fewer risk discussions, then risk discussions are incrementally informative.[12]

Furthermore, I investigate whether foreign and local analysts are distinct in the informativeness of their risk discussions. In other words, for the same amount of risk discussions, I investigate whether discussions from foreign analysts are more useful to investors than those from local analysts. I interact the *foreign* dummy with risk discussions to examine whether foreign analysts have incremental effects on the informativeness of risk discussions.

Table 1.9 examines the informativeness of risk discussions with stock return volatility being the dependent variable. *volatility3* is the total stock return volatility three months after the issuance of an analyst report. I use *RiskTrait* to denote analysts' overall risk discussions in columns (1) and (2) and risk category discussions from columns (3) to (12), listed on the third row of Table 1.9. In column (1), *Riskpct* is significantly positively associated with *volatility3*, suggesting that risk discussions predict the cross-sectional variations in three-month volatility after an analyst report. The coefficient on *foreign* Riskpct* is insignificant in column (2), suggesting that foreign analysts are similar to local analysts in the informativeness of their overall risk discussions.

[12] De Franco et al. (2015) use trading volume as the dependent variable when testing the consequences of more readable analyst reports. The argument is that higher readability of analyst reports lowers investors' cost of acquiring information, thus increases the amount of trading volumes. More importantly, analysts have incentives to issue more readable reports to generate trading commissions that are based on trading volumes. I do not consider trading volume when testing the informativeness of risk discussions, because the direct consequence of risk discussion is volatility and not trade size.

Table 1. 9 Analysts' risk discussions and the subsequent stock return volatility

This table presents the tests on the informativeness of analysts' risk discussions by regressing stock return volatility on risk discussions. The dependent variable is *volatility3*, the total stock return volatility three months after the issuance of an analyst report. The specifications in the odd-numbered columns report the main effect of risk discussions on stock return volatility. The specifications in the even-numbered columns report the incremental effect of foreignness on the informativeness of risk discussions. *RiskTrait* denotes *Riskpct* in columns (1) and (2), *FLS_rkkpct* in columns (3) and (4), *Firm_rkkpct* in columns (5) and (6), *Ind_rkkpct* in columns (7) and (8), *Regu_rkkpct* in columns (9) and (10), and *Macro_rkkpct* in columns (11) and (12). The risk variables are the same as those in Table 1.3. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable is volatility3			Risk Category									
	Riskpct		*FLS_riskpct*		*Firm_riskpct*		*Ind_riskpct*		*Regu_riskpct*		*Macro_riskpct*	
RiskTrait	0.031***	0.032***	0.048***	0.045***	0.030***	0.030***	-0.007	0.005	0.074***	0.088***	0.026***	0.021***
	(8.53)	(7.34)	(8.15)	(7.24)	(7.92)	(6.68)	(-0.77)	(0.50)	(6.98)	(7.15)	(4.50)	(3.29)
*foreign*RiskTrait*		-0.001		0.008		0.001		**-0.042****		**-0.045****		0.016
		(-0.18)		(0.67)		(0.09)		**(-2.48)**		**(-2.42)**		(1.56)
foreign		0.032*		0.027*		0.030*		0.040**		0.039**		0.022
		(1.79)		(1.71)		(1.67)		(2.46)		(2.48)		(1.29)
eps_std	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***
	(16.43)	(16.39)	(16.42)	(16.39)	(16.43)	(16.40)	(16.43)	(16.40)	(16.42)	(16.38)	(16.43)	(16.40)
beta	0.638***	0.637***	0.638***	0.637***	0.639***	0.638***	0.639***	0.638***	0.640***	0.639***	0.638***	0.637***
	(35.27)	(35.15)	(35.26)	(35.13)	(35.27)	(35.14)	(35.24)	(35.12)	(35.34)	(35.24)	(35.24)	(35.12)
preturnover	0.014	0.017	0.013	0.016	0.014	0.017	0.016	0.018	0.015	0.017	0.015	0.018
	(0.51)	(0.59)	(0.48)	(0.56)	(0.52)	(0.60)	(0.56)	(0.65)	(0.53)	(0.62)	(0.54)	(0.63)
logmv	-0.217***	-0.217***	-0.217***	-0.218***	-0.217***	-0.217***	-0.217***	-0.217***	-0.217***	-0.217***	-0.217***	-0.218***
	(-41.76)	(-41.86)	(-41.75)	(-41.85)	(-41.73)	(-41.83)	(-41.69)	(-41.80)	(-41.81)	(-41.93)	(-41.76)	(-41.86)
negbv	0.387***	0.387***	0.387***	0.387***	0.387***	0.388***	0.388***	0.388***	0.388***	0.388***	0.387***	0.388***
	(7.41)	(7.42)	(7.41)	(7.42)	(7.42)	(7.43)	(7.42)	(7.43)	(7.44)	(7.46)	(7.42)	(7.43)
mb	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(7.75)	(7.77)	(7.75)	(7.77)	(7.76)	(7.79)	(7.74)	(7.76)	(7.77)	(7.80)	(7.74)	(7.76)
leverage	-0.071*	-0.072*	-0.069*	-0.070*	-0.072*	-0.072*	-0.070*	-0.070*	-0.074*	-0.075*	-0.069*	-0.069*
	(-1.74)	(-1.75)	(-1.70)	(-1.71)	(-1.75)	(-1.77)	(-1.70)	(-1.72)	(-1.81)	(-1.83)	(-1.68)	(-1.69)
idiorisk	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(15.10)	(15.07)	(15.09)	(15.06)	(15.10)	(15.07)	(15.10)	(15.07)	(15.10)	(15.08)	(15.09)	(15.06)
firmexp	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-6.12)	(-5.90)	(-6.19)	(-5.98)	(-6.13)	(-5.91)	(-6.28)	(-6.06)	(-6.20)	(-5.98)	(-6.18)	(-5.96)
genexp	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.74)	(0.64)	(0.75)	(0.65)	(0.73)	(0.64)	(0.67)	(0.58)	(0.70)	(0.60)	(0.68)	(0.59)
logbrsize	-0.006	-0.005	-0.006	-0.004	-0.006	-0.005	-0.006	-0.004	-0.005	-0.004	-0.006	-0.004
	(-0.47)	(-0.36)	(-0.45)	(-0.34)	(-0.46)	(-0.36)	(-0.45)	(-0.35)	(-0.40)	(-0.31)	(-0.44)	(-0.33)
logwords	-0.001	-0.001	-0.000	-0.000	-0.001	-0.001	0.004	0.004	0.001	0.001	0.001	0.001
	(-0.35)	(-0.39)	(-0.13)	(-0.16)	(-0.40)	(-0.43)	(1.39)	(1.33)	(0.53)	(0.48)	(0.34)	(0.31)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	541,531	541,531	541,531	541,531	541,531	541,531	541,531	541,531	541,531	541,531	541,531	541,531
Adjusted R^2	0.393	0.393	0.392	0.393	0.392	0.393	0.392	0.392	0.393	0.393	0.392	0.392

Columns (3) to (12) test the informativeness of risk category discussions. I find that all risk category discussions (except industry risk) are significantly positively associated with the three-month volatility after an analyst report, suggesting that analysts' discussions regarding forward-looking, firm, regulation and litigation, and macroeconomic risks are informative to investors. The coefficient on *foreign* Regu_riskpct* is significantly negative in column (10). Considering the finding in Panel B of Table 1.3 that there is no significant difference between foreign and local analysts in the amount of regulation and litigation risk discussions, this finding seems to suggest that when local analysts discuss regulatory risks, they are more informative than foreign analysts in such discussions. The possible reason is that local analysts live in the same country as the firm headquarters, and thus they know the regulatory institutions better than foreign analysts. Other than regulatory risk, there is no significant evidence that the informativeness of discussing other risk categories is different between foreign and local analysts.

Since past volatility helps predict future volatility, I use the standard deviation of eps 12 months before the analyst report date (*eps_std*) to control for the past volatility in all the regressions. In unreported robustness tests, I replace *eps_std* with the past 12 months' stock return volatility before the analyst report date. The findings in Table 1.9 are qualitatively unchanged.

Table 1.10 presents the tests on the informativeness of analysts' risk discussions by regressing stock turnover on risk discussions. I redo the regressions in Table 1.9, with the dependent variable being *turnover3*, which is the total stock turnover ratio three months after the issuance of an analyst report. Similarly, I find that analysts' overall risk discussions and risk category discussions are significantly positively associated with the subsequent three-month stock turnover ratio after controlling for other factors affecting stock turnover. The findings are consistent with the argument that analysts' risk discussions are incrementally informative. The coefficients on the interaction of *foreign*RiskTrait* are insignificant from columns (1) to (12), suggesting that there is no significant difference between foreign and local analysts in the informativeness of risk discussions.

Table 1. 10 Analysts' risk discussions and the subsequent stock turnover

This table presents the tests on the informativeness of analysts' risk discussions by regressing stock turnover on risk discussions. This table is similar to the regressions in Table 1.9, with the dependent variable *turnover3*, the total stock turnover ratio three months after the issuance of an analyst report. The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable is turnover3			Risk Category									
	Riskpct		*FLS_riskpct*		*Firm_riskpct*		*Ind_riskpct*		*Regu_riskpct*		*Macro_riskpct*	
RiskTrait	0.001***	0.001***	0.003***	0.002***	0.002***	0.001***	0.002***	0.002**	0.002**	0.002**	0.001**	0.001
	(5.06)	(3.80)	(5.33)	(4.74)	(5.14)	(4.00)	(2.99)	(2.00)	(2.08)	(2.33)	(2.07)	(1.23)
*foreign*RiskTrait*		0.001		0.000		0.001		0.002		-0.001		0.001
		(1.14)		(0.33)		(0.99)		(1.17)		(-0.56)		(1.08)
foreign		-0.005***		-0.004***		-0.005***		-0.004***		-0.004***		-0.005***
		(-4.05)		(-3.86)		(-3.97)		(-4.30)		(-3.77)		(-4.11)
eps_std	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.09)	(0.16)	(0.08)	(0.15)	(0.09)	(0.16)	(0.12)	(0.19)	(0.09)	(0.16)	(0.09)	(0.16)
beta	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(3.22)	(3.33)	(3.21)	(3.33)	(3.22)	(3.34)	(3.26)	(3.39)	(3.25)	(3.37)	(3.21)	(3.33)
preturnover	0.904***	0.904***	0.904***	0.904***	0.904***	0.904***	0.905***	0.904***	0.905***	0.904***	0.905***	0.904***
	(168.49)	(168.23)	(168.46)	(168.21)	(168.49)	(168.23)	(168.56)	(168.30)	(168.50)	(168.27)	(168.50)	(168.25)
logmv	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-13.80)	(-13.65)	(-13.82)	(-13.66)	(-13.79)	(-13.63)	(-13.79)	(-13.63)	(-13.80)	(-13.64)	(-13.82)	(-13.66)
negbv	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**	-0.007**
	(-2.40)	(-2.42)	(-2.40)	(-2.42)	(-2.39)	(-2.41)	(-2.41)	(-2.42)	(-2.39)	(-2.41)	(-2.40)	(-2.42)
mb	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.18)	(-0.25)	(-0.17)	(-0.24)	(-0.16)	(-0.23)	(-0.22)	(-0.29)	(-0.18)	(-0.25)	(-0.19)	(-0.25)
leverage	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(4.56)	(4.59)	(4.59)	(4.63)	(4.54)	(4.58)	(4.57)	(4.61)	(4.54)	(4.58)	(4.60)	(4.64)
idiorisk	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(2.62)	(2.67)	(2.61)	(2.67)	(2.63)	(2.68)	(2.65)	(2.71)	(2.64)	(2.70)	(2.63)	(2.68)
firmexp	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.58)	(-0.93)	(-0.63)	(-0.97)	(-0.58)	(-0.93)	(-0.65)	(-0.98)	(-0.67)	(-1.01)	(-0.65)	(-0.99)
genexp	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.12)	(-0.89)	(-1.10)	(-0.88)	(-1.12)	(-0.90)	(-1.20)	(-0.99)	(-1.16)	(-0.95)	(-1.17)	(-0.95)
logbrsize	0.001***	0.001**	0.001***	0.001**	0.001***	0.001**	0.001***	0.001**	0.001***	0.001**	0.001***	0.001**
	(2.80)	(2.37)	(2.82)	(2.40)	(2.80)	(2.37)	(2.82)	(2.40)	(2.86)	(2.43)	(2.84)	(2.41)
logwords	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.85)	(0.91)	(0.86)	(0.92)	(0.73)	(0.79)	(1.42)	(1.50)	(1.56)	(1.63)	(1.39)	(1.46)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	541,615	541,615	541,615	541,615	541,615	541,615	541,615	541,615	541,615	541,615	541,615	541,615
Adjusted R^2	0.824	0.824	0.824	0.824	0.824	0.824	0.824	0.824	0.824	0.824	0.824	0.824

Table 1.11 examines whether risk discussions affect market reactions to analysts' stock recommendations. The dependent variable is *CAR3*, the market-adjusted cumulative abnormal return starting one day before to three days after the analyst report date. Independent variables are *buy* which equals one if the stock recommendation is to buy, and zero otherwise, and *sell* which equals one if the stock recommendation is to sell, and zero otherwise. I interact *buy* or *sell* with proxies for risk discussions to examine whether risk discussions enhance market reactions analysts' recommendations. Control variables are the same as in Table 1.3 plus the cumulative abnormal stock return 12 months before the analyst report date (*arpre12*).

In Panel A of Table 1.11, *CAR3* is significantly positively associated with *buy* and negatively associated with *sell* in column (1). The coefficient on *buy*Riskpct* is significantly positive and the coefficient on *sell*Riskpct* is significantly negative in column (2). The findings suggest that analysts' overall risk discussions enhance market reactions to analysts' recommendations. For risk categories from columns (3) to (7), I find that forward-looking, firm, and industry risk discussions enhance market reactions to analyst buy recommendations. Only firm-related risk discussions enhance market reactions to analyst sell recommendations.

Panel B of Table 1.11 examines whether foreign analysts have incremental effects on the relation between risk discussions and market reactions to stock recommendations. Most of the coefficients on *foreign*buy*RiskTrait* and *foreign*sell*RiskTrait* are insignificant, suggesting no incremental effect from foreign analysts.

Table 1. 11 Analysts' risk discussions and the market reactions to stock recommendations

Panel A presents the tests on the effect of analysts' risk discussions on market reactions to stock recommendations. The dependent variable is *CAR3*, the market-adjusted cumulative abnormal return starting one day before to three days after the analyst report date. *buy* is a dummy equal to one if the stock recommendation is to buy, and zero otherwise. *sell* is a dummy equal to one if the stock recommendation is to sell, and zero otherwise. From columns (2) to (7), *RiskTrait* denotes *Riskpct, FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct,* and *Macro_riskpct*, respectively. Control variables are the same as in Table 1.3 plus the cumulative abnormal stock return 12 months before the analyst report date (*arpre12*). Panel B examines whether geographic location affects the relation between risk discussions and market reactions to stock recommendations. *RiskTrait* denotes *Riskpct, FLS_riskpct*, *Firm_riskpct*, *Ind_riskpct*, *Regu_riskpct,* and *Macro_riskpct* from columns (1) to (6). The definitions of variables are in Appendix 1.A. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust t-statistics adjusted for firm and analyst clustering. ***, **, and * denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Industry fixed effects use the Fama and French 12-industry classification.

Panel A Analysts' risk discussions and the informativeness of analysts' stock recommendations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable is CAR3							
		Riskpct	*FLS_riskpct*	*Firm_riskpct*	*Ind_riskpct*	*Regu_riskpct*	*Macro_riskpct*
buy	0.573***	0.503***	0.540***	0.500***	0.545***	0.564***	0.548***
	(28.81)	(16.23)	(20.84)	(16.44)	(25.21)	(25.84)	(21.29)
sell	-0.489***	-0.406***	-0.454***	-0.399***	-0.501***	-0.480***	-0.491***
	(-16.15)	(-8.08)	(-10.89)	(-8.01)	(-14.60)	(-14.62)	(-12.38)
RiskTrait		-0.069***	-0.115***	-0.071***	-0.101***	-0.131***	-0.083***
		(-4.36)	(-4.58)	(-4.33)	(-2.83)	(-3.28)	(-3.81)
buy*RiskTrait		**0.060*** **	**0.064***	**0.066*** **	**0.152*** **	**0.056**	**0.042**
		(2.94)	**(1.93)**	**(3.14)**	**(3.20)**	**(1.07)**	**(1.42)**
sell*RiskTrait		**-0.068*** **	**-0.060**	**-0.077*** **	**0.066**	**-0.056**	**0.003**
		(-2.04)	**(-1.07)**	**(-2.24)**	**(0.90)**	**(-0.68)**	**(0.07)**
arpre12	0.022***	0.022***	0.022***	0.022***	0.022***	0.022***	0.022***
	(32.81)	(32.77)	(32.77)	(32.77)	(32.81)	(32.77)	(32.80)
eps_std	-0.017**	-0.017**	-0.017**	-0.018**	-0.018**	-0.017**	-0.017**
	(-2.28)	(-2.28)	(-2.25)	(-2.28)	(-2.30)	(-2.27)	(-2.27)
beta	-0.118***	-0.118***	-0.117***	-0.118***	-0.119***	-0.119***	-0.116***
	(-3.25)	(-3.24)	(-3.21)	(-3.24)	(-3.26)	(-3.27)	(-3.18)
preturnover	-0.393***	-0.390***	-0.388***	-0.390***	-0.393***	-0.392***	-0.392***
	(-4.93)	(-4.89)	(-4.87)	(-4.89)	(-4.93)	(-4.92)	(-4.92)
logmv	-0.098***	-0.098***	-0.098***	-0.098***	-0.098***	-0.098***	-0.098***
	(-8.50)	(-8.48)	(-8.45)	(-8.50)	(-8.51)	(-8.49)	(-8.46)
negbv	-0.041	-0.040	-0.040	-0.041	-0.040	-0.041	-0.040
	(-0.36)	(-0.35)	(-0.35)	(-0.35)	(-0.35)	(-0.36)	(-0.35)
mb	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.37)	(-0.37)	(-0.38)	(-0.38)	(-0.36)	(-0.38)	(-0.37)
leverage	-0.200**	-0.199**	-0.201**	-0.198**	-0.200**	-0.194**	-0.203**
	(-2.51)	(-2.49)	(-2.51)	(-2.47)	(-2.50)	(-2.43)	(-2.54)
idiorisk	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.59)	(-3.58)	(-3.58)	(-3.59)	(-3.60)	(-3.59)	(-3.57)
firmexp	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.45)	(0.34)	(0.37)	(0.35)	(0.43)	(0.40)	(0.35)
genexp	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.43)	(0.37)	(0.35)	(0.37)	(0.44)	(0.40)	(0.41)

logbrsize	0.075***	0.076***	0.075***	0.076***	0.075***	0.074***	0.075***
	(4.43)	(4.46)	(4.43)	(4.45)	(4.45)	(4.37)	(4.41)
logwords	0.028***	0.036***	0.036***	0.037***	0.030***	0.032***	0.035***
	(3.37)	(4.21)	(4.27)	(4.25)	(3.47)	(3.75)	(4.08)
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631	541,631	541,631	541,631
Adjusted R^2	0.045	0.045	0.045	0.045	0.045	0.045	0.045

Panel B Geographic location and the relation between analysts' risk discussions and market reactions to stock recommendations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is CAR3						
	Riskpct	*FLS_riskpct*	*Firm_riskpct*	*Ind_riskpct*	*Regu_riskpct*	*Macro_riskpct*
buy	0.504***	0.546***	0.503***	0.547***	0.561***	0.553***
	(14.06)	(18.27)	(14.26)	(22.18)	(22.42)	(18.81)
sell	-0.424***	-0.474***	-0.415***	-0.526***	-0.496***	-0.497***
	(-6.96)	(-9.47)	(-6.82)	(-12.56)	(-12.39)	(-10.37)
foreign	-0.121**	-0.074	-0.118**	-0.066	-0.089**	-0.098**
	(-2.12)	(-1.55)	(-2.09)	(-1.60)	(-2.18)	(-2.09)
RiskTrait	-0.089***	-0.134***	-0.091***	-0.137***	-0.213***	-0.113***
	(-4.88)	(-4.60)	(-4.81)	(-3.28)	(-4.46)	(-4.54)
*buy*RiskTrait*	0.068***	0.071*	0.073***	0.196***	0.138**	0.052
	(2.78)	(1.79)	(2.89)	(3.57)	(2.22)	(1.50)
*sell*RiskTrait*	-0.071*	-0.063	-0.083*	0.083	-0.090	-0.025
	(-1.70)	(-0.93)	(-1.90)	(0.89)	(-0.88)	(-0.46)
foreign*buy*RiskTrait	**-0.022**	**-0.023**	**-0.020**	**-0.152**	**-0.279*** **	**-0.027**
	(-0.51)	**(-0.34)**	**(-0.44)**	**(-1.54)**	**(-2.71)**	**(-0.46)**
foreign*sell*RiskTrait	**-0.008**	**-0.005**	**-0.001**	**-0.071**	**0.065**	**0.055**
	(-0.12)	**(-0.05)**	**(-0.01)**	**(-0.46)**	**(0.38)**	**(0.61)**
*foreign*RiskTrait*	0.069**	0.067	0.070**	0.127*	0.279***	0.098**
	(2.10)	(1.30)	(2.07)	(1.67)	(3.46)	(2.21)
*foreign*buy*	-0.013	-0.027	-0.018	-0.010	0.009	-0.023
	(-0.21)	(-0.50)	(-0.27)	(-0.22)	(0.21)	(-0.42)
*foreign*sell*	0.076	0.067	0.067	0.079	0.057	0.033
	(0.76)	(0.82)	(0.67)	(1.14)	(0.87)	(0.41)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	541,631	541,631	541,631	541,631	541,631	541,631
Adjusted R^2	0.045	0.045	0.045	0.045	0.045	0.045

Taken together, I offer strong evidence that analysts' risk discussions provide incremental information to investors. However, for the same amount of risk discussions, foreign and local analysts are not significantly different in delivering risk information. Prior literature finds that foreign analysts are less accurate than local analysts in presenting EPS forecasts. This study shows that foreign and local analysts are equally competent in the informativeness of risk discussions.

1.6 Conclusions and Limitations

Using textual analysis for a large sample of analyst reports covering firms from 38 countries from 1997 to 2019, I examine the relation between analysts' geographic location and their risk discussions. I find that foreign analysts discuss more overall risk information than local analysts on the first page of their reports. Further analyses show that foreign analysts discuss more forward-looking and firm-specific risk information than local analysts. There is no significant difference between foreign and local analysts in discussing industry, regulation and litigation, and macroeconomic risk information.

I investigate various potential explanations for the positive association between foreignness and risk discussions. I find that unfamiliarity with the underlying firms stimulates foreign analysts to discuss more risk information than local analysts. Alternative possible explanations related to foreign institutional investor demand and local analysts facing stronger conflicts of interest cannot account for the results.

I find that analysts' risk discussions are positively associated with subsequent stock return volatility and stock turnover after controlling for other predictors of future volatility and turnover. Analysts' risk discussions enhance market reactions to analysts' recommendations. Taken together, there is strong evidence that analysts' risk discussions provide incremental information to investors. I find no significant difference between foreign and local analysts in the informativeness of risk discussions.

This study contributes to previous literature on analysts' risk analysis of the underlying firms by using textual analysis to extract analysts' risk discussions for the underlying firms. More importantly, I find that foreign analysts are similar to local analysts in the informativeness of their risk discussions.

I acknowledge that this study is subject to several limitations. This paper focuses on the impact of foreignness on analysts' risk discussions, but neglects other demographic characteristics such as gender and personal ability that may affect analysts' risk analysis of the underlying firms. For example, Kumar (2010) finds that due to self-selection, female analysts issue bolder and more accurate forecasts than male analysts. De Franco et al. (2015) find that the readability of an analyst report is positively associated with the analyst's ability. Li et al. (2020) find that analysts with better technical and social skills generate more accurate earnings forecasts and receive stronger market reactions. Further, these sociable analysts are more likely to be voted as all-star analysts and move to high-status brokerage firms. As analysts' gender, ability, technical and social skills affect their forecast accuracy, these factors may also play a role in their risk discussions. Given the data limitations, I leave further investigation of these issues to future research.

Another limitation of this study is that it does not consider the impact of nonfinancial information on analysts' risk discussions. Dhaliwal et al. (2012) find that the issuance of stand-alone CSR reports is associated with lower analyst forecast error around the world. It is possible that analysts discuss more risks for firms exposed to climate-related risks or other social matters. In addition, in the empirical tests, I only control for the number of words in analyst reports. Other analyst-report level factors such as the tone and the readability are not considered.

Given these limitations, I acknowledge that this paper is essentially exploratory in nature and the results should be interpreted as suggestive.

Chapter 2: Comparability and the Informativeness of DCF and PE Models by Sell-side Equity Analysts

2.1 Introduction

Bradshaw (2009) regards analysts' valuation process as a "*black box*" that is complex and can be subjective. Tversky and Kahneman (1975) find that people often rely on a limited number of heuristic principles to simplify their judgmental opinions. Consistent with this view, most analyst reports use peer-based multiples such as a price-to-earnings (PE) model to forecast target prices, and the use of direct valuation models such as a discounted cash flow (DCF) model is quite selective (Asquith, Mikhail, and Au, 2005; Huang, Tan, Wang, and Yu, 2021). Theoretically, different valuation models are equivalent, but the usefulness of a valuation model may vary in the practical implementation (e.g., Demirakos, Strong, and Walker, 2010; Gleason, Johnson, and Li, 2013; Huang et al., 2021).

Previous studies offer rich evidence on the benefits of information comparability (e.g., Kim, Kraft, and Ryan, 2013; Zhang, 2018). Greater comparability lowers the costs of analysts' information acquisition and processing (De Franco, Kothari, and Verdi, 2011), which benefits their application of valuation models in forecasting target prices. Comparability is important in analysts' valuation process, even if analysts adjust GAAP earnings to drop nonrecurring items in determining their street earnings. Analysts have various incentives when deciding street earnings. Gu and Chen (2004) find that nonrecurring items that analysts include in street earnings are more persistent and have higher valuation multiples than those items they exclude from street earnings, despite their findings that the excluded nonrecurring items are persistent and value relevant. David et al. (2009) show that analysts are more likely to make income-increasing adjustments to GAAP earnings in determining street earnings for glamour stocks than for value stocks, consistent with their argument that analysts have economic incentives in determining street earnings. As the excluded nonrecurring items in street earnings are not necessarily more comparable than included items, it is essential to examine whether the underlying firm's comparability matters in analysts' valuation process. This study uses textual analysis to detect valuation models used by analysts in their research reports, and examines whether comparability of the underlying firms to their peers plays a role in the informativeness of DCF and PE models.

The PE model valuation process requires analysts to use comparable firms' multiples to estimate the market value of the underlying firms. For example, the sentence in Panel A of Appendix 2.A "Our price target through December 2013 is ¥800, based on our FY2013 EPS forecast and the sector average P/E of 9x" suggests that analysts use the industry average P/E ratio as the benchmark in the valuation. Anchoring literature suggests that individuals are likely to retrieve knowledge consistent with the selected benchmarks, which may cause anchoring and adjustment bias. PE models are expected to have higher noises if the underlying firms are less comparable to their peers in the same industry.

Comparable firms' information is also useful to analysts during the process of a DCF valuation. Panel B of Appendix 2.A shows the pages of an analyst report by J.P. Morgan that uses a DCF model to forecast the valuation of Shanghai Pharmaceutical (SPH). The sentences "The terminal growth is based on the annual growth rate expected in 2015… subject to a minimum of 3% and a maximum of 6% depending on the nature of the industry and the level of maturity in China" suggest that analysts consider the industry nature and the macroeconomic condition in the forecast of terminal growth rate, one of the inputs of a DCF model. In addition, the section “Table 4: SPH-value comparison with peer companies” in Panel B of Appendix 2.A shows that the analysts consider comparable firms’ valuations when valuing the underlying firm’s target price. As analysts may use the industry or market information when forecasting the inputs of a DCF model, I expect that the usefulness of a DCF model is related to the comparability of the underlying firm to its peers in the same industry.

Compared with PE models that rely more on comparable firms’ information for the valuation, DCF models estimate the underlying firm’s value by discounting forecasted cash flows, with less reference to comparable firms’ information. Cen, Hilary, and Wei (2013) find that analysts’ earnings forecasts are anchored to the industry median earnings forecasts, suggesting that analysts could be subject to anchoring bias in their valuations. Given the use of benchmarks, PE models are more likely to suffer from anchoring and adjustment bias than DCF models, especially when the underlying firms are not comparable to other firms. Thus, I expect that for less comparable firms, analysts’ use of DCF models is more informative to investors than PE models.

I examine the impact of comparability on the informativeness of valuation models using a sample of 315,515 analyst reports by 2,447 analysts on 2,797 U.S. firms from 1997 to 2017. I use textual analysis of analyst reports from Investext to identify which valuation models are used by an analyst to justify her investment opinions.[13] Though analysts use various models in their reports, the primary valuation models used are PE models and DCF models. This study focuses on comparisons of the informativeness of DCF and PE models. The variable *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. Following Asquith et al. (2005) and Huang et al.

[13] I thank Hongping Tan for sharing the data on analysts’ use of valuation models in their reports.

(2021), I measure the informativeness of valuation models by testing whether the use of a DCF model affects market reactions to the change of analyst target price forecasts.

I measure a firm's information comparability with four proxies. The first two proxies are based on De Franco et al. (2011) who define comparability as the closeness between two firms' accounting systems in mapping economic events to financial statements.[14] I first estimate the pairwise accounting comparability ($ACCTCOMP_{ijt}$) between firms *i* and *j* that are in the same SIC two-digit industry. I then measure firm-year level comparability with *acctcomp4*, that is the average $ACCTCOMP_{ijt}$ of the four firms with the highest comparability values, and *acctcompind*, that is the median $ACCTCOMP_{ijt}$ of all firms in the same SIC two-digit industry. I construct the other two comparability proxies based on the closeness of a firm's current price-to-earnings ratio to the firm's historical price-to-earnings ratio or to the price-to-earnings ratios of all firms in the same SIC two-digit industry. *comppe* is calculated as (-1) times the absolute difference between a firm's current price-to-earnings ratio and the median value of the firm's price-to-earnings ratio in the past five years, divided by the sum of the two values. *comppeind* is calculated as (-1) times the absolute difference between a firm's price-to-earnings ratio and the median value of the price-to-earnings ratios of other firms in the same industry, divided by the sum of the two values. Higher values of the four comparability proxies indicate greater information comparability.

First, I conduct the baseline tests on the informativeness of DCF models and PE models. Huang et al. (2021) argue that DCF models are more informative than PE models as DCF models provide granular information on cash flows and firm riskiness. This study explores and tests an alternative explanation. Psychology literature suggests that in many situations, estimators start with an initial anchor value which is then adjusted to determine a final value (Tversky and

[14] I thank Rodrigo Verdi for sharing the SAS program for comparability measures on his website.

Kahneman, 1975). The process of adjustment is usually inefficient, resulting in anchoring and adjustment bias (George and Hwang, 2004; Campbell and Sharpe, 2009; Pike et al., 2013). I posit that analysts using PE models are more likely to be subject to anchoring and adjustment bias than analysts using DCF models. As a result, DCF models are more informative than PE models. Consistent with this view, I find that market reactions to the change of analyst target price forecasts based on DCF models are stronger than market reactions to the change of analyst target price forecasts based on PE models.

Next, I examine whether the comparability of the underlying firms to their peers plays a role in the informativeness of DCF and PE models. As analysts are subject to anchoring and adjustment bias when using PE models, the bias becomes more severe when the underlying firms are not comparable to other firms in the same industry. Compared with PE models, DCF models are less influenced by the underlying firms' comparability. I predict that DCF models are more informative than PE models for firms with less comparability. Consistent with this prediction, I find that the incremental effect of DCF models on market reactions to the change of analyst target price forecasts is mainly restricted to firms with less comparability to their peers.

I conduct several robustness tests that provide corroborating evidence on the relation between comparability and informativeness of valuation models. First, I consider all the valuation models used by analysts in their reports and categorize them into two groups: direct valuation models and relative valuation models.[15] I find that direct valuation models are more informative than relative valuation models, especially for firms with less comparable peers. Second, I consider other information signals in analyst reports, such as the revisions of earnings forecasts and stock recommendations. The major findings are unchanged when I include

[15] Appendix 2.D lists valuation models under each category.

additional controls of analysts' information signals. Third, I do the tests using the subsample in which an analyst uses DCF and PE models for different firms in a given year. I find consistent evidence that DCF models are more informative than PE models, especially for less comparable firms.

In addition to firm-level information comparability, I examine whether macro information comparability over time affects the informativeness of valuation models. I use the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016) and recession periods marked by the National Bureau of Economic Research (NBER) to measure macro information comparability. Macro information is less comparable when the economic policy uncertainty is high and during periods of recession. I find that the incremental effect of DCF models on market reaction to the change of analyst target price forecasts is stronger in periods with less macro information comparability than in periods with greater macro information comparability.

This study makes several contributions as follows. First, this study responds to the call from Bradshaw (2011) for more research into *how* analysts perform their tasks, specifically *how* analysts process their earnings or cash flow forecasts to justify stock recommendations. This study is closely related to Gleason et al. (2013) and Huang et al. (2021). Gleason et al. (2013) find that target price investment performance increases when analysts appear to use a rigorous valuation model like residual income valuation (RIV) rather than heuristic models such as PE and PEG. This study extends their study by examining the reasons why PE and PEG are less accurate than rigorous models. Huang et al. (2021) show that DCF models are only more informative than PE models for firms with higher valuation uncertainty, and when the DCF models are accompanied by discussions of cash flow and discount rate information. The contribution of this paper is to identify another scenario (firms with lower comparability) when DCF models are superior to PE models. This paper enriches the findings by Huang et al. (2021).

This study contributes to the literature on accounting information comparability. Previous studies have offered rich evidence on the benefits of information comparability such as improving analyst earnings forecast accuracy (De Franco et al., 2011; Peterson, Schmardebeck, and Wilks, 2015), audit outcomes (Zhang, 2018), and the efficiency of acquisition decisions (Chen, Collins, Kravet, and Mergenthaler, 2018), as well as reducing firms' cost of equity (Li, 2010), cost of debt (Kim, Kraft, and Ryan, 2013), and expected crash risk (Kim, Li, Lu, and Yu, 2016). This study contributes to the literature by examining the impact of comparability on analysts' valuation process. I extend this literature by showing that the informativeness of DCF and PE models is associated with the underlying firms' information comparability to their peers.

This study also extends the literature on anchoring bias. It is well documented that anchoring bias exists in stock market price movement (George and Hwang, 2004; Li and Yu, 2012), the offer price in mergers and acquisitions (Baker et al., 2012), auditors' application of analytical procedures (Pike et al., 2013), experts' macroeconomic forecasts (Campbell and Sharpe, 2009), and analyst earnings forecasts (Frederickson and Miller, 2004; Cen et al., 2013). This study enriches the literature by examining whether anchoring bias exists in analysts' valuation process.

2.2 Related Literature and Hypotheses Development

2.2.1 Information comparability

Comparability enhances the usefulness of financial information by allowing users to identify and understand similarities and differences in the financial performance of two firms. Previous studies mainly use three approaches to empirically measure information comparability: the input-based approach which measures comparability by counting differences in accounting choices across firms or over time (DeFond, Hu, Hung, and Li, 2011; Peterson et al., 2015), the output-based approach which uses outputs of financial reporting, notably earnings information, to measure comparability (De Franco et al., 2011; Kim et al., 2013), and the adoption of IFRS (Li, 2010; Yip and Young, 2012).

Prior literature generally finds that greater comparability with peers lowers information acquisition and processing costs, and enhances the quality of information available to investors. For example, Li (2010) finds that mandatory IFRS adoption in Europe in 2005 reduced firms' cost of equity capital. Kim et al. (2013) find that comparability reduces debt market participants' information uncertainty and asymmetry, thereby lowering the cost of debt capital. De Franco et al. (2011) and Peterson et al. (2015) find that information comparability is positively associated with analyst coverage and forecast accuracy, and negatively associated with the dispersion in analyst forecasts. Kim et al. (2016) find that financial statement comparability is negatively associated with expected crash risk. Zhang (2018) finds that a firm's accounting comparability to its peer firms is negatively associated with audit efforts and the likelihood of audit opinion errors. Chen et al. (2018) find that buyers make more profitable acquisition decisions for target firms with more comparable industry peers, indicating that comparability increases the efficiency of acquisition decisions. Choi et al. (2019) find that comparability improves the informativeness of current stock prices about future earnings.

2.2.2 Analysts' use of valuation models

The existing research on analyst valuation models documents the popularity among analysts of using heuristic models in their reports. Using data collected from participant observations, questionnaires, and semi-structured interviews, Barker (1999) finds that analysts are more likely to use dividend yield than dividend discount model to justify their recommendations and target prices. In a content analysis of 1,126 sell-side analysts' reports, Asquith et al. (2005) show that almost all analysts (99.1% of the analyst reports in their sample) use earnings multiples such as PE multiple and EBITDA multiple in their reports, while only 12.8% of the analyst reports include DCF models. Similarly, using data from 365 analyst surveys, Brown et al. (2015) show that more than 60% of analysts state that they always use PE or PEG valuation models, while only 5% say they use RIV models. Using textual analysis of more than half a million analyst reports on U.S. firms, Huang et al. (2021) find that nearly 90 % of analyst reports use a PE model as the dominant model, and nearly 20 % of analyst reports use a DCF model as the dominant model.

Studies of the performance of different valuation models used by analysts provide mixed evidence. Using manually collected models from 490 analyst reports for 94 firms listed in the United Kingdom, Demirakos et al. (2010) find that analyst target price forecast accuracy is significantly negatively associated with the use of a DCF model without any other controls, but target price forecast accuracy is not associated with the use of valuation models (DCF model or PE models) after controlling for factors that affect analysts' valuation model choice. Asquith et al. (2005) find no evidence that the probability of achieving a target price forecast or the market's reaction to a report is associated with the valuation models used by analysts, such as PE multiples, revenue multiples, book value multiples, DCF models, and enterprise value added (EVA) models. Gleason et al. (2013) use model-based inference for model identifications to examine whether the use of valuation models by analysts in the U.S. affects target price investment performance. They find that target price investment performance is improved when analysts appear to use rigorous RIV models rather than PE and PEG heuristic models. Huang et al. (2021) find that market reactions to analyst target price changes based on DCF models are stronger than market reactions to analyst target price changes based on PE models, especially for firms with high uncertainty and when analysts discuss more DCF inputs such as cash flows and discount rates.

This study adds to the literature by examining whether the underlying firm's comparability to its peers is associated with the performance of DCF and PE models used by analysts.

2.2.3 Hypotheses development

Psychology literature suggests that people often rely on a limited number of heuristic principles to simplify their judgmental opinions. People make estimates by anchoring from an initial value and adjusting to yield the final valuation. The adjustments are often inefficient, resulting in anchoring bias in judgment and decision-making. The bias could happen among not only individual investors (Hirshleifer, 2001; George and Hwang, 2004; Li and Yu, 2012), but also experts such as managers (Baker, Pan, Wurgler, 2012), auditors (Pike, Curtis, Chui, 2013) and analysts (Frederickson and Miller, 2004; Campbell and Sharpe, 2009; Cen, Hilary, Wei, 2013).

The PE model valuation process is one type of heuristics that requires analysts to use comparable firms' multiples (serves as an anchor) to estimate the market value of the underlying firms. Anchoring literature suggests that individuals are likely to retrieve knowledge consistent with the selected benchmarks. This selective activation would result in individuals arbitrarily assessing a limited amount of information (Pike et al., 2013). In a similar vein, analysts tend to limit their attention to a small set of information when using a PE model. In contrast, few benchmarks exist when analysts use DCF models. Analysts thus have a limited basis upon which to be selective. They would access a broader range of knowledge relevant to the valuation task.

This leads to deliberate cognitive processing of all available information since analysts are not affected by the benchmark-influenced subset of information.

As analysts are likely to be subject to anchoring and adjustment bias when using a PE model, I expect a DCF model valuation to be more informative to investors than a PE model valuation. Following Asquith et al. (2005) and Huang et al. (2021), I use the differences in market reactions to analysts' target price forecasts based on different valuation models to capture the informativeness of valuation models. The baseline hypothesis on the usefulness of valuation model is stated as follows.

Hypothesis 1: *Market reactions to the change of analyst target price forecasts based on DCF models are stronger than market reactions to the change of analyst target price forecasts based on PE models.*

Identifying comparable firms is a key issue when analysts use multiples for firm valuation (Young and Zeng, 2015). Information comparability of the underlying firm plays a key role in the performance of PE models. As analysts are likely to be subject to anchoring and adjustment bias when using heuristics (Frederickson and Miller, 2004; Campbell and Sharpe, 2009), the bias becomes more severe when the underlying firms are not comparable to other firms in the same industry. I expect that the informativeness of a PE model would decrease for firms with less comparability to their peers.

Comparable firms' information is also useful to analysts during the process of a DCF valuation. When analysts use DCF models, they often need to forecast multi-period cash flows, terminal growth rate, and the weighted average cost of capital (WACC). The example in Panel B of Appendix 2.A shows that analysts consider industry and macroeconomic information in the forecasts of WACC and terminal growth rate. In addition, the example shows that analysts consider comparable firms' valuations when valuing the underlying firm's target price. Therefore, the usefulness of a DCF model can be influenced by the comparability of the underlying firm to its peers in the same industry.

Greater comparability lowers the costs of analysts' information acquisition and processing, which is expected to benefit both DCF and PE valuation processes. In other words, for firms with greater information comparability to their peers, analysts' DCF and PE models are equally informative to investors. Nevertheless, less information comparability could affect the informativeness of DCF and PE models differently. The anchoring and adjustment bias of using a PE model is more severe when the underlying firms are not comparable to other firms in the same industry. The DCF model is one of the direct valuation methods, in which the underlying firm's value is estimated directly from discounting its expected cash flows without too much reference to the current price of comparable firms. I expect that for less comparable firms, analysts' use of DCF models is more informative to investors than PE models.

It might be argued that anchoring bias also exists in DCF valuation models because analysts might anchor their forecasts of WACC, terminal growth rate, and cash flow forecasts to their prior forecasts or the industry averages. If so, the performance of a DCF model would be attenuated for less comparable firms. Overall, it appears that anchoring bias is more severe in PE models. This is because the process of adjustment from benchmarks to the target firm is not observed. Analysts perceive less justification burden in spending less effort on the adjustment. On the contrary, by using DCF models, analysts need to forecast and provide each item used in the model. Even if analysts use benchmarks in this process, they need to be very careful since investors could see each of the input variables being used.

Following the above arguments, the hypothesis on the relation between the comparability of the underlying firms to their peers and the informativeness of DCF and PE models is stated as follows.

Hypothesis 2: *The incremental effect of DCF models on market reactions to the change of analyst target price forecasts is stronger for firms with less information comparability than for firms with greater information comparability.*

2.3 Research Design, Sample Selection, and Descriptive Statistics

2.3.1 Sample selection

The data on analysts' use of valuation models is obtained from textual analysis of analyst reports from Investext. Due to the high cost of downloading analyst reports from Investext and doing textual analysis, I collect a sample of analyst reports from the top eight brokerage[16] firms in Investext from 1997 to 2017. Analyst reports from Investext are matched to the I/B/E/S U.S. database by brokerage firm names, analyst names, and the underlying company identifiers that include trading symbols and company names. To ensure matching accuracy, I require analyst forecast dates from Investext to be between the forecast announcement dates and review dates from I/B/E/S. I then match the data with Compustat and CRSP to obtain annual financial data and daily stock return data.

My initial sample consists of 622,905 analyst reports using a DCF model or PE model to justify analysts' investment opinions. I delete 95,220 analyst reports with missing values of target price forecasts. I delete 2,379 missing values of market-adjusted cumulative abnormal

[16] The sizes of brokerage firms are calculated as the number of analysts employed by each firm.

return, and 209,791 missing values of information comparability variables[17]. The final sample consists of 315,515 reports by 2,447 analysts on 2,797 U.S. firms from 1997 to 2017. Appendix 2.B shows the procedures of sample selection.

2.3.2 Measures

2.3.2.1 Measures of comparability

The first two measures of information comparability are based on De Franco et al. (2011) who define comparability as the closeness between two firms' accounting systems in mapping economic events to financial statements. They use stock returns as a proxy for the net effect of economic events on a firm's financial statement and use earnings to proxy for financial statements. For each firm-year, they run the following equation using the 16 previous quarters of data to estimate a firm's accounting function.

$$Earnings_{it} = \alpha_i + \beta_i Return_{it} + \varepsilon_{it} \quad (1)$$

where *Earnings* is the quarterly net income before extraordinary items divided by the market value of equity at the beginning of the period, and *Return* is the stock price return during the quarter. The estimated coefficients of $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are firm *i*'s accounting function. Firm *i*'s and firm *j*'s estimated accounting functions are used to predict their earnings, with the assumption that the two firms have the same stock return.

$$E(Earnings)_{iit} = \widehat{\alpha}_i + \widehat{\beta}_i Return_{it} \quad (2)$$

$$E(Earnings)_{ijt} = \widehat{\alpha}_j + \widehat{\beta}_j Return_{it} \quad (3)$$

[17] As described in Appendix 2.B, most of the missing values are *acctcomp4* and *acctcompind*. This is because the calculations of *acctcomp4* and *acctcompind* require that for each firm-quarter, there are at least 14 previous quarters of data. This requirement causes many missing values.

where $E(Earnings)_{iit}$ is the predicted earnings of firm *i*, given firm *i*'s accounting function and firm *i*'s return in period *t*. $E(Earnings)_{ijt}$ is the predicted earnings of firm *j*, given firm *j*'s accounting function and firm *i*'s return in period *t.* The pairwise accounting comparability ($ACCTCOMP_{ijt}$) between firms *i* and *j* is (-1) times the average absolute difference between the predicted earnings using firm *i*'s and firm *j*'s accounting function.

$$ACCTCOMP_{ijt} = -\frac{1}{16} \times \sum_{t-15}^{t} \left| E(Earnings)_{iit} - E(Earnings)_{ijt} \right| \quad (4)$$

A higher value of $ACCTCOMP_{ijt}$ indicates greater financial statement comparability between firms *i* and *j* in period *t*. In the calculation of comparability, firms *i* and *j* are required to be in the same SIC two-digit industry.

I construct two firm-year measures of accounting comparability based on the pairwise comparability $ACCTCOMP_{ijt}$. *acctcomp4* is the average $ACCTCOMP_{ijt}$ of the four firms with the highest comparability values. *acctcompind* is the median $ACCTCOMP_{ijt}$ of all firms in the same SIC two-digit industry.

In addition, I construct two comparability proxies based on the closeness of a firm's price-to-earnings ratio to that of its benchmark. When an analyst uses a PE model to estimate a firm's valuation, the most available benchmark could be the firm's historical performance. In addition, as industry expertise is an important aspect of sell-side analysts' research (Kadan et al., 2012; Brown et al., 2015), the other benchmark could be other firms in the same industry.

Accordingly, I measure the closeness of a firm's current price-to-earnings ratio to its historical ratios with *comppe,* which is (-1) times the absolute difference between a firm's current price-to-earnings ratio and the median value of the firm's price-to-earnings ratios in the past five years, divided by the sum of the two values. I measure the closeness of a firm's price-to-earnings ratio to its peers in the same SIC two-digit industry with *comppeind,* which is (-1) times the absolute difference between a firm's current price-to-earnings ratio and the median value of price-to-earnings ratios of other firms in the same industry, divided by the sum of the two values. Higher values of *comppe* and *comppeind* indicate greater comparability of the underlying firm.

2.3.2.2 Measure of analysts' use of DCF models

Following Huang et al. (2021), I use textual analysis to detect whether a DCF or PE model is used as a dominant valuation model in an analyst report. I first identify whether a DCF or PE model is mentioned in an analyst report. As analysts may mention multiple valuation models in a report, I then identify which valuation model is the dominant model used by an analyst. I examine whether the mention of a valuation model is within 30 words of the keywords related to analysts' investment opinions such as *price target, target price, PT, recommend,* and *recommendation*, or the keywords related to an analyst's action of applying a specific valuation model to justify a target price and recommendation, such as *use, using, based, basing, derive, derived, rating,* and *rate*.

I measure analysts' use of DCF valuation model with the dummy *DCF* which equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions.

2.3.2.3 Other variables

I use the revisions of analyst target price forecasts to measure analysts' investment opinions. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. I use the market-adjusted cumulative abnormal return to measure market reactions to the change of analyst target price forecast. *CARt* is the market-adjusted cumulative abnormal return starting one day before to *t* days after the issuance of an analyst report, multiplied by 100.

The primary interest of this paper is to examine whether information comparability affects the usefulness of the DCF model. I control for a set of firm characteristics that are associated with stock returns. *loss* equals one if a firm experiences negative earnings in year *t*, and zero otherwise. *retstd12* is the standard deviation of daily stock return during the 12 months before an analyst report date, multiplied by 100. *logmv* is the logarithm of a firm's market value in year *t*. *arpre12* is the 12-month abnormal return before the issue of an analyst report. I also control for an analyst's industry experience and firm experience. *expind* is the logarithm of the number of firms in a SIC two-digit industry covered by an analyst in year *t*. *expfirm* is the number of years an analyst has been following a firm. Appendix 2.C lists the definitions of all variables used in this study.

2.3.3 Descriptive statistics

Panel A of Table 2.1 describes the yearly distribution of the number of analyst reports, firms, and analysts, and the corresponding percent of each that use DCF models. The final sample consists of 315,515 reports by 2,447 analysts on 2,797 U.S. firms from 1997 to 2017. Panel A shows that 21.21 % of analyst reports use a DCF model as the dominant valuation model to justify analysts' investment opinions, 60.14 % of firms have been valued with a DCF model at least once during the sample period, 51.82 % of analysts have used a DCF model to justify their investment opinions. There is an increasing trend of using DCF models in the early years of the sample period. The percent of analyst reports using a DCF model have increased from 3.11 % in 1997 to 30.39 % in 2008, while remaining relatively stable in recent years. I observe similar distributions of firms being valued with DCF models and analysts using DCF models over the years.

Table 2. 1 Sample distribution

Panel A describes the yearly distribution of the number of analyst reports, firms, and analysts, and the corresponding percent of each that use DCF models. Panel B describes the use of DCF models by SIC two-digit industry.

Panel A Description by year

Year	N. (Reports)	DCF (% Reports)	N. (Firms)	DCF (% of Firms)	N. (Analysts)	DCF (% of Analysts)
1997	482	3.11	220	5.00	150	5.33
1998	819	3.54	309	7.12	189	8.47
1999	3,827	2.80	648	10.03	382	13.61
2000	11,776	3.20	913	13.36	623	18.78
2001	17,298	4.94	995	21.81	654	25.69
2002	22,130	10.21	1,119	38.34	707	35.93
2003	21,153	16.63	1,111	43.56	613	42.25
2004	21,107	20.45	1,112	46.94	570	45.96
2005	20,719	23.65	1,126	50.27	563	48.85
2006	14,876	23.77	1,017	48.57	455	46.59
2007	15,068	25.95	1,059	49.48	461	48.16
2008	15,546	30.39	1,050	53.90	466	50.43
2009	16,596	27.92	1,047	57.02	458	49.34
2010	19,177	25.94	1,089	54.82	501	50.50
2011	20,058	28.27	1,064	60.53	491	55.19
2012	19,112	28.81	1,018	57.86	497	48.89
2013	17,922	26.48	1,019	53.58	467	47.75
2014	19,681	22.83	1,033	51.02	470	51.28
2015	19,431	21.30	1,019	50.25	464	51.51
2016	18,289	22.60	970	48.66	414	48.79
2017	448	16.52	123	29.27	133	20.30
Total	315,515	21.21	2,797	60.14	2,447	51.82

Panel B Description by industry (SIC two-digit)

Industry (SIC2)	N. (Reports)	DCF (% of Reports)
Agricultural Production - Livestock and Animal Specialties	22	40.91
Amusement and Recreation Services	3,753	11.27
Apparel, Finished Products from Fabrics & Similar Materials	1,174	10.73
Automotive Dealers and Gasoline Service Stations	935	15.19
Building Materials, Hardware, Garden Supplies & Mobile Homes	8	100.00
Business Services	32,020	29.28
Chemicals and Allied Products	45,205	28.68
Coal Mining	70	27.14
Communications	12,457	45.50
Construction - General Contractors & Operative Builders	773	4.40
Depository Institutions	14,294	12.50
Eating and Drinking Places	5,935	12.33
Educational Services	1,233	55.15
Electric, Gas and Sanitary Services	14,621	24.50
Electronic & Other Electrical Equipment & Components	24,404	15.55
Engineering, Accounting, Research, and Management Services	3,030	28.65
Fabricated Metal Products	3,105	12.27

Food Stores	612	4.25
Food and Kindred Products	7,383	29.93
Furniture and Fixtures	913	25.41
Health Services	6,056	5.22
Heavy Construction, Except Building Construction, Contractor	475	1.89
Holding and Other Investment Offices	18,820	24.21
Home Furniture, Furnishings and Equipment Stores	7	0.00
Hotels, Rooming Houses, Camps, and Other Lodging Places	636	11.64
Industrial and Commercial Machinery and Computer Equipment	17,221	8.69
Insurance Agents, Brokers and Service	895	19.11
Insurance Carriers	8,652	5.56
Leather and Leather Products	436	5.50
Lumber and Wood Products, Except Furniture	1,248	7.13
Measuring, Photographic, Medical, & Optical Goods, & Clocks	14,729	22.64
Metal Mining	1,830	24.92
Mining and Quarrying of Non-metallic Minerals, Except Fuels	2	0.00
Miscellaneous Manufacturing Industries	1,344	20.01
Miscellaneous Retail	3,853	20.53
Motion Pictures	556	34.71
Motor Freight Transportation	2,665	13.13
Nonclassifiable Establishments	25	4.00
Nondepository Credit Institutions	3,433	16.84
Oil and Gas Extraction	16,793	20.61
Paper and Allied Products	5,678	6.64
Petroleum Refining and Related Industries	3,800	20.11
Pipelines, Except Natural Gas	39	41.03
Primary Metal Industries	4,032	10.44
Printing, Publishing and Allied Industries	2,914	36.10
Railroad Transportation	823	9.84
Real Estate	313	40.58
Rubber and Miscellaneous Plastic Products	1,069	17.03
Security & Commodity Brokers, Dealers, Exchanges & Services	4,914	21.00
Stone, Clay, Glass, and Concrete Products	394	7.87
Textile Mill Products	104	5.77
Transportation Equipment	11,291	18.10
Transportation Services	230	25.65
Transportation by Air	750	3.87
Water Transportation	487	13.55
Wholesale Trade - Durable Goods	3,413	9.96
Wholesale Trade - Nondurable Goods	3,641	15.85

Panel B of Table 2.1 describes the number of analyst reports and the percent using DCF models in each SIC two-digit industry. The top five industries that are most frequently valued with DCF models are: Building Materials, Hardware, Garden Supplies & Mobile Homes; Educational Services; Communications; Pipelines, Except Natural Gas, and Agricultural

Production - Livestock and Animal Specialties. This is consistent with the fact that firms from these industries tend to have more stable cash flows, which facilitates analysts' application of the DCF valuation process. Less than 4 % of analyst reports use DCF models to evaluate firms from: Mining and Quarrying of Non-metallic Minerals, Except fuels; Home Furniture, Furnishings and Equipment Stores; Heavy Construction, except Building Construction, Contractor; Transportation by Air, and Nonclassifiable Establishments.

Table 2. 2 Summary statistics and Pearson correlations

Panel A Summary statistics

	Mean	Std. Dev.	min	p25	Median	p75	max
DCF	0.212	0.409	0.000	0.000	0.000	0.000	1.000
tpchg	0.010	0.145	-0.500	0.000	0.000	0.040	0.625
CAR30	-9.611	16.524	-59.208	-19.291	-8.011	1.192	30.339
CAR183	-31.620	40.295	-98.720	-66.516	-32.282	0.129	68.382
CAR365	-41.039	50.147	-99.976	-88.266	-51.983	-1.361	100.620
acctcomp4	-0.376	0.678	-4.470	-0.340	-0.150	-0.080	-0.020
acctcompind	-2.031	1.722	-11.050	-2.520	-1.500	-0.980	-0.370
comppe	-0.440	0.925	-6.812	-0.391	-0.187	-0.081	-0.003
comppeind	-0.551	0.895	-6.748	-0.756	-0.267	-0.098	-0.004
loss	0.159	0.365	0.000	0.000	0.000	0.000	1.000
retstd12	2.238	1.244	0.785	1.369	1.899	2.731	7.121
logmv	8.687	1.670	4.938	7.479	8.629	9.873	12.329
arpre12	-36.861	54.405	-99.971	-88.207	-44.889	2.333	128.169
expind	2.178	0.751	0.693	1.609	2.303	2.708	3.584
expfirm	2.749	2.641	0.000	0.764	1.940	3.896	12.038

Panel B Pearson correlations of comparability variables

	acctcomp4	*acctcompind*	*comppe*	*comppeind*
acctcomp4	1.000			
acctcompind	0.752***	1.000		
comppe	0.162***	0.191***	1.000	
comppeind	0.182***	0.356***	0.357***	1.000

Panel A of Table 2.2 describes the summary statistics of key variables used in this study. On average, 21.2 % of the analysts reports use DCF as the dominant valuation model. The change of target price forecasts over stock price is 0.01. The average market-adjusted cumulative abnormal return is negative, ranging from -9.6% in *CAR30* to -41% in *CAR365*. The four comparability variables *acctcomp4, acctcompind, comppe,* and *comppeind* have an average value of -0.376, -2.031, -0.440, and -0.551 respectively.

Panel B of Table 2.2 presents the Pearson correlation analysis of the four comparability proxies. The correlation coefficients range from 0.162 to 0.752, suggesting that the four proxies capture different aspects of information comparability.

2.4 Comparability and the Informativeness of Valuation Models

2.4.1 Informativeness of DCF models compared with PE models

I examine the informativeness of valuation models by testing whether market reactions to analyst target price changes vary with the underlying valuation models.

$$CARt_{ijqy} = \gamma_1 + \gamma_2 tpchg_{ijqy} + \gamma_3 DCF_{ijqy} + \gamma_4 DCF_{ijqy} * tpchg_{ijqy} + \gamma_5 \sum Control + \gamma_6 Year + \gamma_7 Bank + \gamma_8 Industry + \varepsilon \quad (5)$$

where subscript *i* refers to firm, *j* refers to analyst, *q* refers to quarter, and *y* refers to year. *CARt* is the cumulative abnormal return starting from one day before to *t* days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. The coefficient on *tpchg* (γ_2) reflects market reactions to the change of analyst target price forecasts. The coefficient on *DCF*tpchg* (γ_4) captures the differences between market reactions to analyst target price changes based on DCF models and market reactions to analyst target price changes based on PE models. *Control* refers to firm characteristics such as negative earnings (*loss*), return volatility (*retstd12*), firm size (*logmv*), and previous return (*arpre12*), and analyst characteristics such as analysts' industry experience (*expind*) and firm experience (*expfirm*). Appendix 2.C lists the definitions of all the variables. I include year and SIC two-digit industry fixed effect in the above equation. I also control for the fixed effect of the brokerage bank that employs an analyst. Standard errors are clustered by firm and year to account for cross-sectional and time-series dependence.

Table 2. 3 Baseline tests on the informativeness of valuation models

This table examines the informativeness of valuation models. The dependent variable *CARt* is the cumulative abnormal return starting from one day before to *t* days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. The definitions of other variables are provided in Appendix 2.C. Industry fixed effects use SIC two-digit industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and year clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1) *CAR30*	(2) *CAR183*	(3) *CAR365*
tpchg	2.010*	-12.798***	-18.266***
	(2.01)	(-7.07)	(-7.06)
DCF	0.076	0.358	0.523
	(0.45)	(0.96)	(1.08)
DCF*tpchg	**1.913**	**3.638****	**4.796****
	(1.68)	**(2.40)**	**(2.41)**
loss	-0.159	-2.937*	-4.834***
	(-0.28)	(-2.08)	(-3.07)
retstd12	-2.045***	-1.608	-0.078
	(-4.25)	(-1.39)	(-0.05)
logmv	-1.664***	-4.260***	-5.110***
	(-8.31)	(-6.56)	(-5.14)
arpre12	0.159***	0.473***	0.560***
	(24.15)	(24.42)	(19.24)
expind	-0.256	-0.543	-0.570
	(-1.32)	(-1.19)	(-1.08)
expfirm	-0.035	0.033	0.127
	(-0.91)	(0.49)	(1.71)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	315,515	315,515	315,515
Adjusted R^2	0.368	0.549	0.545

Table 2.3 reports the baseline tests on the informativeness of valuation models. The dependent variables are *CAR30*, *CAR183*, and *CAR365* from columns (1) to (3). The coefficient

on *tpchg* is significantly positive in column (1), but significantly negative in columns (2) and (3). The results suggest that the market reacts positively when analysts increase their forecasts in short windows, but there is a reversal of the market reaction to the change of target price forecast in long periods. The coefficients on *DCF*tpchg* are significantly positive in columns (2) and (3), suggesting that there is less return reversal during a half-year and one-year window for analyst target price changes justified by DCF models. The results show that analysts' investment opinions based on DCF models are more informative to investors than their investment opinions based on PE models, consistent with the argument that analysts tend to be subject to anchoring and adjustment bias when using PE models.

In addition, the significantly negative coefficients on *loss*, *retstd12*, and *logmv* suggest that firms with negative earnings, volatile stock returns, and large size tend to experience negative market-adjusted cumulative abnormal returns after the analyst report date. The significantly positive coefficients on *arepre12* suggest that firms with better performance in the past tend to have more positive stock returns in subsequent periods. I do not find a significant effect of analysts' firm and industry experience on market reactions.

2.4.2 The Impact of comparability on the informativeness of DCF models compared with PE models

To examine whether information comparability is associated with the informativeness of valuation models, I partition the full sample into subsamples of firms with high and low information comparability. I then estimate equation (5) in the high and low subsamples to examine whether coefficients on *DCF*tpchg* (γ_4) for the high and low subsamples are significantly different. Analysts are more likely to be subject to anchoring and adjustment bias when using PE models to evaluate less comparable firms. I thus predict that the incremental effect of DCF models on market reactions to analyst target price forecast changes are stronger for firms with less information comparability than for firms with higher information comparability. In other words, I expect to find that the coefficients on *DCF*tpchg* (γ_4) in high comparability subsamples are larger and more significant than those in low comparability subsamples.

Table 2. 4 Comparability and the informativeness of DCF models compared with PE models

This table examines whether comparability of the underlying firms affects the informativeness of DCF models compared with PE models. The dependent variable is *CAR183* which is the cumulative abnormal return starting from one day before to 183 days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. The sample is split into high and low subsamples by the yearly median values of information comparability variables such as *acctcomp4*, *acctcompind*, *comppe*, and *comppeind*. The *Difference of* γ_4 *(H-L)* presents the difference tests of the coefficients on *DCF*tpchg* in the high and low subsamples. Control variables are the same as in Table 2.3 and are not reported for brevity. The definitions of other variables are provided in Appendix 2.C. Industry fixed effects use SIC two-digit industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and year clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	acctcomp4		*acctcompind*		*comppe*		*comppeind*	
	High	Low	High	Low	High	Low	High	Low
tpchg	-10.768***	-13.250***	-11.695***	-12.579***	-13.980***	-11.557***	-13.231***	-11.553***
	(-6.12)	(-6.62)	(-6.47)	(-6.29)	(-7.33)	(-5.37)	(-5.83)	(-5.82)
DCF	0.680	0.132	0.309	0.444	0.045	0.777	0.018	0.651
	(1.48)	(0.26)	(0.86)	(0.71)	(0.11)	(1.45)	(0.03)	(1.13)
***DCF*tpchg* (γ_4)**	0.564	**5.206*** **	1.425	**5.229*** **	3.895	**4.147*** **	1.233	**5.220*** **
	(0.24)	**(3.05)**	(0.78)	**(2.86)**	(1.61)	**(2.88)**	(0.57)	**(3.30)**
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference of γ_4	-4.642**		-3.804**		-0.252		-3.987***	
(H-L)	(-2.44)		(-2.03)		(-0.14)		(-2.64)	
Observations	160,250	155,263	157,810	157,705	158,037	157,477	157,580	157,935
Adjusted R^2	0.618	0.496	0.640	0.488	0.629	0.487	0.607	0.509

Table 2.4 reports the tests in the subsamples of firms with high and low information comparability with the dependent variable being *CAR183*[18]. The sample is split into high and low subsamples by information comparability measures of *acctcomp4, acctcompind, comppe,* and *comppeind.* The odd columns are the tests in the subsamples of firms with higher information comparability and the even columns are the tests in the subsamples of firms with less information comparability. I find that the coefficients on *DCF*tpchg* are insignificant in the subsamples of firms with high information comparability, suggesting that DCF and PE models are not significantly different in their informativeness to investors for firms with comparable peers. The coefficients on *DCF*tpchg* are significantly positive for firms with low information comparability, suggesting that DCF models are more informative to investors than PE models for less comparable firms. *Difference of* γ_4 *(H-L)* at the bottom of Table 2.4 presents the significance tests of the differences in the coefficients on *DCF*tpchg* between high and low subsamples. Three out of four differences in γ_4 *(H-L)* are significantly negative, consistent with the prediction that DCF models are more informative than PE models, especially for firms with less information comparability.

2.4.3 Robustness tests

2.4.3.1 Compare direct valuation models with relative valuation models

In previous sections, I consider and compare analysts' use of a DCF model and a PE model, the valuation models most frequently used by analysts (Imam et al. 2013; Brown et al. 2015). In this section, I consider all the valuation models used by analysts in their reports.

[18] The findings are qualitatively the same if I use *CAR30* or *CAR365* as the dependent variables.

Following Gleason et al. (2013), I classify the valuation models into two broad categories: *direct valuation models*[19] such as DCF, RIV, and net asset value (NAV) models that discount future cash flow forecasts or earnings forecasts with estimated discount rates to generate a fundamental value of the underlying firms, and *relative valuation models*[20] such as PE, price-to-book value (PB), price-to-sales (PSAL), and price-to-cash flows (PCF) models, which use comparable peers to develop a relative value of the underlying firms. Refer to Appendix 2.D for these valuation model classifications and the major accounting items that are used to identify each model.

Table 2.5 reports the tests considering all valuation models used by analysts. As I include all the valuation models, the sample size is larger than that used in the main analyses. The sample consists of 347,197analyst reports with 83,866 reports using direct valuation models. Similar to the measure for using a DCF model, I measure the use of a direct valuation model with *DirModel* which equals one if analysts use a direct valuation model to justify their investment opinions, and zero if analysts use only a relative valuation model to justify their investment opinions. I expect that analysts are more likely to be subject to anchoring and adjustment bias when using relative valuation models compared with using direct valuation models.

Panel A of Table 2.5 reports the yearly distribution of direct and relative valuation models. It shows that DCF and PE are the two most frequently used models, which is one of the reasons why I focus on the comparison between DCF and PE models. Other than the DCF model, another frequently used direct model is the NAV model with an average of 5.22 % usage in

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[19] Direct valuation models are also described as absolute valuation models, fundamental valuation models, or multi-period valuation models.
[20] Relative valuation models are described as heuristic models, multiples models, or single-period valuation models.

analyst reports. Few analysts use a RIV model to justify their investment opinions, with only 0.38 % usage in analyst reports. This is consistent with Hand et al. (2017) who find that the use of a RIV model is only 5% of that of a DCF model. In the relative model category, PB, PSAL, and PCF models are used by analysts in 4.56 %, 3.89%, and 2.45% of their reports as dominant models, respectively.

Panel B of Table 2.5 reports the tests on the impact of comparability on the informativeness of direct valuation models compared with relative valuation models, with *CAR183* being the dependent variable. Column (1) shows the baseline test on the informativeness of valuation models. The significantly negative coefficient on *tpchg* and the positive coefficient on *DirModel*tpchg* suggest that there is less return reversal during a half-year window for analyst target price forecast changes. In other words, analysts' investment opinions based on direct valuation models are more informative to investors than their investment opinions based on relative valuation models.

Columns (2) to (9) report the tests on the effect of information comparability on the usefulness of absolute models compared with relative models. The sample is split into high and low subsamples by the yearly median values of information comparability variables such as *acctcomp4, acctcompind, comppe,* and *comppeind.* The even columns are the tests in the subsamples of firms with higher information comparability and the odd columns are the tests in the subsamples of firms with less information comparability. The coefficients on *DirModel*tpchg* are significantly positive for less comparable firms and insignificant for more comparable firms for three of the four comparability proxies. The *Difference of* γ_4 *(H-L)* at the bottom of Table 2.5 presents the significance tests of the differences in the coefficients on *DirModel*tpchg* between high and low subsamples. Two out of four differences in γ_4 *(H-L)* are significantly negative, consistent with the prediction that direct models are more informative than relative models, especially for firms with less information comparability.

Table 2. 5 Compare direct valuation models with relative valuation models

Panel A describes all the direct and relative valuation models by year. Panel B presents the tests on the informativeness of direct valuation models compared with relative valuation models. *DirModel* equals one if analysts use a direct valuation model to justify their investment opinions, and zero if analysts use only a relative valuation model to justify their investment opinions. The dependent variable is *CAR183* which is the cumulative abnormal return starting from one day before to 183 days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. Column (1) tests the usefulness of absolute valuation models in the full sample. In columns (2) to (9), the sample is split into high and low subsamples by the yearly median values of information comparability variables such as *acctcomp4*, *acctcompind*, *comppe*, and *comppeind*. The *Difference of* γ_4 *(H-L)* presents the difference tests of the coefficients on *DirModel*tpchg* in the high and low subsamples. Control variables are the same as in Table 2.3 and are not reported for brevity. The definitions of other variables are provided in Appendix 2.C. Industry fixed effects use SIC two-digit industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and year clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A Description of valuation models by year

		Direct valuation models				Relative valuation models				
Year	N. (Reports)	*DirModel* (%)	DCF (%)	NAV (%)	RIV (%)	REL (%)	PE (%)	PB (%)	PCF (%)	PSAL (%)
1997	493	4.46	3.04	1.62	0.00	95.54	94.73	2.03	0.41	1.62
1998	850	4.82	3.41	1.53	0.00	95.18	92.94	1.41	0.47	4.82
1999	3,928	4.38	2.72	1.63	0.10	95.62	94.70	1.17	0.87	2.42
2000	12,284	4.68	3.07	1.53	0.20	95.32	92.80	0.83	0.90	2.12
2001	17,929	6.61	4.77	1.70	0.32	93.39	91.71	1.63	0.96	1.89
2002	23,271	11.92	9.71	2.10	0.47	88.08	85.39	2.52	3.21	2.23
2003	22,471	18.67	15.66	3.16	0.53	81.33	78.48	3.78	5.63	2.22
2004	22,704	23.15	19.01	4.35	0.62	76.85	73.96	3.85	3.37	1.88
2005	22,136	25.98	22.14	4.62	0.56	74.02	71.46	4.59	3.93	2.62
2006	15,908	26.23	22.23	4.99	0.95	73.77	71.28	3.09	2.67	2.25
2007	16,269	28.86	24.03	6.18	0.53	71.14	68.58	4.81	3.63	2.59
2008	17,162	33.11	27.53	7.67	0.06	66.89	63.05	5.86	3.53	3.44
2009	18,929	32.18	24.48	9.30	0.29	67.82	63.19	6.03	3.18	3.44
2010	21,303	28.86	23.35	6.66	0.34	71.14	66.67	5.38	3.46	2.81
2011	22,765	30.08	24.91	5.46	0.32	69.92	63.20	5.36	4.25	2.55
2012	22,097	31.41	24.92	6.31	0.36	68.59	61.57	6.18	4.00	3.06
2013	20,659	29.69	22.97	6.39	0.36	70.31	63.78	6.23	4.22	2.28
2014	22,593	26.46	19.89	5.85	0.33	73.54	67.22	5.44	4.43	2.06
2015	22,279	25.08	18.58	6.05	0.17	74.92	68.64	4.93	5.18	1.99

2016	20,660	26.79	20.00	6.81	0.19	73.21	68.52	5.91	7.90	2.31
2017	507	16.57	14.60	0.79	1.18	83.43	73.77	8.68	10.45	1.97
Total	347,197	24.16	19.27	5.22	0.38	75.84	71.60	4.56	3.89	2.45

Panel B Comparability and the informativeness of valuation models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample	*acctcomp4*		*acctcompind*		*comppe*		*comppeind*	
		High	Low	High	Low	High	Low	High	Low
tpchg	-13.244***	-10.959***	-13.784***	-12.032***	-12.967***	-14.058***	-12.113***	-13.291***	-12.177***
	(-6.76)	(-5.98)	(-6.33)	(-5.87)	(-6.33)	(-6.84)	(-5.34)	(-5.52)	(-5.90)
DirModel	0.542	0.704	0.384	0.447	0.615	0.212	0.941*	0.020	1.013*
	(1.45)	(1.53)	(0.71)	(1.17)	(1.06)	(0.52)	(1.78)	(0.04)	(1.77)
*DirModel*tpchg* (γ_4)	**4.161*** **	1.539	**5.375*** **	3.279**	4.891**	3.064	**5.047*** **	0.157	**6.436*** **
	(2.91)	(0.74)	**(2.96)**	(2.23)	(2.47)	(1.39)	**(3.48)**	(0.07)	**(3.57)**
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference of γ_4 *(H-L)*		-3.836**		-1.612		-1.983		-6.279***	
		(-2.08)		(-0.82)		(-1.22)		(-4.30)	
Observations	347,197	175,347	171,848	173,866	173,331	173,565	173,631	173,757	173,440
Adjusted R^2	0.553	0.621	0.502	0.646	0.491	0.633	0.492	0.614	0.510

2.4.3.2 Control for other information signals in analyst reports

Panel A of Table 2.6 presents the tests controlling for other information signals of an analyst report. The dependent variable is *CAR183*. I control for the analyst EPS forecast with *epschg*, which is the change of analyst EPS forecast scaled by the stock price at the beginning of the year, and control for analyst stock recommendation with *recchg*, which is the change of analyst stock recommendation forecast. *recchg* equals one if an analyst upgrades her recommendation, zero if the analyst reiterates her recommendation, and negative one if the analyst downgrades her recommendation. I also add the interaction of *DCF*recchg*, as a stock recommendation is the indirect output of a valuation model.

In column (1), the coefficient on *DCF*tpchg* remains significantly positive after controlling for other information signals, consistent with the evidence that a DCF model is more informative to investors than a PE model in general. Columns (2) to (9) report the tests on the effect of information comparability on the usefulness of DCF models compared with PE models. Similarly, I find that the coefficients on *DCF*tpchg* are larger and more significant for firms with less information comparability than for firms with higher information comparability. Overall, the major findings are unchanged with additional controls for analysts' information signals.

Table 2. 6 Additional control for information signals and subsample analysis

Panel A presents the tests controlling for other information signals of an analyst report. *epschg* is the change of analyst earnings per share forecast scaled by the stock price at the beginning of the year. *recchg* is the change of analyst stock recommendation forecast. Panel B presents the tests in the subsample in which an analyst uses DCF and PE models for different firms in one year. In all panels, the dependent variable is *CAR183* which is the cumulative abnormal return starting from one day before to 183 days after the report date. *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. Column (1) is the test in the full sample. In columns (2) to (9), the sample is split into high and low subsamples by the yearly median values of information comparability variables such as *acctcomp4*, *acctcompind*, *comppe*, and *comppeind.* Control variables are the same as in Table 2.3 and are not reported for brevity. The definitions of other variables are provided in Appendix 2.C. Industry fixed effects use SIC two-digit industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and year clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A Control for other information signals in an analyst report

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample	*acctcomp4*		*acctcompind*		*comppe*		*comppeind*	
		High	Low	High	Low	High	Low	High	Low
tpchg	-12.901***	-10.518***	-13.673***	-11.482***	-12.950***	-13.591***	-12.151***	-11.486***	-12.043***
	(-6.45)	(-5.79)	(-5.95)	(-5.81)	(-5.91)	(-6.67)	(-5.26)	(-5.41)	(-5.12)
epschg	-52.494***	-95.360***	-35.690***	-94.394***	-34.659***	-84.176***	-34.020***	-201.431***	-17.534
	(-4.19)	(-3.27)	(-2.94)	(-4.39)	(-2.97)	(-3.94)	(-3.06)	(-6.36)	(-1.38)
recchg	2.036***	1.576***	2.434***	1.818***	2.250***	2.100***	2.022***	1.974***	2.023***
	(5.81)	(3.92)	(6.22)	(4.86)	(5.52)	(6.54)	(4.63)	(5.63)	(4.79)
DCF	0.434	0.783	0.180	0.478	0.393	0.055	0.963	0.132	0.741
	(1.09)	(1.67)	(0.35)	(1.25)	(0.58)	(0.13)	(1.72)	(0.23)	(1.25)
***DCF*tpchg* (γ_4)**	**3.557***	0.206	**5.217****	0.720	**5.364****	3.476	**4.443****	0.757	**5.311*****
	(2.10)	(0.08)	**(2.68)**	(0.34)	**(2.72)**	(1.35)	**(2.70)**	(0.37)	**(2.88)**
*DCF*recchg*	-0.318	-0.473	-0.262	-0.177	-0.538	-0.370	-0.516	0.328	-0.892
	(-0.62)	(-0.66)	(-0.40)	(-0.33)	(-0.82)	(-0.94)	(-0.66)	(0.61)	(-1.39)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference of γ_4 (H-L)		-5.011**		-4.644**		-0.967		-4.554**	
		(-2.32)		(-2.18)		(-0.33)		(-2.23)	

Observations	282,912	141,807	141,105	138,101	144,811	142,572	140,340	142,558	140,353
Adjusted R^2	0.552	0.619	0.501	0.640	0.495	0.633	0.488	0.614	0.508

Panel B Subsample where an analyst uses different models for different firms in a year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample	*acctcomp4*		*acctcompind*		*comppe*		*comppeind*	
		High	Low	High	Low	High	Low	High	Low
tpchg	-12.730***	-10.081***	-13.701***	-10.941***	-12.826***	-15.565***	-10.650***	-13.526***	-11.281***
	(-5.95)	(-5.00)	(-5.32)	(-5.34)	(-4.70)	(-6.60)	(-4.71)	(-5.47)	(-4.83)
DCF	0.560*	0.544	0.650	0.311	0.797	0.173	1.078**	0.308	0.841
	(1.74)	(1.53)	(1.26)	(0.96)	(1.55)	(0.47)	(2.18)	(0.60)	(1.39)
*DCF*tpchg (γ_4)*	2.640	-0.870	**4.773****	-1.060	**4.388***	5.205	1.656	2.568	**2.964**
	(1.47)	(-0.36)	**(2.28)**	(-0.51)	**(1.77)**	(1.70)	(1.13)	(0.99)	**(1.58)**
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference of γ_4 (H-L)		-5.643** (-2.50)		-5.448** (-2.48)		3.549** (2.15)		-0.396 (-0.47)	
Observations	162,306	82,129	80,177	73,465	88,841	79,427	82,878	74,058	88,248
Adjusted R^2	0.562	0.634	0.508	0.654	0.511	0.646	0.502	0.634	0.520

2.4.3.3 Subsample in which an analyst uses DCF and PE models for different firms in one year

Panel B of Table 2.6 presents the tests in the subsample in which an analyst uses different models for different firms in one year. The dependent variable is *CAR183*. Column (1) reports the main test on the usefulness of DCF models. The coefficient on *DCF*tpchg* is positive but insignificant. In columns (2) to (5), the sample is split into subsamples of firms with high and low comparability according to the yearly median values of *acctcomp4* and *acctcompind*. I find that the coefficients on *DCF*tpchg* are insignificant in high subsamples and significantly positive in low subsamples. Moreover, the differences of coefficients on *DCF*tpchg* for high and low subsamples are significantly negative, suggesting that DCF models are more informative than PE models for firms with less information comparability.

In columns (6) to (9), the sample is split into subsamples of firms with high and low comparability according to the yearly median values of *comppe* and *comppeind*. The coefficients on *DCF*tpchg* are insignificant in both high and low subsamples. Taken together, the findings in Panel B of Table 2.6 provide consistent evidence on the relation between information comparability and the usefulness of DCF models compared with PE models.

2.4.4 Macro information comparability and the informativeness of DCF models compared with PE models

I have provided evidence that low firm-level information comparability enhances the usefulness of DCF models compared with PE models. In this section, I further examine whether macro information comparability affects the usefulness of valuation models. I use two measures to capture the macro information comparability. One is the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016). Macro information is more comparable in periods with a low EPU index than in periods with a high EPU index. The other proxy is an indicator *Recession* that equals one for the recession periods marked by the NBER, and zero otherwise. Macro information comparability is reduced in recession periods. The two measures *EPU* and *Recession* are inversely related to macro information comparability.

Table 2.7 reports the tests on the impact of macro information comparability on the usefulness of DCF models compared with PE models. In columns (1) and (2), the sample is split into subsamples of periods with high and low economic policy uncertainty according to the median value of *EPU*. The coefficient on *DCF*tpchg* is significantly positive in the high subsample and insignificant in the low subsample. The difference of the coefficient on *DCF*tpchg* is significantly positive, suggesting that high economic policy uncertainty enhances the incremental effect of DCF models on market reactions to analyst target price forecast changes. As *EPU* is inversely related to macro information comparability, the finding indicates that DCF models are more useful to investors than PE models, especially when macro information comparability is low.

Table 2. 7 Macro information comparability and the usefulness of valuation models

This table examines whether macro information comparability affects the usefulness of DCF models compared with PE models. I measure macro information comparability with *EPU* which is the economic policy uncertainty index from Baker, Bloom, and Davis (2016), and *Recession* which equals one for the recession periods marked by the National Bureau of Economic Research (NBER), and zero otherwise. *EPU* and *Recession* are inversely related to macro information comparability. The dependent variable is *CAR183* which is the cumulative abnormal return starting from one day before to 183 days after the report date. *DCF* equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. The sample is split into high and low subsamples according to the median value of *EPU* and the value of *Recession.* Control variables are the same as in Table 2.3 and are not reported for brevity. The definitions of other variables are provided in Appendix 2.C. Industry fixed effects use SIC two-digit industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and year clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
	EPU		*Recession*	
	High	Low	Yes	No
tpchg	-14.284***	-8.111***	-19.886**	-10.838***
	(-8.40)	(-5.08)	(-4.93)	(-5.88)
DCF	0.476	0.172	0.878	0.434
	(1.14)	(0.44)	(1.10)	(1.13)
*DCF*tpchg* (γ_4)	**5.152****	1.754	**4.171****	2.838*
	(2.57)	(1.13)	**(4.46)**	(1.81)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Difference of γ_4	3.398**		1.333	
(H-L)	(2.00)		(1.30)	
Observations	157,296	158,219	37,063	278,452
Adjusted R^2	0.541	0.568	0.478	0.569

In columns (3) and (4), the sample is split into subsamples of recession periods and nonrecession periods. The coefficient on *DCF*tpchg* is more significant and larger in recession periods than that in non-recession periods. The difference of the coefficient on *DCF*tpchg* is positive but insignificant. Overall, the findings in Table 2.7 provide further evidence of the effect of comparability on the usefulness of DCF models compared with PE models.

2.5 Conclusions

In this study, I examine the impact of the underlying firms' comparability to their peers on the informativeness of DCF models and PE models. I find that the use of a DCF model is associated with stronger market reactions to analyst target price changes. Further analysis indicates that the incremental effect of DCF models on market reactions to analyst target price changes is mainly restricted to less comparable firms. This is consistent with the argument that analysts are subject to anchoring and adjustment bias when using PE models, and that the bias is more severe when information comparability is low.

This study contributes to the literature on analysts' valuation process by focusing on the comparisons of the informativeness of two widely used valuation models: DCF models and PE models. Moreover, I investigate the impact of comparability on the informativeness of valuation models. This study adds to the literature on the benefits of information comparability. My findings suggest that a lack of comparability results in less informative analyst investment opinions based on PE models. This study also adds to the anchoring literature by showing that analysts are subject to anchoring and adjustment bias when using PE models.

Chapter 3: Analysts' Use of Valuation Models Around the World

3.1 Introduction

Sell-side equity analysts play an important informational intermediary role in the capital market. Previous studies show that country-level factors affect analyst coverage decisions (Sun, 2009; Chang, Khanna, and Palepu, 2000; Lang, Lins, and Miller, 2004), earnings forecast accuracy (Hope, 2003; Barniv, Myring, and Thomas, 2005; Bae, Tan, and Welker, 2008), the profitability of stock recommendations (Barniv, Hope, Myring, and Thomas, 2010), and the target price forecast (Bradshaw, Huang, and Tan, 2018). It is unclear whether the firm country's institutional factors are associated with analysts' choice of performance metrics used in their valuation models.

Accrual accounting is the cornerstone of modern accounting standards. It is generally accepted that earnings information based on accrual accounting is more value-relevant than cash flow information (Dechow, 1994). Consistent with this argument, analysts routinely use valuation models based on the accrual information such as price-to-earnings multiples in their reports (Asquith, Mikhail, and Au, 2005; Huang, Tan, Wang, and Yu, 2021). Analysts' use of cash flow models is quite selective, depending on the underlying firm's size, riskiness, and profitability (Demirakos, Strong, and Walker, 2010; Huang et al., 2021), and analysts' conflicts of interest (Barniv, Hope, Myring, and Thomas, 2009). As accrual models are the default models used by analysts in their reports, the focus of this study is to explore *when* analysts use cash flow models. Specifically, I examine whether a firm country's institutional factors facilitate analysts' choice of cash flow models, and whether the informativeness of cash flow models varies with the firm country's institutional factors. [21]

A country's institutional factors have two offsetting effects on analysts' use of cash flow models. On the one hand, the firm country's institutional environment can be a complement to analysts' research. Analysts are more accurate in their forecasting tasks in countries with sound institutions (Basu et al., 1998; Hope, 2003). In addition, analysts may differentiate themselves by focusing on cash flows when the management reports high-quality earnings in well-governed countries. This line of argument predicts that good institutional factors contribute to analysts' forecasts of cash flow information and the use of cash flow models. On the other hand, analysts' research can be a substitute for the firm country's institutional environment. Earnings are likely manipulated by managers in countries with poor institutions, and investors thus have a stronger demand for cash flow information to sort out the inferior elements of earnings (DeFond and Hung, 2007). In response to investors' demand, analysts are more likely to use cash flow models in countries with weak institutional environments. Therefore, the relation between the firm country's institutional environment and analysts' use of cash flow models is an empirical question.

I use textual analysis to detect analysts' use of valuation models in their reports for non-U.S. firms around the world. To address the research questions, I classify valuation models used by analysts into two categories: accrual models and cash flow models. Accrual models include earnings multiples (PE), book value multiples (PB), sales multiples (PSAL), net asset value (NAV), and residual income valuation (RIV) models which use accrual performance metrics,

[21] Asquith et al. (2005) and Huang et al. (2021) find that more than 90% of analyst reports clearly state that they use accrual models such as PE multiples to justify their valuations. Content analysis in this study reveals that analysts routinely use an accrual model in their reports. Therefore, the purpose of this study is not to compare accrual models and cash flow models, but exploring whether country factors facilitate analysts' use of cash flow models.

such as earnings, sales, and book values, as value drivers. Cash flow models include price-to-cash flow multiples (PCF) and discounted cash flow (DCF) models which use cash flows as firm value drivers. I measure the use of cash flow models with *CFModel*, which equals one if analysts use a cash flow model as the dominant valuation model to support their investment opinions, and zero otherwise.

First, I examine whether a country's institutional environment is associated with analysts' use of cash flow models. I focus on three institutional factors: investor protection, information environment, and economic freedom.[22] I use the revised anti-director rights index, anti-self-dealing index, and public enforcement index from Djankov, LaPorta, Lopez-de-Silanes, and Shleifer (2008) to capture the strength of a country's investor protection. I find that analysts are more likely to use cash flow models in countries with stronger investor protection. This is consistent with the argument that strong investor protection is a complement to analysts' research, which facilitates the use of cash flow models.

I measure a country's information environment with the financial disclosure index from CIFAR (1995), and the negative value of the index of earnings management from Leuz, Nanda, and Wysocki (2003).[23] The regression results show a significant positive relationship between the firm country's information environment and the likelihood of analysts using cash flow models. A good information environment aids analysts in using cash flow models, because analysts have better access to information sources for the predictions of cash flows and discount rates in such conditions.

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[22] I conceptualize that a country's legal, financial, and economic system may play a role in analysts' application of cash flow models. Therefore, I use the level of investor protection to capture a country's legal system, use the information environment to capture a country's financial system, and use the economic freedom to reflect a country's economic system, and examine their impact in facilitating analysts' use of cash flow models

[23] The measures for country-level institutional factors barely change over the years. Therefore, I use CIFAR (1995) as one of the measures to capture the information environment of firm countries.

I use the summary freedom and the legal structure freedom from the Fraser Institute to measure a country's economic freedom. I find that analysts are more likely to use cash flow models in countries with greater economic freedom. The finding is consistent with the conjecture that the average demand for value-relevant information is likely to be greater in countries with greater economic freedom, which offers analysts market incentives to provide more information by using cash flow models. Overall, I find evidence supporting the complementary role of the firm country's institutional environment in analysts' use of cash flow models.[24]

Next, I examine the informativeness of analysts' use of cash flow models. Following Huang et al. (2021), I test the informativeness of cash flow models by investigating whether the use of cash flow models affects market reactions to the change of analyst target price forecasts. The baseline results show that the use of cash flow models is associated with greater market reactions to analyst target price changes, suggesting that cash flow models are informative to investors in general.

I then examine whether the informativeness of cash flow models varies with the firm country's institutional environment. I partition the full sample into subsamples by the median values of proxies for investor protection, information environment, and economic freedom. To the extent that a good institutional environment facilitates analysts' use of cash flow models, I expect that cash flow models are more informative to investors in the subsamples of countries with stronger investor protection, better information environment, and greater economic freedom. Consistent with the predictions, I find that the positive association between a cash flow

[24] The findings suggest that strong country-level institutions facilitate analysts' application of cash flow models. It is not conclusive that analyst research, in general, is a complement to all country-level factors. Previous studies provide mixed evidence on the relation between analyst research and country-level factors. For example, Hope (2003) finds that analysts' earnings forecast accuracy is positively associated with the enforcement of accounting standards in a country. However, DeFond and Hung (2007) find that analysts are more likely to provide cash flow forecasts in countries with weaker investor protection.

model and market reactions to analyst target price changes is more pronounced in countries with a stronger institutional environment. The findings offer corroborating evidence that the institutional factors are a complement to sell-side equity analysts' research.

My contribution to the literature is as follows. First, I augment the research on valuation models used by analysts in their reports. Extant research on valuation models mainly focuses on the impact of firm-level factors. For instance, Demirakos et al. (2010) show that DCF models are more popular than PE models in valuing small firms, risky firms, and loss-making firms. Huang et al. (2021) find that analysts are more likely to use DCF models for uncertain firms, and the use of DCF models increases market reactions to analyst investment opinions. I believe that Barniv, Hope, Myring, and Thomas (2010) (hereafter, BHMT) are the only exception in testing valuation models in an international setting. They find that analysts are more likely to use price-to-earnings-growth (PEG) multiples than RIV models to justify their recommendations in countries with greater investor participation.

This paper differs from BHMT in a few ways. First, unlike BHMT who use model-based inference for valuation models identification, I extract analysts' use of models directly from their reports. Second, unlike BHMT who examine only a couple of valuation models such as PEG and RIV, I examine all the different valuation models used by analysts in their reports and divide them into two groups: accrual models and cash flow models. Although RIV models are popular in recent years, the content analysis in this paper shows that analysts rarely use RIV models to justify their stock recommendation or target prices. Third, unlike BHMT who examine the effect of investor participation, I examine whether the firm country's investor protection, information environment, and economic freedom affect analysts' use of cash flow models.

I also contribute to the literature on sell-side equity analysts in international settings. Existing studies on the impact of country-level factors on analysts' research primarily pertain to their forecasts of EPS, stock recommendations, and target prices. Very little research explores whether a country's institutional environment plays a role in analysts' valuation process. The findings in this paper suggest that analysts tend to use cash flow models to justify their investment opinions in firm countries with sound institutions. In addition, this paper explores the argument on whether a country's institutional environment and analysts' research are substitutes or complements. My findings are consistent with the argument that the firm country's institutional environment is a complement to analysts' research.

3.2 Related Literature

Summary measures in analyst research, such as forecasts of earnings per share, stock recommendations, and target prices, are readily available to researchers through the I/B/E/S database. Analysts' use of valuation models, however, is not included in any financial database. Previous studies have mainly used three approaches to identify analysts' use of valuation models.

One approach is to use surveys or interviews to gather information about the valuation models that analysts use (e.g., Arnold and Moizer, 1984; Pike, Meerjanssen, and Chadwick, 1993; Barker, 1999; Block, 1999). Early evidence from surveys and interviews suggests that price-to-earnings ratio is the dominant model used by analysts. The second approach is to use content analysis of analyst reports to identify analysts' use of valuation models (i.e. Previts, Bricker, Robinson, and Young, 1994; Bradshaw, 2002; Demirakos et al., 2004 and 2010; Asquith et al. 2005; Imam, Barker, and Clubb, 2008; Huang et al., 2021). Similarly, studies based on content analysis find that the most dominant valuation model used by analysts in their reports is earnings multiples, with an increasing trend of using DCF models. The third approach of valuation model identification is to infer how analysts convert their earnings forecasts into investment opinions by correlating recommendations and target prices with the implied estimates from some predefined valuation models (e.g., Bradshaw, 2004; Barniv, Hope, Myring, and Thomas, 2009 and 2010; Simon and Curtis, 2011; Gleason, Johnson, and Li, 2013).

Extant literature generally shows that most analysts use PE multiples to estimate firms' valuations. In other words, PE multiples are the default models used in analyst reports, while the use of other valuation models is selective. Previous studies find that analysts prefer to use DCF models value small, high-risk, and loss-making firms, and firms with a limited number of industry peers (Demirakos et al., 2010)). Analysts are more likely to use DCF models to value firms with greater valuation uncertainty (Huang et al., 2021). Industry characteristics also play a role in analysts' choice of valuation models (Barker, 1999). Demirakos et al. (2004) show that analysts are more likely to use single-period multiples when the industry is characterized with fairly uniform and stable growth. They find that analysts are more likely to use cash flow models rather than accrual models when accounting information in the industry is quite uncertain. Furthermore, analysts' incentives are likely to influence the use of valuation models. Barniv et al. (2009) find that after Reg. FD, analysts are less likely to bias their recommendations by using earnings multiples. Simon and Curtis (2011) find that analysts who want to build good reputations are more likely to align their recommendations with rigorous valuation models such as the RIV model.

There are several studies on the performance of different valuation models, but their conclusions are inconsistent. Asquith et al. (2005) and Demirakos et al. (2010) find that there is no significant performance difference between PE and DCF models. Nevertheless, other evidence shows that the choice of valuation models may systematically influence the accuracy of the target price and the profitability of stock recommendations. Gleason et al. (2013) find that the investment performance of target price improves when analysts appear to use a rigorous valuation model rather than a heuristic. Huang et al. (2021) find that the use of a DCF model is associated with greater market reactions to analysts' investment opinions, especially for firms with greater uncertainty and when analysts provide more discussion of discount rate and cash flow information.

Previous studies on analysts' use of valuation models focus mainly on micro-level factors such as firm, industry, and analyst traits, with limited research examining whether macro-level factors are associated with analysts' choice of valuation models. I contribute to prior literature by examining whether the firm country's institutional environment affects analysts' use of cash flow models and the informativeness of cash flow models.

3.3 Hypotheses Development

Accrual accounting is the cornerstone of modern accounting standards. The FASB Statement of Accounting Concepts No. 1 documents "Information about an enterprise's earnings based on accrual accounting generally provides a better indication of enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial aspects of cash receipts and payments." Academic research provides consistent evidence on the value relevance of earnings and cash flows. Subramanyam and Venkatachalam (2007) classify performance measures into earnings and cash flows, and examine their relative performance in equity valuation. They find that earnings outperform cash flows in the prediction of *ex post* intrinsic value measured by discounted dividends.

Given the importance of accrual accounting, analysts routinely use accrual models in their valuation process,[25] while the use of cash flow models is quite selective. In this study, I examine whether a firm country's institutional factors facilitate analysts' choice of cash flow valuation models. Specifically, I focus on three institutional factors: investor protection, information environment, and economic freedom.

3.3.1 Investor protection and cash flow models

Managers in countries with weak investor protection typically enjoy large "private benefits of control" (Dyck and Zingales, 2004), and thus have strong incentives to mask poor firm performance (Hung, 2000; Leuz et al., 2003). Given that the management's financial disclosure is one of the major information sources for analysts, analysts would face increased difficulty in providing accurate cash flow forecasts in countries with weak investor protection. In addition, DCF models are the most frequently used cash flow models among analysts. It is challenging for analysts to forecast multi-period cash flows and forecast the cost of capital when a firm country has weak investor protection. Moreover, in countries with strong investor protection, investors can easily obtain good quality accrual information from the management, and the demand for accrual information from the analyst can be weakened. As a result, analysts may differentiate themselves by forecasting cash flow information.

There may exist countervailing forces in the effect of investor protection on the use of cash flow models. In countries with weak investor protection, the accrual information is likely manipulated, and investors may have a stronger demand for cash flow information from analysts. For example, DeFond and Hung (2007) find that analysts are more likely to make cash flow

[25] The textual analysis of analyst reports confirms that accrual models are the default models used by analysts.

forecasts in countries with weak investor protection. In response to investor demand for value-relevant information, analysts are likely to use cash flow models in those countries.

The impact of a firm country's investor protection on analysts' use of cash flow models can be two-sided. I therefore posit the following nondirectional hypothesis.

Hypothesis1a: Analysts' use of cash flow models is associated with the level of investor protection of the firm country.

To the extent that strong investor protection may facilitate analysts' choice of cash flow models, I expect the informativeness of cash flow models to be associated with the level of investor protection. Following Huang et al. (2021), I examine the informativeness of cash flow models by testing whether the use of cash flow models increases market reactions to the change of analyst target price forecasts. An incremental effect of cash flow models on market reactions suggests that cash flow models are informative to investors. If a firm country's investor protection affects the informativeness of valuation models, the incremental effect of cash flow models on market reactions will be significantly different for high-protected and low-protected countries. This leads to the following nondirectional hypothesis.

Hypothesis1b: The incremental effects of cash flow models on market reactions to analyst target price changes are associated with the level of investor protection of the firm country.

3.3.2 Information environment and cash flow models

Holland (1998) suggests that a firm's information disclosure can increase investors' understanding of the firm's current and future performance outlook. Previous studies find that analysts are more accurate in countries with a high level of information disclosure (Basu et al., 1998). A good information environment, measured by financial disclosure and earnings quality in this study, can aid analysts in forecasting future cash flows and using cash flow models.

With respect to financial disclosure, analysts can obtain insights about future cash flows through management's discussions about the product, the market strategy, and investments in capital markets. Moreover, in countries with more information disclosure, analysts face less uncertainty in forecasting the systematic and firm-specific risk, the major factors in the application of a DCF valuation model. In countries with higher earnings quality, earnings are more likely to be backed by operating cash flows and tend to be more sustainable and repeatable (Brown, Call, Clement, and Sharp, 2015). As a result, it is easier and less costly for analysts to forecast future cash flows and apply cash flow models in countries with good earnings quality. The above discussion leads to the following two hypotheses.

Hypothesis2a: Analysts' use of cash flow models is associated with the firm country's information environment.

Hypothesis2b: The incremental effects of cash flow models on market reactions to analyst target price changes are associated with the firm country's information environment.

3.3.3 Economic freedom and cash flow models

Countries with greater economic freedom are characterized by high economic growth (Gwartney and Lawson, 2002). The average demand for value-relevant information is likely to be greater in such countries, thus incentivizing analysts to offer more information by using cash flow models. For instance, PCF and DCF models include analysts' predictions of the single-period and multi-period cash flows. DCF models convey analysts' assessment of the underlying firm's potential riskiness. More importantly, institutional factors that guarantee economic freedom may enforce greater penalties for the management's misconduct, restricting the extent of earnings management. Analysts thus have better information sources for use in their forecasting tasks in countries with greater economic freedom. The above discussion leads to the following two hypotheses.

Hypothesis3a: Analysts' use of cash flow models is associated with the extent of economic freedom of the firm country.

Hypothesis3b: The incremental effects of cash flow models on market reactions to analyst target price changes are associated with the extent of economic freedom of the firm country

3.4 Methodology

3.4.1 Sample selection

I obtain analyst reports covering non-U.S. firms from Investext for 1997 to 2017. Following Huang et al. (2021), I use textual analysis to detect analysts' use of valuation models in their reports. Due to the high cost of downloading analyst reports from Investext and doing textual analysis, I focus on analyst reports by nine brokerage firms: Citibank, Credit Suisse, Deutsche Bank, HSBC, Jefferies, JPMorgan, Morgan Stanley, Royal Bank of Canada, and UBS Research. Analyst reports from Investext are matched to the I/B/E/S non-U.S. database by brokerage firm names, analyst names, and the underlying company identifiers that include trading symbols and company names. To ensure matching accuracy, I require analyst forecast dates from Investext to be between the forecast announcement dates and review dates from I/B/E/S. I then match the data with Compustat Global and DataStream to obtain annual financial data and daily stock return data. I adjust the discrepancy in the underlying currency among databases by using daily exchange rates from Compustat.

I do not include U.S. firms in the final sample because the number of U.S. firms constitutes more than a third of all the firms followed by analysts. The research question of this study is whether the variations in country-level factors affect analysts' use of valuation models. As U.S. firms normally have better investor protection, transparency, and economic freedom than non-U.S. firms, including U.S. firms reduces the sample variations.

The sample starts with 537,558 analyst reports covering non-U.S. firms from 1997 to 2017. I keep the first announced analyst report if analysts issue multiple reports in a quarter. I delete 60,088 analyst reports for which I cannot identify the use of valuation models with the textual analysis. I delete an additional 95,458 observations with missing values of proxies for investor protection, information environment, and economic freedom. Another 2,303 observations are deleted due to missing values of cumulated abnormal returns. Finally, I delete 59,693 observations with missing values of control variables. The final sample consists of 320,016 analyst reports by 7,425 analysts on 7,533 non-U.S. firms from 29 countries from 1997 to 2017.

3.4.2 Measures

3.4.2.1 Measure of cash flow models

Following Section 3.2 of Huang et al. (2021), I use textual analysis to detect whether a model is used as a dominant valuation model in an analyst report. I first identify whether a valuation model is mentioned in an analyst report. As analysts may mention multiple valuation models in a report, I then identify which valuation model is the dominant model used by an analyst. I examine whether the mention of a valuation model is within 30 words of the keywords related to analysts' investment opinions such as *price target, target price, PT, recommend,* and *recommendation*, or the keywords related to an analyst's action of applying a specific valuation model to justify a target price and recommendation, such as *use, using, based, basing, derive, derived, rating,* and *rate*.

I classify the models used by analysts into two broad categories: accrual models and cash flow models. Accrual models include earnings multiples, book value multiples, sales multiples, NAV, and RIV. Cash flow models include cash flow multiples and DCF models. Appendix 3.B lists the key items for each model identification. The variable *CFModel* equals one if analysts use cash flow models as the dominant valuation models, and zero otherwise.

3.4.2.2 Measure of investor protection, information environment, and economic freedom

Following Djankov et al. (2008), I use the revised anti-director rights, anti-self-dealing, and public enforcement indexes to measure the level of investor protection in a country. *anti_director* is the sum of (1) vote by mail; (2) shares not deposited; (3) cumulative voting; (4) oppressed minority; (5) pre-emptive rights, and (6) capital to call a meeting. *anti_dealing* is the anti-self-dealing index from Djankov et al. (2008). *public_enforce* is the extent to which the law may deter wrongdoing by controlling shareholders and transaction approvers through punishment such as fines and prison terms.

I measure a country's information environment with *cifar* and *country_eq*. *cifar* is a country's financial disclosure index. The data source is the Center for Financial Analysis and Researchers' International Accounting and Auditing Trends (CIFAR, 1995). A higher value of *cifar* indicates better financial disclosure in a country. *country_eq* is the negative value of the index of earnings management from Leuz et al. (2003). A higher value of *country_eq* indicates better earnings quality in a country. I measure a country's economic freedom with *EF_sum*, the summary of economic freedom index, and *EF_legal,* the freedom of legal structure and security of property rights. The economic freedom data is from the Fraser Institute.

I then construct dummy indicators from the proxies for investor protection, information environment, and economic freedom. For example, *High anti_director* equals one if *anti_director* of country *i* is above the median of the countries in the final sample, and zero otherwise. In a similar vein, I construct other indicators of a country's institutional factors.

3.4.2.3 Other variables

I use the revisions of analyst target price forecasts to measure analysts' investment opinions. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. Target price forecasts are obtained from the textual analysis of analyst reports. I use the market-adjusted cumulative abnormal return to measure market reactions to the change of analyst target price forecast. *CARt* is the market-adjusted cumulative abnormal return starting one day before to *t* days after the issuance of an analyst report, multiplied by 100.

Following Huang et al. (2021), I control for firm-level information uncertainty with *earningsmgt*, *Loss*, and *Retstd12*. *earningsmgt* is the abnormal accruals based on the Modified Jones Model. *Loss* is an indicator of negative earnings. *retstd12* is the standard deviation of daily stock return during the 12 months before an analyst report date, multiplied by 100. In addition, I follow Demirakos et al. (2010) to control for firm size (*logmv*), market to book ratio (*mb*), performance (*arpre6*), and leverage ratio (*leverage*). I control for analyst experience with *firmex*, the number of years an analyst has been following a firm. Appendix 3.A provides the definitions and data sources for all variables used in this study.

3.4.3 Descriptive statistics

Table 3.1 describes the number of reports, firms, and analysts, and the use of valuation models by country (Panel A) and year (Panel B). The final sample consists of 320,016 analyst reports by 7,425 analysts on 7,533 non-U.S. firms. Panel A of Table 3.1 shows that Japan, the United

Kingdom, and Australia have the largest number of analyst reports and unique firms in the final sample. The United Kingdom, France, and Germany have the largest number of analysts following firms.

Table 3. 1 Sample description

This table shows the number of observations, unique firms and analysts, and analysts' use of valuation models by country and year. *CFModel* is an indicator equal to one if analysts use cash flow models as the dominant valuation model, and zero otherwise. Similarly, I define the DCF, PCF, PE, PB, PSALE, and NAV valuation models.

Panel A Sample description by country

Country	Obs	#Firm	#Analyst	CFModel	DCF	PCF	PE	PB	PSALE	NAV
Australia	29,978	705	639	0.59	0.56	0.05	0.64	0.05	0.04	0.10
Austria	1,707	44	191	0.44	0.37	0.14	0.75	0.06	0.05	0.06
Belgium	1,754	45	256	0.54	0.51	0.12	0.61	0.08	0.04	0.10
Canada	17,610	699	663	0.25	0.21	0.06	0.77	0.06	0.03	0.27
Denmark	1,970	36	258	0.49	0.46	0.10	0.65	0.10	0.04	0.03
Finland	2,667	56	241	0.39	0.34	0.09	0.77	0.09	0.06	0.04
France	12,430	276	916	0.50	0.46	0.11	0.68	0.04	0.05	0.06
Germany	15,509	356	870	0.47	0.41	0.11	0.71	0.04	0.07	0.06
Greece	1,989	66	160	0.48	0.45	0.12	0.65	0.09	0.04	0.11
Hong Kong	16,502	366	768	0.42	0.35	0.12	0.67	0.17	0.06	0.21
India	19,300	360	301	0.35	0.29	0.11	0.69	0.20	0.05	0.04
Ireland	3,220	49	363	0.39	0.37	0.08	0.76	0.05	0.05	0.03
Italy	5,293	169	479	0.47	0.42	0.10	0.67	0.09	0.05	0.06
Japan	57,529	1,228	704	0.14	0.08	0.07	0.83	0.19	0.15	0.02
Korea	15,018	314	437	0.30	0.21	0.12	0.67	0.37	0.06	0.04
Malaysia	6,933	191	211	0.48	0.40	0.15	0.63	0.16	0.07	0.10
Netherlands	5,289	163	627	0.43	0.40	0.09	0.72	0.03	0.07	0.05
Norway	1,847	52	223	0.46	0.42	0.10	0.68	0.13	0.05	0.06
Pakistan	296	24	14	0.79	0.75	0.20	0.42	0.24	0.00	0.08
Philippines	2,757	77	138	0.51	0.45	0.11	0.66	0.18	0.07	0.29
Portugal	772	30	124	0.40	0.38	0.13	0.67	0.07	0.05	0.18
Singapore	8,973	184	345	0.50	0.41	0.16	0.58	0.18	0.05	0.17
South Africa	6,225	175	271	0.54	0.48	0.13	0.67	0.10	0.03	0.10
Spain	4,838	117	455	0.46	0.41	0.10	0.66	0.11	0.04	0.09
Sweden	5,237	117	437	0.45	0.41	0.09	0.73	0.05	0.07	0.06
Switzerland	9,469	187	624	0.54	0.50	0.13	0.64	0.04	0.06	0.05
Taiwan	15,362	341	504	0.26	0.17	0.11	0.68	0.35	0.05	0.04
Thailand	6,216	128	214	0.54	0.44	0.14	0.59	0.31	0.05	0.05
United Kingdom	43,326	981	2,043	0.39	0.35	0.10	0.70	0.04	0.05	0.11
Total/Mean	320,016	7,533	7,425	0.38	0.32	0.10	0.71	0.14	0.07	0.09

Panel B Sample description by year

Year	Obs	#Firm	#Analyst	CFModel	DCF	PCF	PE	PB	PSALE	NAV
1997	933	610	322	0.06	0.04	0.02	0.79	0.07	0.16	0.09
2000	6,461	1,910	1,104	0.10	0.09	0.02	0.86	0.06	0.09	0.07
2001	9,603	2,282	1,580	0.11	0.10	0.02	0.84	0.07	0.11	0.05

2002	10,675	2,270	1,552	0.19	0.15	0.04	0.82	0.08	0.07	0.06
2003	13,775	2,310	1,637	0.31	0.25	0.08	0.75	0.10	0.07	0.07
2004	16,692	2,488	1,671	0.34	0.29	0.08	0.74	0.12	0.05	0.07
2005	17,614	2,648	1,669	0.36	0.31	0.08	0.72	0.13	0.06	0.08
2006	15,454	2,789	1,491	0.36	0.32	0.06	0.71	0.12	0.06	0.06
2007	18,443	3,139	1,639	0.43	0.37	0.08	0.69	0.11	0.06	0.07
2008	20,013	3,185	1,633	0.44	0.38	0.08	0.67	0.12	0.06	0.08
2009	18,770	2,842	1,452	0.45	0.39	0.09	0.64	0.17	0.07	0.13
2010	19,371	2,860	1,542	0.43	0.37	0.09	0.67	0.15	0.07	0.09
2011	22,603	3,172	1,713	0.40	0.35	0.09	0.68	0.16	0.10	0.10
2012	24,608	3,219	1,736	0.42	0.34	0.14	0.69	0.17	0.09	0.10
2013	25,009	3,166	1,635	0.42	0.35	0.14	0.70	0.16	0.08	0.10
2014	25,504	3,281	1,661	0.41	0.33	0.16	0.68	0.16	0.07	0.09
2015	25,614	3,267	1,631	0.36	0.31	0.10	0.71	0.15	0.05	0.09
2016	25,929	3,234	1,574	0.41	0.37	0.11	0.69	0.14	0.05	0.09
2017	2,945	1,527	903	0.44	0.37	0.13	0.68	0.14	0.06	0.08

The use of cash flow models has large variations across countries. More than 54% of analyst reports use cash flow models to value firms in Pakistan, Australia, Switzerland, Thailand, Belgium, and South Africa, while less than 30% of analyst reports use cash flow models to value firms in Korean, Taiwan, Canada, and Japan. An average of 38% of analyst reports use cash flow models for firm evaluation, of which 32% of reports use DCF models and 10% of reports use PCF models.[26] Accrual valuation models include PE, PB, PSALE, and NAV. PE models are the most frequently used accrual models, with 71% of reports utilization in the final sample. In addition, 14% of reports use PB models, 9% of reports use NAV models, and 7% of reports use PSALE models. The use of accrual valuation models is almost 100%, consistent with the fact that accrual metrics are the default value drivers for firm valuation. The use of cash flow metrics for firm valuation is quite selective.

Panel B of Table 3.1 presents the yearly description of the final sample from 1997 to 2017. It exhibits an increasing trend in the use of cash flow models over the years, an increase from 6%

[26] As an analyst report may use both DCF and PCF models as the dominant valuation models, the sum of DCF and PCF models is larger than *CFModel*.

in 1997 to 44% in 2017. There is a similar increasing trend of using DCF models, an increase from 4% in 1997 to 37% in 2017, and PCF models, an increase from 2% in 1997 to 13% in 2017. The use of accrual models is relatively stable over the years, with a slight increasing use of PB models, but a decreasing use of PE models. Given the variations of the cash flow models over the years, I include year-fixed effects in all regressions.

Table 3. 2 Country's institutional factors and correlations

Panel A reports the description of the firm country's institutional factors. I use *anti_director*, *anti_dealing*, and *public_enforce* to measure the level of investor protection in a country. *anti_director* is the revised anti-director rights index from Djankov et al. (2008). *anti_dealing* is the anti-self-dealing index from Djankov et al. (2008). *public_enforce* is the extent to which the law may deter wrongdoing by controlling shareholders and transaction approvers through punishment such as fines and prison terms. I measure the information environment in a country with *cifar*, which is the index of financial disclosure for firm country from CIFAR (1995), and *country_eq*, which is the negative value of the index of earnings management from Leuz et al. (2003). I measure the economic freedom in a country with *EF_sum*, the summary of the economic freedom index from the Frazer institute, and *EF_lega,l* the freedom of legal structure and security of property rights from the Frazer institute. Panel B reports the Pearson correlation analysis of country factors and analysts' use of cash-flow-based valuation models. Appendix 3.A provides detailed definitions of all the variables.

Panel A Firm country factors

		Investor protection			*Information environment*		*Economic freedom*	
Country	*anti_director*	*anti_dealing*	*public_enforce*	*cifar*	*country_eq*	*EF_sum*	*EF_legal*
Australia	4.00	0.79	0.50	80	-4.80	8.11	7.94
Austria	2.50	0.21	1.00	62	-28.30	7.82	7.95
Belgium	2.00	0.54	0.50	68	-19.50	7.62	7.09
Canada	4.00	0.65	1.00	75	-5.30	8.23	7.94
Denmark	4.00	0.47	0.75	75	-16.00	7.97	8.23
Finland	3.50	0.46	0.00	83	-12.00	7.88	8.30
France	3.00	0.38	0.50	78	-13.50	7.54	6.96
Germany	2.50	0.28	1.00	67	-21.50	7.86	7.87
Greece	2.00	0.23	0.50	61	-28.30	7.18	6.03
Hong Kong	5.00	0.96	0.00	73	-19.50	8.84	7.43
India	5.00	0.55	0.50	61	-19.10	6.41	5.33
Ireland	4.00	0.79	0.00	81	-5.10	8.11	7.66
Italy	2.50	0.39	0.25	66	-24.80	7.61	6.43
Japan	3.50	0.48	0.00	71	-20.50	7.86	7.45
Korea	3.50	0.46	0.50	68	-26.80	7.56	6.49
Malaysia	5.00	0.95	1.00	79	-14.80	6.77	5.42
Netherlands	3.00	0.21	0.00	74	-16.50	7.81	7.89
Norway	3.50	0.44	1.00	75	-5.80	7.66	8.35
Pakistan	4.00	0.41	0.75	73	-17.80	6.23	4.69
Philippines	3.00	0.24	0.00	64	-8.80	7.23	4.74
Portugal	2.50	0.49	1.00	58	-25.10	7.53	6.97
Singapore	5.00	1.00	1.00	79	-21.60	8.58	7.71
South Africa	5.00	0.81	0.00	79	-5.60	6.83	6.00

Spain	5.00	0.37	0.75	72	-18.60	7.76	6.90
Sweden	3.50	0.34	1.00	83	-6.80	7.74	7.88
Switzerland	3.00	0.27	0.50	80	-22.00	8.44	8.27
Taiwan	3.00	0.56	0.00	58	-22.50	7.57	6.41
Thailand	4.00	0.85	0.00	66	-18.30	6.63	5.20
United Kingdom	5.00	0.93	0.00	85	-7.00	8.20	7.79

Panel B Pearson correlation analysis

	CFModel	(1)	(2)	(3)	(4)	(5)	(6)
(1)anti_director	0.038***						
(2)anti_dealing	0.069***	0.807***					
(3)public_enforce	0.111***	-0.131***	-0.199***				
(4)cifar	0.104***	0.429***	0.514***	-0.026***			
(5)country_eq	0.109***	0.432***	0.510***	0.048***	0.718***		
(6)EF_sum	-0.001	0.048***	0.285***	-0.072***	0.517***	0.206***	
(7)EF_legal	-0.002	-0.109***	0.064***	0.067***	0.591***	0.338***	0.828***

Panel A of Table 3.2 describes proxies for a country's institutional environment, such as the investor protection, the information environment, and the economic freedom. Countries with the highest value of the anti-director right index are Hong Kong, India, Malaysia, Singapore, South Africa, Spain, and the United Kingdom. Countries with the highest values of anti-self-dealing index are Singapore, Hong Kong, Malaysia, and the United Kingdom. Among the countries with the highest values of anti-director right index and anti-self-dealing index, only Singapore and Malaysia have sufficient public enforcement, suggesting that anti-director rights, anti-self-dealing, and public enforcement capture different aspects of a country's investor protections.

Furthermore, the United Kingdom has the best information disclosure based on *cifar* score of 85 ranked by CIFAR (1995). Firms in Australia, Ireland, and Canada have the highest earnings quality based on the negative value of earnings management from Leuz et al. (2003). Hong Kong, and Singapore provide the greatest overall economic freedom, while Norway has the best freedom of legal structure and security of property rights.

Panel B of Table 3.2 reports Pearson correlation analysis of country factors and the use of cash flow models. *CFModel* is significantly positively associated with *anti_director, anti_dealing, public_enforce, cifar,* and *country_eq*, suggesting that analysts' likelihood of using a cash flow model is positively related to the country's investor protection and information environment. I find no significant correlations between *CFModel* and the economic freedom index.

Correlations among country factors are quite high. For example, the correlation between *anti_director* and *anti_dealing* is 0.807, the correlation between *cifar* and *country_eq* is 0.718, and the correlation between *EF_sum* and *EF_legal* is 0.828. The high correlations suggest that there will be potential multicollinearity issues if these variables are pooled into a single regression. As a result, I include only one country factor for each regression.

3.5 Empirical Analysis

3.5.1 Analysts' use of cash flow models

I examine the impact of a country's institutional factors on analysts' use of cash flow models by testing the following logistic regression.

$$CFModel_{ijcqy} = \alpha_1 + \alpha_2 Indep_{icy} + \alpha_3 \sum Controls + \alpha_4 Year + \alpha_5 Bank + \alpha_6 Industry + \varepsilon \ (1)$$

where subscript *i* refers to firm, *j* refers to analyst, *c* refers to country, *q* refers to quarter, and *y* refers to year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. $Indep$ denotes indicators of good investor protection, information environment, and economic freedom, such as *High anti_director, High anti_director, High public_enforce, High cifar, High country_eq, High EF_sum,* and *High EF_legal*. I include year, industry, and bank indicators to control for year, industry, and bank fixed effects. Industry fixed effects use Fama-French 12-industry classification. Bank fixed effects use the brokerage firm that an analyst works for. For brevity, I do not show the results of these indicators in the table. The standard errors are adjusted for firm and analyst clustering to account for potential error correlations within the groups.[27]

Table 3. 3 Investor protection, information disclosure, economic freedom and analysts' choice of cash flow models

This table reports the logistic regression results on the impact of investor protection, information disclosure, and economic freedom on analysts' use of cash flow models. The dependent variable is *CFModel*, which equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. *High anti_director, High anti_director,* and *High public_enforce* are indicators of strong investor protection. *High cifar* and *High country_eq* are indicators of good information disclosure and earnings quality. *High EF_sum* and *High EF_legal* are indicators of high economic freedom. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Variable= CFModel							
High anti_director	0.418***						
	(7.48)						
High anti_dealing		0.350***					
		(6.23)					
High public_enforce			0.556***				
			(10.20)				
High cifar				0.717***			
				(12.54)			
High country_eq					0.519***		
					(8.81)		
High EF_sum						0.243***	
						(4.70)	
High EF_legal							0.287***
							(5.53)
earningsmgt	0.842***	0.971***	1.053***	0.900***	0.948***	1.103***	1.146***
	(4.22)	(4.79)	(5.10)	(4.52)	(4.67)	(5.39)	(5.58)
leverage	-0.276**	-0.258**	-0.423***	-0.223**	-0.420***	-0.302***	-0.348***
	(-2.49)	(-2.32)	(-3.85)	(-2.08)	(-3.78)	(-2.77)	(-3.16)
loss	-0.029	-0.052	-0.067	-0.067	-0.034	-0.058	-0.066
	(-0.60)	(-1.08)	(-1.42)	(-1.43)	(-0.72)	(-1.21)	(-1.38)
retstd12	-0.077***	-0.066***	-0.068***	-0.044**	-0.070***	-0.074***	-0.069***
	(-3.46)	(-2.93)	(-3.05)	(-1.99)	(-3.10)	(-3.28)	(-3.08)
arpre12	-0.001***	-0.001***	-0.001***	-0.001*	-0.001**	-0.001***	-0.001***
	(-2.96)	(-2.63)	(-2.58)	(-1.71)	(-2.49)	(-3.36)	(-3.19)

[27] The results are not clustered by country because there are only 29 countries in the sample.

logmv	-0.081***	-0.082***	-0.083***	-0.076***	-0.080***	-0.094***	-0.090***
	(-5.74)	(-5.76)	(-6.23)	(-5.61)	(-5.69)	(-6.81)	(-6.52)
mb	0.068***	0.071***	0.077***	0.053***	0.064***	0.071***	0.068***
	(12.58)	(12.91)	(15.07)	(11.03)	(12.25)	(13.57)	(13.50)
firmex	-0.038***	-0.038***	-0.035***	-0.036***	-0.037***	-0.039***	-0.040***
	(-5.12)	(-5.20)	(-4.82)	(-4.97)	(-5.12)	(-5.30)	(-5.38)
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES
Observations	320,016	320,016	320,016	320,016	320,016	320,016	320,016
Pseudo R^2	0.111	0.110	0.117	0.121	0.115	0.108	0.109

Table 3.3 provides logistic regression results on the determinants of analysts' use of valuation models. Columns (1) to (3) examine the impact of investor protection on the use of valuation models. The coefficients on *High anti_director, High anti_director,* and *High public_enforce* are significantly positive, indicating that analysts are more likely to use cash flow models to value firms in countries with good investor protection. Columns (4) and (5) test the impact of information environment on the use of valuation models. I find that *High cifar* and *High country_eq* are significantly positively associated with *CFModel*, suggesting that analysts are more likely to use cash flow models to value firms in countries with a good information environment. Columns (6) and (7) examine the impact of economic freedom on the use of valuation models. I find that *High EF_sum* and *High EF_legal* are significantly positively associated with *CFModel*, suggesting that analysts are more likely to use cash flow models to value firms in countries with high economic freedom.

Overall, the findings suggest that analysts tend to use cash flow models to value firms in countries with sound institutional systems. This is because a country's accounting quality and information disclosure are complementary components of the country's legal and economic infrastructures (Bushman and Smith 2001). Accounting quality and information availability are better in countries with stronger investor protection, better information environment, and greater economic freedom, all of which facilitate analysts' acquisition of the value-relevant information and use of cash flow models. The findings are consistent with the argument that the firm country's institutional environment is a complement to analysts' research.

In addition, I find that analysts are more likely to use cash flow models to value firms with low earnings quality and a high market-to-book value ratio. The coefficients on *leverage*, *retstd12, arpre12,* and *logmv* are significantly negative, suggesting that analysts' tendency to use cash flow models is negatively associated with the leverage ratio, stock return volatility, past performance, and firm size. *firmex* is significantly negatively associated with *CFModel*, suggesting that analysts' use of cash flow models decreases with the years of following the underlying firms.

3.5.2 The informativeness of cash flow models

3.5.2.1 Baseline tests

I examine the informativeness of cash flow models by testing whether market reactions to analyst target price changes vary with the underlying valuation models. Below is the regression model.

$$CARt_{ijqy} = \beta_1 + \beta_2 tpchg_{ijqy} + \beta_3 CFModel_{ijqy} + \beta_4 CFModel_{ijqy} * tpchg_{ijqy} + \beta_5 \sum Control + \beta_6 Year + \beta_7 Bank + \beta_8 Industry + \varepsilon \quad (2)$$

where subscript *i* refers to firm, *j* refers to analyst, *q* refers to quarter, and *y* refers to year. *CARt* is the cumulative abnormal return starting from one day before to *t* days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. The coefficient on *tpchg* (β_2) reflects market reactions to the change of analyst target price forecasts. The coefficient on *tpchg*CFModel* (β_4) captures the incremental effect of using a cash flow model on the market reactions to analyst target price changes.

Table 3. 4 The informativeness of cash flow models: Baseline tests

This table examines the informativeness of cash flow models by testing whether the use of models affects market reactions to analyst target price changes. The dependent variable *CARt* is the cumulative abnormal return starting from one day before to *t* days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)
Dep variable=	*CAR3*	*CAR30*	*CAR183*
tpchg	2.129***	0.572***	-7.310***
	(20.84)	(2.81)	(-16.06)
CFModel	0.004	0.082	-0.127
	(0.13)	(0.78)	(-0.53)
*tpchg*CFModel*	0.312**	0.508*	0.473
	(2.22)	(1.83)	(0.77)
earningsmgt	-0.263	-0.778	-3.993
	(-0.75)	(-0.73)	(-1.54)
leverage	-0.087	-0.128	0.469
	(-0.60)	(-0.25)	(0.43)
loss	-0.176**	-0.917***	-2.923***
	(-2.11)	(-3.34)	(-5.29)
retstd12	-0.374***	-1.561***	-2.462***
	(-6.83)	(-9.11)	(-8.38)
arpre12	0.032***	0.149***	0.486***
	(43.55)	(50.22)	(70.91)
logmv	-0.187***	-0.883***	-2.862***
	(-9.15)	(-12.55)	(-18.67)
mb	0.007	-0.033**	-0.227***
	(1.31)	(-2.17)	(-5.40)
firmex	-0.006	-0.015	0.073**
	(-1.21)	(-0.92)	(1.99)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Observations	285,483	285,483	285,483
Adjusted R^2	0.093	0.296	0.473

Table 3.4 reports the baseline tests on the informativeness of cash flow models. The dependent variables are *CAR3*, *CAR3*0, and *CAR183* from columns (1) to (3). The coefficients on *tpchg* are significantly positive in columns (1) and (2), but significantly negative in column (3). The results suggest that the market reacts positively when analysts increase their forecasts in

short windows, but there is a reversal of the market reaction to the change of target price forecast in long periods.

The coefficients on *tpchg*CFModel* are positive in all columns, and significantly positive in columns (1) and (2), suggesting that the use of cash flow models increases market reactions to analyst target price changes. The results show that, in general, analysts' investment opinions based on cash flow models are more informative to investors than their investment opinions based on accrual models. The possible reason is that investors have access to accrual accounting information from the management, thus have less demand for such information from analysts. As a result, analysts' cash flow models provide incremental information to investors compared with accrual models.

In addition, the significantly negative coefficients on *loss*, *retstd12*, and *logmv* suggest that firms with negative earnings, volatile stock returns, large sizes, and high market-to-book value ratios tend to experience negative market-adjusted cumulative abnormal returns after the analyst report date. The significantly positive coefficients on *arepre12* suggest that firms with better performance in the past tend to have more positive stock returns in subsequent periods. Overall, the coefficients on control variables are consistent with the findings of Huang et al. (2021).

3.5.2.2 Investor protection and the informativeness of cash flow models

To examine whether the level of a country's investor protection is related to the usefulness of cash flow models, I partition the full sample into subsamples of high protection and low protection by the median values of investor protection variables. I then estimate equation (2) in the high and low subsamples to examine whether coefficients on *tpchg*CFModel* (β_4) for the high and low subsamples are significantly different. If cash flow models are more informative in countries with stronger investor protection, I expect the coefficients on *tpchg*CFModel* (β_4) in high investor protection subsamples to be larger and more significant than those in low investor protection subsamples.

Table 3. 5 Investor protection and the informativeness of cash flow models

This table reports the regression results on the impact of investor protection on the informativeness of cash flow models. The sample is split into subsamples by the median values of investor protection variables such as *anti_director*, *anti_dealing*, and *public_enforce*. The odd columns are the tests in the subsamples with higher investor protection and the even columns are the tests in the subsamples with lower investor protection. The dependent variables are *CAR3* (*CAR183)*, cumulative abnormal return starting from one day before to *3* (183) days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise.The *Difference of* β_4 *(H-L)* presents the difference tests of the coefficients on *tpchg*CFModel* (β_4) for the high and low subsamples of investor protections. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep variable=	*CAR3*						*CAR183*					
	anti_director		*anti_dealing*		*public_enforce*		*anti_director*		*anti_dealing*		*public_enforce*	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
tpchg	2.128***	2.138***	2.279***	2.046***	2.381***	1.949***	-5.189***	-9.343***	-5.357***	-8.621***	-6.230***	-7.909***
	(14.55)	(14.98)	(14.54)	(15.28)	(14.43)	(15.27)	(-8.11)	(-14.89)	(-8.01)	(-14.13)	(-8.81)	(-13.61)
CFModel	0.008	0.030	0.015	0.040	0.064	-0.044	-0.192	0.573**	0.142	0.369	0.998***	-0.958***
	(0.17)	(0.71)	(0.30)	(1.01)	(1.34)	(-1.00)	(-0.59)	(2.02)	(0.42)	(1.30)	(3.05)	(-2.98)
tpchg*CFModel	**0.373***	0.233	**0.379***	0.185	**0.511****	0.008	**0.895**	-1.135	**1.339**	-0.937	**0.153**	0.307
	(1.94)	(1.21)	**(1.87)**	(1.01)	**(2.36)**	(0.05)	**(1.14)**	(-1.19)	**(1.60)**	(-1.10)	**(0.18)**	(0.35)
earningsmgt	0.215	-0.836	0.378	-0.790	-0.465	0.044	2.418	-9.983**	1.913	-7.321*	-3.311	-3.938
	(0.45)	(-1.54)	(0.75)	(-1.63)	(-0.90)	(0.10)	(0.77)	(-2.21)	(0.57)	(-1.80)	(-0.97)	(-1.01)
leverage	0.038	-0.378**	0.007	-0.354**	0.261	-0.438***	2.457*	-3.988**	0.458	-2.332	3.904**	-3.204**
	(0.19)	(-2.21)	(0.03)	(-2.17)	(1.09)	(-2.85)	(1.70)	(-2.40)	(0.30)	(-1.51)	(2.54)	(-2.12)
loss	-0.276**	-0.069	-0.340***	0.022	-0.185	-0.143	-3.775***	-1.860**	-4.032***	-1.518**	-3.189***	-2.141***
	(-2.08)	(-0.75)	(-2.59)	(0.25)	(-1.48)	(-1.44)	(-4.67)	(-2.53)	(-4.79)	(-2.34)	(-4.51)	(-2.60)
retstd12	-0.461***	-0.235***	-0.446***	-0.272***	-0.445***	-0.256***	-2.764***	-1.650***	-2.589***	-2.084***	-3.075***	-1.445***
	(-6.10)	(-3.36)	(-5.66)	(-4.16)	(-5.79)	(-3.77)	(-6.95)	(-4.13)	(-6.32)	(-5.55)	(-8.61)	(-3.21)
arpre12	0.033***	0.030***	0.035***	0.028***	0.032***	0.031***	0.483***	0.479***	0.496***	0.461***	0.488***	0.472***
	(35.56)	(27.15)	(34.90)	(27.69)	(31.17)	(31.93)	(55.55)	(43.80)	(56.40)	(42.40)	(52.06)	(47.42)
logmv	-0.265***	-0.120***	-0.277***	-0.126***	-0.201***	-0.184***	-3.269***	-2.732***	-3.334***	-2.858***	-2.775***	-3.105***
	(-7.56)	(-5.88)	(-7.56)	(-6.54)	(-6.05)	(-7.22)	(-13.17)	(-14.65)	(-13.03)	(-16.26)	(-12.61)	(-14.26)
mb	0.002	0.009	0.001	0.012	0.012	0.004	-0.237***	-0.096	-0.153***	-0.173**	-0.235***	-0.201***
	(0.37)	(0.98)	(0.23)	(1.51)	(1.58)	(0.69)	(-4.70)	(-1.34)	(-3.02)	(-2.43)	(-3.48)	(-3.79)
firmex	-0.012	0.000	-0.013	0.000	-0.014	-0.000	0.061	0.064	0.085	0.037	-0.024	0.132***
	(-1.37)	(0.09)	(-1.42)	(0.06)	(-1.54)	(-0.08)	(1.10)	(1.46)	(1.54)	(0.90)	(-0.44)	(3.12)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Difference of β_4 ***(H-L)***	**0.140**		**0.194**		**0.503*****		**2.030****		**2.276*****		**-0.154**	
	(0.66)		**(0.93)**		**(2.67)**		**(2.56)**		**(2.88)**		**(-0.02)**	
Observations	148,378	137,105	138,321	147,162	145,047	140,436	148,378	137,105	138,321	147,162	145,047	140,436

Adjusted R^2	0.098	0.087	0.109	0.075	0.094	0.093	0.473	0.472	0.491	0.444	0.473	0.473

Table 3.5 reports the regression results on the impact of investor protection on the informativeness of cash flow models. The dependent variable is *CAR3* from columns (1) to (6), and is *CAR183* from columns (7) to (12).[28] The sample is split into high and low subsamples by investor protection measures of *anti_director, anti_dealing,* and *public_enforce.* The odd columns are the tests in the subsamples of countries with higher levels of investor protection and the even columns are the tests in the subsamples of countries with lower levels of investor protection. The *Difference of* β_4 *(H-L)* at the bottom of the table reports the difference tests of the coefficients on *tpchg*CFModel* (β_4).

In columns (1) to (6), the coefficients on *tpchg*CFModel* are significantly positive in higher investor protection subsamples, and larger than in subsamples with lower investor protection. In columns (7) to (10), the coefficients on *tpchg*CFModel* are positive in higher investor protection subsamples, and negative in lower investor protection subsamples. I find no significant difference of the coefficients on *tpchg*CFModel* in columns (11) to (12). Tests on the *Difference of* β_4 *(H-L)* show that three out of six differences are significantly positive. Overall, the findings suggest that cash flow models are more useful to investors in countries with greater investor protection.

3.5.2.3 Information environment and the informativeness of cash flow models

Previous studies have shown that analysts are more accurate in countries with a high level of information disclosure (Basu et al., 1998). I expect that analysts' cash flow valuation models are more informative to investors for countries with better information environments. I partition the

[28] I only report the tests with *CAR3* and *CAR183* as the dependent variables. The results are qualitatively unchanged if I use *CAR30* as the dependent variable.

full sample into subsamples by the median values of information environment variables. I then estimate equation (2) in the high and low subsamples to examine whether coefficients on *tpchg*CFModel* (β_4) for the high and low subsamples are significantly different.

Table 3. 6 Information environment and the informativeness of cash flow models

This table reports the regression results on the impact of a country's information environment on the informativeness of cash flow models. The sample is split into subsamples by the median values of information environment variables such as *cifar* and *country_eq*. The odd columns are the tests in the subsamples with better information environment, and the even columns are the tests in the subsamples with worse information environment. The dependent variables are *CAR3* (*CAR183)*, cumulative abnormal return starting from one day before to *3* (183) days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. The *Difference of* β_4 *(H-L)* presents the difference tests of the coefficients on *tpchg*CFModel* (β_4) for the high and low subsamples of investor protections. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep variable=	*CAR3*				*CAR183*			
	cifar		*country_eq*		*cifar*		*country_eq*	
	High	Low	High	Low	High	Low	High	Low
tpchg	2.375***	1.942***	2.250***	2.019***	-4.843***	-9.329***	-4.505***	-9.751***
	(14.97)	(14.48)	(14.56)	(14.79)	(-7.47)	(-15.07)	(-7.08)	(-15.72)
CFModel	-0.006	0.006	0.018	0.004	0.012	0.288	0.306	-0.263
	(-0.13)	(0.15)	(0.39)	(0.08)	(0.04)	(0.96)	(1.01)	(-0.83)
tpchg*CFModel	**0.457****	-0.084	**0.450****	0.054	**0.722**	-1.441	**0.459**	-1.194
	(2.33)	(-0.45)	**(2.29)**	(0.29)	**(0.89)**	(-1.52)	**(0.59)**	(-1.24)
earningsmgt	0.064	-0.526	-0.292	-0.215	2.176	-11.622**	2.846	-12.046***
	(0.13)	(-0.97)	(-0.60)	(-0.42)	(0.70)	(-2.45)	(0.89)	(-2.90)
leverage	0.150	-0.625***	0.177	-0.452***	3.059**	-4.414**	4.097***	-4.235***
	(0.75)	(-3.37)	(0.83)	(-2.90)	(2.15)	(-2.50)	(2.82)	(-2.68)
loss	-0.262**	-0.025	-0.274**	-0.037	-3.577***	-1.757**	-4.042***	-1.316*
	(-2.15)	(-0.25)	(-2.10)	(-0.41)	(-4.75)	(-2.24)	(-5.10)	(-1.78)
retstd12	-0.435***	-0.283***	-0.427***	-0.284***	-2.973***	-1.505***	-2.642***	-1.962***
	(-5.79)	(-3.88)	(-5.63)	(-4.13)	(-7.70)	(-3.51)	(-6.62)	(-4.97)
arpre12	0.033***	0.031***	0.032***	0.031***	0.483***	0.479***	0.484***	0.478***
	(35.84)	(27.33)	(35.49)	(28.06)	(57.69)	(42.41)	(56.52)	(43.90)
logmv	-0.240***	-0.130***	-0.243***	-0.140***	-3.180***	-2.673***	-3.183***	-2.749***
	(-6.88)	(-6.38)	(-6.80)	(-6.50)	(-13.26)	(-14.03)	(-12.90)	(-14.12)
mb	-0.003	0.008	0.005	0.003	-0.246***	-0.128	-0.249***	-0.134*
	(-0.54)	(0.93)	(0.89)	(0.28)	(-5.06)	(-1.56)	(-5.06)	(-1.88)
firmex	-0.013	0.001	-0.014	0.002	0.033	0.084*	0.024	0.101**
	(-1.56)	(0.13)	(-1.64)	(0.40)	(0.62)	(1.84)	(0.45)	(2.29)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
	0.541***		**0.396****		**2.163*****		**1.653****	

Difference of β_4 (H-L)	**(2.76)**		**(2.00)**		**(2.65)**		**(2.07)**	
Observations	152,793	132,690	151,306	134,177	152,793	132,690	151,306	134,177
Adjusted R^2	0.097	0.090	0.094	0.092	0.480	0.464	0.476	0.467

Table 3.6 reports the regression results on the impact of the information environment on the informativeness of cash-flow-based valuation models. The dependent variable is *CAR3* in columns (1) to (4), and is *CAR183* in columns (5) to (8). The sample is split into high and low subsamples by information environment measures of *cifar* and *country_eq*. The odd columns are the tests in the subsamples of countries with better information environment and the even columns are the tests in the subsamples of countries with worse information environment.

In columns (1) to (4), the coefficients on *tpchg*CFModel* are significantly positive in better information environment subsamples, and larger than in worse information environment subsamples. In columns (5) to (8), the coefficients on *tpchg*CFModel* are positive in better information environment subsamples, and negative in worse information environment subsamples. The difference tests of the coefficients on *tpchg*CFModel* for the high and low subsamples are statistically significant. Overall, I find evidence consistent with the prediction that cash flow models are more useful to investors in countries with a better information environment.

3.5.2.4 Economic freedom and the informativeness of cash-flow-based valuation models

I examine the impact of economic freedom on the informativeness of cash flow models by partitioning the full sample into subsamples of higher-than- and lower-than-median values of economic freedom variables. I then estimate equation (2) in the high and low subsamples to examine whether coefficients on *tpchg*CFModel* (β_4) for the high and low subsamples are significantly different.

Table 3. 7 Economic freedom and the informativeness of cash flow models

This table reports the regression results on the impact of a country's economic freedom on the informativeness of cash flow models. The sample is split into subsamples by the median values of economic freedom variables such as *EF_sum* and *EF_legal*. The odd columns are the tests in the subsamples with higher economic freedom, and the even columns are the tests in the subsamples with lower economic freedom. The dependent variables are *CAR3* (*CAR183)*, cumulative abnormal return starting from one day before to *3* (183) days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. *CFModel* equals one if analysts use cash flow models as the dominant valuation model, and zero otherwise. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep variable=	*CAR3*				*CAR183*			
	EF_sum		*EF_legal*		*EF_sum*		*EF_legal*	
	High	Low	High	Low	High	Low	High	Low
tpchg	2.454***	1.861***	2.760***	1.655***	-4.779***	-9.425***	-5.306***	-8.587***
	(15.63)	(14.27)	(16.51)	(13.97)	(-7.35)	(-15.42)	(-7.63)	(-15.51)
CFModel	0.016	0.016	-0.002	0.030	-0.265	0.568*	0.029	0.200
	(0.34)	(0.37)	(-0.04)	(0.71)	(-0.81)	(1.90)	(0.09)	(0.65)
tpchg*CFModel	**0.496****	0.044	**0.410***	-0.010	**1.363**	-0.782	**1.666***	-1.359*
	(2.37)	(0.24)	**(1.92)**	(-0.06)	**(1.58)**	(-0.94)	**(1.83)**	(-1.69)
earningsmgt	0.350	-0.935*	0.025	-0.528	2.287	-10.300**	3.477	-11.662***
	(0.70)	(-1.91)	(0.05)	(-1.11)	(0.72)	(-2.41)	(1.09)	(-2.78)
leverage	-0.022	-0.247	0.116	-0.365**	1.780	-2.233	4.517***	-4.353***
	(-0.11)	(-1.43)	(0.53)	(-2.32)	(1.22)	(-1.41)	(3.11)	(-2.91)
loss	-0.216*	-0.120	-0.250**	-0.079	-3.284***	-2.467***	-3.775***	-1.848**
	(-1.81)	(-1.16)	(-2.13)	(-0.75)	(-4.38)	(-3.15)	(-5.11)	(-2.35)
retstd12	-0.426***	-0.328***	-0.365***	-0.393***	-2.805***	-1.982***	-2.463***	-2.646***
	(-5.49)	(-4.37)	(-4.68)	(-5.27)	(-7.06)	(-4.61)	(-6.07)	(-6.38)
arpre12	0.033***	0.031***	0.033***	0.031***	0.482***	0.480***	0.480***	0.481***
	(35.11)	(28.62)	(34.44)	(29.69)	(56.90)	(46.17)	(56.30)	(47.29)
logmv	-0.223***	-0.151***	-0.212***	-0.165***	-3.158***	-2.868***	-3.328***	-2.712***
	(-6.70)	(-7.00)	(-6.11)	(-7.83)	(-14.06)	(-15.14)	(-14.45)	(-14.28)
mb	0.000	0.008	0.002	0.007	-0.254***	-0.032	-0.292***	-0.006
	(0.02)	(0.93)	(0.28)	(0.85)	(-5.23)	(-0.41)	(-6.06)	(-0.07)
firmex	-0.017*	0.002	-0.018**	0.003	0.070	0.066	0.062	0.072*
	(-1.79)	(0.30)	(-1.98)	(0.57)	(1.24)	(1.56)	(1.09)	(1.76)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Difference of β_4	**0.452****		**0.420****		**2.145*****		**3.025*****	
(H-L)	**(2.30)**		**(2.18)**		**(2.74)**		**(3.59)**	
Observations	141,618	143,865	143,613	141,870	141,618	143,865	143,613	141,870
Adjusted R^2	0.097	0.089	0.092	0.096	0.482	0.464	0.471	0.477

Table 3.7 reports the regression results on the impact of economic freedom on the informativeness of cash-flow-based valuation models. The dependent variable is *CAR3* in columns (1) to (4), and is *CAR183* in columns (5) to (8). The sample is split into high and low subsamples by economic freedom measures of *EF_sum* and *EF_legal*. The odd columns are the tests in the subsamples of countries with greater economic freedom and the even columns are the tests in the subsamples of countries with lesser economic freedom. I find that the differences in the coefficients on *tpchg*CFModel* between the high and low subsamples are significantly positive, indicating that cash flow models are more useful to investors in countries with greater economic freedom.

3.5.2.5 Robustness test: Comparisons between DCF and PE models

In this section, I focus on the most frequently used cash flow and accrual models, which are the DCF and PE models. I examine whether the above findings can be extended to the comparisons between DCF and PE models

Panel B of Table 3.1 suggests that the DCF model is the most frequently used cash flow model, and the PE model is the most frequently used accrual model. In this section, I focus on analysts' use of DCF and PE models to examine whether the above findings can be extended to the comparisons between DCF and PE models. Table 3.8 reports the tests of comparing DCF models with PE models.

Panel A of Table 3.8 examines the impact of a country's investor protection, information environment, and economic freedom on analysts' use of DCF models. The dependent variable is *DCFModel* which equals one if analysts use DCF models as the dominant valuation model, and zero if analysts use PE models as the dominant valuation model. The measures of a country's investor protection, information environment, and economic freedom are the same as in Table

3.3. The coefficients on *High anti_director*, *High anti_director*, and *High public_enforce* in columns (1) to (3) are significantly positive, indicating that the likelihood of analysts using DCF models is positively associated with the level of a country's investor protection. In columns (4) and (5), I find that *High cifar* and *High country_eq* are significantly positively related to *DCFModel*, suggesting that analysts are more likely to use DCF models to value firms in countries with a strong information environment. In columns (6) and (7), *High EF_sum* and *High EF_legal* are significantly positively associated with *DCFModel*, suggesting that analysts are more likely to use DCF models to value firms in countries with high economic freedom.

Panel B of Table 3.8 examines whether investor protection affects the informativeness of DCF models. The dependent variable is *CAR183*. The sample is split into high and low subsamples by the investor protection measures of *anti_director*, *anti_dealing*, and *public_enforce*. *Difference of (H-L)* at the bottom of the table reports the difference tests of the coefficients on *tpchg*DCFModel* for the high and low subsamples. Tests on *Difference of (H-L)* show that two out of three differences are significantly positive. Overall, the findings suggest that DCF models are more useful to investors for countries with greater investor protection.

Panel C of Table 3.8 examines whether the information environment and economic freedom affect the informativeness of DCF models. The sample is split into high and low subsamples by information environment measures in columns (1) to (4), and by economic freedom measures in columns (5) to (8). I find that three out of four of the differences in the coefficients on *tpchg*DCFModel* for the high and low subsamples are significantly positive, indicating that DCF models are more useful to investors for countries with a better information environment and higher economic freedom.

Table 3. 8 Robustness test: A comparison between DCF and PE models

This table reports the tests of comparing DCF models with PE models. Panel A examines the impact of a country's investor protection, information environment, and economic freedom on analysts' use of DCF models. *DCFModel* equals one if analysts use DCF models as the dominant valuation model, and zero if analysts use only PE models as the dominant valuation model. *High anti_director, High anti_director,* and *High public_enforce* are indicators of strong investor protection. *High cifar* and *High country_eq* are indicators of good information disclosure and earnings quality. *High EF_sum* and *High EF_legal* are indicators of high economic freedom. Panel B and Panel C examine the impact of a country's investor protection, information environment, and economic freedom on the informativeness of DCF models. The sample is split into subsamples by the median values of country factors. The odd columns are the tests in the subsamples with higher values and the even columns are the tests in the subsamples with lower values. The dependent variable is *CAR183*, cumulative abnormal return starting from one day before to 183 days after the report date. *tpchg* is the change of analyst target price forecast scaled by the stock price at the beginning of the year. Control variables are the same as in Table 3.3 and are not reported for brevity. Appendix 3.A provides detailed definitions of variables. Industry fixed effects use Fama-French 12-industry classification. All continuous variables are winsorized at the 1st and 99th percentiles. In the parentheses below coefficient estimates are robust *t*-statistics adjusted for firm and analyst clustering. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A Country factors and analysts' use of DCF models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Variable= DCFModel							
High anti_director	0.446***						
	(7.08)						
High anti_dealing		0.372***					
		(5.94)					
High public_enforce			0.620***				
			(10.21)				
High cifar				0.774***			
				(12.03)			
High country_eq					0.575***		
					(8.65)		
High EF_sum						0.252***	
						(4.46)	
High EF_legal							0.303***
							(5.35)
Controls	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES
Observations	274,104	274,104	274,104	274,104	274,104	274,104	274,104
Pseudo R^2	0.103	0.101	0.110	0.115	0.107	0.098	0.099

Panel B Investor protection and the informativeness of DCF models

	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable= CAR183						
	anti_director		*anti_dealing*		*public_enforce*	
	High	Low	High	Low	High	Low
tpchg	-4.397***	-8.983***	-4.564***	-8.195***	-5.753***	-7.330***
	(-6.71)	(-13.48)	(-6.56)	(-12.89)	(-7.84)	(-12.16)

DCFModel	-0.227	0.487	0.062	0.309	0.841**	-1.304***
	(-0.67)	(1.48)	(0.18)	(0.96)	(2.47)	(-3.56)
*tpchg*DCFModel*	0.625	-1.405	1.202	-1.311	0.018	0.328
	(0.75)	(-1.38)	(1.33)	(-1.44)	(0.02)	(0.35)
Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Difference of (H-L)	**2.030 ****		**2.513*****		**-0.310**	
	(2.36)		**(2.93)**		**(-0.20)**	
Observations	127,922	115,455	118,155	125,222	126,955	116,422
Adjusted R^2	0.468	0.461	0.482	0.437	0.463	0.469

Panel C Information environment, economic freedom, and the informativeness of DCF models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Information environment				Economic Freedom			
	cifar		*country_eq*		*EF_sum*		*EF_legal*	
	High	Low	High	Low	High	Low	High	Low
tpchg	-3.944***	-9.103***	-3.884***	-9.338***	-3.960***	-9.177***	-4.853***	-8.018***
	(-6.06)	(-13.92)	(-5.90)	(-14.33)	(-6.08)	(-14.03)	(-6.88)	(-13.36)
DCFModel	-0.030	0.247	0.230	-0.441	-0.355	0.560*	-0.083	0.146
	(-0.10)	(0.72)	(0.72)	(-1.20)	(-1.04)	(1.66)	(-0.25)	(0.42)
*tpchg*DCFModel*	0.069	-1.356	0.245	-1.638	0.746	-0.515	1.501	-1.561*
	(0.08)	(-1.32)	(0.29)	(-1.58)	(0.83)	(-0.55)	(1.58)	(-1.75)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Difference of (H-L)	**1.425***		**1.883****		**1.261**		**3.062*****	
	(1.66)		**(2.15)**		**(1.64)**		**(3.39)**	
Observations	133,666	109,711	132,480	110,897	123,792	119,585	126,729	116,648
Adjusted R^2	0.474	0.452	0.470	0.457	0.476	0.453	0.465	0.467

3.6 Conclusions and Limitations

It is widely accepted that accrual accounting is more value-relevant than cash flow information. As a result, accrual models are the default valuation methods used by analysts in their valuation process, while the use of cash flow models is quite selective. In this study, I examine whether a country's institutional factors affect analysts' choice of cash flow models. I find that analysts are more likely to use cash flow models to value firms headquartered in countries with stronger investor protection, better information environment, and greater economic freedom. This is consistent with the argument that the sound institutional environment facilitates analysts' forecasts of cash flow information and the application of cash flow models. The findings support the complementary role of analysts' research to institutional factors.

I also investigate whether a country's institutional factors affect the usefulness of cash flow models. I find that the use of cash flow models is associated with stronger market reactions to analyst target price changes. Further analysis indicates that the incremental effect of cash flow models on market reactions to analyst target price changes is more pronounced in countries with stronger investor protection, better information environment, and greater economic freedom. The findings provide corroborating evidence that analysts' research is more useful to investors in countries with a better institutional environment.

I acknowledge that this paper is subject to several limitations that are associated with cross-country studies (Isidro et al., 2020). Specifically, the proxies for investor protection, information environment, and economic freedom are likely to be associated with other omitted country variables such as the IFRS adoption that might influence the findings. In addition, these country-level variables could be highly correlated, and do not change much over years. Additionally, the sample covers only 29 countries. Given the limited number of country observations, the degree of freedom is small. Given the above limitations, the findings in this paper should be interpreted with caution.

References

Aggarwal, R., I. Erel, M. Ferreira, and P. Matos. 2011. Does governance travel around the world? Evidence from institutional investors. *Journal of Financial Economics* 100 (1):154-181.

Amory, J., C. Muller, S. Page, E. Leifke, E. Pagel, A. Bhandari, B. Subramanyam, W. Bone, A. Radlmaier, and W. Bremner. 2007. Miglustat has no apparent effect on spermatogenesis in normal men. *Human Reproduction* 22 (3):702-707.

Asquith, P., M. B. Mikhail, and A. S. Au. 2005. Information content of equity analyst reports. *Journal of Financial Economics* 75 (2):245-282.

Bae, K.-H., R. M. Stulz, and H. Tan. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics* 88 (3):581-606.

Baik, B., D. B. Farber, and K. Petroni. 2009. Analysts' incentives and street earnings. *Journal of Accounting Research* 47 (1):45-69.

Baker, M., X. Pan, and J. Wurgler. 2012. The effect of reference point prices on mergers and acquisitions. *Journal of Financial Economics* 106 (1):49-71.

Barker, R. G. 1999. Survey and Market-based Evidence of Industry-dependence in Analysts' Preferences Between the Dividend Yield and Price-earnings Ratio Valuation Models. *Journal of Business Finance & Accounting* 26 (3-4):393-418.

Barniv, R., O. K. Hope, M. Myring, and W. B. Thomas. 2009. Do Analysts Practice What They Preach and Should Investors Listen? Effects of Recent Regulations. *The Accounting Review* 84 (4):1015-1039.

Barniv, R., O.K. Hope, M. Myring, and W. B. Thomas. 2010. International Evidence on Analyst Stock Recommendations, Valuations, and Returns*. *Contemporary Accounting Research* 27 (4):1131-1167.

Barniv, R., M. J. Myring, and W. B. Thomas. 2005. The association between the legal and financial reporting environments and forecast performance of individual analysts. *Contemporary Accounting Research* 22 (4):727-758.

Basu, S., L. Hwang, and C. L. Jan. 1998. International variation in accounting measurement rules and analysts' earnings forecast errors. *Journal of Business Finance & Accounting* 25 (9-10):1207-1247.

Beatty, A., L. Cheng, and H. Zhang. 2018. Are risk factor disclosures still relevant? Evidence from market reactions to risk factor disclosures before and after the financial crisis. *Contemporary Accounting Research*.

Bena, J., M. A. Ferreira, P. Matos, and P. Pires. 2017. Are foreign investors locusts? The long-term effects of foreign institutional ownership. *Journal of Financial Economics* 126 (1):122-146.

Block, S. B. 1999. A study of financial analysts: Practice and theory. *Financial Analysts Journal* 55 (4):86-95.

Bochkay, K., and P. Joos. 2020. Macroeconomic Uncertainty and Quantitative vs. Qualitative Inputs to Analyst Risk Forecasts. *The Accounting Review*.

Bradshaw, M. T. 2002. The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizons* 16 (1):27-41.

Bradshaw, M. T. 2004. How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review* 79 (1):25-50.

Bradshaw, M. T. 2009. Analyst information processing, financial regulation, and academic research. *The Accounting Review* 84 (4):1073-1083.

Bradshaw, M. T. 2011. Analysts' forecasts: what do we know after decades of work? *Available at SSRN 1880339*.

Bradshaw, M. T., A. G. Huang, and H. Tan. 2018. The Effects of Analyst-Country Institutions on Biased Research: Evidence from Target Prices. *Journal of Accounting Research* 57 (1):85-120.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan. 2006. The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics* 42 (1-2):53-85.

Brav, A., and R. Lehavy. 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *The Journal of Finance* 58 (5):1933-1967.

Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp. 2015. Inside the "Black Box" of Sell-Side Financial Analysts. *Journal of Accounting Research* 53 (1):1-47.

Campbell, J. L., H. Chen, D. S. Dhaliwal, H.-m. Lu, and L. B. Steele. 2014. The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies* 19 (1):396-455.

Campbell, S. D., and S. A. Sharpe. 2009. Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices. *Journal of Financial and Quantitative Analysis* 44 (02):369.

Cen, L., G. Hilary, and K. C. J. Wei. 2012. The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns. *Journal of Financial and Quantitative Analysis* 48 (01):47-76.

Chan, K., V. Covrig, and L. Ng. 2005. What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *The Journal of Finance* 60 (3):1495-1534.

Chang, J. J., T. Khanna, and K. Palepu. 2000. Analyst activity around the world.

Chen, C.-W., D. W. Collins, T. D. Kravet, and R. D. Mergenthaler. 2018. Financial Statement Comparability and the Efficiency of Acquisition Decisions. *Contemporary Accounting Research* 35 (1):164-202.

Choi, J.-H., S. Choi, L. A. Myers, and D. Ziebart. 2019. Financial Statement Comparability and the Informativeness of Stock Prices About Future Earnings. *Contemporary Accounting Research* 36 (1):389-417.

De Franco, G., O. K. Hope, D. Vyas, and Y. Zhou. 2015. Analyst report readability. *Contemporary Accounting Research* 32 (1):76-104.

De Franco, G., S. P. Kothari, and R. S. Verdi. 2011. The benefits of financial statement comparability. *Journal of Accounting Research* 49 (4):895-931.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals. *Journal of Accounting and Economics* 18 (1):3-42.

DeFond, M. L., and M. Hung. 2003. An empirical analysis of analysts' cash flow forecasts. *Journal of Accounting and Economics* 35 (1):73-100.

DeFond, M. L., and M. Hung. 2007. Investor protection and analysts' cash flow forecasts around the world. *Review of Accounting Studies* 12 (2-3):377-419.

DeFond, M., X. Hu, M. Hung, and S. Li. 2011. The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting and Economics* 51 (3):240-258.

Demirakos, E. G., N. C. Strong, and M. Walker. 2004. What valuation models do analysts use? *Accounting Horizons* 18 (4):221-240.

Demirakos, E. G., N. C. Strong, and M. Walker. 2010. Does Valuation Model Choice Affect Target Price Accuracy? *European Accounting Review* 19 (1):35-72.

Dhaliwal, D. S., S. Radhakrishnan, A. Tsang, and Y. G. Yang. 2012. Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review* 87 (3):723-759.

Djankov, S., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. 2008. The law and economics of self-dealing. *Journal of Financial Economics* 88 (3):430-465.

Dyck, A., and L. Zingales. 2004. Private benefits of control: An international comparison. *The Journal of Finance* 59 (2):537-600.

Frederickson, J. R., and J. S. Miller. 2004. The Effects of Pro Forma Earnings Disclosures on Analysts' and Nonprofessional Investors' Equity Valuation Judgments. *Accounting Review* 79 (3):667-686.

French, K. R., and J. M. Poterba. 1991. Investor diversification and international equity markets: National Bureau of Economic Research.

George, T. J., and C. Y. Hwang. 2004. The 52-week high and momentum investing. *The Journal of Finance* 59 (5):2145-2176.

Gillan, S. L., and L. T. Starks. 2003. Institutional investors, corporate ownership and corporate governance: Global perspectives. In *Ownership and Governance of Enterprises*: Springer, 36-68.

Givoly, D., and J. Lakonishok. 1979. The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency. *Journal of Accounting and Economics* 1 (3):165-185.

Givoly, D., C. Hayn, and R. Lehavy. 2009. The quality of analysts' cash flow forecasts. *The Accounting Review* 84 (6):1877-1911.

Gleason, C. A., W. Bruce Johnson, and H. Li. 2013. Valuation Model Use and the Price Target Performance of Sell-Side Equity Analysts*. *Contemporary Accounting Research* 30 (1):80-115.

Gu, Z., and T. Chen. 2004. Analysts' treatment of nonrecurring items in street earnings. *Journal of Accounting and Economics* 38:129-170.

Gwartney, J., and Lawson, R. 2002. Economic Freedom of the World: 2002 Annual Report. *Fraser institute*.

Hand, J. R., J. G. Coyne, J. R. Green, and X. F. Zhang. 2017. The use of residual income valuation methods by US sell-side equity analysts. *Journal of Financial Reporting* 2 (1):1-29.

Heath, C., and A. Tversky. 1991. Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty* 4 (1):5-28.

Hirshleifer, D. 2001. Investor psychology and asset pricing. *The Journal of Finance* 56 (4):1533-1597.

Holland, J. 1998. Private voluntary disclosure, financial intermediation and market efficiency. *Journal of Business Finance & Accounting* 25 (1-2):29-68.

Hope, O. K. 2003. Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research* 41 (2):235-272.

Hope, O.-K., D. Hu, and H. Lu. 2016. The benefits of specific risk-factor disclosures. *Review of Accounting Studies* 21 (4):1005-1045.

Houston, J. F., B. Lev, and J. W. Tucker. 2010. To guide or not to guide? Causes and consequences of stopping quarterly earnings guidance. *Contemporary Accounting Research* 27 (1):143-185.

Huang, A. H., A. Y. Zang, and R. Zheng. 2014. Evidence on the information content of text in analyst reports. *The Accounting Review* 89 (6):2151-2180.

Huang, A. H., R. Lehavy, A. Y. Zang, and R. Zheng. 2018. Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science* 64 (6):2833-2855.

Huang, Tan, Wang, and Yu. 2021, Valuation Uncertainty and Analysts’ Use of DCF. Accepted at *Review of Accounting Studies*.

Hung, M. 2000. Accounting standards and value relevance of financial statements: An international analysis. *Journal of Accounting and Economics* 30 (3):401-420.

Hutton, A. P., L. F. Lee, and S. Z. Shu. 2012. Do managers always know better? The relative accuracy of management and analyst forecasts. *Journal of Accounting Research* 50 (5):1217-1244.

Imam, S., J. Chan, and S. Z. A. Shah. 2013. Equity valuation models and target price accuracy in Europe: Evidence from equity reports. *International Review of Financial Analysis* 28:9-19.

Imam, S., R. Barker, and C. Clubb. 2008. The use of valuation models by UK investment analysts. *European Accounting Review* 17 (3):503-535.

Isidro, H., D. D. Nanda, and P. D. Wysocki. 2020. On the relation between financial reporting quality and country attributes: Research challenges and opportunities. *The Accounting Review* 95 (3):279-314.

Joos, P., J. D. Piotroski, and S. Srinivasan. 2016. Can analysts assess fundamental risk and valuation uncertainty? An empirical analysis of scenario-based value estimates. *Journal of Financial Economics* 121 (3):645-663.

Kadan, O., L. Madureira, R. Wang, and T. Zach. 2012. Analysts' industry expertise. *Journal of Accounting and Economics* 54 (2-3):95-120.

Kim, J.-B., L. Li, L. Y. Lu, and Y. Yu. 2016. Financial statement comparability and expected crash risk. *Journal of Accounting and Economics* 61 (2-3):294-312.

Kim, S., P. Kraft, and S. G. Ryan. 2013. Financial statement comparability and credit risk. *Review of Accounting Studies* 18 (3):783-823.

Kravet, T., and V. Muslu. 2013. Textual risk disclosures and investors’ risk perceptions. *Review of Accounting Studies* 18 (4):1088-1122.

Kumar, A. 2010. Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research* 48 (2):393-435.

Lang, M. H., K. V. Lins, and D. P. Miller. 2004. Concentrated control, analyst following, and valuation: do analysts matter most when investors are protected least? *Journal of Accounting Research* 42 (3):589-623.

Leuz, C., D. Nanda, and P. D. Wysocki. 2003. Earnings management and investor protection: an international comparison. *Journal of Financial Economics* 69 (3):505-527.

Li, C., A.-P. Lin, and H. Lu. 2020. Analyzing the Analysts: The Effects of Technical and Social Skills on Analyst Performance and Careers. *Available at SSRN 3656427*.

Li, J., and J. Yu. 2012. Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics* 104 (2):401-419.

Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance* 66 (1):35-65.

Lui, D., S. Markov, and A. N. E. Tamayo. 2007. What Makes a Stock Risky? Evidence from Sell-Side Analysts' Risk Ratings. *Journal of Accounting Research* 45 (3):629-665.

Lui, D., S. Markov, and A. N. E. Tamayo. 2012. Equity Analysts and the Market's Assessment of Risk. *Journal of Accounting Research* 50 (5):1287-1317.

Luong, H., F. Moshirian, L. Nguyen, X. Tian, and B. Zhang. 2017. How do foreign institutional investors enhance firm innovation? *Journal of Financial and Quantitative Analysis* 52 (4):1449-1490.

Lys, T., and S. Sohn. 1990. The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics* 13 (4):341-363.

Malloy, C. J. 2005. The geography of equity analysis. *The Journal of Finance* 60 (2):719-755.

O'Brien, P. C., and H. Tan. 2015. Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics* 59 (1):41-59.

Peterson, K., R. Schmardebeck, and T. J. Wilks. 2015. The Earnings Quality and Information Processing Effects of Accounting Consistency. *The Accounting Review* 90 (6):2483-2514.

Pike, B. J., M. B. Curtis, and L. Chui. 2013. How Does an Initial Expectation Bias Influence Auditors' Application and Performance of Analytical Procedures? *The Accounting Review* 88 (4):1413-1431.

Previts, G. J., R. J. Bricker, T. R. Robinson, and S. J. Young. 1994. A content analysis of sell-side financial analyst company reports. *Accounting Horizons* 8 (2):55.

Reading between the lines: An empirical examination of qualitative attributes of financial analysts’ reports. *Journal of Accounting and Public Policy* 31 (1):1-21.

Sherman, R. 1974. The psychological difference between ambiguity and risk. *The Quarterly Journal of Economics*:166-169.Twedt, B., and L. Rees. 2012.

Simon, A., and A. Curtis. 2011. The use of earnings forecasts in stock recommendations: Are accurate analysts more consistent? *Journal of Business Finance & Accounting* 38 (1-2):119-144.

Sun, J. 2009. Governance role of analyst coverage and investor protection. *Financial Analysts Journal* 65 (6):52-64.

Tversky, A., and D. Kahneman. 1975. Judgment under uncertainty: Heuristics and biases. In *Utility, probability, and human decision making*: Springer, 141-162.

Womack, K. L. 1996. Do brokerage analysts' recommendations have investment value? *The Journal of Finance* 51 (1):137-167.

Yip, R. W. Y., and D. Young. 2012. Does Mandatory IFRS Adoption Improve Information Comparability? *The Accounting Review* 87 (5):1767-1789.

Young, S., and Y. Zeng. 2015. Accounting Comparability and the Accuracy of Peer-Based Valuation Models. *The Accounting Review* 90 (6):2571-2601.

Zhang, J. H. 2018. Accounting Comparability, Audit Effort, and Audit Outcomes. *Contemporary Accounting Research* 35 (1):245-276.

Appendices

Appendix 1. A Variables definitions in chapter 1

This appendix describes all variables used in the first chapter. I obtain analyst-level data from I/B/E/S international, and financial and stock trading data from Compustat Global. Variables for risk discussions are from textual analysis of analyst reports from Investext.

Variable	Definition
Geographic location	
foreign	Dummy equal to one if an analyst's domicile country is distinct from the underlying firm's headquarters country, and zero otherwise. I use analysts' telephone numbers disclosed in their reports to detect their calling codes, then match calling codes to country calling codes to identify analysts' domicile countries. Firms' headquarters countries are obtained from Compustat Global.
Risk discussions	
Risk	The number of risk-related keywords discussed on the first page of an analyst report.
Riskpct	*Risk* scaled by the total number of words discussed on the first page of an analyst report.
Risk2pct	The number of risk-related keywords discussed in the full analyst report, scaled by the number of total words in the report
FLS_risk	The number of sentences which include both risk and forward-looking statement keywords on the first page of an analyst report.
FLS_riskpct	*FLS_risk* scaled by the total number of words discussed on the first page of an analyst report.
FLS_risk2pct	The number of sentences which include both risk and forward-looking statement keywords in the full analyst report, scaled by the number of total words in the report.
Firm_risk	The number of sentences which include both risk and firm-level keywords on the first page of an analyst report.
Firm_riskpct	*Firm_risk* scaled by the total number of words discussed on the first page of an analyst report.
Firm_risk2pct	The number of sentences which include both risk and firm-level keywords in the full analyst report, scaled by the number of total words in the report.
Ind_risk	The number of sentences which include both risk and industry-related keywords on the first page of an analyst report.
Ind_riskpct	*Ind_risk* scaled by the total number of words discussed on the first page of an analyst report.
Ind_risk2pct	The number of sentences which include both risk and industry-related keywords in the full analyst report, scaled by the number of total words in the report.
Regu_risk	The number of sentences which include both risk and regulation and litigation keywords on the first page of an analyst report.
Regu_riskpct	*Regu_risk* scaled by the total number of words discussed on the first page of an analyst report.
Regu_risk2pct	The number of sentences which include both risk and regulation and litigation keywords in the full analyst report, scaled by the number of total words in the report.
Macro_risk	The number of sentences which include both risk and macroeconomic-related keywords on the first page of an analyst report.
Macro_riskpct	*Macro_risk* scaled by the total number of words discussed on the first page of an analyst report.

Macro_risk2pct	The number of sentences which include both risk and macroeconomic-related keywords in the full analyst report, scaled by the number of total words in the report.
Foreign analyst unfamiliarity hypothesis test	
mixlocfor	Dummy equal to one if an analyst team has both local and foreign analysts, and zero otherwise.
foreignpure	Dummy equal to one if a report is written by foreign analyst(s) only, and zero otherwise.
chgtolocal	Dummy equal to one when an analyst changes her location to the same country as the underlying firm's headquarters, and zero when this analyst lives in a different country from the firm's headquarters country.
foreignfirmexp	The number of foreign firms followed by an analyst in one year
indexp	The number of firms an analyst has followed for an industry in one year
antidir	Anti-director rights index from Djankov et al. (2008)
anti_dealing	Anti-self-dealing index from Djankov et al. (2008)
cifar	The index of financial disclosures from the Center for International Financial Analysis and Research (CIFAR)
earnmgmt	The index of earnings management of a country from Leuz et al. (2003) multiplied by (-1)
trust	Average trust in firm country. The trust index is based on the percentage of people in each country who answered "Most people can be trusted" to the following World Values Survey question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" Data source: http://www.worldvaluessurvey.org/WVSOnline.jsp
Foreign institutional investor demand hypothesis test	
avgio_for	The sum of the holdings of all institutions domiciled in a country different from the firm country divided by the firm's market capitalization. The data source is Facet.
avgio_fordum	Dummy equal to one if the foreign institutional ownership is at the top decile in one year, and zero otherwise
Conflicts of interest hypothesis test	
deltadebt	The change of total debt divided by the firm's total assets
deltaequity	The change of shareholders' equity divided by the firm's total assets
The informativeness of risk discussions test	
volatility3	The total stock return volatility three months after the issuance of an analyst report
turnover3	The total stock turnover ratio three months after the issuance of an analyst report
CAR3	The market-adjusted cumulative abnormal return starting one day before to three days after the analyst report date.
buy	Dummy equal to one if the stock recommendation is to buy, and zero otherwise.
sell	Dummy equal to one if the stock recommendation is to sell, and zero otherwise.
Control variables	
eps_std	The standard deviation of eps 12 months before the analyst report date.
beta	Market beta calculated from CAPM model.
preturnover	Stock turnover ratio 12 months before the analyst report date
Logmv	The logarithm of firm market value.
negbv	Dummy equals one if the underlying firm has a negative book value and zero otherwise.
mb	The market-to-book value of the underlying firm.

leverage	The leverage ratio of the underlying firm.
idorisk	The idiosyncratic risk of a stock calculated from CAPM model.
firmex	Time interval in years since an analyst provides the first earnings forecast for the target firm in the I/B/E/S.
genex	Time interval in years since an analyst provides the first earnings forecast in the I/B/E/S.
brsize	Brokerage size in a given year, defined as the logarithm of the number of analysts working for the I/B/E/S brokerage with which that the analyst is associated.
logwords	The logarithm of the number of total words in an analyst report.
arpre12	The cumulative abnormal stock return 12 months before the analyst report date

Appendix 1. B Sample selection

	# Reports	#Firm	#Analyst	#Country
Analysts reports with telephone numbers identified	871,714	17,279	11,917	61
Keep Firms covered by both foreign and local analysts	(318,683)			
	553,031	5,834	10,662	44
Delete missing values of key variables	(11,400)			
Final sample	541,631	5,495	10,544	38

Appendix 1. C Keywords Lists

This appendix lists the keywords for risk discussions, and the keywords for categories such as forward-looking statement, firm, industry, regulation and litigation, and macroeconomic. Keywords are listed in alphabetical order. For the sake of brevity, I list only the top 50 most frequently discussed phrases.

Risk	Forward-looking statement	Firm	Industry	Regulation and litigation	Macroeconomic
affect	aim	asset	business conditions	amended	coal
affected	also assume	assets	compete	appeal	commodities
affecting	also expect	balance sheet	competed	appealing	commodity
affects	also expects	business	competes	casualty	concentration
can	and assume	capacity	competing	charged	consumer spending
cannot	and estimate	capital	competition	claim	consumption
catalysts	and estimates	cash	competitions	claims	cyclical
concern	and expect	close	competitive	compliance	discounting
concerned	and expects	competitive	competitiveness	contract	domestic
concerning	and forecast	consumer	competitor	contracted	economic
concerns	and forecasts	cost	competitors	contracting	economics
could	and plans	costs	differentiation	contracts	economy
depend	and project	dcf	downstream	contractual	electricity
depends	and target	debt	entrants	conviction	energy
downside	anticipate	demand	industrial	court	eu
expose	are expected	discount	industrialization	environmental	euro
exposed	are expecting	dividend	industrially	Fda	exchange rate
exposure	are forecasting	earnings	industrious	federal	foreign exchange
fluctuate	assume	ebitda	industry	herein	fuel
fluctuates	but expect	eps	industrywide	Ifrs	gas
fluctuation	company estimates	equity	innovation	intellectual property	gdp
fluctuations	company expects	expense	line of business	investigation	global
hedge	company plans	expenses	market demand	investigations	gold
hedged	currently forecast	financial	market power	Law	growth rate
hedges	do not expect	gross	market supply	Laws	growth rates
hedging	does not expect	income	monopolistic	lawsuit	hedge
influence	estimate	industry	monopoly	legal	hedging
influenced	expect	interest	nonindustrial	legislation	housing
influencing	forecast	leverage	oligopoly	legislative	inflation
likely to	future	loss	porter's	litigation	macroeconomic
may	hope	maintain	price pressure	medicaid	market
might	intend	margin	pricing power	medicare	markets
possible	is expected	margins	prisoner's dilemma	moreover	materials
potential	is expecting	market	quasi-industrial	notwithstanding	metal
risk	is targeting	multiple	regulatory compliance	penalty	metals
riskier	management estimates	net	regulatory environment	regulated	middle east
risking	management expects	operating	rival	regulation	mortgage
risks	next quarter	operations	rivaled	regulations	natural gas
risky	next year	performance	rivaling	regulator	oil
sensitivity	not expected	product	rivalry	regulators	ore

subject to	plan	profit	rivals	regulatory	pricing power
susceptible	project	ratio	sectorial	ruling	raw material
uncertain	seek	return	semi-industrial	Sec	raw materials
uncertainties	we anticipate	revenue	subsector	settlement	recession
uncertainty	we assume	sales	substitutes	settlements	reit
upside	we estimate	segment	supply chain	severance	rmb
varies	we expect	service	upstream	statutory	saving
vary	we forecast	stock	value chain	thereafter	seasonal
volatile	we project	tax	win-win	whereas	steel
volatility	will	yoy	zero-sum	whereby	yen

Appendix 1. D First pages of analyst reports with risk keywords highlighted

J.P.Morgan

Japan Equity Research
18 December 2012

Sharp (6753)

Risk of 2H Profit Shortfall Owing to No. 2 Kameyama Plant Remains

Underweight

6753.T, 6753 JT
Price: ¥327
Price Target: ¥115

Industrial Electronics, Consumer Electronics

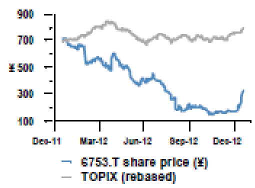
Yoshiharu Izumi [AC]
(81-3) 6736-8637
yoshiharu.izumi@jpmorgan.com
JPMorgan Securities Japan Co., Ltd.

We recently visited the company and, as we indicated in our December 13 company memo, confirmed that there is still a risk of a 2H profit shortfall owing to conditions at the No. 2 Kameyama plant. The share price has risen a further 31% since we issued the December 13 memo (versus a 2.2% rise for TOPIX in the same period), but in this visit we could not identify any definitive factors that could explain the stock's performance.

- **We estimate a 3Q operating loss of around ¥7 billion:** The company forecasts a 2H operating profit of ¥13.9 billion. It has not disclosed a 3Q-4Q breakdown of its estimates, but we look for a loss in 3Q and profit in 4Q. Sales in October and November were apparently in line with plan, as was total LCD TV shipment volume for the two months (down more than 30% YoY). And while the utilization rate of the No. 2 Kameyama plant was below plan (at around 30% compared with 40-50%), the company expects to ensure sales by drawing down inventory and therefore thinks any 3Q shortfall in profits will not be significant. Based on this, we also think the possibility of a much greater than planned 3Q operating loss is small. Sharp reported a 2Q operating loss of ¥74.8 billion, but we expect the disappearance of inventory valuation losses (¥20 billion) on LCD panels and electronic devices, falling costs to reduce large panel inventories, and fixed cost reductions (cuts in salaries and bonuses, layoffs overseas) to greatly reduce losses in 3Q. Incidentally, the cost-reduction effect of a domestic early retirement program (netting 2,960 employees) will be felt in 4Q.

- **Risk of 4Q shortfall:** The amount of glass being fed into the No. 2 Kameyama plant has been falling month after month and there is a risk 2H results will come in below plan. With shipments of PC-related panels to new customers not expected before 1H FY2013, additional emergency measures (e.g., an increase in external sales of amorphous LCD panels for TVs) are needed. If we assume an opportunity loss at the No. 2 Kameyama plant equal to six million 9.7-inch panels, we calculate a shortfall of ¥40-50 billion in sales and ¥10 billion in operating profit in 4Q.

Price Performance



Price (¥)	327
Date Of Price	18 Dec 12
Market Cap (¥ bn)	359.87
Shares O/S (mn)	1,101
52-week Range (¥)	729-142
TOPIX	816.85
DPS (¥)	0.00
Dividend Yield	0.0%
ROE	-116.7%

Source: Bloomberg, J.P. Morgan estimates
Note: DPS, DY, ROE are forecasts as of FY start

Deutsche Bank Group
Markets Research

Rating
Hold

Japan

Financials / Banks

Company
Joyo Bank

Reuters	Bloomberg	Exchange	Ticker
8333.T	8333 JT	TYO	8333

Date
16 January 2015

Forecast Change

Price at 16 Jan 2015 (¥)	559
Price target - 12mth (¥)	615
52-week range (¥)	613 - 460

NP growth intact: Raising TP

Yoshinobu Yamada
Research Analyst
(+81) 3 5156-6754
yoshinobu.yamada@db.com

Takayasu Kudo
Research Analyst
(+81) 3 5156-6319
takayasu.kudo@db.com

New TP of ¥615, maintaining Hold rating

We revise our forecasts for Joyo Bank and raise our target price from ¥595 to ¥615. Our higher TP reflects a hike to our benchmark FY3/16E P/E from 16.0x to 16.5x (Figure 1). We have raised our base P/E for regional banks from 13.0x to 13.5x to reflect a revision to our Nikkei Average assumption from 15,000 to 17,000. However, we apply 3x premium for Joyo Bank in light its past share performance. We maintain Hold rating as our forecasts are close to guidance.

Earnings forecasts (FY3/15): In line with guidance

Joyo Bank raised FY3/15 consolidated NP guidance from ¥24.5bn to ¥26bn last November including a deferred tax asset adjustment of ¥1.5bn due to a cut in the corporate tax rate. However, at this stage we think a roughly ¥2bn adjustment is necessary. At the same time, recent declines in long-term interest rates could likely deliver greater-than-planned JGB-related gains. We expect these two factors to offset each other, and look for FY3/15 NP broadly in line with guidance.

Earnings forecasts (FY3/16-FY3/17): We project a rebound in NII

Joyo Bank's 1H FY3/15 lending rose 5.5% YoY, delivering the strongest growth among the six regional banks we cover and topping Suruga (+5.3%) and Fukuoka FG (+4.6%). The outcome reflected strong 11.4% growth in lending to individuals (Figure 2). However, we also attribute it to brisk mortgage lending and apartment loans for inheritance tax purposes, and see this trend persisting in FY3/16 and after. Stronger lending growth in Saitama, Chiba and Tokyo than in Ibaraki suggests that recent branch openings have proven successful. Assuming that lending growth is 5.2% for FY3/15 and 4.3% for FY3/16 and that the loan-deposit spread for FY3/16 narrows by about half the rate of FY3/15 (ie, by 5bp), we forecast net interest income to rebound in FY3/16 even if the bank recognizes no gains from investment trust sales. We project consolidated NP to increase steadily in both FY3/16 and FY3/17 even if credit costs double to 7-8bp from 4bp currently. However, we also estimate that the loan-deposit spread needs to stop narrowing if Joyo Bank is to meet the current medium-term plan's consolidated NP target of ¥30bn in FY3/17 (Figure 3).

Capital policy: Impact of continued dividend hikes

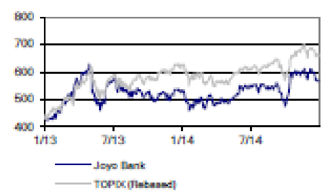
We base our TP for Joyo on a P/E of 16.5x, compared with 13.5x for Yokohama (Current price: ¥621.5) and Chiba (¥748) and 15.5x for Shizuoka (¥1,011) and Fukuoka FG (¥594). Although Joyo Bank's FY3/15 payout ratio is a high 73%, its five-year average of 45% through FY3/15 is not particularly high relative to its peers (Figure 4). However, we estimate that continued dividend hikes (Figure 5) have helped reassure investors. The bank's target payout ratio is a minimum of 40% of parent NP, but we think it will likely repurchase its shares every financial year for the foreseeable future. Considering the current conversion price of ¥918 for the $300m dollar-denominated CB, we see negligible concerns of dilution.

Key changes

Target price (¥)	595 to 615	↑	3.4%
EPS (¥)	34 to 36	↑	5.3%
Actual net OP (¥bn)	37.0 to 38.0	↑	2.7%
RP (¥bn)	39.0 to 42.7	↑	9.5%

Source: Deutsche Securities Inc.

Price/price relative



Performance (%)	1m	3m	12m
Absolute	-2.3	15.3	5.5
TOPIX	1.7	15.1	6.4

Source: Deutsche Securities Inc.

Valuation and risk

Our TP of ¥615 is based on an FY3/16E P/E of 16.5x (previously 16.0x). Our base P/E for regional banks is 13.5x, but we apply 3x premium in light of past share performance. Potential upside risks include better spreads due to higher short-term interest rates. Possible downside risks include higher credit costs due to slower regional economic growth.

Forecasts And Ratios

Year End Mar 31	2014A	2015E	2015CoE	2016E	2017E
EPS (¥)	34	36	33	37	38
P/E (x)	15.6	15.5	17.0	15.1	14.7
P/B (x)	0.8	0.9	–	0.9	0.9

Source: Deutsche Securities Inc. estimates, company data

CREDIT SUISSE

Sonic Healthcare

(SHL.AX / SHL AU)

Rating	UNDERPERFORM*
Price (17 Feb 15, A$)	18.91
Target price (A$)	(from 18.30) 19.00¹
Market cap. (A$mn)	7,590.50
Yr avg. mthly trading (A$mn)	399
Last month's trading (A$mn)	416
Projected return:	
Capital gain (%)	0.48
Dividend yield (net %)	4.3
Total return (%)	4.8
52-week price range	19.5 - 16.6

** Stock ratings are relative to the relevant country benchmark.*
¹Target price is for 12 months.

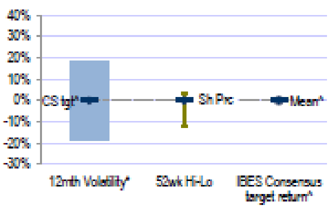
Research Analysts
Saul Hadassin
61 2 8205 4679
saul.hadassin@credit-suisse.com
David Bailey
61 2 8205 4739
david.bailey@credit-suisse.com

RESULTS

1H15 result: Turning the corner, but risks remain

- **Following SHL's 1H15 result, we have made incremental changes to EPS (+ ~2%) over the forecast period. Coupled with DCF model rollover, our target price increases by ~4% to A$19.00 (from A$18.30). Based on Credit Suisse total return parameters, this continues to generate an UNDERPERFORM rating.** SHL's 1H15 result was in line with expectations. Negative earnings growth in AUS pathology (muted 1Q15 volumes, ACC rollout) and the US (weak volumes) more than offset strong operating performance in Germany/UK and uplift in AUS imaging margins. Gross cash conversion of 93% was robust, although free cash flow was impacted by a 25% uplift in PP&E investment (new laboratories) and intangibles (IT/GPs).
- **Volume recovery/new contracts bode well, domestic health policy still an unknown.** Despite our forecast for volume growth recovery in the US/AUS and the medium-term benefits from the UCLH/Alberta contracts, our outlook for the group remains somewhat tempered due to uncertainty over three key issues that could impact the Australian pathology division. These include: **(1)** the potential for continued deployment by SHL (and other industry participants) of Approved Collection Centres as a defensive move, with an ongoing increase in operating costs, assuming no mandated rent relief; **(2)** the passage of the revised Federal Government GP co-pay (A$5 on non-concession card holders) into legislation and indirect impact on pathology referrals; **(3)** The willingness of the government to sustain pathology outlays (Medicare) growth of ~5-6% on a normalised basis, noting ~A$300mn overspend versus the industry agreement as at end FY14 and therefore risk of further funding cuts.
- **Catalysts. (1) Outcome of government review of ACC rents.**
- **Valuation.** SHL is currently trading on 17.3x our revised 12-month forward EPS (average 16.7x), representing a 6% premium to the ASX200 (and below the long-term average of 11%).

Total return forecast in perspective



Performance over	1M	3M	12M
Absolute (%)	5.3	2.8	11.4
Relative (%)	-5.2	-6.3	2.5

Relative performance versus S&P ASX 200.See Reference Appendix for a description of the chart. Source: Credit Suisse estimates, ^ consensus, mean range from Thomson Reuters

Financial and valuation metrics

Year	06/14A	06/15E	06/16E	06/17E
Revenue (A$mn)	3,910.2	4,227.8	4,684.3	4,963.7
EBITDA (A$mn)	733.0	767.6	876.7	953.9
EBIT (A$mn)	572.4	590.7	687.3	757.9
Net income (A$mn)	385.0	399.8	469.9	522.8
EPS (CS adj.) (Ac)	95.49	98.85	115.40	127.15
Change from previous EPS (%)	n.a.	-0.6	2.3	2.9
Consensus EPS (Ac)	n.a.	101.70	114.50	124.00
EPS growth (%)	13.3	3.5	16.7	10.2
P/E (x)	19.8	19.1	16.4	14.9
Dividend (Ac)	67.00	74.00	85.00	93.00
Dividend yield (%)	3.5	3.9	4.5	4.9
P/B (x)	2.5	2.3	2.2	2.1
Net debt/equity (%)	55.9	55.3	47.0	38.6

*Source: Company data, ASX, Credit Suisse estimates, * Adj. for goodwill, notional interest and unusual items. Relative P/E against ASX/S&P200 based on pre GW in AUD. Company PE calculation is based on displayed EPS Currency*

Appendix 2. A Examples of Analyst reports use PE models and DCF models

Panel A A sample of analyst report that uses a PE model to develop the price target of the reported firm

Kohei Takahashi
(81-3) 6736-8621
kohei.x.takahashi@jpmorgan.com

Japan Equity Research
19 December 2012

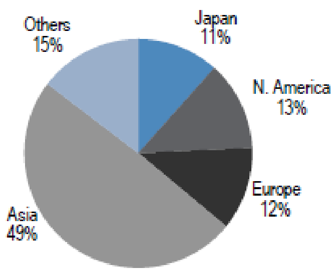
J.P.Morgan

Yamaha Motor (7272)

Company Profile

Established in 1955. Businesses include motorcycles, marine products, and power products. 2011 motorcycle shipments totaled 6.982 million units with 6.632 million units in Asia. Strengthened capital and business tie up with Toyota from 2000. Toyota holds a 3.57% stake.

Retail Composition Ratio by Region, FY2011



Source: Company data.

Investment Thesis Risk Analysis

Upside Scenario to Target Price/Rating

- Greater-than-expected improvement in domestic earnings from restructuring
- Rapid recovery in US ATV, large motorcycle, and outboard motor markets

Downside Scenario to Target Price/Rating

- Inventory growth due to sluggishness in Europe markets
- Slowdown in Indonesia motorcycle market
- Yen appreciation against the dollar and euro

Operating Profit Forecasts: J.P. Morgan versus Consensus

¥ billion

	J.P. Morgan	Consensus
FY2012E	26.0	29.1
FY2013E	55.0	49.1

Source: J.P. Morgan estimates, Bloomberg.

Assumptions & Sensitivity Metrics (Impact on FY2013 Profits)

Factor	Current Assumption	Change	Impact OP	Impact NP
US motorcycle sales	90,000 units	1%	0.3%	0.3%
Europe motorcycle sales	162,000 units	1%	0.4%	0.5%
Indonesia motorcycle sales	2,939,000 units	1%	1.2%	1.5%
Marine Sales	352,000 units	1%	0.7%	0.7%
¥/$ rate	¥78	¥1/$	4.0%	4.7%
¥/Euro rate	¥100	¥1/Euro	0.9%	1.1%

Source: J.P. Morgan estimates.

Valuation

Our price target through December 2013 is ¥800, based on our FY2013 EPS forecast and the sector average P/E of 9x. We calculate our price target based on FY2013 earnings because the earnings deterioration in FY2012 is attributable to a sharp slowdown in the motorcycle business in emerging markets and does not reflect Yamaha's fundamental earnings structure.

Peer Valuations Based on Bloomberg Consensus

Company name	Bloomberg Ticker	Currency	Price	Date	Market Cap ($mn)	P/E(x) 12E	P/E(x) 13E	P/E(x) 14E	P/B(x) 12E	P/B(x) 13E	P/B(x) 14E	ROE(%) 12E
Toyota Motor Corp	7203 JT	JPY	3,720	Dec-18	153,226	13.5	11.1	9.5	1.06	0.99	0.93	7.9
Honda Motor Co Ltd	7267 JP	JPY	2,892	Dec-18	62,581	12.3	10.1	9.0	1.13	1.04	0.97	9.4
Yamaha Motor Co Ltd	7272 JT	JPY	932	Dec-18	3,894	19.8	12.1	8.8	1.11	1.03	0.94	5.7
Suzuki Motor Corp	7269 JT	JPY	2,042	Dec-18	13,686	15.5	13.7	12.4	1.10	1.03	0.96	7.2
Piaggio & C SpA	PIA IM	EUR	2.030	Dec-17	574	17.7	13.8	10.9	1.63	1.57	1.47	9.1
Arctic Cat Inc	ACAT US	USD	36.99	Dec-17	490	13.0	11.0	9.4	2.75	2.15	--	23.9
Brunswick Corp/DE	BC US	USD	26.57	Dec-17	2,379	15.3	12.1	10.3	16.30	7.43	--	133.1
Harley-Davidson Inc	HOG US	USD	49.22	Dec-17	11,136	17.8	14.7	12.7	4.32	5.04	7.67	24.5
Polaris Industries Inc	PII US	USD	80.4	Dec-17	5,549	18.4	15.5	13.3	8.01	6.12	--	54.7
Bajaj Auto Ltd	BJAUT IN	INR	2,107	Dec-17	11,116	19.1	16.2	15.1	7.83	6.23	5.39	45.8

Source: Bloomberg Note: Market caps are calculated using forex rates as of December 17

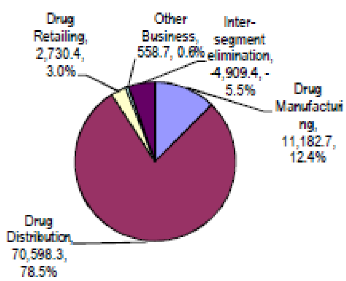
Panel B A sample of analyst report that uses a DCF model to develop the price target of the reported firm

Sean Wu
(852) 2800-8538
sean.wu@jpmorgan.com

Company description

Shanghai Pharmaceutical is a leading manufacturer of various products, including chemical drugs/APIs, TCMs, biological drugs and medical devices. It is also China's second-largest distributor of drugs and medical products, and holds the largest market share in its home base of Shanghai. SPH was established through a merger of the original Shanghai Pharma, mostly a drug distributor, with two A-share listed manufacturers, Shanghai Industrial Pharmaceutical Investment and Zhongxi Pharmaceutical in 2009.

Revenue mix (2013E)



Source: J.P. Morgan estimates

EPS: J.P. Morgan vs consensus (Rmb)

Rmb	J. P. Morgan	Consensus
FY12E	0.75	0.76
FY13E	0.83	0.85
FY14E	0.92	0.97

Source: Bloomberg, J.P. Morgan.

P&L sensitivity metrics

FY13E	EBIT impact (%)	EPS impact (%)
Acquisition contributed growth		
Impact of each 5 percentage increase	3.9%	7.6%
Selling cost		
Impact of each 5 percentage points increase	3.9%	9.1%
Demand for products under EDL		
Impact of each 5 percentage points increase	2.7%	6.3%
GM: 1% Increase		
Impact of each 1% increase	2.8%	8.2%

Source: J.P. Morgan estimates.

Price target and valuation analysis

Our Dec-13 PT of HK$15 for SPH-H is based on DCF. The nature of the industry leads us to apply a terminal growth rate of 4% (the lower end of the 3%-6% growth rate used for healthcare stocks). Please see page 10 for more details of our DCF valuation. Currently, the market-cap-weighted average A/H premium for 79 dual-listed Chinese companies is 2%, while SPH's H shares are trading at an 11% premium to the A shares. As a result, we believe it is reasonable for us to set our A-share Dec-13 PT based on the H-share target converted into Rmb at the current exchange rate. This comes out to Rmb12.

Risk free rate:	4.20%
Market risk premium:	6.00%
Beta:	1.00
WACC	11.7%
Terminal "g":	4.00%

Source: J.P. Morgan estimates.

Our PT implies a 2013E P/E of 14.6x. Key risks to our rating and PT include a slower pace of acquisition of new distributors and a faster pickup in sales volume arising from the implementation of the Essential Drug List, resulting in low points taken by SPH because of low profitability to manufacturers who would ask for shared sacrifice of profits from distributors. In addition, we see risks from: (1) an unexpected industry-wide slowdown; (2) acquisitions becoming prohibitively expensive; and (3) a further deterioration of manufacturing businesses.

Sean Wu
(852) 2800-8538
sean.wu@jpmorgan.com

Valuation and share price analysis

DCF valuation and Dec-13 PT of HK$15/Rmb12

Our Dec-13 price target for the H share is based on our DCF valuation, which assumes a market premium of 6.0% and risk-free rate of 4.2% (yield on 10-year government notes in China). We assume a beta of 1.0 because of the short history of SPH trading on HKEX. Accordingly, we assume a WACC of 11.8%, which contains a 2% premium as SPH is trading in a foreign stock exchange. We estimate free cash flow for SPH until 2015 and assume a terminal growth rate of 4.0%. The terminal growth is based on the annual growth rate expected in 2015 (the final year of the estimate period), subject to a minimum of 3% and a maximum of 6% depending on the nature of the industry and the level of maturity in China. We use 4% as we believe faster-growing distribution businesses will be balanced out by slower growth of SPH's manufacturing businesses.

Currently, the market-cap-weighted average A/H premium for 79 dual-listed Chinese companies is 2% as of Dec.17, 2012 close. Meanwhile SPH's H shares are trading at an 11% premium to the A shares. As a result, we believe it is reasonable for us to set our A-share Dec-13 price target based on the H-share target converted into Rmb at the current exchange rate. This comes out to Rmb12, implying 13.5% upside from the current share price; hence we rate the A share Neutral as well.

We also analyze the DCF price sensitivity to WACC, and the terminal multiple.

Table 2: SPH - Base-case DCF analysis indicates an equity value per share of HK$15/Rmb12

Rmb MM	2008	2009	2010	2011	2012E	2013E	2014E	2015E
Cash flow estimates								
Sales	27,441	31,181	38,692	54,900	66,457	80,161	93,359	107,362
EBIT	1,466	2,290	2,481	3,289	3,232	3,567	4,021	4,450
NOPAT	1,466	1,891	1,939	2,690	2,605	2,854	3,177	3,471
Capex, net	(560)	(776)	(574)	(414)	(501)	(1,500)	(2,100)	(600)
Depreciation	402	422	437	513	482	553	691	779
Change in working capital	(320)	327	127	(989)	(1,093)	(1,206)	(1,272)	(1,335)
Free operating CF (FoCF)	**988**	**1,865**	**1,929**	**1,800**	**1,493**	**701**	**496**	**2,314**
DCF Parameters			**Assumptions**					
Liabilities as a % of EV	20%		Terminal growth			4.0%		
WACC	11.8%		Risk-free rate			4.2%		
			Market risk			6.0%		
Enterprise NPV (10E-16E)	**28,591**		Beta			1.0		
+ Net cash (debt), current	10,367		Cost of debt			6.8%		
- Minorities (Market value)	(10,416)							
+/- Other items	0		Implied exit P/E multiple (x)			11.4x		
= Equity value	**28,542**							
/ Number of shares	2,400							
= Equity value per share (HK$)	15.0							

Source: Company data, J.P. Morgan estimates.

Sean Wu
(852) 2800-8538
sean.wu@jpmorgan.com

Table 3: SPH - Sensitivity analysis based on WACC and perpetual terminal growth rate

	Terminal growth rate 3.5%	4.0%	4.5%	5.0%
WACC 10.3%	17.3	18.6	20.1	21.9
10.8%	16.1	17.1	18.4	19.9
11.3%	15.0	15.9	*17.0*	*18.2*
11.8%	14.0	$\boxed{14.8}$	*15.7*	*16.7*
12.3%	13.1	13.8	*14.6*	*15.5*
12.8%	12.3	13.0	13.7	14.4
13.3%	11.7	12.2	12.8	13.5

Source: Company data, J.P. Morgan estimates.

Table 4: SPH - Value comparison with peer companies

Company Name	Code	Price (TP)	MCAP US$M	Vol US$m	1M Chg	3M Chg	YTD Return	12e PE (x)	13e PE (x)	EPS CAGR 11_13e	PEG '12E	PEG '13E
Covered Companies												
SHANGHAI PHARM-H (N)	2607 HK	14.7 (15)	4,795	1.4	(3.5)	6.8	16.9	19.6	17.7	-0.8%	(23.1)	(20.9)
SHANG PHARM -A (N)	601607 CH	10.84 (12)	3,859	1.2	1.8	(8.1)	(2.2)	12.8	14.4	1.3%	9.6	10.8
CHINA SHINEWAY (UW)	2877 HK	12.92 (12)	1,379	1.6	8.4	17.5	19.0	11.9	10.7	3.0%	3.9	3.6
CONCORD MEDICAL (USD)	CCM US	4.1 (5.5)	195	0.2	(6.8)	12.0	26.9	8.7	6.7	nm	nm	nm
SHANGHAI FOSUN-H (OW)	2196 HK	11.52 (17)	3,461	2.5	3.8	na		14.8	15.5	10.2%	1.5	1.5
SHANGHAI FOSUN-A (OW)	600196 CH	9.7 (14)	2,786	4.6	0.8	(9.3)	13.6	15.8	12.4	31.2%	0.5	0.4
MICROPORT (N)	853 HK	4.28 (4.5)	779	0.8	(0.9)	19.6	11.7	16.5	14.3	4.7%	3.5	3.1
MINDRAY (OW)	MR US	34.25 (39)	3,963	15.3	5.7	(1.7)	33.6	20.5	17.7	17.4%	1.2	1.0
SHANDONG WEIGAO (N)	1066 HK	8.14 (9.5)	4,702	12.1	(17.8)	(10.0)	16.5	28.6	24.6	11.0%	2.6	2.2
SIHUAN (OW)	460 HK	3.44 (4.9)	2,297	4.4	12.8	15.8	28.7	15.2	13.5	13.7%	1.1	1.0
SINO-BIOPHARM (OW)	1177 HK	3.95 (3.8)	2,519	5.3	12.5	33.9	71.0	25.5	21.5	40.1%	0.6	0.5
SINOPHARM (OW)	1099 HK	25 (31)	7,750	6.7	0.6	3.1	34.0	24.7	19.7	24.3%	1.0	0.8
UNITED LAB (OW)	3933 HK	3.88 (4.5)	814	0.9	(0.5)	4.6	(5.4)	20.4	11.5	105.0%	0.2	0.1
WUXI PHARMAT-ADR (OW)*	WX US	15.6(17)	1,092	5.2	(1.6)	8.3	41.3	12.0	10.9	10.9%	1.1	1.0
Coverage Universe Average			**2,645**	**5.0**	**1.4**	**8.5**	**26.4**	**17.9**	**14.9**	**0.2**	**1.6**	**1.4**
Distribution Average			**1,560**	**3.9**	**(3.2)**	**(14.9)**	**12.2**	**26.5**	**21.1**	**8.7%**	**(0.3)**	**(0.2)**
Chemical Drugs Average			**861**	**3.8**	**(1.9)**	**(4.3)**	**5.3**	**25.9**	**23.6**	**23.1%**	**(0.5)**	**(0.4)**
TCM Average			**1,367**	**6.9**	**(2.0)**	**(6.7)**	**12.7**	**25.9**	**20.3**	**20.3%**	**1.5**	**1.2**
Medical Devices Average			**500**	**2.3**	**(1.1)**	**(3.8)**	**(3.2)**	**25.6**	**18.5**	**21.1%**	**1.3**	**1.0**
Hospital Services Average			**1,714**	**4.3**	**(0.2)**	**1.9**	**17.8**	**25.8**	**22.7**	**6.9%**	**(1.0)**	**(1.1)**
Biologicals Average			**775**	**3.2**	**(5.7)**	**(12.5)**	**16.3**	**25.3**	**19.3**	**20.8%**	**1.7**	**1.4**
HK/China Average			**1,012**	**4.0**	**(2.8)**	**(8.4)**	**8.7**	**25.8**	**20.6**	**18.8%**	**0.7**	**0.6**

Source: J.P. Morgan estimates, Bloomberg. Prices are as of the close on Dec. 17, 2012.

Appendix 2. B Sample selection

	Number of Analyst reports	Number of Firms	Number of Analysts
Analyst reports using DCF model or PE model	622,905	5,782	3,499
Less missing values of the revisions of target price forecasts	-95,220		
	527,685	5,051	3,069
Less missing values of *CARt*	-2,379		
	525,306	5,007	3,063
Less missing values of *compe* and *comppeind*	-27,542		
	497,764	4,531	2,864
Less missing values of *acctcomp4* and *acctcompind*	-182,249		
Final Sample	315,515	2,797	2,447

Appendix 2. C Variable definitions in chapter 2

Variables	Definitions
Dependent variable	
DCF	Dummy equals one if analysts use a DCF model to justify their investment opinions, and zero if analysts use only a PE model to justify their investment opinions.
CARt	Market-adjusted cumulative abnormal return starting one day before to *t* days after the issuance of an analyst report, multiplied by 100.
Independent variable	
tpchg	Change of analyst target price forecast scaled by the stock price at the beginning of the year. The target prices are extracted from analyst reports from Investext and stock price data is from CRSP.
acctcomp4	The average $ACCTCOMP_{ijt}$ of the four firms with the highest comparability values. I follow De Franco, Kothari, and Verdi (2011) to calculate $ACCTCOMP_{ijt}$ which is the pairwise accounting comparability between firms *i* and *j* in period *t.*
acctcompind	The median $ACCTCOMP_{ijt}$ of all other firms in the same SIC two-digit industry. I follow De Franco, Kothari, and Verdi (2011) to calculate $ACCTCOMP_{ijt}$ which is the pairwise accounting comparability between firms *i* and *j* in period *t.*
comppe	The negative one (-1) times the absolute difference between a firm's price-to-earnings ratio and the median value of the firm's price-to-earnings ratio in the past five years, divided by the sum of the two values.
comppeind	Equals (-1) times the absolute difference between a firm's price-to-earnings ratio and the median value of price-to-earnings ratios of other firms in the same industry, divided by the sum of the two values.
Other variables	
loss	Dummy equals one if a firm experiences negative earnings. and zero otherwise.
retstd12	Standard deviation of daily stock return during the 12 months before an analyst report date, multiplied by 100.
logmv	The logarithm of firm market value.
arpre12	12-month abnormal return before the issue of an analyst report.
expind	The logarithm of the number of firms in a two-digit SIC industry covered by the analyst in year *t.*
expfirm	The number of years an analyst has been following a firm.
DirModel	Dummy equals one if analysts use a direct valuation model to justify their investment opinions, and zero if analysts use only a relative valuation model to justify their investment opinions.
epschg	The change of analyst earnings per share forecast scaled by the stock price at the beginning of the year.
recchg	The change of analyst stock recommendation forecast.
EPU	The economic policy uncertainty index from Baker, Bloom, and Davis (2016).
Recession	Dummy equals one for the recession periods marked by the National Bureau of Economic Research (NBER), and zero otherwise.

Appendix 2. D Classification of valuation models

Valuation model	Key items
Relative valuation models	
Earnings multiples (PE)	P/E, PEG, P/EBITDA, EV/EBITDA, EV/EBIT, EV/EBITA, EBITDA/MV, EV/EBIAT
Sales multiples (PSAL)	P/S, EV/Sale, MV/sale, Revenue
Book value multiples (PB)	P/B, EV/B, MV/B
Cash flow multiples (PCF)	CF/EV, P/CF, DY
Direct valuation models	
Cash flow based (DCF)	DCF, DDM, GGM, CRR, CFROI, Real Options
Accrual based	NAV, Residual income valuation (RIV)

Appendix 3. A Variable definitions in chapter 3

Variable	Definitions and data sources
Dependent variables	
CFModel	Dummy variable equal to one if analysts use cash flow models as the dominant valuation model, and zero otherwise. Following Section 3.2 of Huang et al. (2021), I use textual analysis of analyst reports from Investext to identify whether a model is the dominant valuation model.
DCFModel	Dummy variable equal to one if analysts use DCF models as the dominant valuation model, and zero if analysts use PE models as the dominant valuation model.
CARt	Market-adjusted cumulative abnormal return starting one day before to 3 days, 30 days, and 183 days after the issuance of an analyst report, multiplied by 100.
Independent variables	
anti_director	The revised anti-director rights index from Djankov et al. (2008). The index is the sum of (1) vote by mail; (2) shares not deposited; (3) cumulative voting; (4) oppressed minority; (5) pre-emptive rights, and (6) capital to call a meeting.
anti_dealing	Anti-self-dealing index from Djankov et al. (2008). The index measures the extent of minority shareholders' protection by preventing controlling shareholders from self-dealing.
public_enforce	The extent to which the law may deter wrongdoing by controlling shareholders and transaction approvers through punishment such as fines and prison terms. The data source is Djankov et al. (2008).
cifar	The index of financial disclosure for the firm country. The data source is the Center for Financial Analysis and Researchers' International Accounting and Auditing Trends (CIFAR, 1995).
country_eq	The negative value of the index of earnings management from Leuz et al. (2003). A higher value of country_eq indicates better earnings quality for the firm country.
EF_sum	Summary of economic freedom index. The degree of economic freedom in five broad areas: (1) size of government: expenditures, taxes, and enterprises; (2) legal structure and security of property rights; (3) access to sound money; (4) freedom to trade internationally, and (5) regulation of credit, labor, and business. The data source is https://www.fraserinstitute.org/studies/economic-freedom.
EF_legal	The freedom of legal structure and security of property rights. The data source is https://www.fraserinstitute.org/studies/economic-freedom.
High anti_director	Dummy variable equal to one if *anti_director* of country *i* is above the median of the countries in the final sample, and zero otherwise.
High anti_dealing	Dummy variable equal to one if *anti_dealing* of country *i* is above the median of the countries in the final sample, and zero otherwise.
High public_enforce	Dummy variable equal to one if *public_enforce* of country *i* is above the median of the countries in the final sample, and zero otherwise.
High cifar	Dummy variable equal to one if *cifar* of country *i* is above the median of the countries in the final sample, and zero otherwise.
High country_eq	Dummy variable equal to one if *country_eq* of country *i* is above the median of the countries in the final sample, and zero otherwise.

High EF_sum	Dummy variable equal to one if *EF_sum* of country i is above the median of the countries in the final sample, and zero otherwise.
High EF_legal	Dummy variable equal to one if *EF_legal* of country i is above the median of the countries in the final sample, and zero otherwise.
Control variables	
earningsmgt	The abnormal accruals based on Modified Jones Model for the underlying firm.
leverage	Total liabilities divided by total assets.
Loss	An indicator of negative earnings in Compustat.
Retstd12	The standard deviation of daily stock return during the 12 months before an analyst report date, multiplied by 100.
arpre12	12-month abnormal return before the issue of an analyst's report.
Logmv	The logarithm of firm market value.
mb	The market value divided by book value.
firmex	The number of years an analyst has been following a firm.

Appendix 3. B Lists of cash flow models and accrual models

Valuation model	Key items
Cash-flow-based valuation models	
Cash flow multiples (PCF)	CF/EV, P/CF, DY
Cash flow based (DCF)	DCF, DDM, GGM, CRR, CFROI, Real Options
Accrual-based valuation models	
Earnings multiples (PE)	P/E, PEG, P/EBITDA, EV/EBITDA, EV/EBIT, EV/EBITA, EBITDA/MV, EV/EBIAT
Sales multiples (PSAL)	P/S, EV/Sale, MV/sale, Revenue
Book value multiples (PB)	P/B, EV/B, MV/B
Others	NAV, RIV