Brokerage trading volume and analysts' earnings forecasts: a conflict of interest?

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Abstract

Using unique new data, we examine whether brokerage trading volume creates a conflict of interest for analysts. We find that earnings forecast optimism is associated with higher brokerage volume, even controlling for forecast and analyst quality, recommendations, and target prices. However, forecast accuracy is also significantly associated with higher volume. When analysts change brokerage houses, they bring trading volume with them, influencing trading volume at the new brokerage. This indicates that analysts drive the volume effects we observe. Consistent with a reward for generating volume, brokerage houses are less likely to demote analysts who generate more volume. Finally, analysts strategically adjust forecast optimism based on expected volume impact. Analysts become more (less) optimistic if their optimistic forecasts in the prior year were more (less) successful at generating volume. However, consistent with higher costs to increasing accuracy, analysts do not update accuracy based on expected volume impact. Overall, our results are consistent with a brokerage trading volume conflict of interest moving analysts towards more optimistic earnings forecasts, despite the volume reward for accuracy.

Keywords Sell-side analysts · Brokerage houses · Trading volume · Commissions · Conflict of interest · Incentives · Earnings forecasts

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1 Introduction

Sell-side security analysts play a significant role in financial markets. They provide research and investment advice to institutional and retail investors, and they contribute to firms' information environments.¹ However, analysts face conflicts of interest that may cause them to bias their research. We focus on the potential biasing of one of analysts' most salient research outputs: earnings forecasts. Historically, analyst research has been funded mainly through investment banking and brokerage commissions (Cowen et al. 2006). Numerous studies have documented the conflicts of interest caused by investment banking relationships, yet few of these studies address conflicts related to commissions.^{2,3} The literature has provided evidence that, across brokerage houses, more optimistic recommendations are associated with higher trading volume. (See discussion of the literature in Section 2.) Whether this creates a conflict of interest for analysts and whether and how this extends to earnings forecasts is unclear.

Understanding the potential commissions-related conflict of interest is of particular importance, given changes to the analyst research funding model. Several new rules and regulations established in the early 2000s attempted to address conflicts of interest related to investment banking. In particular, these new rules included NASD Rule 2711, NYSE Rule 472, and the Global Analyst Research Settlement. These rules aimed to separate investment banking from research, thus lowering the probability that brokers bias analyst research to gain investment banking business. Research suggests that these regulations mitigated the investment banking conflict of interest (Kadan et al. 2009; Corwin et al. 2017). As a result, these changes may have increased the importance of brokerage commissions, since they are the primary remaining source of funding.⁴ On the other hand, unbundling of brokerage commissions from payment of research in Europe, as required by the revised Markets in Financial Instruments Directive (MiFID II), may decrease the impact of trading volume-related incentives on analyst behavior.⁵ The SEC is still considering what permanent changes will be made in the United States in response.⁶

¹ See Beyer, Cohen, Lys, and Walther (2010); Bradshaw (2011); and Kothari, So, and Verdi (2016) for reviews of the literature on sell-side analysts and Bradshaw, Ertimur and O'Brien (2017) for a more complete discussion of the history and current institutional context in which sell-side analysts operate and their role in financial markets. See also Chen, Cheng, and Lo (2010); Li and You (2015); Amiram, Owens, and Rozenbaum (2016); and Huang, Lehavy, Zang, and Zheng (2016) for more recent evidence on the roles of analysts in information discovery and interpretation.

² For research on conflicts of interest related to investment banking relationships, see, for example, Dugar and Nathan (1995); Lin and McNichols (1998); Michaely and Womack (1999); Dechow, Hutton, and Sloan (2000); and Barber, Lehavy, and Trueman (2007) for evidence on the relative optimism of investment banking-affiliated analysts versus unaffiliated analysts.

³ Firth, Lin, Liu, and Xuan (2013); and Gu, Li, and Yang (2013) discuss the relative lack of research on conflicts of interest related to trading commissions. Beyer, Cohen, Lys, and Walther (2011) suggest that there is evidence that trading commissions play a significant role in optimistic recommendations but not in optimistic earnings forecasts. The primary papers examining whether analyst optimism relates to trading volume are by Jackson (2005) and Irvine (2004). These papers are discussed in more detail in Section 2.2.

⁴ Call, Sharp, and Wong (2019) find that enforcement of these and other rules by FINRA helps to mitigate the effects of several types of conflicts of interest on analyst research. However, currently FINRA monitoring does not include the type of trading-related conflict of interest we examine.

⁵ For more information on MiFID II, its different provisions, and implementation guidance, see the European Securities and Markets Authority page on MiFID II, <https://www.esma.europa.eu/policy-rules/mifid-ii-and-mifir>.

⁶ On November 4, 2019, the SEC issued a press release that extends a no-action letter to market participants in regard to MiFID II as they evaluate the effects of the regulation (see <https://www.sec.gov/news/press-release/2019-229>), SEC 2019.

In this study, we exploit new trading volume data at the brokerage-stock-day level, for brokerages operating in the United States, to test for conflicts of interest derived from analysts' incentive to increase trading volume.⁷ We collect brokerage volume data for S&P 1,500 firms and for 18 major brokerages over the five years from 2011 to 2015, and we focus on the analyst's impact on the brokerage's *share* of trading volume in a given stock. We begin by extending prior research by examining whether more optimistic analyst earnings forecasts are associated with a larger share of trading volume for the analyst's brokerage when the forecasts are released. However, even for recommendations, research has not established whether a positive optimism-volume relation leads to a conflict of interest. The remainder of our paper focuses on unique new tests to better address the potential conflict of interest. Our results are consistent with trading volume creating a conflict of interest for analyst earnings forecasts.

We focus on earnings forecasts for several reasons. First, earnings forecasts are informative to market participants. They occur more frequently than recommendations, provide more precise information, and allow investors to define their own valuation models, incorporating earnings forecasts as an input. Brown et al. (2016) report that buy-side analysts rank earnings forecasts as more useful than recommendations.⁸ In general, individual investors react more to recommendations while institutional investors react more to earnings forecasts (Mikhail et al. 2007; Malmendier and Shanthikumar 2007, 2014). It is therefore not clear that the market reaction to optimistic bias will be the same for these two.

Second, analysts' careers depend on earnings forecasts. Mikhail, Walther, and Willis (1999) find that analysts with higher relative earnings forecast accuracy experience lower job turnover, while recommendation profitability has no association with turnover. Hong and Kubik (2003) and Groysberg et al. (2011) show that the direction of the resulting career move—to a more or less prestigious bank—depends positively on forecast accuracy. Overall, earnings forecasts matter to both investors and analysts, and it is unclear from extant research whether brokerage trading volume incentives will drive bias in earnings forecasts.

Trading volume is likely to increase with analyst forecast optimism in the short run, due to short-sale costs. If investors reward a brokerage house that publishes relevant analyst research by trading through that brokerage, then the brokerage house's share of trading volume will also increase with analyst optimism. This relation could break down for two reasons. First, it is not clear whether investors will reward an analyst's brokerage house with an increased share of trading volume immediately surrounding that analyst's research. They may trade through their normal brokerage houses, leaving the brokerage share of volume unchanged. Second, in the long run, investors may learn not to respond to analysts who are consistently biased and may instead respond more strongly to high-quality analysts. Institutional investors allocate commissions based, at least partly, on their evaluations of the usefulness of various analysts' research. (See Groysberg and Healy (2013) for an overview of relevant evidence.) Industry participants argue that they use commissions to pay for high-quality analyst service (Greenwich Associates 2015). Thus analysts will trade off incentives to generate volume through optimistic bias with incentives to generate volume through quality and will have to balance any incentives toward bias with incentives towards accuracy.

⁷ We obtain data from Bloomberg. The data are described in detail in Section 3.

⁸ Quotes from buy-side analysts suggest this is at least in part because buy-side analysts view sell-side recommendations as biased and value information that can be used as inputs into their own valuation models.

The first step in examining the potential trading-volume conflict of interest is to examine whether optimistic earnings forecasts yield a higher share of volume for the analyst's brokerage house. Research has documented a correlation between analyst coverage characteristics and brokerage trading volume (e.g., Irvine 2001; Irvine 2004; Jackson 2005; Cowen et al. 2006; Agrawal and Chen 2012; Grant et al. 2015). Our first set of tests extends these papers. We find strong and consistent evidence that more positive forecasts (measured relative to other analysts' forecasts) increase the brokerage house's share of trading volume in the days around the forecast's publication.

We also find that several dimensions of earnings forecast quality and analyst quality increase trading volume. Specifically, the accuracy of a specific earnings forecast and how early in the year the given forecast is issued (used in the literature as a proxy for information content; e.g., Clement and Tse 2003) are positively associated with the brokerage's share of trading volume. The analyst's prior-year forecast accuracy and firm-specific forecasting experience are also associated with a trading volume increment. Thus, based purely upon the analyst-coverage-volume relation, it is not clear whether the incentive to generate trading commissions will drive analysts to be more optimistic or to issue higher quality earnings forecasts.

The economic magnitudes of the given effects appear to be significant. Based upon a model that includes optimism and accuracy variables simultaneously, we find that both have significant explanatory power for trading volume. An interquartile-range increase in earnings forecast optimistic bias increases brokerage house share of trading volume by 1.0% of the mean. Comparable increases in forecast accuracy and prior-year accuracy correspond to increases in volume share of 1.3% and 2.1% of the mean, respectively. With a typical commission of US \$0.03 per share traded (Levine 2015), this would result in an annual increase in a single analyst's commission generation from EPS forecasts of \$19,260, \$27,002, and \$42,674, for optimistic bias, current forecast accuracy, and prior-year forecast accuracy, respectively.⁹ Thus increases in forecast optimistic bias and forecast accuracy both appear to have economically large impacts on trading volume and commissions. However, it is not clear *ex ante* whether these effects are large enough to drive analyst behavior. Analysts must also weigh the costs and benefits of optimism and accuracy. For example, it may require little effort to increase optimistic bias; however, forecast bias may damage an analyst's reputation.

Having confirmed the *potential* conflict of interest, we conduct three additional analyses to address whether a push for volume generation induces a conflict of interest. First, we examine analyst moves to determine whether analysts have a causal effect on the brokerage share of trading volume. We find that, when an analyst switches brokerage houses, the new brokerage's share of trading volume around the analyst's coverage of the given stock relates positively to the volume the analyst generated at their prior brokerage house. In other words, if the analyst generated more volume at the old brokerage house, the analyst does so at the new one as well. This suggests that analysts have a causal impact on the share of trading volume, and brokerages are likely to consider trading volume generation as a transferrable skill.

Second, we examine analysts' career progress to observe more directly whether brokerage houses reward or penalize analysts for volume generation. We examine whether the volume share associated with a given analyst's research in a given year is

⁹ All dollar values in the paper are U.S. dollars.

associated with that analyst's career changes in the subsequent year. Since the 18 brokerage houses in our sample are all relatively large and high status, we focus on *demotion*, defined as moving to a smaller or lower-status brokerage. We find that analysts who generate lower volume are significantly more likely to be demoted in the subsequent year. Thus analysts face a strong incentive to generate trading volume.

Finally, we employ a novel technique to examine whether analysts strategically update the optimistic bias of their forecasts, the accuracy of their forecasts, or both, with the goal of generating volume. If analysts are strategic about this bias, versus being honestly optimistic, we should find that analysts strategically update their biasing. If a strategic analyst is more (less) successful in generating trading volume with more optimistic forecasts, then that person should be more (less) likely to issue optimistically biased forecasts in the future. We find that optimism increases with prior-year optimism-volume sensitivity. This shows that analysts strategically update their forecast optimism; that is, they are more optimistic when their experience suggests that optimism will increase their brokerage's share of volume. We do not find that accuracy increases with prior-year accuracy-volume sensitivity. This is consistent with the additional resources and effort required to become more accurate in the subsequent year being too high for analysts to update accuracy. Our results do not preclude the possibility that analysts improve accuracy over a longer period, but they suggest that, at least on the one-to-two year horizon, analysts are more likely to strategically update optimism than accuracy.

Ultimately, proving that an analyst is being influenced by a conflict of interest is almost impossible. Analysts' motivations are unobservable. Despite a large literature on investment banking conflicts of interest, the literature has had difficulty establishing whether underwriting analysts intentionally bias their research upward or whether firms simply choose underwriters whose analysts are optimistic about them. (See discussions by Bradshaw (2011) and Malmendier and Shanthikumar (2014).) However, understanding potential conflicts of interest is important. Literature on brokerage trading volume has described the relationship between optimism and trading volume. We take the first meaningful step in establishing that a resulting conflict of interest affects analyst behavior.

Our study contributes to the literature on sell-side analysts by addressing one of the major potential conflicts of interest that analysts face: commissions-related incentives under the current analyst funding model. This contribution is particularly relevant, due to the implementation of the revamped Markets in Financial Instruments Directive (MiFID II) in Europe, which requires that asset managers pay for sell-side research directly and not through trading commissions (Financial Conduct Authority 2017). All brokerages that distribute research to European clients fall under the new regulation (e.g., Engler 2017). In this paper, we show that trading commissions reward analyst research for both optimism and quality. It is unclear what effects MiFID II will have. On the one hand, institutional investors argue that direct payments, with clearly defined fee structures, will not allow them to reward quality in the same way that the current structure allows (Greenwich Associates 2015). On the other hand, analysts will have less motivation to bias their research optimistically if trading commissions are reduced.

Our study also contributes to the open question of why analyst earnings forecasts are optimistically biased. It has long been observed that earnings forecasts, excluding those just before the earnings announcement, are overly optimistic (O'Brien 1988). Yet current literature does not satisfactorily explain this observed pattern, given weak and sometimes conflicting results across studies. (See Beyer et al. (2010) and Bradshaw

(2011) for surveys of explanations and evidence.) Hong and Kubik (2003) show that analysts are rewarded for forecast optimism with career advancement, controlling for accuracy, but it is unclear why brokerages value optimism. Our results suggest that forecast optimism leads to a larger brokerage share of trading volume and thus explains (U.S.) brokers' preference for optimistic forecasts.

Overall, our results are relevant for researchers, regulators, and investors. Our results show evidence of a conflict of interest based on trading volume: an incentive to upwardly bias research. Optimism has a significant effect, despite a brokerage-volume reward for quality. Evidence of analysts becoming more or less optimistic based on past success in generating trading volume suggests that analysts are aware of this and that they are—at least in part—strategically optimistic.

The remainder of the paper is organized as follows. Section 2 presents relevant institutional details, theory, and empirical evidence, and develops hypotheses. Section 3 describes the data and the sample used in this study. Section 4 presents results. Section 5 concludes.

2 Background and hypothesis development

2.1 Analyst incentives and institutional details

In practice, sell-side analyst research is primarily funded indirectly through revenues brought in by other activities of the brokerage house. While some research, particularly that of standalone research companies, is funded through direct payments for research, the two primary sources of funding for research in the United States have been investment banking and brokerage. However, in the wake of several scandals, most notably the trial of former Merrill Lynch analyst Henry Blodget, NASD Rule 2711 and the amended NYSE Rule 472, effective in 2002, required virtually all investment banks that provided sell-side analyst services to cut the ties between investment banking and analysts. These regulations limited communication between the two departments and stipulated that analysts could not be compensated based on generating investment banking business. The terms of the Global Analyst Research Settlement between the SEC, NYSE, NASD, the New York Attorney General, and 12 investment banks (published in December 2002) required additional separation for the affected banks. These regulations likely reduced the investment banking component of analysts' compensation, increasing the relative importance of brokerage trading commissions.

Brokerage houses can increase their share of market trading volume in two ways. The first is directly inducing customers to trade, for example, through broker calls to customers with updated investment advice. Anecdotally, this appears to be a primary method of generating trading volume with retail investment clients and smaller portfolio managers. The second method is providing a high level of service to larger institutional clients who then allocate more of their trading to the bank as a form of compensation. This is typically done through “broker votes,” in which buy-side clients evaluate brokerage houses quarterly, semiannually, or annually for the services they provide—including analyst coverage. These votes are used by the trading desk in the subsequent period to allocate trades across brokers (Greenwich Associates 2015).

While analysts potentially play an important role in both methods of increasing brokerage trading commissions, their effect on broker votes is likely to be harder to measure. The lag

between analyst coverage and the trade allocated to the brokerage house is likely to range from less than a quarter to over a year. The trade allocated in the subsequent period to the analyst's brokerage could also be for any stock, not just the ones that the given analyst covered. In addition, since broker votes aggregate the evaluation of all the brokerage's analysts and other services, the effect of a given analyst's research becomes harder to measure.

In contrast, the effect of analyst research on inducement of trade (e.g., through brokerage calls) is much more direct. Consider the following example. An analyst issues an earnings forecast. The brokerage house's brokers call clients to relay this investment advice, and a subset of those investors trade. As a result, there is an increase in the recommending analyst's brokerage's share of trading volume for that stock. In our study, we focus on this aspect of trade: the immediate increase in a brokerage's share of trading volume around that brokerage's analyst research.^{10,11}

Evidence on analyst compensation supports the premise that analysts are rewarded for generating trading volume and, in turn, for generating commissions. Cowen et al. (2006) state that brokerage houses without investment banking arms "... usually reward their research analysts using a single measure of performance: trading volume in the stocks they cover" (p. 125). According to analysts surveyed by Brown et al. (2015), an analyst's "standing in analyst rankings or broker votes" is one of the most important factors that affects compensation (p. 25). Forty-four percent describe "success at generating underwriting business or trading commissions" as "Very Important" to compensation Brown et al. (2015) (Table 8, p. 28).

2.2 The potential for bias

The literature has extensively examined the risk of investment banking conflicts of interest among equity analysts. (See Beyer et al. (2010) and Bradshaw (2011) for reviews of the literature.) While the investment banking conflict of interest has garnered much attention, the actual occurrence of these conflicts is infrequent. For example, Hong and Kubik (2003) report that, in their sample, only 3% of an analyst's portfolio consists of stocks that have an underwriting relationship with the analyst's brokerage house. These infrequent conflicts leave open the question of why earnings forecasts and stock recommendations are optimistically biased (Beyer et al. 2010, p. 333). Theory and intuition suggest that the incentive to generate trading volume and brokerage commissions for the brokerage house may account for part of this optimistic bias.

Beyer and Guttman (2011) develop a model in which, if analysts are rewarded based on both higher trading volume in the stocks they cover and lower forecast error, they bias their forecasts upwards on average. The incentive to generate trading volume leads to optimistic bias on average, despite all agents acting rationally and an explicit reward

¹⁰ Our research design may fail to capture the full effects of analyst research on brokerage share of trading volume, and the impacts of brokerage-volume incentives on analysts' careers and behavior. However by using a shorter window, focusing on the period during which we expect the research-volume relation to be strongest, we minimize noise and increase our power to detect a direct relation between analyst research and volume.

¹¹ The investors responding to broker calls could be retail or institutional investors. Retail investors may be unlikely to trade through multiple brokerage houses. If a retail investor has a TD Ameritrade account, for example, and sees that a Morgan Stanley analyst updated their recommendation, that investor is most likely to trade through the TD Ameritrade account. However, retail investors may trade more often when prompted by their brokerage firm to do so.

for forecast accuracy. In their model, the interaction among informed investors, uninformed but strategic investors, and noise traders leads to more trade for positive information than for negative information, with the exception of extremely negative news, and thus leads to the analyst's strategic biasing of research. Informed investors are on average better off using the information contained in the analyst's forecast, even if it is biased, as it still has some information content. While the model predicts that analysts will bias extremely negative news downward, it predicts that they more frequently bias positive news upward, leading to an average optimistic bias to generate trade. In reality, many investors face short sale constraints or at least significant costs for short selling, which would further increase the asymmetry between trade generated by positive analyst research versus negative analyst research. Beyer and Guttman (2011) establish theoretically that positively biased research can generate incremental trading volume, even with utility-maximizing investors, and biasing forecasts can be an optimal strategy for analysts, even when they face costs for inaccurate forecasts.¹²

Beyer and Guttman (2011) model a game in which the analyst issues a single forecast, precluding reputation building. However, even in a repeated-game setting, investors might continue to react to (biased) analysts' earnings forecasts. First, investors are imperfect. There is debate even among experts on whether and to what extent analysts' incentives to generate brokerage trading volume would drive bias or quality. It is not clear that investors could determine this and undo any resulting bias. Second, even if investors update their beliefs about analyst bias in a fully rational manner and are fully informed about analysts' objective functions, as long as information signals are noisy, it is impossible to verify whether the analyst is honest or strategic, and prolonged bias can persist with rational investors still using the possibly biased signals (Benabou and Laroque, 1992). Factors such as the relatively small number of realizations—quarterly or annually—and the potential for bias to change over time, making investor learning and adjustment even more difficult.

Overall, it is unlikely that investors can fully adjust for optimistic bias in analysts' forecasts. Thus, particularly given short-sale constraints, more optimistic earnings forecasts may generate more trading volume for an analyst's brokerage house, even if that optimism is due to bias. This can create an incentive for analysts to optimistically bias forecasts.¹³

2.3 Prior empirical evidence

Empirical evidence suggests that the incentive to generate trading volume helps drive positive stock recommendations; however, the results for earnings forecasts are mixed, with no clear evidence that trading-volume incentives drive optimistic forecasts (Beyer et al. 2010, p. 133). Irvine (2004), using 1993–1994 Toronto Stock Exchange data, finds that buy (sell) recommendations are (are not) positively associated with trading volume. However, more positive/optimistic forecasts fail to generate additional trading volume. Jackson (2005), using 10 years of Australian data, shows that annual

¹² Hayes (1998) also models the impact of trading commissions on analyst behavior, assuming that the analyst reports truthfully. The analyst then chooses to allocate more effort to covering stocks for which positive information is likely. The result is that the analyst is optimistic, on average, due to bias in coverage decisions and effort allocation.

¹³ Consistent with the idea that brokerage incentives can drive optimistic bias even if investors (at least partially) discount biased analyst research, Agrawal and Chen (2008) find that recommendations are optimistically biased, if an analyst has specific investment banking or brokerage incentives related to the given stock, but also that the market as a whole discounts biased recommendations.

brokerage share of trading volume increases with the prior-year survey-based ranking of the analyst covering the stock and with the analyst's current-year average recommendation level. However, Jackson (2005) finds mixed results for earnings forecasts, with no positive relation between one-year-ahead forecast optimism and volume, after controlling for analyst quality. Grant et al. (2015) also use Australian data and find a positive relation between the monthly brokerage share of trading volume and top 20% forecast optimism, but do not control for quality. Juergens and Lindsey (2009) and Neihaus and Zhang (2010) use Nasdaq data but focus exclusively on recommendations.^{14,15}

Overall, these studies fail to find evidence that optimistic earnings forecasts drive additional brokerage share of trading volume, after controlling for analyst quality. However, these papers largely use non-U.S. or pre-Global Settlement data. The U.S. setting differs from Canada and Australia in important ways.¹⁶ It is not clear that findings regarding analyst behavior documented in one of these countries extend to the others.¹⁷

Overall, the evidence from these papers is highly mixed. Most importantly, there is no clear evidence (1) that optimistic analyst *earnings forecasts* bring in a larger

¹⁴ Juergens and Lindsey (2009) find increased trading for recommendation upgrades and downgrades, suggesting indirectly that trading volume does not incentivize upward bias in recommendation levels. Neihaus and Zhang (2010) find a higher brokerage share of trading in the months in which analysts issue above-median recommendations, with increases in trading for both upgrades and downgrades.

¹⁵ Cowen, Groysberg, and Healy (2006) and Agrawal and Chen (2012) take a cross-brokerage approach to examining the impact of brokerage trading volume incentives on analyst research. Cowen, Groysberg, and Healy (2006) show that brokerage houses that lack an underwriting business (and thus presumably rely more on brokerage business) issue more optimistic earnings forecasts and recommendations. However, Agrawal and Chen (2012) directly measure the revenue breakdown for brokerage houses, and find no evidence that quarterly earnings forecasts are more optimistic for brokerage houses that depend more on brokerage business as a source of revenue. Firth, Lin, Liu and Xuan (2013) and Gu, Li, and Yang (2013), using Chinese data, find evidence consistent with analysts issuing more optimistic recommendations for stocks owned by mutual funds that pay the brokerage firm higher fees. Our focus is on trade-generation: whether more optimistic (or higher quality) analyst research output, such as recommendations and earnings forecasts, generate higher trade for the brokerage house.

¹⁶ Canada and Australia both have smaller financial markets, in terms of number of stocks actively traded, the market value of publicly traded stocks, and the number of analysts covering stocks. As of March 29, 2019, the market value of Canadian (Australian) publicly listed stocks was \$2.4 (1.5) trillion, while the market value of U.S. publicly traded stocks was \$32.1 trillion (<https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?>). The research industry is also smaller in Australia and Canada than in the United States. IBES reports 10% (20%) as many earnings forecasts in Australia (Canada) as in the United States over the 20 years from 1995 through 2014. Based upon IBES data, the average covered stock in the United States has 25% higher analyst coverage than the average covered stock in Australia or Canada. In addition, both the Canadian and Australian stock markets are dominated by financial services and commodities-based industries (e.g., mining, oil and gas, other commodities) (<https://www.tsx.com> and <https://www.asx.com/au>, accessed March 2019). Earnings predictability is likely to be very different for financial services and commodities-based industries than most others.

¹⁷ Using several different measures, Habib and Hossain (2008) fail to find evidence of "meet or beat" earnings management. Thus one of the key incentives that differentiate earnings forecasts from recommendations in the United States is less likely to be present in Australia. The role of the Global Settlement is also extremely important when examining broker-volume incentives. Some countries responded to the Global Settlement with changes in analyst behavior that were similar to the United States, but Canadian and Australian analysts did not significantly change their behavior (Hovakimian and Saenyasiri 2014). This suggests that the incentives for analysts in Canada and Australia differ from the incentives for analysts in the United States. While the exact differences in incentives are unclear from the literature, it is clear that there are important differences.

brokerage share of volume, particularly when controlling for forecast and analyst quality, (2) whether analysts' careers are impacted by their volume generation, and (3) whether analysts modify their behavior, due to the volume-generation incentive.

Ultimately, prior evidence is mixed as to whether analyst earnings forecast optimism is associated with higher brokerage trading volume and does not directly address whether optimism-volume relations create a conflict of interest, for either recommendations or forecasts.

2.4 Hypotheses

Based on the theory and evidence described in Sections 2.1 through 2.3, we state two sets of formal hypotheses, in alternative form. First, extending prior research, we expect that more optimistic earnings forecasts will lead to higher trading volume for the analyst's brokerage house around the issuance of that estimate.

H1a. More optimistic analyst earnings forecasts will lead to a larger brokerage share of trading volume for the analyst's brokerage house.

We also expect that higher-quality forecasts and forecasts from higher-quality analysts will lead to higher trading volume. We examine this directly, testing the following two hypotheses.

H1b. Higher-quality forecasts will lead to a larger brokerage share of trading volume for the analysts' brokerage house.

H1c. The forecasts of higher-quality analysts will lead to a larger brokerage share of trading volume for the analysts' brokerage house.

Finally, we jointly examine the effects of optimism, forecast quality, and analyst quality. It is an empirical question whether any one of these categories dominates.

Our remaining hypotheses address conflict of interest more directly. Assuming that optimistic forecasts are associated with a larger brokerage share of trading volume, the next question is whether the analyst drives the incremental volume. If the analyst is generating trading volume, then when that analyst moves to another brokerage houses, we should find that the volume response at the new brokerage house changes.

H2a. When an analyst switches brokerage firms, the new brokerage house's share of trading volume around analyst coverage of the given stock is positively related to the volume the analyst generated at their prior brokerage house.

We examine analyst incentives more directly by examining career progression.

H2b. Analysts who fail to generate brokerage trading volume are more likely to move to lower-tier brokerage houses.

Finally, we examine whether analysts strategically bias their earnings forecasts or strategically improve accuracy to generate trading volume. Intuitively, an analyst will choose a level of optimism that increases trading volume but minimizes costs, such as

reduced reputation. However, an analyst will not automatically know what the optimal level of optimism is. The analyst will learn from experience whether to increase or decrease their level of optimism. We design a test to examine whether analysts consider trading volume generation when updating their level of optimism. If Analyst A is more successful at generating trading volume with optimistic forecasts than expected in one year, we would expect that Analyst A will place a heavier weight on optimism in trading off the expected volume generation effects of optimism and the quality and reputation costs of optimistic bias in the subsequent year and will thus increase optimism in the subsequent year.¹⁸ Similarly, analysts will trade off the costs of more accurate forecasts—additional time, effort, research, and use of resources—with the potential benefits. We similarly examine whether analysts' experience with the volume-generation benefit of accuracy affects their subsequent accuracy, as follows.

H3. An analyst's earnings forecast optimism (accuracy) is positively related to the volume that analyst generated through earnings forecast optimism (accuracy) in the prior year.

3 Data and sample

We obtain trading volume data from the Bloomberg Terminal database. The Terminal provides information on the total number of shares traded for each stock-day-broker, which satisfies certain data selection criteria over a five-year period. However, the format requires manual downloading for specified stock-broker pairs. We focus on S&P 1,500 firms and select a sample of 18 brokerage houses that have a matching broker code in the Bloomberg Terminal and produce the highest number of recommendations in IBES for the S&P 1,500 firms. The inclusion of 18 brokerage houses ensures that we examine both “bulge bracket” firms (i.e., the largest investment banks) and nonbulge firms.

We obtain data for all 18 brokerage houses for the five years from 2011 to 2015, covering 1,436 firms from the S&P 1,500 list that have matching Bloomberg tickers and matching Compustat and CRSP identification codes.¹⁹ We obtain analyst one-year-ahead earnings per share (EPS) forecasts, price targets, and recommendation data from IBES, using unadjusted files and adjusting for share splits, as appropriate, as well as stock price data from CRSP and firm characteristics from Compustat. There is a total of 179,417 analyst-firm-day observations that have a one-year-ahead earnings forecast and all other required data.

Table 1 shows descriptive statistics related to the 18 brokerages included in our sample, which cover a wide range in terms of brokerage trading activity, analyst employment and coverage, and investment banking activity. Panel A focuses on

¹⁸ This learning and updating does not imply that analysts will become more optimistic over time. Instead, it suggests that analysts are learning over time what the “optimal” level of optimism is for themselves. This optimum may also change as their experience and reputation evolves, requiring further updating. An analyst who goes too far with optimistic bias should experience a decreased optimism-volume relation as investors decrease their reaction to that analyst's overly optimistic forecasts. The analyst would then reduce optimism in the subsequent year.

¹⁹ Bloomberg provides only five years of data at any given time. We could not obtain data earlier than 2011.

brokerage trading volume. The mean number of shares traded by a given brokerage ranges from 2.56 million to 3.76 billion. Panel B provides summary statistics on the number of analysts who are employed each year by the brokerage house and who provide one-year-ahead EPS forecasts.

Our sample selection methodology biases our sample towards brokerage houses that provide higher levels of overall analyst coverage. However, there is still significant variation in the size of brokerage houses' sell-side research departments (*Brokerage Size*) included in our sample. The mean number of analysts at each brokerage ranges from 49 to 236, and the average number of stocks followed by the average analyst at each firm ranges from six to 17.

Finally, Table 1 Panel C provides the ratio of the number of shares traded through the given brokerage to the total brokerage net revenue for each year. The mean annual number of sample shares traded per dollar of revenue for each brokerage house ranges from 0.002 to 0.177 for the brokerages with nonmissing revenue.²⁰ Overall, our sample includes a wide range of brokerage houses that produce analyst research, although our sample is weighted towards larger firms. Our sample, by construction, excludes independent research firms.

Table 2 provides descriptive statistics for the variables used in our tests (Panel A) and correlations between these variables (Panel B). The dependent variable used in our tests, *Volume Share*, is the total number of shares traded in a given stock through the brokerage house over the $[-1, 5]$ day window, divided by the total number of shares traded in the given stock during the window, where day 0 is the day on which an analyst issues an earnings forecast. We include day -1 , given the evidence of Juergens and Lindsey (2009) that analysts release reports to some customers before the official IBES estimate date; however, results are qualitatively similar using alternate windows $[0, 1]$ and $[0, 10]$. *Volume Share* ranges from 0.005% to 25.21%, with a mean of 5.31% of shares traded in a firm by a particular brokerage over the seven-day window of interest.

Optimism variables include *Forecast Bias*, *Buy*, *Sell*, and *Target Optimism*. The variable *Forecast Bias* is the rank (by deciles, scaled from 0 to 1) of the difference between the one-year-ahead earnings forecast, in earnings per share (EPS), and the actual value of EPS, normalized by the fiscal year-end share price. Higher *Forecast Bias* indicates a higher earnings forecast, relative to other analysts who have issued forecasts for the same firm at the same time. The variable *Buy (Sell)* is an indicator variable that takes the value 1 if the analyst issued a *buy* or *strong buy (sell or strong sell)* recommendation and 0 otherwise. The variable *Target Optimism* is a ranked variable, ranging between 0 and 1, of the newly issued price target with a horizon equal to 12 months, normalized by the prior trading day's stock price. To avoid small denominators, we require that the stock price is greater than or equal to \$5.

The forecast quality variables used in our analyses include *Current Accuracy*, *Herding*, *First*, and *Forecast Age*. The variable *Current Accuracy* captures the relative accuracy of the forecast, following the ranking method of Hong and Kubik (2003) and the benchmark periods of Cowen et al. (2006). The variable *Herding* is an indicator variable that takes the value 1 if a forecast falls between the analyst's prior forecast and

²⁰ We hand-collected revenue data for 17 out of the 18 brokerages. One of the privately owned brokerages in our sample did not provide revenue information in company statements or on the company website.

Table 1 Brokerage Descriptive Statistics**Panel A. Brokerage-specific trading volume**

Brokerage	Total Share Volume Traded (in millions)						Std. Dev.
	2011	2012	2013	2014	2015	Mean	
1	3518.96	3968.92	3960.81	4062.82	3302.94	3762.89	332.65
2	3194.20	2292.88	3026.30	3366.51	2380.38	2852.05	486.63
3	3136.17	2903.73	2801.48	2618.73	2457.70	2783.56	260.98
4	2543.33	2251.41	2280.61	2021.63	1880.43	2195.48	255.37
5	2059.29	2518.29	1625.95	1322.08	950.45	1695.21	614.15
6	1545.63	1958.61	1810.29	1669.09	1643.30	1725.38	161.11
7	1070.93	1902.23	1320.79	1413.80	2024.77	1546.50	403.11
8	2035.32	1531.46	1365.64	1223.04	995.52	1430.19	391.30
9	1370.62	1190.26	1209.46	1124.09	1124.55	1203.79	100.84
10	405.86	439.87	336.93	325.04	319.26	365.39	54.20
11	215.69	261.43	319.52	338.18	475.80	322.13	98.61
12	93.01	108.92	155.21	152.00	140.64	129.96	27.59
13	169.42	181.46	206.23	117.84	100.16	155.02	44.50
14	101.42	98.67	120.17	85.29	80.20	97.15	15.64
15	66.55	101.58	121.39	94.14	84.90	93.71	20.27
16	71.33	126.03	111.57	103.16	60.61	94.54	27.59
17	5.49	9.46	3.69	79.60	90.95	37.84	43.54
18	2.78	3.13	2.80	2.60	1.49	2.56	0.63

Panel B. Number of analysts by brokerage

Brokerage	Brokerage Size (# of analysts)						Average # of Stocks Followed by Analysts at Each Brokerage
	2011	2012	2013	2014	2015	Mean	
1	233	232	243	241	231	236	6
2	107	112	136	169	169	139	8
3	125	126	96	79	78	101	7
4	129	117	114	118	116	119	10
5	93	90	85	90	82	88	12
6	111	105	103	117	115	110	10
7	122	117	145	199	187	154	9
8	78	91	91	93	92	89	12
9	116	110	103	112	178	124	9
10	92	95	100	110	123	104	10
11	100	81	90	117	133	104	10
12	64	68	70	76	83	72	14
13	88	103	83	78	74	85	13
14	49	51	50	55	42	49	15
15	110	134	115	101	99	112	11
16	44	42	39	41	52	44	17
17	33	30	43	67	67	48	10
18	75	85	92	84	59	79	10

Table 1 (continued)

Panel C. Brokerage Revenue Breakdown**Shares Traded per Dollar of Revenue**

Brokerage	2011	2012	2013	2014	2015	Mean
1	0.038	0.048	0.045	0.048	0.040	0.044
2	0.114	0.087	0.104	0.127	0.099	0.106
3	0.106	0.104	0.090	0.092	0.080	0.094
4	0.147	0.124	0.067	0.059	0.056	0.090
5	0.050	0.074	0.040	0.037	0.027	0.046
6	0.048	0.075	0.056	0.049	0.047	0.055
7	0.011	0.020	0.014	0.015	0.022	0.016
8	0.064	0.050	0.041	0.037	0.029	0.044
9	0.034	0.028	0.029	0.030	0.032	0.031
10	0.015	0.015	0.011	0.011	0.012	0.013
11	0.084	0.085	0.108	0.113	0.192	0.116
12	0.001	0.001	0.002	0.002	0.002	0.002
13	0.122	0.114	0.105	0.053	0.043	0.087
14	0.110	0.103	0.112	0.071	0.062	0.092
15	0.020	0.027	0.027	0.019	0.016	0.022
16	0.165	0.258	0.213	0.159	0.090	0.177
17	0.006	0.005	0.000	0.001	0.000	0.003
18	.	.	.	.	.	.

Panel A displays the total number of shares traded by each brokerage of all 1436 sample firms in each year in the sample period as well as the mean and standard deviation by brokerage. All amounts are in millions of shares

Panel B displays the number of analysts associated with each brokerage as well as the mean number of analysts at each brokerage over the sample period. The last column displays the average number of stocks followed by all analysts at each brokerage house during the sample period. Amounts are extracted from IBES and are not restricted to the analysts in our final sample

Panel C displays the ratio of shares traded by each brokerage of all 1436 sample firms in each year in the sample period to yearly total brokerage revenue as well as the mean by brokerage. No information was found for brokerage 18, as it is private and does not publicly share any revenue data

the consensus forecast and 0 otherwise. A herding forecast is likely to convey less new information to the market and thus will have lower value (Gleason and Lee 2003; Clement and Tse 2005). The variable *First* is an indicator variable denoting the first forecast made by a particular analyst after the prior annual earnings announcement, and *Forecast Age* is the number of days before the next earnings announcement date that the forecast was made, divided by 365. Earlier forecasts (*First* = 1 and a higher *Forecast Age*) are likely to have higher value (Clement and Tse 2003).

The analyst quality variables include *Prior Accuracy*, *# Forecasts*, *# Years Followed*, *# Firms Followed*, and *# Analysts Following*. The variable *Prior Accuracy* is defined similarly to *Current Accuracy*, but *Prior Accuracy* uses the latest forecast made by the analyst in the $[-90, 0]$ day window before the prior earnings announcement. The variables *# Forecasts*, *# Years Followed*, and *# Firms Followed* are relative-

Table 2 Descriptive Statistics

Panel A. Descriptive statistics									
Variable	N	Mean	Std. Dev.	Min	p25	Median	p75	Max	
<i>Volume Share</i>	179,417	5.311	5.016	0.005	1.217	4.246	7.678	25.207	
<u>Optimism</u>									
<i>Forecast Bias</i>	179,417	0.502	0.312	0	0.222	0.556	0.778	1	
<i>Buy</i>	179,417	0.030	0.170	0	0	0	0	1	
<i>Sell</i>	179,417	0.006	0.078	0	0	0	0	1	
<i>Target Optimism</i>	73,913	0.503	0.305	0	0.222	0.556	0.778	1	
<i>Ind_Rec</i>	179,417	0.067	0.251	0	0	0	0	1	
<i>Ind_Target</i>	179,417	0.414	0.493	0	0	0	1	1	
<u>Forecast Quality</u>									
<i>Current Accuracy</i>	179,241	0.506	0.295	0	0.25	0.506	0.761	1	
<i>Herding</i>	142,908	0.428	0.495	0	0	0	1	1	
<i>First</i>	179,417	0.223	0.417	0	0	0	0	1	
<i>Forecast Age</i>	179,417	0.551	0.292	0	0.288	0.537	0.789	1.501	
<u>Analyst Quality</u>									
<i>Prior Accuracy</i>	92,249	0.513	0.307	0	0.25	0.5	0.773	1	
<i># Forecasts</i>	129,611	0.540	0.287	0	0.333	0.524	0.75	1	
<i># Years Followed</i>	126,443	0.385	0.336	0	0.095	0.30	0.625	1	
<i># Firms Followed</i>	129,856	0.473	0.271	0	0.278	0.452	0.655	1	
<i># Analysts Following</i>	177,237	21.625	9.112	1	15	21	27	57	
Brokerage House Characteristics									
<i>Sum Volume</i>	179,417	1.554	1.178	0.001	0.318	1.529	2.290	4.041	
<i>Brokerage Size</i>	179,417	114,098	44,864	30	90	107	118	243	
<i>Percent of Underwriting</i>	179,417	6.699	4.089	0	2.181	7.993	10.132	14.014	
<i>Shares per Revenue Dollar</i>	178,885	0.062	0.045	0	0.028	0.050	0.092	0.258	
<i>Med. Analyst Volume</i>	179,417	4.600	3.734	0.005	1.043	4.345	6.402	25.207	

Table 2 (continued)

Panel B. Correlations														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Volume Share	Forecast Bias	Buy	Sell	Target Opt.	Current Acc.	Herding	First	Forecast Age	Prior Acc.	# Forecasts	# Years	# Firms	# Analysts
1	Volume Share	1	-0.006	0.034*	-0.043*	0.005	-0.016*	-0.036*	0.016*	0.005	0.048*	0.012	-0.010	-0.079*
2	Forecast Bias	0.014*	1	-0.028*	0.066*	0.031*	-0.002	-0.013	0.100*	0.034*	0.005	-0.011	0.002	0.001
3	Buy	0.016*	0.014*	1	-0.019*	0.138*	-0.013*	0.060*	-0.003	0.000	-0.008	0.004	0.001	-0.002
4	Sell	0.019*	-0.014*	1	-0.109*	-0.018*	-0.022*	0.010	-0.009	-0.005	0.008	-0.013	-0.008	-0.020*
5	Target Optimism	-0.019*	0.087*	-0.122*	1	0.001	-0.006	-0.023*	-0.022*	0.015*	-0.010	0.033*	0.024*	0.026*
6	Current Accuracy	-0.011*	0.041*	-0.018*	0.010*	1	-0.052*	-0.002	-0.038*	0.035*	-0.019*	0.002	0.002	0.001
7	Herding	-0.006*	0.015*	-0.021*	-0.015*	-0.037*	1	0.008	-0.041*	-0.014*	-0.005	-0.012	0.019*	-0.026*
8	First	-0.003	0.014*	0.135*	0.027*	-0.013*	-0.001	1	0.049*	0.003	0.002	-0.012	-0.011	-0.012
9	Forecast Age	0.003	0.076*	-0.029*	-0.019*	-0.028*	-0.016*	0.468*	1	0.008	0.022*	-0.004	-0.006	-0.020*
10	Prior Accuracy	0.007*	0.027*	-0.002	-0.006	0.016*	-0.011*	-0.004	-0.007*	1	0.010	-0.002	-0.015*	-0.008
11	# Forecasts	0.013*	0.002	-0.014*	0	-0.003	-0.012*	-0.043*	-0.001	0.009*	1	0.168*	0.086*	-0.082*
12	# Years	-0.0002	-0.011*	0.003	-0.007*	0.027*	-0.000	0.006*	0.007*	-0.000	0.113*	1	0.213*	0.008
13	# Firms	-0.010*	-0.003	0.001	-0.006*	0.014*	0.006	-0.007*	0.008*	-0.020*	0.072*	0.180*	1	-0.033*
14	# Analysts	-0.070*	-0.002	-0.034*	-0.017*	-0.000	-0.018*	-0.046*	-0.018*	0.010*	-0.035*	-0.056*	-0.075*	1
	Following													

Panel A displays descriptive statistics for the main variables used in the analyses. Appendix 1 provides detailed descriptions of each variable

Panel B displays the Pearson (Spearman Rank) correlation coefficients below (above) the diagonal. The asterisks represent correlations significant at the 5% level or better. Appendix 1 provides detailed descriptions of each variable

rank measures for the number of forecasts an analyst has made in the prior firm year, the number of years the analyst has followed the firm, and the number of firms the analyst follows in a given year, respectively. These variables are normalized to range from 0 to 1, calculated on a stock-year basis as the value for the given analyst minus the minimum for all analysts, divided by the maximum minus the minimum for all analysts. All three are positive indicators of analyst quality. Higher *# Forecasts* indicates an analyst who is more active in updating research for the firm. Higher *# Years Followed* indicates more firm-specific experience. Last, *# Firms Followed* is a positive indicator of analyst quality, since covering more firms is likely to develop greater industry expertise (Leone and Wu 2007).²¹ We also include *# Analysts Following*, the total number of analysts who follow a firm in a given year, although it is not clear which directional effect to predict for *# Analysts Following*.²²

Table 2 Panel B reports correlations between the main variables. These correlations suggest that the variables capture distinct dimensions of optimism, forecast quality, and analyst quality.

4 Results

4.1 Analyst and forecast characteristic effects on trading volume

To assess whether analyst optimism affects the share of the total volume traded by the brokerage at the time of the analyst forecast, we estimate the following regression.

$$Volume\ Share_{ijt} = a_0 + a_1 Optimism_{ijt} + a_2 Quality_{ijt} + a_3 Analyst\ Quality_{ijt} + e_{ijt}, \quad (1)$$

for analyst i , covered firm j , at time t ; where *Optimism* includes *Forecast Bias*, *Buy*, *Sell*, and *Target Optimism*; *Quality* includes *Current Accuracy*, *Herding*, *First*, and *Forecast Age*; and *Analyst Quality* includes *Prior Accuracy*, *# Forecasts*, *# Years Followed*, *# Firms Followed*, and *# Analysts Following*. We include all earnings forecast dates. Thus a_0 captures the effect analysts have on *Volume Share* purely from issuing a forecast.

We include year fixed effects, brokerage fixed effects, and firm fixed effects in the model to control for time, brokerage, and firm effects on volume share. In particular, we might expect the brokerage share of trading volume to shift over time with consolidation in the industry. If there are also time trends in analyst behavior, we might erroneously find a relation between the two if we fail to control for year fixed

²¹ If our sample included very small brokerages and independent research firms, high *# Firms Followed* could indicate a brokerage that has few resources and is forced to stretch analysts into covering more firms. However, for our sample of larger brokerages, we find that the most experienced analysts cover the most firms. The correlation between experience and *# Firms Followed* is a statistically significant 0.1804, which is consistent with more experienced, more senior, and more respected analysts covering more firms.

²² A firm followed by fewer analysts may have less public information available. For such a firm, an individual analyst's forecasts are likely to have higher value. Conversely, higher analyst following may indicate more investor interest in the firm, and thus analyst research is valuable to more investors and is more likely to drive incremental trading. Thus we make no directional prediction for *# Analysts Following*, but we include it as a firm-analyst-year attribute that is likely to impact the incremental volume associated with an individual analyst's research.

effects. Brokerage firm fixed effects control for the overall size and market share of each brokerage as well as other brokerage characteristics, such as resources, accuracy, or the number of analysts, which impact both analyst behavior and the brokerage's share of trading volume.²³ Finally, we include firm fixed effects (for the covered firm). Analysts compete with each other for volume in a given firm. Our use of brokerage *share* of trading volume and our relative optimism variables helps to address this, but this may not fully adjust for firm-specific effects. To assist in the interpretation of results throughout the paper, we report an intercept term that captures the average of the estimated values for any included fixed effects. We also allow for arbitrary within-firm correlations in standard errors.²⁴

We examine each of the sets of variables: *Optimism*, *Quality*, and *Analyst Quality*, in turn. We also examine all three together, to provide insight into the incremental importance of each one for trading volume. The results are presented in Table 3.

We find the expected coefficients on the control variables for recommendation and target price optimism. *Buy (sell)* recommendations are positively (not) related to the brokerage share of volume (coefficient = 0.248, *p* value <0.001 for *buy*), and *Target Optimism* is positively and significantly related to *Volume Share* (coefficient = 0.148, *p* value <0.01).^{25,26} The combined effects of the intercept and slope terms imply that earnings forecasts with concurrent sell and hold (buy) recommendations experience lower (higher) *Volume Share* than earnings forecasts not associated with a concurrent

²³ In particular, there may be style differences which affect both analyst behavior and trading volume, but these are not due to analyst behavior driving trading volume (e.g., brokerage firm culture, client type, communication style), which is difficult to measure. Cowen, Groysberg, and Healy (2006) state in their conclusion that brokerage house status and reputation likely explain some of the differences in optimism observed across brokerages in their sample. They also point out that analysts' decisions to stop covering, rather than issuing more negative coverage, may differ systematically across brokerage houses. Including brokerage firm fixed effects allows us to control for this type of difference between brokerage houses.

²⁴ In addition to these fixed effects, we control for the informativeness of earnings forecasts when examining the relation between optimistic bias and volume share by including forecast and analyst quality variables together with optimism variables. We also test the robustness of our results to two other variables that may impact the informativeness of the forecast but that do not capture forecast quality per se. In particular, first, a new forecast may be more informative to the market and lead to higher overall trading volume (though not necessarily brokerage share of trading volume) if there are higher differences of opinion for the stock. In additional tests, we include an additional control variable for forecast dispersion to capture differences of opinion. We find an insignificant negative coefficient on forecast dispersion and find that results reported in Table 3 remain qualitatively similar. Second, investment banking relationships can increase both the potential informativeness of the analyst's forecast to the market and the market's perception of analyst bias. To examine whether investment banking relationships significantly affect our results, we focus on the subset of forecasts for which investment banking relationships are unlikely. We restrict to the subsample of brokerage houses with little or no investment banking business. The results reported in Table 3 remain qualitatively similar.

²⁵ Given evidence of Juergens and Lindsay (2009) that downgrades are leaked to clients several days before the recommendation becomes public, we also examine the robustness of the optimism-volume relation using a wider window for *Volume Share*. Results for *Forecast Bias* are similar for $[-3, 5]$, focusing more directly on the pre-forecast period, $[-3, -1]$, or including both the pre-period and the immediate forecast window, $[-3, 1]$.

²⁶ In additional analyses, we examine whether recent news events affect the bias-volume relation. We focus on the subset of earnings forecasts made in the five days following an earnings announcement and partition based upon whether the earnings announcement is positive or negative, using both the earnings forecast error and the announcement-window three-day return. We find significantly positive coefficients on *Forecast Bias* in three of the four subsamples, with no significant differences in coefficient between positive and negative news. Thus preceding news does not appear to significantly impact the bias-volume relation. Conversely, we examine earnings forecasts that are isolated from other forecasts, suggesting no significant recent news has been released. Results are robust.

recommendation. Similarly, earnings forecasts associated with pessimistic (optimistic) target price forecasts experience lower (higher) *Volume Share* than those that are not associated with concurrent target price forecast.

Table 3 Column 2 presents the results for earnings forecast *Quality*. We find no significant relation between *First* and *Volume Share*. However *Current Accuracy*, *Herding*, and *Forecast Age* are significantly associated with *Volume Share*, in the expected directions. Column 3 presents the results for the effect of *Analyst Quality*. As expected, the analyst *Prior Accuracy* and *# Years Followed* are positively associated with *Volume Share* (coefficient = 0.196, *p* value <0.01 and coefficient = 0.211, *p* value <0.05, respectively). The variable *# Analysts Following* is negatively related to *Volume Share* (coefficient = -0.009, *p* value <0.1). However, we find no association between *# Forecasts* and *# Firms Followed* with *Volume Share*.

Table 3 Column 4 presents results including optimism, forecast quality, and analyst quality in the same model. The results are relatively unchanged. We continue to find evidence that earnings forecast optimism leads to a larger brokerage share of volume, even after controlling for forecast and analyst quality. Similarly, quality is associated with volume, controlling for optimism. *Volume Share* is positively and significantly related to *Forecast Bias*, *Current Accuracy*, *Forecast Age*, *Prior Accuracy*, and *# of Years Followed*, and it is negatively and significantly related to *# Analysts Following*. These results provide evidence consistent with H1. They are also robust to a large set of additional robustness tests.^{27,28,29} Thus we find a forecast-volume relation, which provides a potential incentive toward optimistic bias as well as evidence of a potential incentive towards quality.

The economic significances implied by the results in Column 4 also indicate similar levels of economic impact of optimism and quality on volume. In particular, an analyst going from the 25th percentile to the 75th percentile of analysts covering the given firm, an interquartile-range increase in the ranked variable, increases brokerage house

²⁷ The results in Table 3 show that within-broker variation in analyst forecast quality relates to variation in the brokerage's share of trading volume surrounding the analyst's forecast. We replicate Table 3, including analyst fixed effects rather than broker fixed effects, to examine within-analyst variation in forecast quality. We find similar results. All coefficients remain statistically significant at the 10% level or better, with magnitudes ranging from 85% to 115% of those reported in Table 3. Thus the results reported in Table 3 and in Section 4.1 are robust to including analyst fixed effects. We also estimate Table 3 including only year and firm fixed effects (i.e., excluding both broker and analyst fixed effects). This better captures whether more optimistic analyst research relates cross-sectionally to a larger brokerage share of volume. Consistent with Jackson (2005), when not including brokerage fixed effects, we include an additional control variable for total brokerage firm volume in the given year, to adjust for the overall brokerage firm market share of trading. We find similar results.

²⁸ The results presented in Table 3 are robust to estimation using a fractional logit model, instead of an ordinary least squares model. Focusing on Column 4, all coefficients on optimism and quality variables that are significant at the 10% level or better remain significant using a fractional logit model, while no other coefficients are significant with the fractional logit. Thus the results are robust to estimation using a fractional logit model.

²⁹ If forecasts cluster in time, they may be associated with lower brokerage share of trading volume, due to increased competition for volume during these forecast-cluster windows. We examine whether clustering affects our results in two ways. First, we examine whether forecast optimism is a function of whether other forecasts occur during the [-5, 5] window, or a wider [-10, 10] window, surrounding the given forecast. We find no relation. Second, we replicate our main Table 3 tests including an indicator for whether the forecast is isolated. We find similar results when including an additional control variable for whether there are other forecasts in the [-5, 5] or [-10, 10] window surrounding the given forecast.

Table 3 Effect of Analyst Characteristics on Brokerage Share of Trading Volume

	(1) Optimism	(2) Forecast Quality	(3) Analyst Quality	(4) All Characteristics
<i>Forecast Bias</i>	0.069** [2.32]			0.102** [2.05]
<i>Buy x Ind_Rec</i>	0.248*** [3.30]			0.146 [0.99]
<i>Sell x Ind_Rec</i>	-0.011 [-0.09]			-0.286 [-1.27]
<i>Target Optimism x Ind_Target</i>	0.148*** [2.62]			0.082 [0.92]
<i>Ind_Rec</i>	-0.124** [-2.52]			0.038 [0.39]
<i>Ind_Target</i>	-0.061* [-1.67]			0.011 [0.19]
<i>Current Accuracy</i>		0.070* [1.92]		0.143** [2.57]
<i>Herding</i>		-0.034* [-1.69]		-0.037 [-1.28]
<i>First</i>		0.031 [0.60]		-0.077 [-0.81]
<i>Forecast Age</i>		0.128*** [3.32]		0.114** [1.98]
<i>Prior Accuracy</i>			0.196*** [2.73]	0.226*** [3.04]
<i># Forecasts</i>			0.025 [0.25]	0.032 [0.31]
<i># Years Followed</i>			0.211** [2.49]	0.224** [2.57]
<i># Firms Followed</i>			0.020 [0.17]	0.029 [0.23]
<i># Analysts Following</i>			-0.009* [-1.81]	-0.010* [-1.93]
Constant	11.862*** [122.63]	11.764*** [108.12]	11.671*** [60.48]	11.391*** [54.56]
Year FE	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	179,417	142,805	72,202	60,468
Adj. R-squared	0.509	0.514	0.548	0.552

Table 3 displays the results of ordinary least squares regressions, relating *Volume Share* to analyst optimism variables (Column 1), forecast quality variables (Column 2), and analyst quality variables (Column 3), for dates on which an earnings forecast is issued. Column 4 displays the results of all characteristics. The intercept term captures the average of the estimated values for the included fixed effects. Appendix 1 contains detailed descriptions of the variables. t-statistics are provided in parentheses, with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

share of trading volume by 1.0% of the mean for earnings forecast optimistic bias, by 1.3% of the mean for forecast accuracy, and by 2.1% of the mean for prior-year earnings forecast accuracy.³⁰ While additional assumptions are required to convert this to trading commissions, doing so can be useful to quantify the potential incentive towards optimistic bias. With a typical commission of \$0.03 per share traded (Levine 2015), an interquartile range increase in bias, ex-post accuracy, and prior accuracy would result in an annual increase in analyst-generated commission of \$19,260, \$27,002, and \$42,674, respectively, for an average analyst. Earlier papers use even larger per-share or percentage commissions to estimate economic significance.³¹ Applying the lowest of these, \$0.05 per share, implies commission increases of \$32,100, \$45,004, and \$71,125, respectively.

Overall, these results suggest that the incentives tied to increased bias and improved accuracy are both statistically and economically significant. However, economically, they are in a range where it is unclear whether they will affect analyst behavior.

4.2 Trading volume following an analyst's move between brokerage houses

The results presented above show that analyst forecast optimism and accuracy are associated with a larger brokerage share of trading volume. However, as with research on analyst recommendations, this does not establish a causal relationship between the analyst's research and trading. To address whether the analyst drives the volume effect, we examine whether brokerage trading volume follows analysts who change brokerage houses. Figure 1 illustrates the expected dynamics. When an analyst moves from brokerage house A to B, a portion of trading volume should move with the analyst. If so, it suggests that the analyst, rather than other factors, drives the brokerage share of volume effects. It is also more likely that brokerage houses consider trading volume in their hiring decisions, and it is more likely that analysts will thus be concerned with generating volume, if analysts can generate similar volume after moves.

We limit our analysis to analysts who moved between brokerage houses within our sample between 2012 and 2015. We require that analysts spend at least one year in each of the brokerages and that they cover at least one firm that is the same at both brokerage houses. We identify 58 analysts who moved between brokerages within our sample. Among these analysts, 45 (35) covered at least three (five) of the same firms in both brokerage houses. We then estimate the following regression.

$$\begin{aligned} \text{Med. Volume Share New Broker}_{ijt} = & a_0 + a_1 \text{Med. Volume Share Analyst}_{ijt-1} \\ & + a_2 \text{Med. Volume Share New Broker}_{ijt-1} \\ & + e_{ijt}, \end{aligned} \quad (2)$$

where *Med. Volume Share New Broker_{ijt}* is the median *Volume Share* from the

³⁰ A change in rank from the 25th percentile to the 75th percentile for *Forecast Bias* is equivalent to the analyst changing from being on average pessimistic, relative to the consensus, to being on average optimistic relative to the consensus.

³¹ Jeurgens and Lindsey (2009) cite commission rates ranging from \$0.05 to \$0.91 per share. Jackson (2005) uses a percentage commission that would amount to \$0.075 per share for a stock trading at \$50 per share.

analyst's research dates in a given year t covering firm j after the move to the new brokerage house b , capturing the median trading volume that the analyst generates throughout the calendar year. The variable *Med. Volume Share Analyst_{ijt-1}* is the analyst *Volume Share* covering firm j in year $t - 1$ prior to the move to the new brokerage house. The variable *Med. Volume Share New Broker_{bjt-1}* is the *Volume Share* of the new brokerage covering firm j in year $t - 1$ before the analyst's move.

The results are presented in Table 4 Panel A. Column 1 presents the results for the full sample. Column 2 (3) displays results when the analyst forecasted a minimum of three (five) of the same firms at both the old brokerage and the new one. Our variable of interest, *Med. Volume Share Analyst_{ijt-1}*, relates positively and significantly to *Med. Volume Share New Broker_{bjt}* in each sample (coefficients between 0.120 and 0.147, p value < 0.05).³² The magnitude ranges from 15% to 18% of the effect of the brokerage house trading volume in the previous year. This suggests that the new analyst causes an economically significant shift in broker volume share. These results suggest that analysts have a causal impact on the share of trading volume and that brokerage houses are likely to consider trading volume generation to be a transferrable analyst skill.

We further address whether it is analyst's earnings forecast accuracy and optimism that drive this transferrable skill by examining subsamples of below(above)-median accuracy and optimism analyst transfers. The results are reported in Table 4 Panel B. Column 1 (2) displays the results when analyst accuracy is higher (lower) than the median in year $t-1$. Column 3 (4) displays the results when analyst optimism is higher (lower) than the median in year $t-1$. The results show that the volume transfer effect is only significant for above-median analysts on each dimension. These results are consistent with both optimism and accuracy being important for the transferrable skill of generating trading volume. However, the differences between the high and low groups are statistically insignificant. This may be due to low power, given our small sample of analyst moves among the 18 brokerage houses in our sample.

4.3 Analyst career concerns

The results thus far suggest that analysts have incentives to increase optimism and accuracy if they aim to increase trading volume to generate trading commissions for their brokerage houses. However, it is not clear whether analysts are rewarded for generating volume. While anecdotal and survey evidence suggests that analysts are compensated based partly on generating volume (see the discussion in Section 2.1), there is no large-sample empirical evidence regarding the effect of generating volume on analysts' compensation or careers.

To examine this issue, we focus on analysts' career moves. We employ a methodology similar to that of Hong and Kubik (2003) and examine whether an analyst's moves across brokerage houses of varying statures are predicted by prior-year performance. Since our sample focuses on the largest brokerage houses and thus captures analysts who are already in strong positions, we focus on downward career changes. In particular, we test whether there is a negative relation between the trading volume a given analyst generates and the likelihood that the analyst is *demoted* to a smaller brokerage. We model analysts' demotion from their employers, using the following analyst-year logistic regression.

³² The results presented in Table 4 are robust to estimation using a fractional logit model, instead of an ordinary least squares model.

Fig. 1 Analyst Moves between Brokerage Houses

$$\Pr(\text{Demotion}_{it+1}) = d_0 + d_1 \text{Med. Volume Share Analyst}_{it} + \text{Controls} + e_{it}, \quad (3)$$

where we use two different measures for *Demotion*. Consistent with the approach of Hong and Kubik (2003), we use brokerage size, measured by the number of analysts it employs, as a proxy for prestige. The first measure, *Demote1_NextYear*, is a dummy variable that takes the value of 1 if, in the following year, the analyst moves to a brokerage house that is smaller than their current employer and 0 otherwise. The second measure, *Demote2_NextYear*, takes the value of 1 if the analyst moves from one of the largest brokerage houses (i.e., a brokerage that employs more than 25 analysts) to one of the smallest (i.e., one that employs fewer than 25 analysts) and 0 otherwise. We estimate the model both with and without controls for other dimensions of analyst performance that may affect their career moves, including forecast accuracy, herding, and optimism.³³

Table 5 presents the results of this analysis. We find that the volume share that the analyst creates is significantly and negatively associated with analyst demotions in all specifications. If an analyst generates more trading volume with their research, that analyst is less likely to move to a lower-status brokerage house in the following year. This remains true using either measure of demotion and with or without controls for forecast and analyst quality and optimism.³⁴ This creates a clear incentive, above and beyond any compensation related to trading commissions, for analysts to act strategically to increase trading volume.

³³ We observe a rate of demotions similar to Hong and Kubik (2003). In their data, roughly 1.5% of analyst-years include a move from a high-status to a low-status brokerage house (Hong and Kubik 2003, Table III, p. 321). In our sample, we find that 2.45% of analyst-years include a demotion to a smaller brokerage house, while 1.02% of the eligible analyst-years include a demotion from a “large” to a “small” brokerage house.

³⁴ Hong and Kubik (2003) find that bottom 10% relative forecast accuracy is positively (negatively) predictive of analysts moving to a lower-status (higher-status) brokerage house. Groyberg, Healy, and Maber (2011) find that analysts who move from the high-status investment bank they examine to a lower-status bank or exit I/B/E/S had lower prior-year forecast accuracy. While the coefficient on *Med. Current Accuracy* in Table 6 is insignificant, we find results similar to those of Hong and Kubik (2003) and Groyberg, Healy, and Maber (2011) under certain specifications—for example, ranking analysts over a wider period, such as [−360, −90] or [−360, −30]. Thus, in our sample, the relation between analyst forecast accuracy and demotion is sensitive to the definition of forecast accuracy used, with or without the inclusion of *Med. Analyst Volume* in the analyses. The coefficient on *Med. Analyst Volume* remains positive and statistically significant at the 5% level or better in all such variations, when included.

Table 4 Trading Volume Following an Analyst Move between Brokerage Houses**Panel A. Full Sample**

	(1) All Obs.	(2) Min 3 Firms Covered	(3) Min 5 Firms Covered
<i>Med. Volume Share Analyst_{ijt-1}</i>	0.139** [2.61]	0.120** [2.45]	0.147** [2.46]
<i>Med. Volume Share New Broker_{bjt-1}</i>	0.816*** [7.88]	0.814*** [7.81]	0.840*** [7.52]
Constant	-0.943 [-1.05]	-0.840 [-1.00]	-1.192 [-1.36]
Year FE	Y	Y	Y
Broker FE	Y	Y	Y
Observations	371	354	319
Adj. R-squared	0.609	0.646	0.660

Panel B. Cross-Sectional Analysis

	(1) High Current Accuracy	(2) Low Current Accuracy	(3) High Forecast Bias	(4) Low Forecast Bias
<i>Med. Volume Share Analyst_{ijt-1}</i>	0.177** [2.63]	0.064 [0.80]	0.161*** [2.91]	0.114 [1.50]
<i>Med. Volume Share New Broker_{bjt-1}</i>	0.903*** [12.57]	0.747*** [8.58]	0.889*** [10.00]	0.779*** [11.72]
Constant	-1.355* [-1.95]	-0.233 [-0.26]	-1.190 [-1.45]	-0.643 [-0.86]
Year FE	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y
Observations	171	183	177	177
Adj. R-squared	0.722	0.589	0.659	0.643

Table 4 examines a sample of analysts' moves between brokerage houses and whether *Volume Share* follows the analyst from the old brokerage to the new one. Panel A displays the results of ordinary least squares regressions, relating *Volume Share* of firm *j* covered by analyst *i* in year *t* to the analyst *Volume Share* in year *t* - 1 before the move and to the *Volume Share* of the new brokerage *b* covering firm *j* in year *t* - 1. Column 1 displays the results of all observations. Column 2 (3) displays results when the analyst forecasted a minimum of three (five) firms in both the old and new brokerage house.

Panel B displays results in the indicated subsamples. Column 1 (2) displays the results when analyst accuracy is higher (lower) than the median in year *t*-1. Column 3 (4) displays the results when analyst optimism is higher (lower) than the median in year *t*-1.

In both panels, the intercept term captures the average of the estimated values for the included fixed effects. Appendix 1 contains detailed descriptions of the variables. t-statistics are provided in parentheses, with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Analyst Volume and Subsequent Demotion

	(1) Demote1 Next Year	(2) Demote1 Next Year	(3) Demote2 Next Year	(4) Demote2 Next Year
<i>Med. Volume Share Analyst</i>	-0.0825** [-2.330]	-0.0806** [-2.282]	-0.180** [-2.088]	-0.180** [-2.028]
<i>Med. Current Accuracy</i>		-0.641 [-1.155]		-1.151 [-1.126]
<i>Med. # Forecasts</i>		-0.293 [-0.889]		-0.868 [-1.216]
<i>Avg. Herding</i>		-0.587* [-1.650]		-0.425 [-0.695]
<i>Avg. First</i>		0.197 [0.263]		-0.671 [-0.477]
<i>Med. # Firms Followed</i>		0.0433 [0.146]		0.527 [1.265]
<i>Med. Forecast Bias</i>		0.342 [0.496]		0.458 [0.662]
Constant	-2.882*** [-16.66]	-2.433*** [-5.275]	-2.429*** [-4.978]	-1.545 [-1.282]
Year FE	Y	Y	Y	Y
Brokerage FE	Y	Y	Y	Y
Observations	4,705	4,705	4,375	4,375
Pseudo R-squared	0.0568	0.0594	0.0642	0.0714

Table 5 displays the results of logistic regressions of indicator variables for demotion, Demote1_NextYear and Demote2_NextYear, on Med. Analyst Volume and a set of control variables. Demote1_NextYear takes the value 1 if the analyst moved to a smaller brokerage house in the following year, and 0 otherwise. Demote2_NextYear takes the value 1 if the analyst was in a large brokerage house (25 or more analysts) in the current year and moved to a small brokerage house (25 or fewer analysts) in the following year. All median or average variables are calculated on an analyst-year basis. Appendix 1 contains detailed descriptions of the variables. z-statistics are provided in parentheses, with standard errors clustered at the brokerage level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.4 Strategic bias

The results described in Sections 4.1 and 4.2 suggest that forecast optimism and accuracy creates trading volume, and the results reported in Section 4.3 indicate that analysts have an incentive to generate volume. In this section, we test whether analysts strategically bias their forecasts, strategically modify their accuracy, or both with the goal of generating trading volume. If an analyst is more (less) successful in generating trading volume with more optimistic forecasts, then they should be more (less) likely to issue optimistically biased forecasts in the future to generate trading volume. Similarly, if an analyst is more (less) successful in generating trading volume with more accurate forecasts, then they should be more (less) likely to strive to issue more accurate forecasts. We use *Forecast Bias (Current Accuracy)* as the dependent variable, and we examine whether forecast bias (accuracy) in one year relates to the analyst-specific

optimism (accuracy)-volume sensitivity from the prior year, while controlling for analyst-specific accuracy (optimism)-volume sensitivity from the prior year.

We limit our analysis to analysts who have a minimum of two years of data within our sample between the years 2011 and 2015. We also require that the analyst issued at least 30 forecasts in a given year to all firms she covered. This restriction allows for a more reliable estimate in the first stage, with a minimum of 30 observations for each regression. In the first stage, we estimate the following regressions for each analyst-year pair.

$$\text{Volume Share}_{ijt} = a_0 + a_1 \text{Forecast Bias}_{ijt} + a_2 \text{Current Accuracy}_{ijt} + e_{ijt}. \quad (4a)$$

The first stage measures how much trading volume each analyst was able to create using forecast bias and forecast accuracy. In the second stage, we use the analyst-year $\hat{a}_1$ and $\hat{a}_2$ coefficients estimated in the first stage, and we test whether analysts who have experienced optimism (accuracy) yielding higher trading volume are more optimistic (accurate) in the subsequent year. Conversely, we test whether analysts who have experienced optimism (accuracy) failing to generate trading volume are less optimistic (accurate). The second stage is estimated using the following pooled regression.

$$\text{Forecast Bias (Accuracy)}_{ijt+1} = b_0 + b_1 * \hat{a}_{1it} + b_2 * \hat{a}_{2it} + e_{ijt+1}. \quad (4b)$$

A significantly positive coefficient on b_1 indicates that the analyst is strategically updating optimistic bias—becoming more (less) optimistic if optimism has been more (less) successful in generating volume in the prior year. A significantly positive coefficient on b_2 has a similar implication for accuracy. The results of the second-stage regression are reported in Table 6. The results in Panel A (B) examine whether forecast bias (accuracy) in one year relates to the analyst-specific optimism (accuracy)-volume sensitivity from the prior year. Column 1 presents results in which we limit the sample in the first stage to analyst-years in which the analyst issued at least 30 forecasts. In Panel A, we can see that the coefficient on our variable of interest, $\hat{a}_{1it}$, is positive (0.001) and statistically significant at the 5% level in Column 1. Columns 2–4 present the results when we limit the sample in the first stage to analyst-years in which the analyst issued at least 50–100 forecasts. These more stringent restrictions serve two purposes. First, they increase the reliability of the estimation of the analysis. Second, they increase the likelihood that the analyst faces a large enough sample to learn and adjust behavior. Thus, both econometrically and conceptually, we expect a greater capacity to detect strategic updating when restricting our sample to analyst-years that contain more forecasts. The results are consistent with this. Panel A Column 4 shows the strongest effect. The coefficient on $\hat{a}_{1it}$ is equal to 0.01 and is statistically significant at the 1% level. The results show that optimism is increasing in prior-year optimism-volume sensitivity, suggesting that analysts strategically update their forecast optimism.³⁵

³⁵ Results presented in Panel A (B) control for prior-year volume-accuracy (volume-optimism) sensitivity. However volume-optimism and volume-accuracy sensitivity are negatively correlated at the analyst-year level: analysts who experience higher rewards to optimism typically experience lower rewards to accuracy. To ensure that this negative correlation is not driving results, we estimate the model without the inclusion of these controls. Results are similar.

Table 6 The Effect of Analyst Past Success in Creating Trading by Optimism and Accuracy on Analyst Future Optimism and Accuracy

	(1) Min of 30 Obs.	(2) Min of 50 Obs.	(3) Min of 80 Obs.	(4) Min of 100 Obs.
Panel A. Optimism				
$\hat{a}_{1it}$	0.001** [2.20]	0.002** [2.19]	0.003** [2.16]	0.010*** [4.17]
$\hat{a}_{2it}$	0.002*** [3.39]	0.002** [2.28]	0.001 [0.84]	0.003 [1.32]
Constant	0.503*** [525.73]	0.503*** [376.01]	0.508*** [191.74]	0.508*** [137.89]
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	108,047	80,861	38,969	21,717
Adj. R-squared	0.000159	0.000132	0.000256	0.00128
Panel B. Accuracy				
$\hat{a}_{1it}$	-0.000 [-0.43]	-0.000 [-0.41]	0.001 [0.37]	-0.004 [-1.40]
$\hat{a}_{2it}$	-0.000 [-0.12]	-0.000 [-0.04]	0.001 [0.59]	0.002 [0.99]
Constant	0.501*** [321.96]	0.498*** [258.01]	0.498*** [144.04]	0.497*** [104.15]
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	107,961	80,797	38,939	21,711
Adj. R-squared	0.000217	0.000313	0.000421	0.000353

Table 6 displays the results of the second stage of a two-stage least squares regression. The first stage tests whether the analyst can create trading volume from optimism and accuracy in their earnings forecasts. The regression is of the form $Volume\ Share_{ijt} = a_0 + a_1 Forecast\ Bias_{ijt} + a_2 Current\ Accuracy_{ijt} + e_{ijt}$ and is estimated for each analyst-year, yielding an analyst-year specific estimate of $\hat{a}_{1it}$ and $\hat{a}_{2it}$. We limit the sample to analyst-years for which the number of forecasts available to estimate the first-stage regression is at least 30, 50, 80, and 100 in Columns 1, 2, 3, and 4, respectively. The second stage tests whether the analyst has learned that optimism (accuracy) yields trading volume and becomes more optimistic (accurate) as a result. The results are presented in Panel A (B). The regression is of the form $Forecast\ Bias\ (Accuracy)_{ijt+1} = b_0 + b_1 \hat{a}_{1it} + b_2 \hat{a}_{2it} + e_{ijt+1}$ and is estimated across all analysts. The intercept term captures the average of the estimated values for the included fixed effects. t-statistics are provided in parentheses, with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results from the analysis of the effects of past accuracy creating trading volume on future accuracy are presented in Panel B. The coefficient of our variable of interest, $\hat{a}_{2it}$, is not statistically significant across any of the specifications. These results suggest that analysts are unable or unwilling to create more accurate forecasts even when more accurate forecasts in the prior year created trading volume. This is consistent with it requiring significantly more resources, time, effort, and access to management to increase accuracy than to increase optimism. It may be that analysts cannot update accuracy significantly in a single year, or it may be that the volume-related reward is insufficient to incentivize such an update.

4.5 Robustness tests

We conduct several additional analyses to examine the robustness of the results presented in Table 3. To control for time-varying broker-specific characteristics that could affect both the brokerage share of volume and analyst forecast characteristics, we include broker-year fixed effects instead of separate broker and year fixed effects. The results are presented in Table 7 Panel A columns 1–3. Column 1 includes only broker-year fixed effects. Column 2 includes both broker-year and firm fixed effects. Finally, Column 3 includes both broker-year and firm fixed effects and further excludes any firm-years with fewer than five analysts covering the given firm. Results for *Forecast Bias*, *Forecast Age*, and *Prior Accuracy* remain consistent across all specifications. The coefficients on *Current Accuracy* and *# Years Followed* are insignificant in the model without firm fixed effects, Column 1 but are otherwise significant. Overall, the relations between broker share of trading volume and forecast optimism and analyst quality appear robust.

One analyst incentive for optimistic recommendations is improving or maintaining access to management, which is valued by buy-side clients (Brown, Call, Clement and Sharp 2016). Chen and Matsumoto (2006) find evidence that optimistic recommendations improve access to management before Regulation Fair Disclosure (Reg FD). Mayew (2008), Soltes (2014), and Green, Jame, Markov, and Subasi (2014) all provide evidence that differential access to management persists even after Reg FD. If more optimistic analysts have better access to management, investors may reward the analyst's brokerage house with trading volume, due to greater access to management, rather than responding directly to the optimism in the recommendation.

While it is not clear how this incentive would translate to earnings forecasts, we conduct an additional test to assess whether access to management is driving results. Following Chen and Matsumoto (2006), we define the variable *Access*, which takes the value of one if the analyst's last recommendation prior to the most recent earnings announcement is larger than the consensus recommendation and the analyst's last earnings forecast before the prior earnings announcement is lower than the firm's actual earnings and zero otherwise. We then supplement Eq. 1 with this new variable, *Access*, or with both *Access* and the interaction between *Access* and *Forecast Bias*. Results are reported in Columns 4–5 of Table 7 Panel A. We find that the coefficient on *Access* is statistically insignificant in both models, the coefficient on the interaction term is insignificant, and the coefficient on *Forecast Bias* remains significantly positive in both models. Overall, these results suggest that the relation between brokerage share of volume and forecast optimism is not driven by analyst access to management.

Finally, following a recommendation in Ohlson (2019), we conduct an alternative analysis, similar to Fama-MacBeth regressions, to examine robustness. In the first step, we estimate Eq. 1 at the month level. We exclude firm, year, and broker-year fixed effects from Eq. 1. In place of firm fixed effects, we include firm controls: market value of equity, market to book, sales growth, R&D intensity, capital expenditures, leverage and return on assets. This first step results in 50 sets of regression coefficients (one for each month with sufficient observations). In the second step, we conduct a t-test for each of our main variables of interest to examine whether the coefficients differ from zero. Results are reported in Table 7 Panel B. Coefficients on *Forecast Bias*, *Prior Accuracy*, and *# Years Following* remain significantly positive, indicating that the associations between

Table 7 Effect of Analyst Characteristics on Brokerage Share of Trading Volume – Robustness Tests**Panel A. Brokerage–Year Fixed Effects and Management Access**

	(1)	(2)	(3)	(4)	(5)
	Broker–Year FE			Management Access	
<i>Forecast Bias</i>	0.101**	0.094*	0.100**	0.160***	0.178***
	[2.02]	[1.93]	[2.05]	[2.67]	[2.58]
<i>Buy x Ind_Rec</i>	0.117	0.134	0.126	0.267	0.267
	[0.79]	[0.92]	[0.86]	[1.48]	[1.49]
<i>Sell x Ind_Rec</i>	−0.353	−0.263	−0.250	−0.108	−0.107
	[−1.56]	[−1.21]	[−1.14]	[−0.41]	[−0.40]
<i>Target Optimism x Ind_Target</i>	0.171**	0.148*	0.147*	0.035	0.035
	[1.98]	[1.77]	[1.77]	[0.33]	[0.33]
<i>Ind_Target</i>	−0.018	−0.031	−0.031	0.064	0.063
	[−0.29]	[−0.55]	[−0.56]	[0.93]	[0.92]
<i>Ind_Rec</i>	0.090	0.038	0.036	−0.124	−0.125
	[0.93]	[0.41]	[0.39]	[−1.09]	[−1.10]
<i>Current Accuracy</i>	0.087	0.120**	0.118**	0.184***	0.183***
	[1.59]	[2.20]	[2.18]	[2.84]	[2.83]
<i>Herdling</i>	−0.019	−0.030	−0.024	−0.029	−0.029
	[−0.63]	[−1.07]	[−0.86]	[−0.85]	[−0.84]
<i>First</i>	−0.120	−0.067	−0.063	−0.130	−0.128
	[−1.20]	[−0.72]	[−0.67]	[−1.23]	[−1.22]
<i>Forecast Age</i>	0.164***	0.125**	0.125**	0.094	0.095
	[2.72]	[2.18]	[2.19]	[1.33]	[1.35]
<i>Prior Accuracy</i>	0.236***	0.214***	0.189***	0.192**	0.192**
	[2.88]	[2.99]	[2.65]	[2.40]	[2.40]
<i># Forecasts</i>	0.016	0.073	0.081	0.173	0.173
	[0.18]	[0.74]	[0.82]	[1.41]	[1.41]
<i># Years Followed</i>	0.100	0.175**	0.174**	0.141	0.141
	[1.14]	[2.09]	[2.09]	[1.26]	[1.26]
<i># Firms Followed</i>	0.242*	0.078	0.089	−0.016	−0.016
	[1.88]	[0.66]	[0.76]	[−0.11]	[−0.11]
<i># Analysts Following</i>	−0.018***	−0.009*	−0.008*	−0.010	−0.010
	[−3.39]	[−1.74]	[−1.67]	[−1.58]	[−1.58]
<i>Access to Management</i>				−0.046	−0.004
				[−0.69]	[−0.04]
<i>Access to Management *Forecast Bias</i>					−0.086
					[−0.59]
Constant	10.186***	10.066***	10.063***	11.333***	11.324***
	[40.78]	[43.47]	[43.44]	[45.59]	[45.41]
Firm FE		Y	Y	Y	Y
Broker FE				Y	Y
Year FE				Y	Y

Table 7 (continued)

Broker-Year FE	Y	Y	Y		
Observations	60,468	60,468	60,287	39,189	39,189
Adj. R-squared	0.527	0.574	0.576	0.572	0.572
Panel B. 2–Stage Analysis					
	N	Mean Coefficient	t-Statistics	Pr > t	% Positive Coefficients
Optimism Measures					
<i>Forecast Bias</i>	50	0.2293	3.41	0.0013	68%
<i>Buy x Ind_Rec</i>	50	−0.1732	−0.53	0.6011	60%
<i>Sell x Ind_Rec</i>	50	−0.7811	−2.98	0.0045	28%
<i>Target Optimism x Ind_Target</i>	50	0.2723	2.83	0.0068	70%
<i>Ind_Rec</i>	50	0.1861	1.03	0.3087	50%
<i>Ind_Target</i>	50	−0.0871	−1.33	0.1903	44%
Forecast Quality Measures					
<i>Current Accuracy</i>	50	0.0725	0.62	0.5353	52%
<i>Herding</i>	50	−0.0248	−0.71	0.4815	40%
<i>First</i>	50	−0.0109	−0.05	0.9584	38%
<i>Forecast Age</i>	50	0.4866	1.40	0.1667	54%
Analyst Quality Measures					
<i>Prior Accuracy</i>	50	0.1958	2.87	0.0060	70%
<i># Forecasts</i>	50	−0.0733	−0.88	0.3827	48%
<i># Years Followed</i>	50	0.1170	1.95	0.0570	54%
<i># Firms Followed</i>	50	0.1467	1.54	0.1302	60%
<i># Analysts Following</i>	50	0.1670	1.67	0.1011	68%

Table 7 Displays the results of robustness analysis. Panel A displays the results of ordinary least squares regressions, relating *Volume Share* to analyst optimism variables, forecast quality variables, and analyst quality variables, for dates on which an earnings forecast is issued. Columns 1–3 display the results including Broker-Year FE. (Column 3 excludes observations where the firm is covered by fewer than five analysts in a fiscal year.) Columns 4–5 displays the results controlling for *Access to Management*. The intercept term captures the average of the estimated values for the included fixed effects. Appendix 1 contains detailed descriptions of the variables. t-statistics are provided in parentheses, with standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel B displays the results of a two-stage analysis, similar to Fama-MacBeth analysis. In the first step, we estimate Eq. 1 (without firm and year fixed effects) at the month level. In place of firm fixed effects, we include firm controls: market value of equity, market to book, sales growth, R&D intensity, capital expenditures, leverage and return on assets. The first step results in 50 sets of regression coefficients (one for each month with sufficient observations). In the second step, we conduct a t-test for each of our main variables of interest to examine whether the coefficients differ from zero.

brokerage share of volume and forecast optimism and analyst quality are robust over time. Results for forecast quality, however, are not robust to this alternative approach.

Overall, the relations between forecast bias and analyst quality, as measured by prior-year-accuracy, and brokerage share of trading volume are strongly robust.

Statistical significance of the coefficients on other quality variables are more sensitive to specification and controls but remain largely consistent with those reported in Table 3.

5 Conclusion

We examine the potential conflict of interest derived from one of the primary funding mechanisms for modern sell-side security analysis: brokerage trading commissions. We find that optimism in earnings forecasts is associated with a higher brokerage share of trading volume, even after controlling for forecast and analyst quality, recommendations, and target prices. This statistically and economically significant association is consistent with analysts' incentive to optimistically bias their research, which is also consistent with the theoretical predictions of Beyer and Guttman (2011). However, we also find that forecast and analyst quality are associated with a larger brokerage share of trading volume, with similar economic magnitudes for the effects of optimism and quality.

We address whether analysts drive the increased brokerage share of volume by examining analyst moves across brokerage houses. We find that, when an analyst changes brokerage houses, the new brokerage house earns a brokerage trading volume that is consistent with the analyst having a causal effect on the brokerage's share of volume.

Furthermore, we examine analysts' incentives to generate volume by examining their career progress. We find that analysts who generate more trading volume for their brokerage houses are less likely to move to a lower-status firm in the subsequent year. Failure to generate volume increases the likelihood of demotion to a lower-status brokerage house. Thus analysts are incentivized to generate trading volume, even if they are not directly compensated for it.

Finally, we examine whether analysts strategically update their optimism and accuracy in response to volume-generation incentives. We find that analysts become more (less) optimistic if their prior-year experience demonstrated that optimism is more (less) successful at generating volume, consistent with strategic updating of optimism. However, we find no evidence for strategic updating of accuracy.

Taken together, our evidence points to a conflict of interest that can at least partially explain analysts' optimistic earnings forecasts. This paper is relevant for researchers in accounting, finance, and economics, as our findings speak to the incentives of sell-side analysts, whose research impacts stock prices, investor behavior, and the information environment of firms. Our results also speak to a more general issue: the potential disciplining effect of incentives generated by customer behavior. The link between analyst research and trading volume is not automatic; it is decided by brokerage customers (i.e., investors). Certain features of these customers (in this case, risk aversion and short sale constraints) can lead to incentives for bias. However, customers can also reward quality and thus incentivize analysts to produce valuable research. This tension between incentives for bias and incentives for quality will likely be found in other settings in which customers choose how to reward service providers.

Last, these results have relevance for current policy questions in the era of MiFID II. We can measure only the direct trading volume around an analyst's research; therefore the full economic magnitude of commissions-related incentives is likely even larger than the measurement we find in this study. Our findings also lend some credence to

institutional investors' claims that commissions serve as an incentive for brokerage houses to produce high-quality research, given the results for our forecast and analyst quality variables; however, this incentive may not be sufficient to drive analyst behavior. The impact of MiFID II unbundling on incentives toward optimism and quality will be an important question for future research.

Appendix 1 Variable Definitions

Volume Share Variables

Volume Share The sum of the share volume traded in firm j over the $[-1, 5]$ trading-day window by brokerage k divided by the sum of the total number of shares traded in firm j over the same $[-1, 5]$ trading-day window, multiplied by 100. $[(\text{sum daily brokerage volume over } [-1, 5]) \div \text{sum total volume over } [-1, 5]) \times 100]$. Day 0 is the day the analyst issued the research.

Med. Volume Share Analyst The median *Volume Share* (as defined above) for analyst i in year t covering firm j .

Med. Volume Share New Broker The median *Volume Share* (as defined above) for broker b in year t covering firm j .

Optimism Variables

Forecast Bias $(\text{EPS Forecast}_{i,j,t} - \text{EPS Actual}_{j,t}) \div \text{Price}_{j,t}$; EPS Forecast i,j,t is analyst i 's forecast at time t for company j . This forecast is then compared to actual EPS. This difference is divided by the price per share for company j at the end of fiscal year t . The measure is ranked into 10 deciles between 0 and 1 for all analysts covering firm j in year t .

Buy Indicator variable that receives the value of 1 if the analyst issued a *strong buy* or a *buy* recommendation and 0 otherwise.

Sell Indicator variable that receives the value of 1 if the analyst issued a *strong sell* or a *sell* recommendation and 0 otherwise.

Target Optimism Price target of analyst i for company j divided by the prior trading day's price. The measure is ranked into 10 deciles between 0 and 1 for all analysts covering firm j in year t .

Ind_Forecast Indicator variable that receives the value of 1 if analyst i issued an EPS forecast for company j and 0 otherwise.

Ind_Rec Indicator variable that receives the value of 1 if analyst i issued a recommendation for company j and 0 otherwise.

Ind_Target Indicator variable that receives the value of 1 if analyst i issued a target price for company j and 0 otherwise.

Forecast Quality Variables

Current Accuracy $|(\text{EPS Forecast}_{i,j,t} - \text{EPS Actual}_{j,t})| \div \text{Price}_{j,t}$; The measure is ranked separately for three different time horizons: [0, 90], [91, 180], and more than 180 days until the earnings announcement. Following Hong and Kubik (2003), the measure is divided by 100, to range between 0 and 1 as follows: $\{100 - [(\text{rank} - 1) \div (\text{number of analysts} - 1)] \times 100\} \div 100$. The measure uses all forecasts made for firm j in year t in each of the three different time horizons.

Herding Indicator variable that receives the value of 1 for forecasts that are between the analyst's own prior forecast and the consensus forecast (the consensus is calculated as the median outstanding forecast for company j made within 90 days from analyst i forecast) and 0 otherwise.

First Indicator variable that receives the value of 1 for the first EPS forecast made by analyst i for company j in year t and 0 otherwise.

(continued)

<i>Forecast Age</i>	The number of days the EPS forecast, target, or recommendation was made before the closest earnings announcement date, divided by 365.
<i>Analyst Quality Variables</i>	
<i>Prior Accuracy</i>	Calculated similarly to <i>Current Accuracy</i> , but using the latest forecast made in the $[-90, 0]$ day window before the earnings announcement for year $t-1$.
<i># Forecasts</i>	The number of forecasts issued by analyst i following firm j in year $t-1$ minus the minimum number of forecasts issued by analysts who follow firm j in year $t-1$, with this difference scaled by the range of the number of forecasts issued by analysts who follow firm j in year $t-1$.
<i># Years Followed</i>	A measure of analyst i 's firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year $t-1$, minus the minimum number of years of firm-specific experience for analysts who follow firm j in year $t-1$, with this difference scaled by the range of years of firm-specific experience for analysts who follow firm j in year $t-1$.
<i># Firms Followed</i>	A measure of the number of companies that analyst i follows in year $t-1$. It is calculated as the number of companies followed by analyst i following firm j in year $t-1$, minus the minimum number of companies followed by analysts who follow firm j in year $t-1$, with this difference scaled by the range in the number of companies followed by the analysts who follow firm j in year $t-1$.
<i># Analysts Following</i>	The number of analysts who cover firm j at time $t-1$.
<i>Brokerage Statistics</i>	
<i>Sum Volume</i>	The sum of the daily volume of shares traded by brokerage k in year t , in billions.
<i>Brokerage Size</i>	Number of analysts employed by brokerage k in year t .
<i>Percent of Underwriting</i>	The ratio of the total dollar amount of U.S. equity underwriting deals a brokerage participated in year t to the total dollar volume of U.S. equity offerings (as reported by Bloomberg) in year t , multiplied by 100.
<i>Shares per Revenue Dollar</i>	The ratio of the total number of shares traded by a brokerage divided by the total net revenue of the brokerage in year t .
<i>Analyst Demotion Variables</i>	
<i>Demote1_Next Year</i>	Indicator variable equal to 1 if the analyst moved from a larger to a smaller brokerage in the following year and 0 otherwise.
<i>Demote2_Next Year</i>	Indicator variable equal to 1 if the analyst moved from a brokerage with greater than or equal to 25 analysts to one with less than 25 analysts in a given year and 0 otherwise.

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