FinTechs and the Market for Financial Analysis*

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ABSTRACT

Market intelligence FinTechs streamline and synthesize many data sources, including non-traditional ones, relevant for equity investment decisions. Using novel data on such FinTechs and investors' internet history, we evaluate their relationship with investors' behavior, traditional information producers, and market efficiency. We find a significant substitution between the investors' use of traditional information sources and FinTechs. Second, an associated crowd-out effect reduces the quality of the information provided by sell-side analysts, the traditional information producers, suggesting investors are prudent to look to FinTechs for investment recommendations. Finally, the increased use of these FinTechs result in an overall increase in price informativeness.

JEL classification: G1, G2, O3, D14, G11, G14, G23, O35

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"With 80% of the data in the world created in the last two years, judgment matters more than ever. Technology is a complement to sound judgment and knowledge, not a substitute."

— Joyce Chang, Global Head of Research, J.P. Morgan, September 2017

I. Introduction

Technology is changing how information is produced and discovered in financial markets. Yet the sheer quantity of information available is making it more difficult for investors to extract what matters most. To combat information overload and restore effective decision-making when one has too much information, market intelligence FinTechs[1] are streamlining and synthesizing many data sources relevant for equity investment recommendations. Yet by aggregating information, FinTechs have the potential to distort the incentives of those that produce information, and thereby, the quality of information that is being extracted.

Our study considers how FinTechs are changing investors' behavior and the possibility that some unintended consequence of this information aggregation could actually reduce the information content in prices from traditional information-producers. We explore the implications of FinTech entry in three different ways. First, at the investor level, we analyze internet click data to determine if FinTechs are changing the way financial advice is discovered online and potentially diverting attention from original-content financial analysis. Second, at the data-producer level, we analyze the quality of analysts' research reports as a function of FinTech coverage. And third, at the market level, we analyze how price informativeness and market reactions to analysts' recommendations change with FinTech entry.

Understanding the response to FinTech entry is important for at least three reasons. First, FinTechs significantly disrupt the information environment. As is illustrated in Figure 1, FinTech use has steadily risen in the last decade to 20% of U.S. households, but this change comes with a big decrease in visits (31%) and page views (17%) to websites with traditional financial information. Given that FinTechs are already a force to be reckoned with, this means they are likely changing

[1] Financial technology firms or FinTechs cover digital innovations and technology-enabled business model innovations in the financial sector (Philippon (2016)). In this paper, we focus on market intelligence FinTechs, referring to them simply as "FinTechs" throughout the paper. They represent a single segment among many in the FinTech space. Sometimes these market intelligence FinTechs get categorized into wealth management or capital market FinTechs as static delineation is blurred in this rapidly evolving space.

the incentives of traditional information producers, namely, sell-side analysts. Most importantly, this means FinTechs could also be changing price efficiency. In an ideal financial market prices fully reflect available information, and thereby, the prices provide accurate signals for investors to allocate capital (Fama (1970); Bond, Edmans, and Goldstein (2012)). While efficient outcomes depend on the accuracy of information, gains to informational efficiency since 1960 have been modest (Bai, Philippon, and Savov (2016)). FinTechs have the potential to disrupt this status quo and create positive change. By revolutionizing how information is produced and delivered, FinTechs could help investors make better decisions by allowing them to sieve through the noise. Yet FinTechs function as "aggregators" may be counterproductive. Our analysis considers the potential for both positive and negative disruption.

As a motivating example of how aggregation could have negative effects, consider what happened when the movie ticketing firm Fandango integrated the score from Rotten Tomatoes into its platform. Ticket sales plummeted for movies receiving low scores because consumers relied on the aggregated score. Yet some of the movies received critical acclaim from prominent reviewers, but consumers did not realize this because Rotten Tomatoes aggregates reviews from bloggers and YouTubers too. This aggregation feature lowers the informativeness of the overall score. It also incentivizes prominent reviewers when treated as the equals of YouTubers to generate less accurate reviews moving forward (New York Times (2017)). As a second example of the aggregation criticism, consider the election forecasting errors for Clinton-Trump. Slate (2016) argues when people pay more attention to Nate Silver's FiveThirtyEight forecast than to individual polls, the pollsters cater to a particular candidate and bias the poll in favor of that candidate.

The Rotten Tomatoes example is just one of many channels through which the entry of firm that aggregates and streamlines information could change the incentives of market incumbents. What is important to emphasize is that unlike traditional competition which has a disciplinary effect on incumbents, FinTechs have the potential to influence incumbents in a non-disciplinary way. This stems from how FinTechs provide investors with information. In practice, FinTechs typically use computer algorithms to condense the vastly expanded set of financial information into a buy or sell recommendation. As an example consider FirstAccess; they "turn big data into smart data, by separating the signal from the noise and delivering simple, reliable investment recommendations." Another approach is to present "unbiased" information by evaluating and/or ranking information. As an example consider TipRanks; they provide a platform that allows investors to see a ranking of the historical performance of anyone who could be considered a financial expert (i.e., analysts, bloggers, corporate insiders, hedge fund managers, etc.).

These two different approaches to streamlining information matter because they have the potential to change the incentives of those that traditionally produce information about equities. The FinTechs that only provide a signal divert attention from traditional information-producers, but those that rank information could increase attention, especially on those that provide the best information. By increasing or decreasing the attention paid to traditional information-producers, these FinTechs could, in turn, generate changes in the production of financial information. Specifically, producers of financial information such as sell-side analysts could respond with more or less effort, ultimately, increasing or decreasing the quality of their reports. Thus, from a theoretical perspective, the entry of FinTechs is more complicated than the competition that stems from increasing the supply of analysts.

This idea that FinTechs could level the playing field and alter private information production is akin to theoretical arguments from the literature on optimal information disclosure (e.g., see reviews by Bond, Edmans, and Goldstein (2012) and Goldstein and Yang (2017)). While the disclosure literature suggests that FinTechs could crowd-out the production of private information and decrease market efficiency, it is unclear if FinTechs necessitate the same logic. There are several reasons to believe FinTechs are their own distinct phenomenon (Philippon (2016)). For example, FinTechs introduce the possibility that trustworthy non-traditional information producers could be identified and that potential investors who were previously excluded from the market could participate and bring their own private information to the market when they join. In this sense, even if the overall quality of some information-producers declines because of the crowd-out effects predicted by the disclosure literature, the overall effect on market efficiency from FinTechs is likely positive.

To disentangle these theoretical alternatives, data is necessary. One of the purposes of this paper is to gather a large, comprehensive database on FinTechs, non-traditional sources of financial analysis, and investors' internet use that allows us to explore these issues. To gather data on FinTechs we hand-collect information from Crunchbase, FinTech award lists, and current and historical versions of the FinTechs' websites. Commentary suggests 2007 is the year when cloud computing and processing power improved enough to make data intelligence start-ups viable (Friedman (2016)). Consistent with this timeline, for the 290 FinTechs we observe, the mean founding year is 2008. The most common capabilities for these FinTechs are aggregating financial news (83% do this), datamining for investment signals (57% do this), evaluating and ranking existing financial advice (27% do this), crowdsourcing financial advice (16% do this), and aggregating financial experts' opinions (11% do this). 72% of the FinTechs target retail investors and 60% target professional investors with some targeting both. Our analysis suggest these equity FinTechs are able to raise capital, which is consistent with venture capital reports indicating large investments in this space, although the capital allocated toward market intelligence FinTechs like the ones we study totals much less than those going to payments or lending technologies (Accenture (2018)).

The most common sources of non-traditional analysis is financial blogs and social media. Given that we are interested in the blogs that people actually read, we first matched a larger sample of blogs to internet click data from ComScore, which provides the most comprehensive data of this type available for Americans. To be included in our sample, at least one internet user tracked by ComScore had to visit the financial blog. Our data indicate that these investors want equity recommendations and they want that information quickly. While 90% of financial blogs that investors visit do not make buy or sell recommendations, investors strongly prefer to visit financial blogs that make equity recommendations. The financial blogs with stock recommendations rank 40 percentiles above blogs without stock recommendations in terms of pages visits and dwell time.

Next, to understand if the quality of stock recommendations from non-traditional sources, we examine 1.3 million blog posts analyzed by FinTechs between 2010 and 2017. This data comes from TipRanks, a FinTech operating in this space. First, it shows the typical blog post can be several paragraphs long and similar in nature to an equity analysts' report. But when we match this data with the ComScore data, we learn that investors rarely consume the whole report. In a given month, the average investor views 16 financial blog posts in only 6.6 minutes. The low dwell time per page may stem from the noisy nature of the analysis provided by bloggers. Our analysis of the 1.3 million blog posts across the 20 financial blogs that make buy-sell recommendations shows that 90% of the time, the market-adjusted returns to bloggers' recommendations were negative at an investment horizon of 6 or 12 months.

At the investor level, we find that investors are 31 percentage points less likely to visit an original-content website when they also visit a FinTech website. Among those who do visit an original content website, they cut their page views by 17% and spend 5% less time on those websites. This evidence suggests that FinTechs can have a meaningful economic effect on market quality through this investor channel. But these results also suggests that FinTechs act as a substitute for the reading of traditional financial analysis. Thus, this finding also suggests the potential for meaningful feedback effects onto the production of information by incumbents. Thus, to determine the overall effect on market quality, we next examine the relationship between FinTechs and traditional information producers (i.e., sell-side analysts).

We proxy for FinTech coverage using the quantity of non-traditional sources that also provide financial analysis on that stock. We examine two important attributes of analysts' reports: (1) aggregate earnings forecast accuracy and (2) aggregate optimism bias. We use an instrumental variable (IV) approach to test for analysts' responses. The IV approach helps to address the challenge that FinTech coverage is not randomly assigned. The ideal instrument is one that varies the amount of non-traditional information on an equity without impacting an analysts' reporting quality.

Our IV uses the insight that bloggers follow what's popular, often only adding their own commentary. While popularity is not random, variation in popularity can come from things that are quasi-random. For example, using a randomized experiment, Umar (2017) showed that internet users are more likely to click on an article when the title is short even when the information content is exactly the same. We build on this short title idea. Using data from RavenPack, our IV is an indicator for an equity having newspaper headline lengths below the median headline length. Unsurprisingly, weak instrument tests suggest this short-title instrument is associated with increased blogging, which is consistent with bloggers chasing popularity. This IV plausibly satisfies the exclusion restriction because title length is assigned by an editor in a way that is independent of an articles content. To further test if headline length is quasi-random, we regress headline length on firm characteristics for over 7 million articles and find no evidence of selection. This also holds true when we use variable selection techniques to determine the words associated with headline length; the words do not convey content. Finally, by controlling for total newspaper coverage, we ensure the IV captures incremental popularity differences.

Using the IV strategy, we find analysts respond to FinTech entry by reducing their reporting quality. We find higher aggregate absolute forecast errors and more optimistic bias for analysts where FinTechs concentrate. A one standard deviation increase in FinTech concentration is associated with a 0.14 standard deviation increase in aggregate optimistic bias and a 0.23 standard deviation decrease in forecast accuracy. To put this number in context of prior research, we compare our point estimate to that of other standard covariates in the literature (i.e., analyst coverage, firm size, recent stock returns) and we see that FinTech coverage ranks in the middle relative to other variables used to explain analyst reporting quality. When we focus on the highest quality alternative information, defined as non-traditional investment recommendations that generate positive abnormal returns, we find the vast majority of the association between FinTech coverage and analyst reporting quality is attributable to the incorporation of high quality alternative information.

So far, our evidence depicts a tension between the investor channel of FinTechs which through participation increases market efficiency and the analyst channel which through lower reporting quality decreases market efficiency. Thus, in our third step, we examine if the market reacts differently to analysts' recommendations where FinTechs concentrate. We find weaker market reactions in terms of both excess returns and volume where FinTechs concentrate. We then perform a placebo test that allows us to compare analyst-equity pairs before and after the entry of FinTechs, and again we find less responsive to analyst recommendations even using such a within-comparison. As a final test, we create a measure of analysts' contribution to price informativeness using the share of size-adjusted returns for an equity that occur on the days when analysts update their forecasts. We observe a decrease in analysts' contribution to price informativeness where FinTech coverage is highest. Overall, these results suggest that indeed analysts' information has less impact on prices, possibly because more information is impounded in prices even before they changes their recommendations, consistent with increased price efficiency.

To further understand the aggregate contribution of FinTechs, we analyze how price informativeness and analysts' contribution to price informativeness vary with FinTech coverage. We measure price informativeness using price nonsynchronicity, a common measure of market quality (Roll (1988); Durnev et al. (2003)). We observe an increase in price informativeness in the stocks where FinTech coverage is highest. While our IV specification and control variables help to recover an unbiased point estimate, we probe the robustness of this finding using an alternative measure. Namely, we examine the price jump ratio (Weller (2018)), which is a better measure of efficiency that accounts for changes brought about by algorithmic trading. We find evidence of significant improvements in market quality for stocks with both high and low price jump ratios. Overall, our evidence suggests the dissemination of information channel dominates the negative effect brought about by reductions in the information content of the traditional information providers.

As a final test, we assess three possible channels through which FinTechs influence equity analysts: change in analysts' talent pool and effort. If the lower reporting quality stems from a change to the talent pool for analysts, this would be more difficult to reverse, suggesting any unintended consequences would take time to fix. In contrast, an effort problem can likely be fixed faster. The best analysts are quitting and leaving the profession, which suggests a permanent reduction in the quality of analysts' reports rather than a strategic response.

Overall, our study extends FinTech research (Philippon (2016)). By examining the economic implications of market intelligence FinTechs, our research helps to show where they parallel and diverge from related phenomenon. FinTechs are comparable to internet news aggregators in that they both change how information is consumed (Chiou and Tucker (2015); Calzada and Gil (2016)). The non-traditional data sources that are being analyzed by FinTechs rarely provide good investment advice which is consistent with prior research (Tumarkin and Whitelaw (2001); Antweiler and Frank (2004) Das and Chen (2007); Cookson and Niessner (2017)). While crowd-sourced advice can be useful (Jame et al. (2015); Da and Huang (2017)), we show this is an uncommon feature of

FinTechs. In fact, our evidence suggests that, on average, FinTechs crowd-out private information production by decreasing the reporting quality of analysts. This finding parallels the information disclosure literature (Bond, Edmans, and Goldstein (2012); Goldstein and Yang (2017)) in that both generate crowd-out effects. This findings diverges from research on competition and bias. FinTechs do not produce the same incentives for analysts that more analysts do (Hong and Kacperczyk (2010); Berger, Ham, and Kaplan (2016)). This finding also helps to explain the forces shaping analysts' recommendations (Hong and Kubik (2003); Barber, Lehavy, and Trueman (2007); Fang and Yasuda (2009); Merkley, Michaley, and Pacelli (2017)). By showing FinTechs improve market quality, we relate to work on big data (Dugast and Foucault (2017); Zhu (2018)) and equity market efficiency (Durnev, Morck, and Yeung (2004); Bai, Philippon, and Savov (2016)), as well as research examining the impact of financial innovation (Allen and Gale (1994)) on mortgage markets (Fuster et al. (2018); Bartlett et al. (2018)) and bond markets (Grennan and Musto (2017)). Such market improvements have meaningful consequences for investment (Goldstein, Ozdenoren, and Yuan (2013); Dow, Goldstein, and Guembel (2017)).

II. Data

A. Market Intelligence FinTechs

To generate a comprehensive list of market intelligence FinTechs, we use three techniques. First, we search for relevant business descriptions on Crunchbase, a database of company information where the firms range from early-stage ventures to Fortune 500 firms. Specifically, business category is a variable in Crunchbase, so we include all firms that categorized as "FinTech," "Aggregator," or "Crowdsourcing," etc .... Similarly, Crunchbase also lists business descriptions, which are typically about 3-4 sentences long, and we do a key word search of the business descriptions. Second, we search the internet for "Best of" FinTech lists. For example, we extract firm names from the Finovate conference series focused on financial and banking technology innovations that began in 2007. Similarly, we extract firm names from the FinTech 100 list, which is a collaboration between FinTech investment firm H2 Ventures and KPMG. Third, we use Google search to identify potentially relevant firms again using keyword searches. Based on our initial list of potentially relevant FinTechs (1400 firms), we then examine each firm's website to gather additional information about its' business and confirm that it provides a service that is relevant to the market for financial analysis. This process reduces potential measurement error from business descriptions in Crunchbase not matching the actual services provided. To reduce measurement error from survivorship bias and business plan adaptations, we use Wayback Machine to examine earlier versions of potential FinTech websites. This allows us to include a firm even if it got acquired or stopped being a market intelligence FinTech.

For each FinTech, data is collected on attributes of the business such as what the firm does, its intended user, and if it specializes in only a specific type of stock or industry. Table I summarizes our sample of FinTechs and provides a high-level overview of their businesses. We observe 290 FinTechs operating in the market for financial analysis. We categorize the business operations of these FinTechs into: (1) those that aggregate and synthesize data from financial experts (e.g., sell-side research analysts and/or financial bloggers), (2) those that aggregate financial news, (3) those that crowdsource equity recommendations, (4) those that datamine financial analysis and news for investment signals, and (5) those that rank and evaluate existing financial commentary. These categories are not mutually exclusive. To be included in our sample, a FinTech's capabilities must include at least one of these functions.

As an example of a firm that aggregates data from financial experts, consider `benzinga.com`, which describes itself "a hub for actionable information on capital markets." Whenever sell-side analysts take action (e.g., initiate coverage, revise a price target, reiterate a rating, etc.), Benzinga condenses that action into to a short write-up about five sentences long with info on the analyst, their thesis, and any actions to take. Then, Benziga provides a daily summary with one sentence blurbs about their "top rated" changes from sell-side analysts. Benzinga also aggregates financial news by providing a free newsfeed (i.e., frequently updated headlines with links to content covering the most current financial news).

When FinTechs provide a newsfeed, they typically also try to sell a related product or service associated with the newsfeed. The three most common add-ons are: (i) a stock screening tool, (ii) a wealth management service, and (iii) an investment signal derived via datamining. For example, Benzinga also has "Benzinga Pro" which is a paid streaming service with additional features like sentiment indicators based on the news for each equity and real-time buy/sell alerts. Given that creating a sentiment indicator requires natural language processing (NLP) algorithms to aggregate and analyze the news. It is important to note that FinTechs do not need to have a free newsfeed. For example, tradethenews.com provides a similar service but markets its comparative advantages as speed (providing information that moves markets before markets move) and depth of coverage (capturing harder-to-cover news in real-time such as live transcripts of speeches). Speed can be contentious, so FinTechs often combine that feature with other services. For example, flyonthewall.com was sued by several investment banks for publishing analysts' reports when they came out (Bradley, Clarke, and Zeng (2018)). The FinTech survived a court-ordered injunction that prevented it from continuing to provide such information by offering other features.

FinTechs that datamine to provide equity investment signals exhibit significant heterogeneity in terms of how they get to the signal. These firms differentiate their signals by the degree of customization, the frequency, and the sources of data being analyzed. For example, some FinTechs offer custom signals where investors provide their list of equities and receive daily buy-sell alerts based off of selected data sources, including unstructured data such as satellite images and/or sensor data. Other firms provide lower-frequency signals which try to capture harder-to-measure aspects of future firm performance such as consumers' mindest about that firms brand. While sources of data can vary widely, the most common data sources being analyzed by FinTechs in this space are financial news, financial commentary (e.g., financial blog posts), and data from social media. For example, dataminr.com markets itself as removing the middle-man by providing the market-moving information that breaks on social media first. Such signals can be derived from text of social media or semi-structured social media data such as number of retweets or who accessed the shared content.

An additional offering from FinTechs in this space is the ranking or evaluation of financial commentary. Supported by academic research, there is a notion that much of the existing financial advice is heterogeneous in its quality and biased (Barber et al. (2001); Loh and Mian (2006); Michaely et al. (2018)). Rather than just providing a signal based on the accurate information, some firms rank and evaluate the quality of financial commentary. For example, tipranks.com provides a platform that allows investors to see a ranking of the historical performance of anyone who could be considered a financial expert (i.e., analysts, bloggers, corporate insiders, hedge fund managers, investment advisors, etc.).

While many of the FinTechs in this space aggregate financial commentary and then streamline it or datamine it for signals, others aggregate to find more accurate or representative views via the "wisdom of crowds" phenomenon. Commonly referred to as crowdsourcing investment advice, FinTechs like estimize.com, collect forward-looking financial estimates from members, who are typically analysts and retail investors, and allow those that contribute to see others recommendations. Crowdsourcing is not just limited to forward-looking financial estimates. For example, slingshotinsights.com groups members together into potential investment ideas and then they work together to perform due diligence and leverage their collective nature to get interviews with management.

In summary, as is shown in Table I, the most common capabilities of FinTechs are aggregating financial news (83% do this), datamining for investment signals (57% do this), and evaluating and ranking existent financial advice (27% do this). Column (2) shows the mean founding year of FinTechs in our sample is 2008, which is consistent with commentary suggesting the technology for datamining signals became more manageable around then (Friedman (2016)). Column (3) and (4) reveal that 72% of FinTechs target retail investors and 60% target professional investors with some targeting both. Among the different business functions, FinTechs that crowdsource financial advice primarily target retail investors (89%) while those that datamine primarily target professional investors (70%). Column (5) shows that one-in-five FinTechs focus only on a specific type of stock such as consumer goods rather than try to cover all stocks. Columns (6) through (8) demonstrate that many of these FinTechs are credible businesses in the eyes of the investment community. With the average FinTech in the market for financial analysis raising $10.4 million from 4.8 investors and employing 74 workers. Overall, our analysis of these FinTechs business plans reveals that a key feature is that they aggregate and streamline pre-existing financial analysis, commentary, news, and other non-traditional sources of data.

B. Financial Analysis Online

One of the most common sources of financial analysis that investors read online is financial blogs. The information contained in financial blogs is also commonly aggregated by FinTechs. In our main analysis, we use the quantity of financial blogging as our primary proxy for FinTech coverage. While financial blogging is not representative of all non-traditional data sources that encompass big data, financial blogging does provide insight as a proxy for quantify the amount of non-traditional information that FinTechs aggregate and synthesize. As such it is important to understand what financial blogs are being read, why they are being read, and the quality of financial commentary that is being aggregated by these FinTechs.

In order to quantify the information contained in financial blogs, we needed a comprehensive list of financial blogs. We used two approaches. First, we received all the financial blog data collected by the FinTech firm TipRanks, which collects data from financial bloggers that either implicitly or explicitly make equity recommendations. Buy or sell equity recommendations are implicitly derived with a NLP algorithm of financial blogs posts or explicitly extracted from the blog post when it is structured such that the buy or sell recommendation is listed or tagged as such. Given that TipRanks focuses on blogs with equity recommendations, our second approach to identifying financial blogs was to collect data on other financial blogs from "Best of" lists of financial blogs and internet searches. To be part of the final sample of financial blogs, at least one internet user from the ComScore sample had to visit the website between 2010 and 2017. This visit by at least one internet user was often the binding constraint as we had many more names of financial blogs than were actually visited. Given that we have a rotating and small sample of users, one visit implies much heavier use of the data source in general, so we do not believe this constraint meaningfully changes our results.

Table II begins to summarize the financial blog data. The statistics reveal that the vast majority of financial blogs (448 or 92.5% of our sample) do not make stock recommendations. A popular example of such a financial blog is `zerohedge.com`, which provides commentary on information that its contributors believe will "move the markets" or "break your trades." Rather than blog about specific stocks, these financial bloggers write about financial markets and investments. Internet users, however, prefer the financial blogs with specific stock recommendations. The mean (median) percentile for page views at financial blogs with stock recommendations is 75.5 (78.8) as compared to 38.7 (37.4) at those without recommendations. Similarly, the mean page views (8.3 vs. 2.4) and minutes per visit (3.3 vs. 2.3) are higher at the websites with recommendations.

Table III summarizes the data from financial blog websites that make buy and sell recommendations. On some of the blogs, buy or sell recommendations are made explicit at the end of the blog post, whereas other bloggers explain their thesis without summarizing their overall recommendation. For those that do not provide a summary, natural language processing techniques are used to extract the recommendation. Overall, our data includes blog posts from 20 different financial blogs where bloggers make buy or sell recommendations on stocks. The data on financial blog posts comes from TipRanks. Columns (2) through (6) characterize the internet traffic at the financial blogs. Specifically, Columns (2) and (3) rank the financial blog websites relative to all other websites in terms of page views and minutes spent on the website.

The most popular financial blogs based on page views and minutes spent on the website are Market Watch, Motley Fool, The Street, Seeking Alpha, and Investor Place. Columns (4) through (6) of Table IV present statistics about the typical users visit to the website. For example, among users that visit Market Watch, they visit the website 5 times per month and view 3 pages per visit spending a total of 4 minutes on the website per visit. Columns (7) through (10) show what the internet users are likely to encounter in terms of number of bloggers, blog posts, and stocks covered when they visit the financial blogs. There is no consistent format across blogs nor does there appear to be a correlation between format and popularity. For example, Seeking Alpha has over 10,000 unique bloggers whereas on average across the other financial blogs there are less than 300 bloggers per website. Despite significant variation in the number of unique bloggers, the number of stocks covered is more consistent across blogs. On average, each financial blog covers approximately 2000 stocks. Finally, Columns (11) through (13) present evidence on the average market-adjusted returns for stocks recommendations made on the blogs for a 1-month, 6-month, and 12-month period, respectively. The columns demonstrate how difficult it is to find useful financial advice among the blog posts. Financial blogs consistently earn negative market-adjusted returns, on average, over time. Moreover, the performance appears to be worst, on average, over longer horizons.

Table IV provides more descriptive statistics about the sample of financial blog posts. In particular, we are interested in characterizing the way in which financial bloggers provide analysis similar in nature to that of sell-side analysts. Our sample includes 1,315,898 blog posts between 2010 and 2017. About 35% of blog posts provide a buy or sell recommendation on a stock. One-fifth of those blog posts have bearish recommendations while four-fifths are bullish. Among all blog posts there are 14,754 unique bloggers that cover 6,722 stocks. Among those that make buy or sell recommendations, there are 10,488 unique bloggers covering 6,385 stocks. Finally, among those that make at least 25 recommendations, there are 1,585 unique bloggers covering 6,210 unique stocks. These bloggers that are making multiple buy and sell recommendations across a variety of different stocks are those that are most similar to financial analysts. In term of the stocks covered in blogs posts, we observe 196 posts per stock and 12 posts per stock per quarter. We observe 73 recommendations per stock and 5 buy or sell recommendations per stock per quarter. Among those bloggers that make at least 25 recommendations, we see that they post to 1.4 different websites, on average, and have a total of 268 posts over our 7 year sample period. This translates into a new blog post approximately every 16 days. The mean (median) number of stocks they cover is 94 (43). Similar to the performance at the blog-level, the performance of the bloggers with at least 25 recommendations (i.e., those that are most similar to equity analysts) demonstrate significant noise. The average financial blogger earns negative market-adjusted returns over time. Appendix Table CI provides a list of the top equities discussed by financial bloggers. In comparison to recent research from stock twits (i.e., micro-blogging), bloggers are not as concentrated on big name stocks like Apple and Facebook and appear to more evenly allocate their time across equities (Cookson and Niessner (2017)).

C. Investor Behavior Online

We use internet traffic data to help us understand how investors discover financial analysis online. Our internet traffic data comes from ComScore and is based on a nationally representative sample of about 50,000 U.S. internet users per month who have given ComScore permission to confidentially record their detailed browsing behavior at the website level. User sessions are recorded with date and time stamps as well as click data to show within a session the number of pages viewed and time spent on a particular website.

The ComScore sample of internet users changes on a monthly basis, which prohibits within-person comparisons over time. ComScore, however, does provide detailed demographic data, which allows us to create virtually identical individuals that we can follow over time. Using demographic data on education, race, age, income, household size, number of children, internet connection speed, and census location, we create about 36,000 pseudo-individuals that perfectly match on these categories and follow them over time. Then for each month, we calculate the total number of pages views and seconds spent on each website. In addition, we calculate the relative percentile for the FinTechs and the original-content financial analysis websites among all websites. Percentiles allow for comparison over time as the total number of websites on the internet fluctuates over time.

D. Analysts

We use comprehensive analyst earnings forecast and recommendation data from IBES to derive our main measures of analyst reporting quality. We supplement this data with data from Zacks in some analysis as IBES no longer provides broker or analyst identity. Our definition for variables match across the datasets. Share price data from the Center for Research in Security Prices (CRSP). Accounting data come from the CRSP-Compustat merged database. Supplementary sources of data include equity ownership data from Thomson-Reuters, mergers and acquisition (M&A) and securities issuance data from SDC. Our main dependent variables of interest are analyst forecast consensus optimism bias and accuracy.

To caluclate the quality measures for analysts' reports, we compute signed forecast errors for each firm as the difference between the consensus earnings per share (EPS) forecast minus actual EPS, scaled by the absolute value of the consensus EPS forecast, such that positive forecast error indicate greater optimism bias. Our consensus number is taken from Compustat given data issues with IBES (Ljungqvist, Malloy, and Marston (2009)). We follow the prior literature and exclude firms with absolute consensus bias less than $0.10 per share from our analysis to avoid issues with small numbers. We compute absolute forecast error as the absolute value of signed forecast error. Intuitively, aggregate absolute forecast error is a proxy for accuracy. Again, similar to prior studies that use aggregate measures, we equal-weight forecast errors. This procedure essentially weights all analyst forecasts equally so as not to obscure any individual forecast.

Analysts' revisions to their earnings estimates and recommendations are associated with many other factors. As such, our main control variables include those that are standard in the literature. For our primary specification the main controls are newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, and membership in the S&P 500. These controls match those used by Hong and Kacperczyk (2010) to study the effect of analyst supply on bias with the exception of newspaper coverage. We add newspaper coverage to our main analysis for two reasons. First, it helps ensure our instrument headline length is not simply serving as a noisy proxy for newspaper coverage. Second, research suggests that greater newspaper coverage is associated with both greater analyst coverage (Fang and Peress (2009)) and lower analyst bias (Bradshaw, Wang, and Zhou (2017)).

When using data at the analyst level as opposed to the equity level, we include several analyst-level control variables; they are general experience, firm experience, firms covered, industries covered, forecast frequency, forecast horizon, days since last forecast, employer affiliated with firm, brokerage size, and independent broker status. These reflect insights from a broad literature showing the importance of analysts' career paths (Mikhail, Walther, and Willis (1999); Hong and Kubik (2003); Groysberg, Healy, and Maber (2011)), potential conflicts of interest (Michaely and Womack (1999); Agrawal and Chen (2008)) and the mitigating role of institutions (Ljungqvist et al. (2007)), herding (Clement and Tse (2005)), reputation (Fang and Yasuda (2009)), communication with insiders (Cohen, Frazzini, and Malloy (2010)), and industry expertise (Kadan et al. (2012)).

Beyond analysts' earnings estimates, we look at analysts' recommendations to determine the market's reaction to anlaysts' upgrades and downgrades. Specifically, we examine recommendation changes where an analyst upgraded a stock to a buy or a strong buy or downgraded a stock to a sell or a strong sell. For each recommendation, we estimate the cumulative abnormal returns (CARs) from the announcement of a dividend increase. We use daily data to estimate the parameters of a Carhart Four Factor Model where the four factors are: (1) the market return, which is the CRSP value-weighted index; (2) SMB (Small Minus Big), which is a mimicking portfolio to capture risk related to size; (3) HML (High Minus Low), which is a mimicking portfolio to capture risk associated with book-to-market characteristics; and (4) UMD (Up Minus Down), which is a mimicking portfolio designed to address risk associated with prior returns by subtracting a portfolio of low prior return firms from a portfolio of high prior return firms. The event period is days 0 to +1 and we measure it relative to the recommendation announcement at day 0. To align the signs correctly for downgrades, we multiply the CARs by -1. Abnormal volume is defined in a similar manner but using the log transformed volume relative to a market model. Downgrades are not multiplied by -1 for volume.

E. Market Quality

Our measures of market quality are price informativeness and analysts' price informativeness ratio. We measure price informativeness using price nonsynchronicity (Roll (1988); Durnev et al. (2003)). It is computed on the basis of the correlation between the stock's return and the return of the corresponding industry and of the market. The idea is that if a firm's stock return is strongly correlated with the market and industry returns, then the firm's stock price is less likely to convey firm-specific information, and hence the stock price contains less firm-specific information. This measure has been used to understand market quality in the context of analysts' information (Asquith, Mikhail, and Au (2005)) as well as more generally to understand the role of information in markets (Chen, Goldstein, and Jiang (2007)).

Our second measure of market quality – analysts' price informativeness ratio – is computed as a quarterly measure by summing the absolute size-adjusted returns for all earnings forecast revisions dates and recommendation change dates in a given quarter. We exclude days where the firm also announced earnings or had simultaneous financial blog recommendations, and then we divide this amount by the sum of all absolute size-adjusted returns for all trading days in a quarter. Intuitively, this measure asks if the market updates more on days when analyst reveal information or on days when analysts do not. The idea that not all analyst recommendation changes are influential and could be redundant is consistent with prior research (Loh and Stulz (2011)). Examples of studies that include similar measures for analysts contribution to informativeness are Frankel, Kothari, and Weber (2006) and Lehavy, Li, and Merkley (2011).

For robustness purposes, we also evaluate the price jump ratio (Weller (2018)), which captures how much information enters equity prices early relative to how much is potentially acquirable. This measure helps to account for the concurrent market trend of increased algorithmic trading. Given that this measure is only available for a short time period and for a limited number of stocks, we use this measure as a robustness check to help rule out the potentially confounding effect.

F. Summary Statistics

Table V provides descriptive statistics about the key dependent and independent variables used in this study. We winsorize all variables at the 1st and 99th percentile levels to minimize the influence of outliers. The formulas for the variables derived from these databases are included in Appendix B. Do to the merging of various datasets, our main sample period runs from 2010Q1 to 2016Q3, resulting in 81,597 observations at the equity-quarter level. We note that despite our more recent time period, the summary statistics are similar to previous time periods that have been sampled.

III. Hypotheses Development

The overall desirability of FinTechs that aggregate and synthesize financial information depends on how they change the underlying information production process and ultimately, market quality. FinTechs through their aggregation function incorporate many non-traditional data sources synonymous with "big data." By providing access to this data or more aggregated information signals, FinTechs serve as an intermediary in the disclosure of information to financial markets. As such, we borrow from the information disclosure literature to develop testable predictions for the aggregate impact of FinTechs (Bond, Edmans, and Goldstein (2012); Goldstein and Yang (2017)). While FinTechs have the potential to change the type of information being consumed from an individual piece of information to a more aggregated information signal, their entry into this market also changes the incentives of incumbents. From a market efficiency perspective, the potential feedback effect from incumbents' distorted incentives is critical for analyzing FinTechs overall desirability because consequences from the feedback effect could outweigh the benefits of incorporating novel data sources in a timely manner.

Early research on information disclosure showed that it can increase the precision of public information, and thereby increase liquidity and market efficiency and decrease the cost of capital for firms and return volatility (e.g., Verrecchia (1982)). However, once the acquisition of private information is endogenized, disclosure can lead to the crowding out of private information (Diamond (1985)). Thus, disclosure could decrease market efficiency and increase return volatility. Other negative consequences highlighted in the literature include the reduction of trading opportunities (Kurlat and Veldkamp (2015)) and the promotion of destabilizing beauty-contest incentives where investors all want to do the same thing (Morris and Shin (2002)). In such a case, the greater precision of public information from disclosure leads investors to put too much weight on the information.

While there are similarities to the information disclosure literature, FinTechs are distinct phenomenon. For example, Dugast and Foucault (2017) argue big data decreases the cost of access to information and consequently reduces the demand for more precise signals, which can ultimately result in lower price informativeness. Another unique dimension of FinTechs is the possibility that trustworthy information producers can be identified. In this sense, even if the overall quality of some information-producers declines, this will not matter if FinTechs through their inclusion of alternative sources of information actually enhance price informativeness by filtering out lower quality information providers.

We examine the possible effect of FinTech entrance on (i) how investors consume information (ii) the quality of information produced by incumbents, the sell-side analysts, and (iii) on market quality. We state and explain our hypotheses on each of these dimensions in turn.

A. Investors and FinTech Entry

A critical component for understanding the impact of FinTechs on financial market and sells-side analysts is how investors perceive and consume the information conveyed by FinTechs. As discussed FinTechs provides three type of services: they speed up the discovery of financial analysis with a particular characteristic set, say research reports. Second, they aggregate financial analysis. Thus, FinTech could increase the quantity of analysis that can be consumed. Further, FinTech websites have a format that includes partial financial analysis such as buy or sell recommendations from a large variety of sources just from visiting the website. In fact, many FinTech websites that aggregate financial analysis have lists or rankings of top stocks based on their aggregation algorithm as well as links to various sources of financial analysis discussing those stocks. Appendix A provides examples of FinTech website interfaces.

Overall, the different interfaces introduce three ways an investor can use his time to find and read financial analysis: (1) finding and reading original-content financial analysis from traditional search sources, (2) clicking-through to original-content financial analysis from a FinTech website, and (3) partially reading financial analysis via the FinTech website itself. The end-result can be that investors read the content of the FinTech websites rather than reading the original content, and in that respect, FinTechs serve as a substitute for reading of original-content financial analysis. Alternatively, FinTechs can enhance the reading of original-content financial analysis when they generate more interest in the original content (we label this the complementarity effect). The heightened interest can be proxied for using the volume of click-throughs. One way these FinTech websites generate greater interest is by evaluating and ranking the quality of the analysis; thus, potentially disproportionately pushing investors' to click-through to the highest-quality analysis. To empirically assess investors' response to FinTech etnry, we examine if FinTechs act as substitutes (or complements) for the reading original-content financial analysis and if investors spend less (or more) time on original-content after visiting a FinTech.

B. The Effect of FinTechs on Information Produced by Sell-side Analysts

FinTechs through their ability to aggregate and synthesize financial analysis can have an indirect effect on the production of information through their effects on sell-side research analysts. Specifically, the presence of FinTechs can change the competitive landscape for analysts, can change their incentives to rationally produce biased research, and/or alter the amount of effort they put into creating accurate forecasts vis-à-vis career concerns.

First, consider the role of competition. Theory suggests competition makes it more difficult for financial analysts to suppress unfavorable information (Gentzkow and Shapiro (2006)). Hence, competition incentivizes analysts to produce less biased, more accurate financial reports. Empirically, there is support for this view when the number of analysts covering a stock increases (Hong and Kacperczyk (2010)). While FinTechs do not increase the supply of analysts covering a stock, they have the potential to make the supply of non-traditional sources of financial analysis such as financial blogs more salient. Doing so, would allow for the independence channel of competition (Gentzkow and Shapiro (2008)) to manifest. Namely, with a greater amount of financial analysis, there is a greater likelihood of drawing at least one supplier of financial analysis such as an independent blogger whose preferences cannot be bought or suppressed by the firm under study. In isolation, this theory suggests competition disciplines analysts.

There are many potential channels through which FinTechs can have a negative effect on the quality of analyst's output. For example, FinTechs, through their inclusion of non-traditional financial analysis and other big data sources can serve as a substitute for the readership of traditional analysis. A reduction in readership for the same quality of report may encourage analysts to reduce his or her effort to provide quality financial analysis. Similarly, while FinTechs provide more information, it is more coarse and less detailed. As such, it may lower investors incentive to acquire more detailed and time-consuming information (Dugast and Foucault (2017)).

Alternatively, analysts can rationally introduce bias into their reports. Potential conflicts of interest could lead analysts to strategically cater to clients who have relationships with their employer's brokerage house and/or investment bank (Michaely and Womack (1999)). Relatedly, Laster, Bennett, and Geoum (1999) and Lamont (2002) argue that a desire for publicity leads analysts to exert effort to attract it at the expense of accuracy. A strategic response by analysts then would be to make a forecast that is bolder in an attempt to garner publicity Gleason and Lee (2003)).

FinTechs can also have an anti-competitive effect via career concerns. Bar-Isaac (2005) argues for a non-monotonic relationship between reputation for quality and competition. In the context of analysts, the idea is that as competition increases from FinTechs, at some point an analyst's reputation will no longer be a concern as the analyst knows their industry is changing, so they care less about their reputation in that industry as they plan to leave it soon. Thus, FinTechs could encourage some more experienced analysts to leave their institutions given their reduced position of prominence and prestige. Further, as the marginal value of information production by analysts decrease (due to FinTechs entrance), their compensation is likely to decrease, resulting in lower incentives to stay. The FinTechs, therefore, can change the overall composition of who chooses to be sell-side analysts (Merkley, Michaley, and Pacelli (2017)). In this case, the pool of analysts would be younger and less qualified compared to previous generations. In other cases, it can depend on the relationships the analyst has if he or she chooses to stay. For example, an unaffiliated analyst could leave and the ones who stay are the affiliated analysts.

The discussion above suggests that analysts reporting quality (i.e., accuracy and bias) as well as their strategic responses (i.e., boldness), conflicts of interest (i.e., catering to affiliated stocks), reputation (i.e., experience and previous accuracy), and composition effects (i.e., patterns of exit and entry into the profession) are all factors that can be affected by the entrance of FinTechs.

Finally, it is important to recognize that the possible impacts of FinTechs on sell-side analysts' incentives and efforts are to a large extent independent on whether analysts are "active" or "passive" with respect to the FinTechs. That is, perhaps analysts simply ignore the presence of FinTechs and the information they provide altogether (they are "passive"). Still feedback effect from prices (e.g. Grossman and Stiglitz (1980)) will results in the same outcomes. For example, if prices reflect more information due to the presence of FinTechs, this will feedback into analysts' reports (Chen, Goldstein, and Jiang (2007)). Hence, the analysis and recommendations provided by sell-side analysts will be less valuable, investors will pay less for analysts' services, trading commission will decline and as a consequence analysts' compensation will decline. This in turn, as discussed above may result in less efforts, talented analysts seeking alternative employment and greater bias. Hence, being passive or active (i.e., being cognizant of the presence and impact of FinTechs) will eventually lead to the same outcome. Albeit, due to the inherent signal extraction problem, perhaps at a different speed.

C. FinTechs and Market Quality

One of the most economically meaningful aspect of FinTechs is their overall effect on market quality. If investors extract more information from FinTechs and at the same time they incentivize sell-side analysts to produce better quality information, then market quality improves. The prediction is straightforward also at the other end of the spectrum – if both investors and traditional information providers either ignore FinTech's information or find the information not useful, then, none of the measures of market quality should change.

The prediction is more nuanced if, as we expect, investors find the information FinTech's provide useful and incorporate it into their investment decisions. This in turn will affect the price process. But at the same time, FinTechs could have a negative effect on the quality of information produced by traditional information providers. This results in an ambiguous prediction about the overall effect. On one hand, price efficiency will improve if the investor channel dominates the analyst channel for the informativeness of prices. It is also possible, however, that overall price efficiency will deteriorate if the opposite holds. Thus, it is necessary to examine how FinTechs changes investors' consumption of information, the information produced by the traditional information providers, and price efficiency, to fully clarify the economic consequences of FinTech entry.

IV. Empirical Strategy

A. Investors Response to FinTech Entry

To test the hypothesis that FinTech entry in the market for financial analysis changes how an investor discovers financial information, we examine internet traffic data to detect changes in what investors read online. Specifically, we estimate the following equation:

$$OriginalAnalysis_{it} = \alpha + \beta FinTechVisit_{it} + f_i + \delta_t + \epsilon_{it} \tag{1}$$

where $OriginaAnalysis_{it}$ represents a visit to the website containing original-content financial analysis (i.e., all the websites with financial analysis online whether it be one with equity recommendations and forward-looking financial analysis or more general analysis on what moves markets) in month t for investor i where that investor is defined according his demographics to allow for within-investor comparison, $FinTechVisit_{it}$ indicates if the investor visited a FinTech website in that month, f_i is a user fixed effect, δ_t is a month fixed effect, and ϵ_{it} is the unobservable error component.

B. The Effect of FinTechs on Information Produced by Sell-side Analysts

To test the hypothesis that information producers respond to FinTech entry, we study changes in the optimism bias and accuracy of analysts' earnings forecasts as a function of FinTech concentration in the stocks they cover. We proxy for FinTech coverage using the frequency of financial blog posts in a given quarter about a stock that the analyst covers. Given that FinTechs aggregate and streamline such financial analysis, their presence directly corresponds to the frequency of financial blog coverage. Our first set of tests use OLS regressions; however, OLS estimates are difficult to interpret because of the endogeneity of FinTech coverage. For example, if analyst bias is correlated with consumer popularity, which is unobservable econometrically, then the point estimate on FinTech coverage in the OLS regression is likely bias by this unobservable factor. In practice, there is likely to be more than one unobservable factor correlated with FinTech coverage, and each factor is likely to push the bias to be positive or negative. As such, the likely net effect of these unobservable factors is to push the point estimate from the OLS regression toward 0.

To provide a credible point estimate and mitigate the influence of factors endogenous to the data generating process for analysts' reporting quality, we use an IV approach. Our IV is an indicator for if the equity has below median headline length in a given quarter. The intuition for why this instrument is relevant is that it generates variation in the frequency of non-traditional sources of information like financial blogs or social media writing about that equity in a given quarter. Using a randomized experiment, Umar (2017) showed that internet users are more likely to click on an article when the title is short even if the information conveyed by the title was constant. This translates exactly into our context. Non-traditional information producers such as financial bloggers are more likely to click on a newspaper article about an equity when it has a short headline. Given that they clicked on the article, they are also likely to be inspired to write their own commentary on such a stock.

More specifically, the relevance condition is that financial bloggers focus on what is popular so are more likely to write a blog about an equity after reading an article about that equity. The exclusion restriction for IV identification requires the short headline newspaper coverage only alter analysts' aggregate accuracy or bias via the effect of additional blogging about an equity increasing the concentration of FinTechs in that equity. The main argument supporting the plausibility of the instrument is financial news headlines are quasi-random since they are selected at the discretion of the editor.

To construct a quarterly headline length indicator, we gathered newspaper headline data from RavenPack. We limited the newspapers to those that have the highest national readership in the United States. Newspapers included in the analysis are: USA Today, the Wall Street Journal, the New York Times, the Los Angeles Times, the Chicago Tribune, the Washington Post, the Financial Times, and the DowJones Newswire. As reported in Appendix Table CI, both the mean and the median headline length is 57 characters, while the 25th percentile and the 75th percentile are 48 and 63, respectively.

Appendix Table CII provides several example headlines for the firm Apple when the length is at the 25th percentile and the 75th percentile. The example headlines show that there is no discernable difference in content conveyed by the length of the headline. To provide additional evidence that headline length is quasi-random, Appendix Table CIII provides regression evidence where headline length is the dependent variable and firm characteristics such as market-to-book, profitability, ROE, momentum, and firm size are the explanatory variables. No variable is statistically significant at the 95th percentile. Moreover, the R-squared from a regression with more than 7 million observations is only 0.10%. In contrast, studies that have looked at the sentiment of financial news in relation to these exact same variables show highly significant correlations with these characteristics (Niessner and So (2017)).

As a final argument for the plausibility of the IV, we employ the model selection technique of LASSO (Efron et al. (2004)) to determine if the words associated with title length systematically convey something meaningful. Table CIV shows the words selected by the variable selection model along with how much variation they explain. Inspecting the words reveals that they are not associated with content but with their own length. For example, the word "available" or "financial" are associated with longer headlines while the words "talk" and "mgmt" are associated with shorter headlines. In contrast, if we thought the instrument was erroneously capturing sentiment or conveying content, we would expect to see words like "beat" as in "beat earnings estimates" or "fear" as in "fear trade conflicts," but we do not see any of these words.

Finally, given that we control for total newspaper coverage in the first stage of IV regressions, the instrumented value for FinTech coverage is being identified from the incremental effect of having short headlines over and above having any headline. Hence, even if analysts also read the news about the equities they cover, which is likely given that being current on the latest developments is exactly what analysts are supposed to do, this is not the incremental variation we are using. Rather we are relying on shorter headlines increasing clicks, an important metric for those providing free financial analysis online in hopes of gaining advertisement revenue.

Our exact IV specification is as follows:

$$ReportQuality_{it} = \alpha + \beta FinTechCov_{it} + \theta X_{it} + f_i + \delta_t + \epsilon_{it} \tag{2}$$

where $ReportQuality_{it}$ represents characterizes the analysts' report quality in terms of optimism bias and accuracy in quarter t for equity i, $FinTechCov_{it}$ proxies for FinTech coverage using the quantity of alternative data sources such as financial blog posts that discuss equity i in quarter t, X_{it} is a vector of observables (newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly return, log market-to-book ratio, volatility of ROE, profitability, and an indicator for if the stock is a member of the S&P 500), f_i is an firm fixed effect, δ_t is a quarter fixed effect, and ϵ_{it} is the unobservable error component.

In performing the analyses, both cross-sectional and within-firm variation is considered. However, in our context, cross-sectional variation likely captures the variation of interest because the point estimate based off of cross-sectional variation captures the full range of FinTech coverage from no coverage to very high coverage. In contrast, within-firm estimates likely only capture small variations ranging from no to low coverage or high to very high coverage. This is due to the fact that once FinTech coverage occurs, the level of coverage a firm receives is fairly persistent. Hence, in reality, there are only two types of firms that exhibit within-firm variation. First, FinTech coverage is associated with large firms, and these large firms exhibit more within-firm variation in FinTech coverage as additional sources of information on these firms are incorporated by the FinTechs. Second, most small firms do not have FinTech coverage, but when these small firms gain FinTech coverage this generates within-firm variation. As such, the point estimate from the within-firm analysis then will be driven by these two tails of the FinTech coverage distribution.

C. Market Response to FinTech Entry

To test the hypothesis that the type of aggregation services that FinTechs provide improves market quality, we examine price informativeness and analysts' contribution to price informativeness. We perform the exact same regression as in Eq.(2) but we replace $ReportQuality_{it}$ with $Info_{it}$ where $Info_{it}$ represents price informativeness or analysts' contribution to price informativeness in quarter t for equity. For this specification, we focus on the cross-sectional variation.

We also examine the market's response to changes in analysts' recommendations by analyzing excess returns and excess volume associated with a recommendation change. Specifically, we use the OLS estimates of the CARs along with our measure for FinTech coverage. The regression specification is as follows:

$$CAR_{ijt} = \alpha_{ijt} + \beta FinTechCov_{it} + a_j + \delta_t + e_{ijt} \tag{3}$$

where β is the coefficient of interest, and it represents the market's relative change in response to analysts' recommendations as a function of $FinTechCov_{ijt}$. To allow for analyst-specific effects, we include a_j. We also include δ_t, a quarter fixed effect.

V. Results

A. *Investors Response to FinTech Entry*

Figure 1 illustrates how the use of FinTech websites is changing over time. The line of best fit shows a positive linear relationship and the dispersion of the binned scatterpoints around the line produce a statistically significant relationship. From 2006 to 2016, the percentage of investors visiting FinTech websites increased by 50% from a baseline of 12% to 18% of investors by the end of the sample. Given the rotating nature of the ComScore sample, some observations suggest the percent of FinTech users is even greater than 20%. The increasing use of FinTechs over time suggests that their effects on investors are unlikely to be a temporary phenomenon but a permanent change in the way investors discover and consume financial analysis.

Table VI presents OLS estimates of investors' discovery of financial analysis online. The primary independent variable of interest is the investor's decision to visit a FinTech website in a given month. By examining how readership of additional financial analysis online is associated with visits to FinTech websites, these regressions help determine if FinTechs are being used to discover the best financial analysis (complements view) or if FinTechs serve as an alternative to reading financial analysis (substitutes view). If visits to Fintech websites enhance the readership of traditional financial analysis, (i.e., a positive coefficient on the "visit a FinTech website" variable), we label it as complement. If, however, visits to FinTech websites are associated with a reduction in the readership of traditional financial analysis, (i.e., a negative coefficient on the "visit a FinTech website" variable), we label it as substitute.

Column (1) of Table VI reveals investors are 31 percentage points less likely to visit a second website with original-content financial analysis when they visit a FinTech website in a given month. This 31% difference is economically and statistically significant with a p-value less than 1%. The regressions used to estimate this relationship include both user and time fixed effects, so the relationship cannot be explained by selection on user characteristics or trends over time. The variation explained by the regression is 26% which suggests these variables capture a meaningful portion of what is driving investors' visits to these websites.

Column (2) and (3) of Table VI examine additional aspects of how investor's spend their time online to further test the complements versus substitutes hypothesis about FinTechs. Column (2) shows that the page views at websites with original-content financial analysis are reduced by 17% when an investor visits a FinTech website in a given month. Similarly, column (3) reports that the time spent at the original-content website is reduced by 5% when an investor visits a FinTech website in a given month. In both cases, these relationships are highly statistically significant.

Observing these negative associations with FinTech visits are consistent with two channels by which original content is being read less when FinTechs are present. First, FinTechs lead investors to read a smaller portion of financial analysis than without FinTechs. Second, given that FinTechs aggregate and condense the financial analysis that is available, they are reducing investors' propensity, and possibly need, to read financial analysis altogether. While we cannot definitively say which interpretation dominates, our evidence does strongly suggest that investor's discovery of financial analysis is changing as a result of FinTechs entry. Moreover, our analysis also suggests the consumption of original-content financial analysis is declining as investors' attention is diverted away from such analysis consistent with Dugast and Foucault (2017).

Appendix Table CV provides additional regression tests exploring what type of investors use FinTech websites; these tests report coefficients for demographics such as age, race, and education. The regressions reveal that race explains the most variation in FinTech use. Even in the United States, FinTech use is highest among Asians, followed by Whites, Blacks, and Other. We also find that FinTech use increases with income; investors that earn more than $100,000 a year are 3 times as likely to use FinTechs as those making less than that. FinTech use exhibits a non-monotonic relationship with education. Those that are college educated are twice as likely to use FinTechs as those with a graduate degree. Finally, we find that FinTech use is not concentrated among the young. Rather those with accumulated wealth that are nearing retirement age are more likely to visit FinTech websites. Also, we note that gender data is not available.

Our analysis is predicated on the notion that there is overlap on coverage between FinTechs and sell-side analysts. Table VII shows a positive correlation between FinTech coverage and traditional sources of financial analysis. Columns (1) through (4) of Panel A correlate analyst, newspaper, FinTech, and high quality FinTech coverage, defined as a FinTech signal that if followed would have resulted in a positive investment performance over six months. Analyst coverage and FinTech coverage have a correlation of 0.51. FinTech coverage and high quality FinTech coverage having the strongest correlation (0.79) and newspaper coverage and high quality FinTech coverage having the weakest correlation (0.26).

Panel B of Table VII relates each type of coverage to firm fundamentals. Across each type of coverage, larger firms with high market-to-book ratios receive significantly more coverage. This suggests the equities for which gains in overall market quality have the potential to be the weakest are large stocks given that large stocks are where the potential feedback effects from altered data production by analysts could outweigh the benefits from investors incorporating these alternative data sources into their investment decisions. We note, however, that FinTech and analyst coverage diverges significantly in terms of investor base. Analysts cover stocks with greater institutional ownership, all else equal. This suggests to some extent FinTechs are filling a gap by covering the stocks smart money does not own. We explore these cross sectional differences when examining analysts reaction to FinTechs in the next subsection. For additional details on the stocks with the highest FinTech coverage, see Appendix Table CVI.

B. Analysts Response to FinTech Entry

In this subsection, we seek to understand if analysts respond to the entry of FinTechs by changing their reporting quality. Table VIII presents OLS estimates for analysts' responses. Columns (1) through (4) reveal a small but significant positive partial correlation between FinTech coverage and analysts' aggregate optimism bias. Columns (5) through (8) reveal a small, negative partial correlation between FinTech coverage and analysts' accuracy. The control variables used in the regressions include newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, and membership in the S&P 500.

A discussion of the data used to construct these variables appears in Section 2 while the exact formulas are contained in Appendix B.

We run a variety of specifications to understand how sensitive the relationship is, including tests of the mean and median response as well as tests relying on within-firm rather than between-firm variation. Across all specifications, the same associations emerge. When FinTech coverage increases, the quality of analysts' reports exhibit increased bias and reduced accuracy. The point estimates from using time fixed effects in the regression are presented in Columns (1), (3), (5), and (7), and the results from using both time and firm fixed effects are presented in Columns (2), (4), (6), and (8). The results examining mean bias and accuracy are presented in Columns (1), (2), (5), and (6), respectively. While the results with median bias and accuracy are presented in Columns (3), (4), (7), and (8), respectively.

Table IX extends the analysis of analysts' response to FinTech coverage by using an IV regression specification, which helps to mitigate concerns about endogeneity associated with the OLS regressions. The pattern observed with the OLS regressions is the same as with the IV regressions. Specifically, we find that when FinTech coverage increases, analysts' consensus optimism bias increases while their consensus accuracy declines. Column (1) shows a one standard deviation increase in FinTech coverage is associated with a 0.14 standard deviation increase in mean aggregate optimism bias. Similarly, Column (5) shows a one standard deviation increase in FinTech coverage is associated with a 0.23 standard deviation decrease in mean aggregate accuracy.

The statistical evidence for the deterioration in reporting quality is significant at the 99th percentile. The F-statistic from the first stage of the instrumental variable regression is 195.9, which exceeds the requisite 10 to ensure minimal bias of the point estimate. The t-statistic on the instrument in the first-stage is 14.0, which suggests the instrument is not weak. The IV specification includes controls for newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, and membership in the S&P 500. These controls help to account for other firm-level dynamics that could lead to a deterioration in analysts' reporting quality.

The details of the point estimates on the additional controls convey useful information. First, FinTech coverage is not changing any traditional relationships observed in the data. For example, increased analyst coverage and greater average monthly stock returns are both still associated with lower bias (Hong and Kacperczyk (2010)). Second, our results confirm recent research which suggests that increased newspaper coverage is associated with reduced bias (Bradshaw, Wang, and Zhou (2017)). Third, the results help put FinTech coverage in context by showing where FinTech coverage ranks relative to other firm-specific controls. Our point estimates suggest that FinTech coverage has an economically meaningful effect on reporting quality, ranking near the middle of the point estimates reported. The point estimate for FinTech coverage is smaller than that of firm size, return volatility, and profitability but also larger than that of newspaper coverage, market-to-book, and monthly returns.

In summary, we find FinTech coverage is associated with lower reporting quality both in terms of greater optimism bias and lower accuracy. The evidence suggests that, at least to some extent, investors use FinTechs in lieu of traditional information sources, and that the effect of FinTechs on the quality of information provided by sell-side analysts is negative. Thus, the overall effect on the informativeness of prices is, at this stage ambiguous: investors have more information sources but at the same time traditional information providers provide information of lower quality. Before turning to directly examine the impact on information efficiency, we examine how FinTech affect three strategic decisions by analysts: the effort they devote, their decision to switch careers, and the extent to which they bias their recommendations to cater to their corporate clients.

C. What Drives Analysts' Response to FinTech Entry

An important factor in determining the long-run consequences of FinTechs on market efficiency is knowing the channel through which FinTechs influence analysts. If the lower reporting quality stems from a change to the talent pool for analysts, this would be more difficult to reverse, suggesting any negative effects on market quality would take time to fix. In contrast, if the lower reporting quality stems from low effort, contractual mechanisms could more easily be introduced to reverse the negative effects on market quality. We begin by testing for strategic responses by analysts. Table X presents evidence testing the hypothesis that FinTech coverage of high quality financial analysis is driving the changes in analysts' reporting quality. Columns (1), (2), (5), and (6) focus on the best short-term financial analysis (under six month holding period), and Columns (3), (4), (7), and (8) focus on the best long-term financial analysis (over one year holding period). As reported in Column (1), a standard deviation increase in high quality short-term financial analysis is associated with 0.14 standard deviation increase in mean aggregate optimism bias. In comparison, Column (3) indicates a standard deviation increase in high quality long-term financial analysis is associated with 0.22 standard deviation increase in mean aggregate optimism bias. In both cases, the results are significant at the 99th percentile. What is striking about these results is that they account for all of the increase in bias uncovered when looking at any FinTech coverage.

Next, we examine the hypothesis that FinTechs have an anti-competitive effect on analysts' reporting quality via career concerns. Table XI Panel A presents evidence supporting a career concerns channel. As reported in Column (1), a standard deviation increase in FinTech coverage is associated with 0.11 standard deviation increase in the number of analysts covering that equity that quit and leave the profession. Columns (4) and (7) show that the analysts who leave are among the 10% most accurate and 25% most accurate analysts, respectively. The remaining columns analyze the same dependent variables but categorize the independent variable FinTech coverage into growing coverage and no change in coverage. For each outcome, growing coverage vs. no change in coverage produce asymmetric responses. For stocks with growing FinTech coverage, 1.6 more analysts quit and leave the profession, while 3.2 fewer analysts quit and leave the profession when there is no change in FinTech coverage. All the results are statistically significant at the 95th or 99th percentile, but the instrument is weaker when the independent variable is no change in FinTech coverage.

Table XI Panel B tests another channel for strategic responses, analysts generating bolder forecasts that may garner publicity or attention. While bolder forecasts might generate more visibility and attention, they also require more effort, as analysts are typically reluctant to deviate from the consensus since the consequences of being wrong are high (Gleason and Lee (2003)). We follow the prior literature and classify forecasts as bold if they are above both the analysts own prior forecast and the consensus forecast immediately prior to the analyst's forecast, or else below both. In Columns (1) through (6), we examine both the percent of bold forecasts made and the distance the forecast is from the consensus forecast. We find no evidence to suggest that analysts are strategically responding to FinTech entry by generating more audacious forecasts. In fact, we find the opposite. As in Panel A, when we examine growing coverage vs. no change in coverage, we find an asymmetric response. Thus, this test is consistent with analysts exerting less effort. Ameliorating an effort problem can likely be fixed faster than having to recruit a more talented pool of analysts.

Given that analysts' compensation and career concerns are not solely determined by the accuracy of their forecasts (e.g., only about a third of Institutional Investors ranking is based on forecast accuracy), our final set of analyst tests considers an alternative strategic response whereby analysts start catering to their potential conflicts of interest. This is likely to occur if the returns to reputation are lower when the stocks they cover also have high FinTech coverage. To this end, we disaggregate the data and instead use analyst-equity-quarter level observations. We then analyze sub-samples of the data to understand which economic incentives, if any, are generating analysts' change in reporting quality. For example, we separately analyzes forecasts for affiliated and non-affiliated stocks, forecasts by independent and non-independent analysts, and forecasts by inexperienced and experienced analysts. Our analysis of analysts' incentives suggest the change in reporting quality is stronger for analysts covering affiliated stocks and for inexperienced analysts. While these results are mostly suggestive, they support the notion that both catering to conflicts of interest and changes in the attractiveness of outside employment opportunities are driving analysts' responses. These results are reported in Appendix Table CIX. Given that they are based on a separate dataset that allows us to identify analysts brokerage house, we also summarize that data in Table CVII and replicate our main equity-level finding in Table CVIII.

D. Market Response to FinTech Entry

Thus far, the results indicate that FinTech coverage is an important factor explaining the quality of the information reported by analysts. While we document that FinTechs reduce the worth of the information analysts provide at the same time they also increase investors' consumption of fintech data in lieu of traditional data. What remains unclear is the extent to which FinTech coverage is changing the information environment. The relative magnitudes of these effect determines whether the overall effect is positive or negative . To test the hypotheses that FinTechs are beneficial to market efficiency, our next set of tests examine the relationship between FinTech coverage and the markets reaction to the information analysts' produce, price informativeness, and analysts' contribution to price informativeness.

Table XII presents the results for tests of market responsiveness to analysts' recommendation revisions as a function of FinTech coverage. The evidence suggests the market is less responsive to analyst recommendations when FinTech coverage is high. The point estimates reported in Columns (1) and (2) of Panel A suggest a decrease in excess returns of around 24 to 27 basis point when FinTech coverage is high. These estimates are significant at the 99th percentile. The inclusion of analyst and time fixed effects ensures that these results are robust to factors affecting analyst recommendations such as general experience and all-star status as well as trends over time. Consistent with the results for excess returns, Columns (3) and (4) of Panel A show statistically significant decreases in excess trading volume when FinTech coverage is high for an equity. Both results indicate the information produced in analysts' reports are, increasingly, less relevant and possibly already impounded in prices, when FinTechs are part of the market for financial analysis.

Panel B of Table XII uses an alternative approach to identify the market responsiveness to analysts when FinTech coverage is high. In Panel A, the associations come from variation in the cross-section of stocks covered by analysts. Yet a comparison of the market's reaction to analyst recommendations for the same firm before and after FinTechs entered the market for financial analysis is also prudent. Given that the exact date upon which different FinTechs started covering different equities varies is unknown to the econometrician, we instead compare mean changes in market responsiveness over multiple years. Specifically, we run a placebo-like test that compares the five years before our sample starts to the years of data in our sample. We add the analyst recommendation changes in the five years prior (2005-2009) and set the FinTech coverage to 0. We then focus on the within analyst or within analyst-equity variation. Thus, our coefficient of interest is similar to the coefficient in a triple difference-in-differences estimator.

As reported in Columns (1) and (2) of Panel B, the estimates indicate that the market is 28 and 25 basis points less responsive to analysts' recommendation revisions for the same firm over time when that firm has greater FinTech coverage. These results are significant at the 99th and 90th percentile, respectively. Columns (3) and (4) of Panel B run the same test using the earlier data and reveal a negative point estimate that is significant at the 90the percentile. Overall, both the cross-sectional estimates in Panel A and the more restrictive, within-analyst-firm estimates in Panel B are consistent with the substitute view of FinTechs and suggest the marginal impact of the information analysts convey to the market is being reduced as FinTechs help to incorporate non-traditional sources of analysis.

Table XIII examines whether FinTech coverage is increasing price informativeness or not. Panel A examines price informativeness, measured using price nonsynchronicity, while Panel B examines analysts' contribution to the price informativeness, measured as the returns realized on days when analysts announce earnings forecasts or investment recommendations relative to the returns realized in the quarter. Column (1) of Panel A reports a one standard deviation increase in FinTech coverage is associated with a 0.46 standard deviation increase in price informativeness. The result is significant at the 99th percentile and is estimated using the IV specification. Column (2) repeats the analysis but examines high quality FinTech coverage rather than just any FinTech coverage. The point estimates are similar and statistically significant, which suggests it is the high quality content that is driving the relationship.

Panel B of Table XIII examines the extent to which analysts' information is being replaced by more precise information that FinTechs aggregate from non-traditional data sources. Column (1) of Panel B reports a one standard deviation increase in FinTech coverage is associated with a 0.11 standard deviation decrease in analysts' contribution to price informativeness using the IV specification. This result is significant at the 99th percentile. Finally, as with Panel A, Column (2) of Panel B indicate that it is the high quality FinTech coverage driving these findings.

Overall, the results on price informativeness complement the results on the market's reaction to analyst recommendation. Both sets of results indicate that FinTechs coverage of high quality non-traditional financial analysis is serving as a substitute for the information found in analysts' reports.

Our evidence suggests analysts have diminished role to play in markets. While the net effect of the information they produce is positive, some of the information that we previously relied on them to produce is being incorporated through alternative sources. These findings are consistent with recent research showing shrinking salaries for analysts and falling numbers of analysts (Merkley, Michaley, and Pacelli (2017)).

E. Robustness

To understand the robustness and generalizability of our findings, we conduct additional tests. We consider alternative definitions for measuring changes in the quality of information being produced by analysts. Appendix Table CX shows that using alternative definitions of accuracy and bias does not change the results. Specifically, we replace the EPS reported by IBES with that reported in Compustat (Ljungqvist, Malloy, and Marston (2009)). In addition, we normalize by the previous quarter's stock price rather than consensus EPS as in Hong and Kacperczyk (2010). In Appendix Table CXI, we repeat our test for changes in price informativeness for samples of equities with high and low algorithmic trading. We find an increase in price informativeness in both samples, although the effect is significantly larger in the subsample of equities with greater algorithmic trading. Such a test helps to ensure that our results are not being erroneously driven by this contemporaneous change in the information environment for equities.

F. Economic Implications

Our evidence suggests that FinTechs by presenting big data to investors in a streamlined manner are improving market quality. They are doing so, despite incumbents offsetting some of the efficiency gains by producing lower quality information. Thus, an important implication for any FinTech attempting to extract a signal from all this data is that their algorithms cannot be static. If the FinTechs combine non-traditional data with traditional data, they need to incorporate the potential for bias-inducing feedback effects between the two sources. Otherwise, the algorithms that are meant to synthesize all data into an optimal signal could produce systematically biased predictions. In fact, when algorithm place a meaningful weight on traditional information, these biases can magnify existing errors and reverse the gains to efficiency over time.

To assess the potential for growing bias over time in our sample, we re-estimate the change in reporting quality for each year in the sample. Doing so helps us to understand if the analyst channel is getting stronger or weaker over time. If the analyst channel is getting stronger over time, this implies FinTechs need to improve their methods for dealing with bias-inducing feedback effects. Figure 2 plots the evolution of the IV coefficient estimate over the years in the sample. The first two years of our sample, 2010 and 2011, also have the strongest point estimate (double the sample average) for declining reporting quality. For the remaining years in the sample, the reduction in reporting quality is significantly different than zero but less severe. This suggests that the gains to efficiency from FinTechs are likely to grow over time.

The source of the reduction in reporting bias overtime is unclear. For example, given the rapid expansion of FinTechs in the early years. Investors could recognize that some FinTechs have weak algorithms and stop using their services. Alternatively, changes to the FinTech business model even among market intelligence FinTechs could be at play. For example, FinTechs that crowd-source earnings estimates were late entrants to this market, but evidence from a single FinTech suggests that one had competitive effects (Chen et al. (2014)).

While it is beyond the scope of this paper to characterize what the long-run equilibrium for market intelligence FinTechs will be and which ones will survive, it is worth emphasizing that insights can be gained from the literature on credit rating agencies. For example, credit rating agencies that also aggregate and synthesize information into a grade have had problems with the quality of the ratings they produce (Baghai, Servaes, and Tamayo (2014)). While rating agencies are subject to more conflicts of interest than FinTechs and needed to become monopolies to make profits, similar changes to the quality of information brought about by FinTechs could increase systemic risk and potentially render traditional early warning systems unreliable (Hanley and Hoberg (2018)).

Finally, FinTechs that are selling aggregation services and signals to investors are not subject to the same regulatory standards as analysts or financial advisors, so to some extent are benefitting from regulatory arbitrage. While our paper suggests that these FinTechs are helping to incorporate non-traditional data sources, some could be trying to manipulate investors. There is no professional stature among FinTech leaders, so the incentives to manipulate investors and prices are relevant. Thus, as this industry continues to mature an important next step for policymakers will to be think about the regulation of algorithms and data.

VI. Conclusion

While new technology promises to remedy the information inundation problem investors' face, little is known about the extent to which market intelligence FinTechs actually improve the information environment and facilitate gains to market efficiency. Answering this question is not straight-forward given that FinTechs could bring about unintended consequences. By aggregating and streamlining financial information from big data sources, FinTechs have the potential to change the type of information being consumed from an individual piece to a more aggregated signal. Yet their entry into this market also changes the incentives of incumbents. The potential feedback effect from incumbents' distorted incentives could outweigh the benefits of incorporating non-traditional data and attracting new investors to the market.

To assess the overall desirability of FinTechs, we assemble a new, comprehensive dataset on FinTechs, financial analysis online, and investors' internet histories. First, we document the many options investors have for discovering financial analysis brought about by the entry of FinTechs. The services provided by the FinTechs range from the aggregation of existing financial analysis to the creation of customized buy-sell signals compiled from traditional and non-traditional data sources (financial news, analyst reports, blog posts, social media, etc.). We then examine the implications of FinTech entry into the market for financial analysis in three ways – at the investor level, at the analyst level, and at the market level.

Overall, our econometric investigation of this data suggests FinTechs are beneficial to the underlying goal of market efficiency but there are some unintended consequences. First, we find investors use FinTechs and the investment signals that they provide as a substitute for reading original-content financial analysis. While this can save investors' time, this also distorts the incentives of those that produce financial information. We observe significant decreases in analysts' accuracy and increases in optimism bias for the equities covered by FinTechs. That FinTechs are altering private information production is an unintended consequence that finds support in the theoretical literature on optimal information disclosure. However, we find price informativeness increases where FinTechs concentrate, suggesting that analysts' information is being replaced by more precise information aggregated from these non-traditional sources. This is supported by changes in analysts' contribution to price informativeness and the market's reaction to their recommendations.

Finally, our analyses of what drives analysts' responses suggest the drop-off in their reporting quality will not be easily remedied. The best analysts are quitting and leaving the profession, which suggests a permanent reduction in the quality of analysts' reports rather than a strategic response. Thus, the information presented to investors by FinTechs is likely to play an increasingly important economic role. This, in turn, introduces new challenges as regulators learn how to best provide oversight for big data providers and the algorithms they use.

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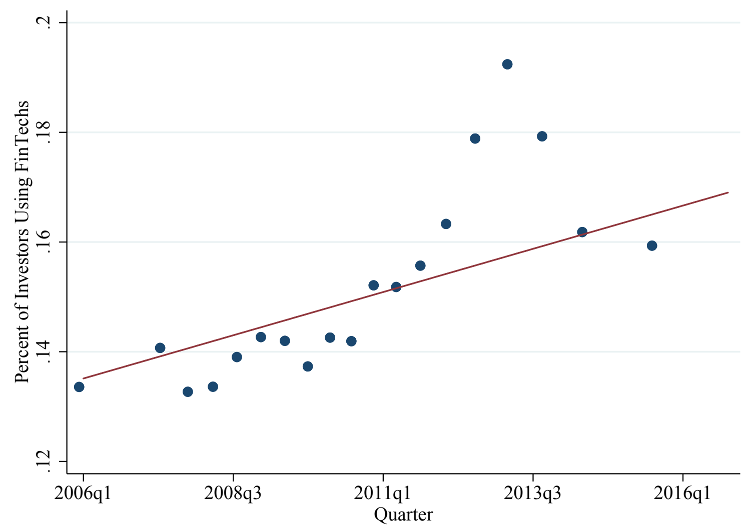
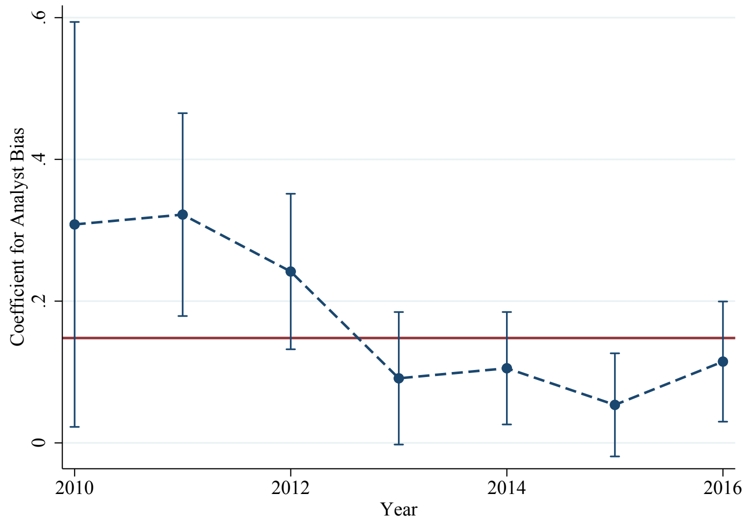


Figure 1. Growth in FinTech Use: This figure plots the percent of investors visiting FinTech websites over time. Each dot shows the percent of users visiting a FinTech website for a given time period, after controlling for basic demographic characteristics such as race, age, education, income, household size, connection speed, and geographic region. The plotted line represents the best linear approximation to the conditional expectation function. The data comes from comScore and tracks the internet usage of a set of households reflective of the U.S. population. For a detailed description of each variable, see the definitions in Appendix B.



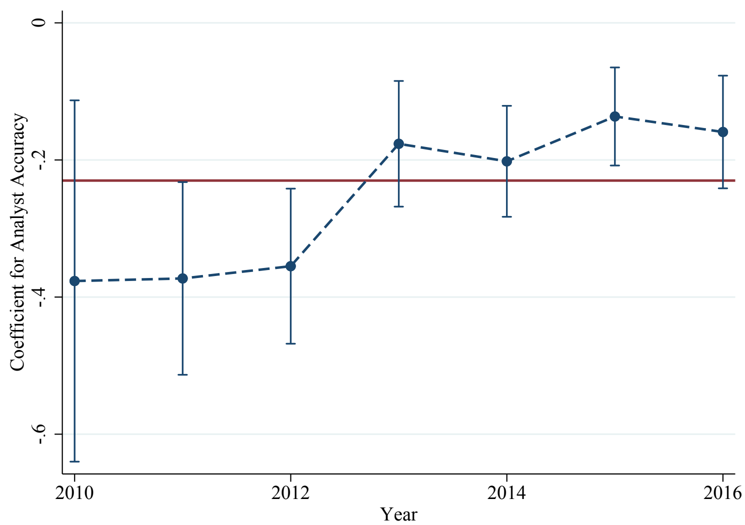


Figure 2. Changes in Analyst Reporting Quality Over Time: This figure plots the relationship between FinTech coverage and analysts' reporting quality over time. For the graph on top, the dependent variable is analysts' optimism bias, and for the graph on bottom, the dependent variable is analysts' accuracy. In each plot, the dots represent the coefficient estimate from an IV regression at the equity-quarter level for a given year and the bands represent 90% confidence intervals based on robust standard errors clustered at the equity-level. The maroon solid line represents the coefficient estimate when using all years of data. The primary independent variable of interest, FinTech Coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. The instrument for FinTech Coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. The control variables used in the regressions include newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, membership in the S&P 500, momentum, institutional ownership. For a detailed description of each variable, see the definitions in Appendix B.

Table I. FinTechs in the Market for Financial Analysis

This table describes the main functionalities associated with a broad sample of FinTechs in the market for financial analysis. To be part of the sample of FinTechs, at least one internet user from the comScore sample of nationally representative U.S. households must visit the firm's website between 2010 and 2017. For a detailed description of each variable, see the definitions in Appendix B.

Characterizing FinTechs	Obs. (1)	Mean Year Founded (2)	Targets Retail Investors (3)	Targets Prof. Investors (4)	Covers Specific Stocks (5)	Mean Num. of Investors (6)	Mean Funding ($mil) (7)	Mean Num. of Workers (8)
All FinTechs in the market for financial analysis	290	2008	72%	60%	19%	4.8	10.4	73.8
FinTechs that aggregate financial experts	31	2008	84%	48%	10%	4.0	11.9	17.5
FinTechs that aggregate financial news	242	2008	69%	66%	18%	5.3	11.9	85.7
FinTechs that crowdsource financial advice	45	2011	87%	47%	13%	6.2	18.1	13.9
FinTechs that datamine for financial signals	166	2007	63%	70%	17%	5.2	12.0	114.9
FinTechs that rank financial advice	77	2007	84%	60%	22%	3.5	7.5	53.1

Table II. Internet Users and Financial Analysis

This table summarizes how internet users access financial analysis online by describing their visits to websites with financial analysis. Columns (1) through (4) summarizes visits to websites where the financial analysis can be accompanied by a buy or sell stock recommendation. Columns (5) through (8) For a website to be included in the analysis, at least one internet user from the comScore sample of nationally representative U.S. households must visit the website between 2010 and 2017. For a detailed description of each variable, see the definitions in Appendix B.

	Financial analysis with stock recs.				Financial analysis without stock recs.			
	Mean	Std. Dev.	Median	Max	Mean	Std. Dev.	Median	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Page view percentile	75.46	20.91	78.81	99.73	38.73	22.85	37.39	99.92
Minutes on site percentile	72.16	23.12	78.40	99.88	36.50	23.03	33.43	99.92
Monthly visits per user	2.0	1.2	1.5	6.5	1.4	1.4	1.1	17.9
Page views per visit	8.3	22.4	2.7	109.3	2.4	2.0	1.9	17.1
Minutes per visit	3.3	3.4	2.5	19.3	2.3	2.9	1.5	36.0
Observations (websites)	36				448			

Table III. Financial Blogs with Stock Recommendations

This table presents summary statistics for our sample of financial blog websites that make stock recommendations over the sample period from 2010-2017. Columns (2) through (6) characterize the mean internet traffic at the blogs. Columns (7) through (10) characterize the content investors would encounter when they visit these blog sites. Columns (11) through (13) report market-adjusted returns based on the recommendations made on the blog for 1-month, 6-months, and 12-months, respectively. For a detailed description of each variable, see Appendix B.

Blog Site (1)	Page View Percentile (2)	Minutes on Site Percentile (3)	Monthly Visits per User (4)	Page Views per Visit (5)	Minutes per Visit (6)	Pct. of Tot. Blog Posts (7)	Pct. of Posts with Rec. (8)	Num. of Unique Bloggers (9)	Num. of Stocks Covered (10)	Market-adjusted 1-month Returns (11)	Market-adjusted 6-month Returns (12)	Market-adjusted 12-month Returns (13)
MarketWatch	99.7	99.9	4.8	2.7	3.8	1.6%	11%	953	2,110	-0.5%	-3.0%	-4.6%
MotleyFool	99.3	99.5	2.0	1.9	2.4	17.1%	30%	1,204	4,424	0.2%	-2.4%	-5.4%
TheStreet	99.2	99.4	2.5	3.3	4.8	18.5%	18%	664	5,172	0.7%	-4.3%	-8.6%
SeekingAlpha	97.0	97.2	2.8	2.4	4.3	32.9%	43%	10,442	6,501	0.3%	-2.5%	-5.7%
Zacks	96.9	96.6	1.8	2.9	2.8	10.6%	23%	111	4,369	0.2%	-3.7%	-6.9%
InvestorPlace	95.0	95.0	2.2	3.3	3.2	7.8%	83%	207	5,040	0.0%	-4.0%	-6.7%
MoneyMorning	92.4	93.1	1.3	1.2	1.6	0.1%	35%	46	482	0.4%	-3.3%	-6.4%
StreetAuthority	89.0	89.6	1.7	2.3	2.3	0.3%	67%	82	1,219	0.1%	-2.4%	-5.4%
GuruFocus	85.8	82.1	1.8	5.0	3.1	3.2%	34%	796	4,168	0.0%	-2.1%	-3.4%
Kapitall	81.6	60.6	1.3	5.8	2.0	0.3%	51%	40	1,764	0.1%	-2.6%	-5.4%
MarketRealist	79.7	70.4	1.4	2.7	2.5	0.7%	20%	47	287	0.1%	0.8%	0.9%
Amigo Bulls	78.0	60.5	1.1	4.1	3.4	0.1%	47%	46	157	0.0%	-0.1%	-0.2%
MoneyShow	73.1	71.1	1.9	6.3	3.5	0.3%	47%	352	1,231	0.0%	-4.0%	-8.3%
Investing	68.1	69.3	4.7	7.5	3.8	1.4%	28%	480	3,105	0.1%	-1.8%	-3.8%
Who Trades	67.8	54.7	1.1	1.9	1.1	0.3%	28%	67	856	0.7%	1.3%	1.2%
TopStockAnalysts	66.8	65.5	1.4	1.8	1.7	0.4%	34%	175	1,647	0.2%	-3.3%	-7.6%
SmarterAnalyst	65.1	47.0	1.6	2.2	1.5	0.1%	97%	75	546	0.6%	-1.7%	-4.8%
ProfitableTrading	57.8	58.2	1.3	1.6	1.8	0.0%	95%	24	405	0.5%	0.0%	-3.7%
SumZero	38.9	29.8	1.5	2.6	2.1	0.0%	98%	1	90	1.5%	10.6%	14.6%
WSObserver	34.4	34.7	1.5	1.5	1.3	4.3%	27%	18	3,335	0.1%	-3.9%	-3.8%

Table IV. Characterizing Financial Blog Posts

This table presents summary statistics for our sample of financial blog websites that make stock recommendations over the sample period from 2010-2017. This table provides descriptive statistics about bloggers posts, their recommendations, the stocks they cover, the number of sites the bloggers post to, the days between posts, and the market-adjusted returns associated with their recommendations. For a detailed description of each variable, see the definitions in Appendix B.

Year	Freq.
2010	46,360
2011	110,606
2012	144,868
2013	180,293
2014	257,444
2015	291,201
2016	196,637
2017	88,489
Total	1,315,898

Among all blog posts	Freq.
Unique bloggers	14,754
Unique stocks	6,722

Among posts with non-neutral recs	Freq.
Unique bloggers	10,488
Unique stocks	6,385

Among bloggers with at least 25 recs	Freq.
Unique bloggers	1,585
Unique stocks	6,210

Among all bloggers	Mean	Median
Number of sites bloggers post to	1.1	1.0
Number of posts per blogger	89.2	4.0
Days between blog posts	65.8	23.3
Number of stocks covered	24.8	3.0

Among bloggers with at least 25 recs	Mean	Median
Number of sites bloggers post to	1.4	1.0
Number of posts per blogger	267.8	70.0
Days between blog posts	16.3	10.2
Number of stocks covered	94.6	43.0

Sentiment	Freq.
Bearish	81,063
Neutral	851,708
Bullish	383,127
Total	1,315,898

Stocks covered in blog posts	Mean
Blog posts per stock	196
Blog posts per stock per quarter	12
Recs per stock	73
Recs per stock per quarter	5

Performance with at least 25 recs	Mean	Median
Market-adjusted 1-month Return	0.2%	0.0%
Market-adjusted 3-month Return	-1.5%	-0.2%
Market-adjusted 6-month Return	-3.1%	-0.8%
Market-adjusted 12-month Return	-6.1%	-2.0%

Table V. Summary Statistics

This table presents summary statistics for the main dependent and independent variables. After combining the datasets, the main sample period is limited to 2010Q1 to 2016Q3. For a detailed description of each variable, see the definitions in Appendix B.

	Freq.	Mean	Median	Std. Dev.	Obs.
	(1)	(2)	(3)	(4)	(5)
Dependent Variables					
Investor Reads Financial Analysis Online	M	0.92	1.00	0.27	260,003
Investor's Page Views of Financial Analysis Online	M	21	3	1131	260,003
Investor's Time Spent Reading Financial Analysis Online	M	27	2	292	260,003
Analysts' Mean Bias (As % of the Abs. Value of Cons. EPS)	Q	38.6%	6.7%	80.0%	81,597
Analysts' Median Bias	Q	37.5%	4.4%	84.0%	81,597
Analysts' Mean Accuracy	Q	60.9%	24.6%	77.1%	81,597
Analysts' Median Accuracy	Q	57.2%	19.6%	80.5%	81,597
Analyst Quits and Leaves the Profession	Q	0.16	0.00	0.42	81,597
Analyst Quits and Is Top 10% of Accuracy	Q	0.01	0.00	0.11	81,597
Analyst Quits and Is Top 25% of Accuracy	Q	0.02	0.00	0.14	81,597
Bold Revision	Q	0.65	0.66	0.19	81,597
Distance from Consensus	Q	0.37	0.35	0.16	81,597
General Experience (Avg. Years of Experience)	Q	4.26	4.18	1.69	81,597
Equity Price Informativeness	Q	0.62	0.65	0.25	79,543
Equity Price Informativeness Ratio for Analysts	Q	0.07	0.05	0.07	81,597
Independent Variables					
Investor Visits a FinTech Website	M	0.22	0.00	0.41	260,003
FinTech Coverage	Q	10.1	4.0	17.2	81,597
High Quality FinTech Coverage	Q	2.7	1.0	6.0	81,597
Newspaper Coverage	Q	81.1	10.0	666.7	81,597
Analyst Coverage	Q	7.0	5.3	5.7	81,597
Firm Size	Q	13.9	13.9	1.7	81,597
Daily Return Volatility	Q	37.9%	32.9%	20.6%	81,597
Mean Monthly Return	Q	1.1%	1.2%	6.6%	81,597
Log Market-to-Book	Q	0.8	0.8	0.4	81,597
Volatility of ROE	Q	98.8%	0.2%	685.1%	81,597
Profitability	Q	1.8%	2.3%	4.5%	81,597
Member of S&P 500	Q	15.0%	0.0%	35.7%	81,597
ROE	Q	1.0%	2.2%	13.4%	81,597
Momentum	Q	3.5%	0.6%	15.1%	81,597
Institutional Ownership	Q	59.8%	67.1%	30.6%	81,597
Hedge Fund Ownership	Q	5.0%	0.6%	8.1%	81,597

Table VI. Are FinTechs Directing Investors to the Best Analysis?

This table presents OLS estimates of investors' discovery of financial analysis online as a function of their decision to visit a FinTech website. Column (1) examines the binary choice to reading additional original-content financial analysis online. Column (2) and (3) examine how visiting a FinTech website changes aspects of readership. The dependent variable in Column (2) is the log of total page views of financial analysis and Column (3) is the log of time spent reading financial analysis. All specifications have user fixed effects, making demographic, income, etc ... controls redundant. The data comes from comScore and tracks the internet usage of a set of households reflective of the U.S. population. For a detailed description of each variable, see the definitions in Appendix B.

	Dependent variable =		
	Investor reads financial analysis online	Log of investor's page views of financial analysis online	Log of investor's time spent reading financial analysis online
	(1)	(2)	(3)
Visits a FinTech website	-.307***	-0.17***	-0.05***
	(0.00)	(0.01)	(0.01)
Time Fixed Effects	Y	Y	Y
User Fixed Effects	Y	Y	Y
Adjusted R-squared	25.5%	1.2%	2.0%
Observations	260,003	260,003	260,003

Table VII. Analyst, Newspaper, and FinTech Coverage

This table examines the correlation between and the determinants of analyst, newspaper, and FinTech coverage. Panel A reports some cross-correlations among the coverage variables. Panel B presents OLS regression estimates at the equity-quarter level. In Columns (1) through (4), the dependent variable is the type of coverage: analyst, newspaper, FinTech, and high quality FinTech coverage, respectively. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

Panel A. Correlation Matrix	Analyst Coverage (1)	Newspaper Coverage (2)	FinTech Coverage (3)	High Quality FinTech Coverage (4)
Type of Coverage				
(1) Analyst Coverage	1.00			
(2) Newspaper Coverage	0.36	1.00		
(3) FinTech Coverage	0.51	0.27	1.00	
(4) High Quality FinTech Coverage	0.45	0.26	0.79	1.00

	Dep. Var. = Type of Coverage			
Panel B. Determinants of Coverage	Analyst Coverage (1)	Newspaper Coverage (2)	FinTech Coverage (3)	High Quality FinTech Coverage (4)
Firm Size	0.41***	0.41***	0.71***	0.50***
	(0.01)	(0.04)	(0.02)	(0.01)
Profitability	0.03***	0.10***	0.01	-0.00
	(0.01)	(0.02)	(0.01)	(0.01)
ROE	-0.02***	-0.00	-0.02***	-0.02***
	(0.00)	(0.01)	(0.01)	(0.01)
Market-to-book	0.22***	0.26***	0.41***	0.28***
	(0.01)	(0.02)	(0.01)	(0.01)
Momentum	0.02***	-0.08***	0.12***	0.06***
	(0.00)	(0.01)	(0.01)	(0.01)
Institutional Ownership	0.20***	0.62***	0.08***	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Hedge Fund Ownership	0.00	0.01	-0.08***	-0.03***
	(0.01)	(0.02)	(0.01)	(0.00)
Adjusted R-squared	41%	17%	33%	26%
Observations	81,597	81,597	81,597	81,597

Table VIII. OLS Regression of Analysts' Response to FinTechs

This table presents OLS estimates of the relationship between FinTech coverage and analysts' reporting quality at the equity-quarter level. In Columns (1) through (4), the dependent variable is analyst bias, defined as a consensus forecast bias of all analysts tracking stock i in quarter t. Forecast bias is the difference between the forecast of analyst j in quarter t and the actual EPS, expressed as a percentage of the consensus EPS. The consensus is obtained either as a mean as in Columns (1) and (2) or median as in Columns (3) and (4). In Columns (5) through (8), the dependent variable is analyst accuracy, defined as a consensus absolute forecast error of all analysts tracking stock i in quarter t. The primary independent variable of interest, FinTech Coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Bias (As % of EPS)				Accuracy (As % of EPS)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FinTech Coverage	0.05***	0.01***	0.05***	0.01**	-0.06***	-0.02***	-0.06***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Newspaper Coverage	-0.01**	0.01	-0.01**	0.01	0.01**	-0.01*	0.01**	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Analyst Coverage	0.00	0.07***	0.00	0.07***	0.04***	-0.03***	0.03***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm Size	-0.18***	-0.11***	-0.18***	-0.11***	0.17***	0.45***	0.17***	0.43***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)
Daily Return Volatility	0.33***	0.07***	0.33***	0.07***	-0.38***	-0.06***	-0.37***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean Monthly Return	-0.09***	-0.03***	-0.09***	-0.03***	0.07***	0.00	0.07***	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Market-to-Book	0.12***	0.00	0.11***	-0.00	-0.07***	0.02	-0.08***	0.02*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Volatility of ROE	0.01	-0.01	0.00	-0.02	-0.01	0.02	-0.00	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Profitability	-0.39***	-0.13***	-0.37***	-0.13***	0.38***	0.13***	0.36***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	0.02***	-0.00	0.02***	-0.01	-0.00	-0.01	-0.01*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	N	Y	N	Y	N	Y	N	Y
Adjusted R-squared	39%	76%	36%	72%	41%	79%	38%	74%
Observations	81,597	81,597	81,597	81,597	81,597	81,597	81,597	81,597

Table IX. Instrumental Variable Test of Analysts' Response to FinTechs

This table presents IV estimates of the relationship between FinTech coverage and analysts' reporting quality at the equity-quarter level. In Columns (1) through (4), the dependent variable is analyst bias, defined as a consensus forecast bias of all analysts tracking stock i in quarter t. Forecast bias is the difference between the forecast of analyst j in quarter t and the actual EPS, expressed as a percentage of the consensus EPS. The consensus is obtained either as a mean as in Columns (1) and (2) or median as in Columns (3) and (4). In Columns (5) through (8), the dependent variable is analyst accuracy, defined as a consensus absolute forecast error of all analysts tracking stock i in quarter t. The primary independent variable of interest, FinTech coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. The instrument for FinTech Coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Bias (As % of EPS)				Accuracy (As % of EPS)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FinTech Coverage	0.14***	0.15	0.14***	0.19	-0.23***	-0.34**	-0.22***	-0.44**
	(0.04)	(0.19)	(0.04)	(0.20)	(0.04)	(0.18)	(0.04)	(0.19)
Newspaper Coverage	-0.02***	-0.00	-0.02**	-0.01	0.03***	0.03	0.03***	0.04
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Analyst Coverage	-0.01	0.03	-0.01	0.015	0.08***	0.07	0.07***	0.11*
	(0.01)	(0.06)	(0.01)	(0.07)	(0.01)	(0.06)	(0.01)	(0.06)
Firm Size	-0.22***	-0.12***	-0.22***	-0.12***	0.24***	0.48***	0.24***	0.46***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Daily Return Volatility	0.31***	0.06***	0.30***	0.05***	-0.33***	-0.03	-0.32***	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mean Monthly Return	-0.09***	-0.03***	-0.08***	-0.03***	0.06***	0.00	0.06***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Market-to-Book	0.11***	-0.01	0.11***	-0.02	-0.07***	0.05**	-0.07***	0.06***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
Volatility of ROE	0.00	-0.02	0.00	-0.02*	-0.00	0.03*	-0.00	0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Profitability	-0.39***	-0.13***	-0.37***	-0.13***	0.38***	0.14***	0.36***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	0.00	-0.02	0.01	-0.02	0.02**	0.01	0.01	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	N	Y	N	Y	N	Y	N	Y
First Stage F-Stat	195.9	38.9	195.9	38.9	195.9	38.9	195.9	38.9
T-Stat on Instrument	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0
Adjusted R-squared	38.7%	75.8%	36.1%	71.5%	40.6%	78.5%	38.3%	74.2%
Observations	81,597	81,597	81,597	81,597	81,597	81,597	81,597	81,597

Table X. Analysts' Response to Higher Quality FinTechs

This table presents IV estimates of the relationship between high quality FinTech coverage and analysts' reporting quality at the equity-quarter level. In Columns (1) and (2), the dependent variable is analyst bias, defined as the mean consensus forecast bias of all analysts tracking stock i in quarter t, expressed as a percentage of the consensus EPS. In Columns (3) and (4), the dependent variable is analyst bias, defined as the mean consensus forecast bias of all analysts tracking stock i in quarter t, expressed as a percentage of the previous quarter's stock price. The primary independent variable of interest measures the quantity of financial blog posts identified by FinTechs as high quality in quarter t that discuss equity i. In Columns (1)-(2) and (5)-(6), quality is defined by short-term investment performance (i.e., less than six months) and in Columns (3)-(4) and (7)-(8) quality is defined by long-term investment performance (i.e., one year or more). The instrument for FinTech coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Mean Bias (As % of EPS)				Mean Accuracy (As % of EPS)			
	Best Short-term		Best Long-term		Best Short-term		Best Long-term	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quality FinTech Coverage	0.14***	0.11	0.17***	0.14	-0.22***	-0.26**	-0.27***	-0.32**
	(0.04)	(0.14)	(0.05)	(0.18)	(0.04)	(0.13)	(0.05)	(0.16)
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	N	Y	N	Y	N	Y	N	Y
First Stage F-Stat	183.6	64.1	165.5	41.0	183.6	64.1	165.5	41.0
T-Stat on Instrument	13.5	13.5	12.9	12.9	13.5	13.5	12.9	12.9
Adjusted R-squared	39%	76%	39%	76%	40%	78%	40%	78%
Observations	81,597	81,597	81,597	81,597	81,597	81,597	81,597	81,597

Table XI. Analysts' Strategic Responses to FinTech Entry

This table presents IV estimates of the relationship between FinTech coverage and strategic responses by analysts at the equity-quarter level. Panel A examines analyst turnover. Columns (1) through (3) examines the number of analysts quit and leave the profession, Columns (4) through (9) examine if more accurate analysts quit and leave the profession. Panel B examines strategic responses related to reputation. Columns (1) through (6) examine bold forecasts by analysts and Columns (7) through (9) examine analyst experience. The primary independent variable of interest, FinTech coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. Other independent variables of interest are an indicator for if there is an increase in FinTech coverage and an indicator for no change in FinTech coverage. The instrument for FinTech coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Dep. Var. =								
	Analyst Quits			Top 10% for Accuracy & Quits			Top 25% of Accuracy & Quits		
Panel A. Talent Pool for Analysts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FinTech Coverage	0.114***			0.059***			0.075***		
	(0.023)			(0.021)			(0.022)		
Growing FinTech Coverage		1.626***			0.959***			1.027***	
		(0.466)			(0.356)			(0.376)	
No Change in FinTech Coverage			-3.216***			-1.896**			-2.031**
			(1.062)			(0.784)			(0.829)
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
First Stage F-Stat	195.9	35.5	15.7	195.9	35.5	15.7	195.9	35.5	15.7
T-Stat on Instrument	14.0	2.7	2.4	14.0	2.7	2.4	14.0	2.7	2.4
Adjusted R-squared	11%	10%	10%	1%	1%	1%	1%	1%	1%
Observations	81,597	63,544	63,544	81,597	63,544	63,544	81,597	63,544	63,544

	Dep. Var. =								
	Bold Revision			Distance from Consensus			General Experience		
Panel B. Strategic Response by Analysts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FinTech Coverage	0.015			-0.077***			-0.078***		
	(0.019)			(0.026)			(0.024)		
Growing FinTech Coverage		0.191			-1.278***			-0.938***	
		(0.255)			(0.413)			(0.355)	
No Change in FinTech Coverage			-0.377			2.528***			1.856**
			(0.511)			(0.945)			(0.772)
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
First Stage F-Stat	195.9	35.5	15.7	195.9	35.5	15.7	195.9	35.5	15.7
T-Stat on Instrument	14.0	2.7	2.4	14.0	2.7	2.4	14.0	2.7	2.4
Adjusted R-squared	19%	22%	22%	5%	6%	6%	74%	70%	70%
Observations	81,597	63,544	63,544	81,597	63,544	63,544	81,597	63,544	63,544

Table XII. Market Reaction to Analysts' Recommendations with FinTechs

This table presents estimates abnormal returns and volume following analysts' recommendation revisions, where revisions are limited to an upgrade to a buy or strong buy or a dowgrade to a sell or strong sell. Returns are in excess of benchmark portfolios matched on size, book-to-market, and momentum. Log volume is relative to a market model. Panel A displays abnormal returns over the main sample period from 2010Q1 to 2016Q3, whereas Panel B includes recommendations from the prior 5 years as a further benchmark. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Returns		Volume	
	[0,1]	[0,5]	[0,1]	[0,5]
Panel A. Reaction to Analyst Recommendations	(1)	(2)	(3)	(4)
FinTech Coverage	-0.24%***	-0.27%***	-0.047***	-0.034*
T-stat	(5.01)	(5.25)	(5.91)	(1.76)
Time Fixed Effects	Y	Y	Y	Y
Analyst Fixed Effects	Y	Y	Y	Y
Observations (Recommendations)	39,454	39,454	39,454	39,454

	Dep. Var. = Excess Returns			
	[0,1]			
Panel B. Change in Reaction Pre & Post FinTech En	(1)	(2)	(3)	(4)
FinTech Coverage	-0.28%***	-0.25%*	-0.10%*	-0.05%
T-stat	(3.36)	(1.87)	(1.93)	(0.54)
Time Fixed Effects	Y	Y	Y	Y
Analyst Fixed Effects	Y	-	Y	-
Firm Fixed Effects	Y	-	Y	-
Firm-Analyst Pair Fixed Effects	-	Y	-	Y
Include 5 Years Before FinTech	N	N	Y	Y
Observations (Recommendations)	35,790	18,905	75,165	42,087
Firm-Analyst Pairs	-	7,593	-	14,418

Table XIII. Price Informativeness with FinTechs

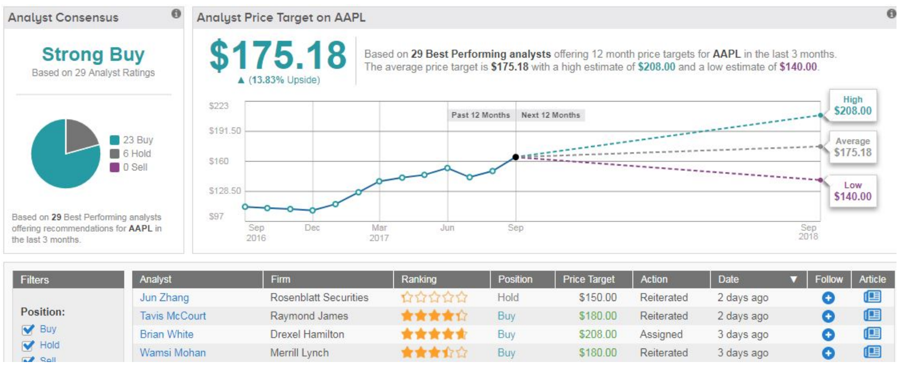
This table presents estimates of the change in price informativeness for stocks where FinTechs concentrate. In Columns (1) through (2) of Panel A, the dependent variable is price nonsynchronicity. In Columns (1) through (2) of Panel B, the dependent variable is analysts' contribution to price informativeness. In Column (1), the independent variable of interest is FinTech coverage. In Column (2), the independent variable of interest is high quality FinTech coverage. The ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Dep. Var. = Price Informativeness	
Panel A.	(1)	(2)
FinTech Coverage	0.460***	
	(0.046)	
High Quality FinTech Coverage		0.454***
		(0.046)
Additional Controls	Y	Y
Time Fixed Effects	Y	Y
First Stage F-Stat	190.4	179.9
T-Stat on Instrument	13.8	13.4
Adjusted R-squared	48%	48%
Observations	79,543	79,543

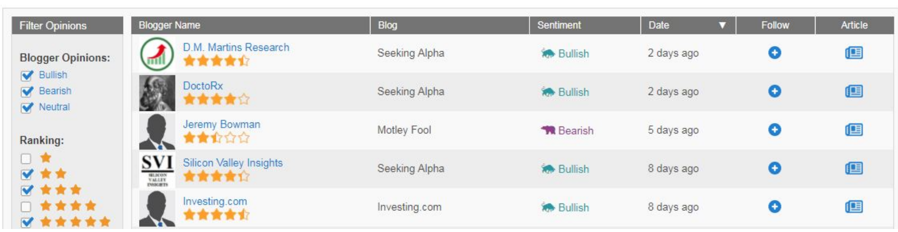
	Dep. Var. = Analyst Informativeness Ratio	
Panel B.	(1)	(2)
FinTech Coverage	-0.107***	
	(0.037)	
High Quality FinTech Coverage		-0.106***
		(0.037)
Additional Controls	Y	Y
Time Fixed Effects	Y	Y
First Stage F-Stat	195.9	183.6
T-Stat on Instrument	14.0	13.5
Adjusted R-squared	24%	23%
Observations	81,597	81,597

Appendix A. FinTechs as Complements or Substitutes

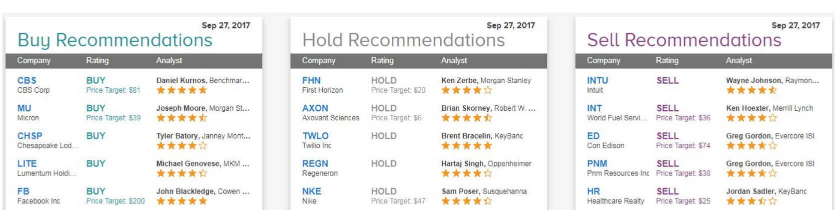
FinTechs are a complement to financial analysts when investors learn the best analysts and click-through to their research. The graphic below shows a website where analysts are ranked using a star rating and investors can click through to read the original article.



FinTechs are a substitute for financial analysts when investors learn the best analysis is from bloggers so skip analysts' research. The graphic below shows a website where bloggers are ranked using a star rating in a manner that leads to easy comparison with analysts.



FinTechs are also a substitute for financial analysts when investors rely only on the signal and forgo reading original-content financial analysis altogether. The graphic below shows a website where clicking-through isn't an option rather only the extracted signal is displayed.



Appendix B. Variable Definitions

We use data from IBES, Zacks, CRSP, Compustat, and Thomson Reuters to construct our financial analyst sample. To construct our various measures of accuracy and bias, we use diluted, U.S. currency quarterly earnings per share (EPS) forecasts from 1 to 8 quarters out as well as diluted, U.S. currency annual EPS forecasts from 1 to 2 years out. The remaining EPS forecasts that are greater than 2 years out or more than 8 quarters out represent less than 2% of the universe of forecasts and are not well populated to evaluate the consensus; hence, this is our reason for excluded them. We include in our set of forecasts those that are original forecasts, announced confirmations of previous forecasts, and revised forecasts. Each variable is winsorized at the 1st and 99th percentile to mitigate the influence of extreme observations. Definitions are as follows:

Mean (Median) Bias As a Percentage of the Absolute Value of Consensus EPS is the difference between the analyst's forecast and the actual EPS divided by the absolute value of the consensus EPS for equity i in quarter t. Because our analysis is conducted at the equity level, we further aggregate forecast biases and consider the consensus bias expressed as the mean (median) bias among all analysts covering a particular equity.

Mean (Median) Accuracy As a Percentage of the Absolute Value of Consensus EPS is the absolute value of the signed forecast error (i.e., the difference between the analyst's forecast and the actual EPS) divided by the absolute value of the consensus EPS for equity i in quarter t. Because our analysis is conducted at the equity level, we further aggregate forecast biases and consider the consensus bias expressed as the mean (median) forecast error among all analysts covering a particular equity.

Mean (Median) Bias As a Percentage of the Previous Quarter's Stock Price is the difference between the analyst's forecast and the actual EPS divided by the closing price for equity i in quarter $t-1$. To match the definition of bias used in Hong and Kacperczyk (2010), we use EPS from Compustat rather than IBES. Because our analysis is conducted at the equity level, we further aggregate forecast biases and consider the consensus bias expressed as the mean (median) bias among all analysts covering a particular equity.

Mean (Median) Accuracy As a Percentage of the Previous Quarter's Stock Priceis the absolute value of the signed forecast error (i.e., the difference between the analyst's forecast and the actual EPS) divided by the closing price for equity i in quarter $t-1$. To match the definition of accuracy used in Hong and Kacperczyk (2010), we use EPS from Compustat rather than IBES. Because our analysis is conducted at the equity level, we further aggregate forecast biases and consider the consensus bias expressed as the mean (median) forecast error among all analysts covering a particular equity.

Analyst Coverage is the number of analysts covering stock i in quarter t. ($NUMEST$)

Forecast Dispersion is the standard deviation of all analyst forecasts covering stock i in quarter t. ($VALUE$)

Firm Size is the logarithm of stock i's market capitalization at the end of quarter t. ($\log(PRCC\_F \times CSHO)$)

Daily Return Volatility is the annualized variance of daily raw returns of stock i in quarter t. ($\sigma_{RET} \times \sqrt{252}$).

Mean Monthly Return is the average monthly return on stock i in quarter t. ($R\bar{E}T$)

Log Market-to-book $= log(\frac{PRCC\_F \times CSHO + DLC + DLTT + PSTKL - TXDITC}{AT})$

Return on Equity (ROE) $= \frac{NI}{SEQ_{t-1}}$

Volatility of ROE comes from estimating an AR(1) model for each equity's ROE using a rolling, 10-year series of the company's valid annual ROEs. The variance of the residuals from this regression is the volatility of ROE.

Profitability $= \frac{OIBDP}{AT}$

Member of S&P 500 is an indicator variable that takes the value of one if stock i is included in the S&P 500 index in quarter t.

Institutional Ownership data comes from Thomson-Reuters via 13F SEC filings. Ownership percentages are based on the number of shares outstanding and correspond to calendar dates.

Hedge Fund Ownership data comes from Factset and we use the classification technique created by Ferreira and Matos (2008). (IO_CAT6)

Affiliated Analyst is an indicator variable for if an analyst works at a brokerage house with a pre-existing relationship with the firm through business underwriting an IPO, SEO, or as an advisor on an M&A deal. IPO, SEO, and M&A deal data are pulled from SDC.

Brokerage Size is the number of analysts at the brokerage firm.

Brokerage Prestige is an indicator variable that takes the value of one if the brokerage firm is listed that year as one of Institutional Investor Magazine's top brokerage houses.

Firm Experience is the number of years analyst j covered stock i.

General Experience is the number of years since the analyst first appeared in the IBES database.

Number of Firms Covered is the total number of unique stocks covered by the analyst during the year.

Number of Industries Covered is the total number of unique two-digit SIC industries covered by the analyst during the year.

Days Since Last Forecast is the average number of days elapsed since the most recent forecast for that same stock by i by analyst j in a given quarter t.

Forecast Horizon is the average number of days between the estimate date and the reference date, which is the fiscal period end date, in a given quarter t for a stock i covered by analyst j.

Forecast Frequency is the number of forecasts for stock i issued by analyst j during the previous year.

Bold Revision is the percent of forecast revisions for a given quarter t for a stock i that are bold. To define bold, we follow the construction in Clement and Tse (2005) where bold is an indicator variable for each analyst j's forecast revision for stock i in quarter t. It is equal to 1 if analyst j's forecast is above both the analyst's prior forecast and the mean forecast immediately before the forecast revision, or else below both. It is set to 0 otherwise.

Distance from Consensus is the average distance from the consensus for forecast revisions by all analysts covering stock i in quarter t. This measure is a continuous measure of the boldness of the forecast revision. To define this continuous measure of boldness, we follow the construction in Clement and Tse (2005). We calculate the distance of analyst j's revised forecast for firm i

from the pre-revision consensus forecast. We take the absolute value of the distance of the revised forecast from the consensus minus the minimum absolute distance for analysts who follow firm i in quarter t, with this difference scaled by the range in absolute distances for analysts following firm i in quarter t.

Analyst Quits is an indicator variable for if $ANALYS$ stops appearing in the IBES dataset altogether. Given that our analyst data extends beyond the sample period for our FinTech data, we can calculate quits even in the final quarter.

Analyst Quits and is in Top % of Accuracy is an indicator variable for if $ANALYS$ stops appearing in the IBES dataset for stock altogether and was in the top 10% (or 25%) of accuracy across all analysts in quarter $t-1$. For each stock i in quarter t, the analyst with the minimum signed forecast error is identified as the most accurate. Then, we calculate for what percent of stocks the analyst covers that he or she had the most accurate forecast (e.g., an analyst covers 5 stocks and is most accurate 1 time, the analyst is most accurate 20% of the time). Then, based on analyst-quarter observations for our sample period, we define the percentiles for percent of time most accurate.

Price Informativeness is estimated as $1 - R^2$, where R^2 is the R-square from the following regression: $r_{ijt} = \beta_{i,0} + \beta_{i,m} * r_{m,t} + \beta_{i,j} * r_{j,t} + \epsilon_{i,t}$ where $r_{i,j,t}$ is the return of firm i in industry j at time t, $r_{m,t}$ is the CRSP value-weighted market return at time t, and $r_{j,t}$ is the return of 3-digit SIC industry j at time t. If there are fewer than 30 daily price observations in a quarter the observation is set as missing.

Price Jump Ratio is a new price informativeness measure derived by Weller (2018). It captures how much information enters equity prices early relative to how much is potentially acquirable by dividing the return at the time of information's public disclosure to the total return over the pre-announcement period. A higher jump ratio corresponds to greater price informativeness.

Analysts Contribution to Price Informativeness is estimated as $AC_{j,t} = \frac{\sum_{d=1}^{NREVS} |Ret_{j,d} - DecRet_{j,d}|}{\sum_{d=1}^{63} |Ret_{j,d} - DecRet_{j,d}|}$ where d denotes trading days in a quarter, $NREVS$ denotes the number of unique days for which there is at least one analyst forecast, j denotes firm, and t denotes quarter. To mitigate the potential concern for the AC measure of analysts "piggybacking" off of management or other experts analysis, we exclude from the numerator days where earnings announcements are made and days when bloggers post about the equity.

To construct our dataset of FinTechs and financial analysis, we use data provided to us by TipRanks. We supplement this data with data from Crunchbase, ComScore, and internet searches. Definitions are as follows:

Year Founded is pulled from Crunchbase. If it is not available on Crunchbase, founding date is pulled from the FinTech's website. If the founding date is not on Crunchbase or the FinTech's website, then the first year in which Wayback Machine made a copy of the website is used as the founding year.

Targets Retail Investors is an indicator variable equal to one if the FinTech's business plan suggests the product is meant for retail investors.

Targets Professional Investors is an indicator variable equal to one if the FinTech's business plan suggests that the product is meant for insitutional investors.

Appendix C. Additional Tables

Table CI. Summary Statistics for Newspaper Headlines

This table provides summary statistics related to newspaper headline length by year for the sample period from 2009-2016. Headline data comes from Ravenpack. Newspapers included in the analysis are: USA Today, the Wall Street Journal, the New York Times, the Los Angeles Times, the Chicago Tribune, the Washington Post, the Financial Times, and the DowJones Newswire.

Year (1)	Obs. (2)	Mean (3)	25th Percentile (4)	Median (5)	75th Percentile (6)
2009	619,854	55.4	50	56	60
2010	1,119,096	52.6	45	53	60
2011	988,949	55.4	47	56	62
2012	1,055,145	57.0	48	58	63
2013	846,705	56.1	48	57	63
2014	1,004,774	57.8	49	58	65
2015	998,023	58.6	49	58	66
2016	905,906	58.9	48	58	67
All	7,538,452	56.5	48	57	63

Table CII. Example Newspaper Headlines

This table presents example headlines for Apple where the headline length falls exactly at the 25th percentile and 75th percentile, respectively.

25th Percentile of Headline Length	75th Percentile of Headline Length
Apple's Schiller Rides to the App Store's Rescue	Apple to Unveil New Software Tuesday; Netbook Speculation Swirls
Apple Mac Sales Did Better Than Expected in June	Apple CFO: Consumer Spending Stronger Than Business, Government
Nokia Sues Apple Over iPhone Patent Infringement	Elan to Expand Patent Lawsuit Against Apple to Include the iPad
Analysts Ask If the iPad Can Live Up to Its Hype	Apple Urges Respect for Workers After Death Over Missing iPhone
Apple Adds 2 Publishers to Its Store for E-Books	iPad 3g Shortage Spurs At&T Discussions About Its New Data Plan
Apple Unveils iPad Tablet With Onscreen Keyboard	Apple Launches Ad System for Mobile Devices in Race With Google
Tablet? Slate? New Devices Emerge As Apple Looms	FTC Said to Prepare Review of Apple Tactics in Mobile Ad Market
Apple's Mac Sales Shine, iPhone Lags Street View	Jobs Wears Tech Crown As Apple Eclipses Microsoft in Market Cap
Apple Still Underdog in China, Despite New Store	Android Sales Top Apple iPhone in First-Half 2010, Says Nielsen
Are Hedge Funds Hoping for an Apple 'Slingshot'?	Apple Closes In on Nintendo With 40 Million iPod, iPhone Gamers
Apple Gives App Developers Its Review Guidelines	Did Steve Jobs Accidentally Confirm Cameras for Next Gen iPads?
Apple Gearing Up for Newspaper Subscription Plan	Once Again, Apple's New Design Won't Accommodate Your Old Cords

Table CIII. Headline Length and Firm Characteristics

This table presents OLS estimates where the dependent variable is headline and the explanatory variables are firm and newspaper characteristics. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

	Dep. Var. = Headline Length (1)
Log Market-to-Book	0.00
	(0.00)
Profitability	-0.53
	(0.77)
ROE	0.01
	(0.00)
Momentum	1.32*
	(0.79)
Firm Size	-0.02
	(0.05)
Newspaper FE	Y
Adjusted R^2	0.10%
Observations	7,538,452

Table CIV. LASSO Selection of Words Associated with Headline Length

This table presents estimates connecting common words to headline length. The estimates are based off of a LASSO regression. Such a technique helps with the problem of picking out the relevant words from a larger set (i.e., variable selection) by pushing estimates of some coefficients to be exactly zero. The words are listed in the order that they are selected to be included in the model. Column (1) shows the LASSO adjusted coefficient estimate for the word and Column (2) displays the cumulative variance explained when that word is included. Given that the variance explained plateaus toward the end, only the first 20 words selected into the model are listed.

	Dep. Var. = Headline Length (1)	R-squared When Variable Is Included (2)
quarterly	24.89	2.25%
available	10.69	7.42%
annual	5.76	7.94%
stories	-6.21	8.11%
market	4.18	8.34%
talk	-14.78	8.41%
events	-8.25	8.71%
financial	10.47	10.78%
agreement	11.25	10.87%
million	8.84	10.96%
morning	5.07	11.08%
mgmt	-4.32	11.26%
billion	6.79	11.31%
investors	6.53	11.59%
capital	6.95	11.62%
sells	-0.28	11.76%
china	5.32	11.89%
week	7.13	12.22%
fund	5.79	12.37%
bank	4.40	12.37%
Additional Word Controls	Yes	
Firm Characteristic Controls	Yes	
Observations	7,538,452	

Table CV. Robustness: Investor Response (Alt. Specification)

This table presents OLS estimates of investors' discovery of financial analysis online as a function of their decision to visit a FinTech website. This table contrasts with which relies upon within-user variation to estimate the relationship between visits to FinTech websites and readership of original-content financial analysis. Instead, this table relies upon cross-sectional variation to estimate the relationship while attempting to condition upon user-type with available demographic controls.

	Dependent Variable =			
	Internet user reads financial analysis or visits a FinTech website	Investor reads financial analysis online	Log of investor's page views of financial analysis online	Log of investor's time spent reading financial analysis online
	(1)	(2)	(3)	(4)
FinTech Use				
Visits a FinTech website		-57.4***	-0.550***	-0.337***
		(0.10)	(0.00)	(0.00)
Income				
50-100k	1.15***	0.79***	0.05***	0.05***
	(0.03)	(0.05)	(0.00)	(0.00)
100k+	3.06***	2.04***	0.12***	0.10***
	(0.04)	(0.06)	(0.00)	(0.00)
Race				
White	6.83***	1.27***	0.20***	0.21***
	(0.04)	(0.06)	(0.00)	(0.00)
Black	1.89***	0.32***	0.03***	0.05***
	(0.05)	(0.08)	(0.00)	(0.01)
Asian	9.24***	3.01***	0.25***	0.23***
	(0.09)	(0.10)	(0.01)	(0.01)
Age of Head of Household				
30-39	0.28***	0.19**	0.04***	0.05***
	(0.05)	(0.08)	(0.00)	(0.00)
40-49	0.70***	0.43***	0.05***	0.06***
	(0.04)	(0.07)	(0.00)	(0.00)
50-59	1.74***	0.76***	0.11***	0.13***
	(0.05)	(0.07)	(0.00)	(0.00)
60+	3.66***	1.95***	0.23***	0.27***
	(0.05)	(0.08)	(0.00)	(0.00)
Education				
College degree	4.93***	0.88***	0.08***	0.07***
	(0.05)	(0.06)	(0.00)	(0.00)
Graduate degree	2.27***	0.42*	0.06***	0.06***
	(0.12)	(0.22)	(0.01)	(0.01)
Additional Control Variables	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Adjusted R-squared	2.4%	55.3%	6.5%	6.7%
Observations	7,241,817	1,090,746	1,090,746	1,090,746

Table CVI. Top Stocks Financial Bloggers Post About

This table presents a list of the top stocks blogged about by financial bloggers.

Ticker (1)	Name (2)	Percent of Total Blog Posts (3)	Percent of Total Recs (4)
AAPL	Apple Inc.	2.78%	1.92%
AMZN	Amazon.com, Inc.	0.86%	0.60%
FB	Facebook Inc.	0.70%	0.49%
MSFT	Microsoft Corporation	0.70%	0.54%
TSLA	Tesla Motors Inc.	0.67%	0.41%
BAC	Bank of America	0.67%	0.59%
INTC	Intel	0.66%	0.58%
NFLX	Netflix Inc.	0.56%	0.43%
F	Ford Motor Company	0.51%	0.51%
GOOG	Alphabet Inc.	0.42%	0.28%
BBRY	BlackBerry Limited	0.41%	0.33%
BA	Bank of America Corp.	0.39%	0.26%
DIS	The Walt Disney Company	0.37%	0.32%
IBM	International Business Machines Corp.	0.36%	0.34%
CSCO	Cisco Systems, Inc.	0.36%	0.39%
WMT	Wal-mart	0.36%	0.33%
MCD	McDonald's	0.35%	0.37%
T	AT&T Inc.	0.35%	0.34%
TWTR	Twitter Inc.	0.34%	0.22%
GE	General Electric	0.34%	0.35%
GILD	Gilead Sciences, Inc.	0.33%	0.33%
JNJ	Johnson & Johnson	0.32%	0.40%
JPM	J.P. Morgan	0.31%	0.24%
XOM	Exxon Mobil	0.30%	0.35%
GM	General Motors	0.30%	0.26%
CVX	Chevron Corporation	0.30%	0.36%
YHOO	Yahoo! Inc.	0.29%	0.21%
C	Citigroup, Inc.	0.29%	0.25%
SBUX	Starbucks Corporation	0.28%	0.28%
KO	The Coca-Cola Company	0.28%	0.28%

Table CVII. Robustness: Summary Statistics (Alt. Dataset)

This table presents summary statistics for the main dependent and independent variables. After combining the datasets, the main sample period is limited to 2010Q1 to 2016Q3. For a detailed description of each variable, see the definitions in Appendix B.

	Freq. (1)	Mean (2)	Median (3)	Std. Dev. (4)	Obs. (5)
Dependent Variables					
Analysts' Mean Bias (As % of the Abs. Value of Cons. EPS)	Q	38.2%	4.9%	86.3%	69,532
Analysts' Median Bias	Q	37.8%	3.9%	88.0%	69,532
Analysts' Mean Accuracy	Q	36.0%	15.7%	53.8%	69,532
Analysts' Median Accuracy	Q	34.1%	13.7%	56.0%	69,532
Independent Variables					
FinTech Coverage	Q	10.6	4.0	17.2	69,532
Newspaper Coverage	Q	89.5	12.0	714.2	69,532
Analyst Coverage	Q	7.6	5.9	5.7	69,532
Firm Size	Q	14.1	14.0	1.7	69,532
Daily Return Volatility	Q	37.1%	32.2%	20.0%	69,532
Mean Monthly Return	Q	1.1%	1.2%	6.5%	69,532
Log Market-to-Book	Q	0.84	0.77	0.44	69,532
Volatility of ROE	Q	95.5%	0.2%	681.9%	69,532
Profitability	Q	1.92%	2.33%	4.41%	69,532
Member of S&P 500	Q	16.7%	0.0%	37.3%	69,532

Table CVIII. Robustness: Analyst Response (Alt. Dataset)

This table presents IV estimates at the equity-quarter level for analysts' responses to FinTechs coverage of the equities the analysts cover. This table contrasts with Table VIII in the dataset used to define all of the analyst variables. This table uses Zacks data whereas the main specification uses IBES data. In Columns (1) through (4), the dependent variable is analyst bias, defined as a consensus forecast bias of all analysts tracking stock i in quarter t. Forecast bias is the difference between the forecast of analyst j in quarter t and the actual EPS, expressed as a percentage of the consensus EPS. The consensus is obtained either as a mean as in Columns (1) and (2) or median as in Columns (3) and (4). In Columns (5) through (8), the dependent variable is analyst accuracy, defined as a consensus absolute forecast error of all analysts tracking stock i in quarter t. The primary independent variable of interest, FinTech Coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. The instrument for FinTech Coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Bias (As % of EPS)				Accuracy (As % of EPS)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FinTech Coverage	0.17***	0.34*	0.17***	0.39**	-0.30***	-0.50**	-0.29***	-0.48**
	(0.04)	(0.19)	(0.04)	(0.19)	(0.04)	(0.24)	(0.04)	(0.24)
Newspaper Coverage	-0.03***	-0.05	-0.03***	-0.06*	0.04***	0.06	0.04***	0.05
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.04)
Analyst Coverage	0.01	-0.04	0.01	-0.06	0.02	0.15*	0.03**	0.16*
	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.09)	(0.01)	(0.09)
Firm Size	-0.25***	-0.03	-0.24***	-0.04	0.29***	0.24***	0.28***	0.24***
	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)
Daily Return Volatility	0.27***	0.03	0.26***	0.02	-0.19***	0.02	-0.17***	0.022
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Mean Monthly Return	-0.09***	-0.03***	-0.09***	-0.03***	0.032***	0.000	0.031***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Log Market-to-Book	0.12***	-0.06**	0.12***	-0.07***	0.04***	0.10***	0.04***	0.10***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.04)
Volatility of ROE	0.00	-0.02	0.00	-0.02*	-0.00	0.07***	0.00	0.07***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.03)
Profitability	-0.36***	-0.13***	-0.35***	-0.13***	0.03***	0.07***	0.01**	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Member of S&P 500	-0.00	-0.04*	-0.00	-0.05*	0.06***	0.032	0.05***	0.027
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	N	Y	N	Y	N	Y	N	Y
First Stage F-Stat	195.8	27.1	195.8	27.1	195.8	27.1	195.8	27.1
T-Stat on Instrument	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0
Adjusted R^2	37%	73%	35%	70%	14%	51%	12%	46%
Observations	69,532	69,532	69,532	69,532	69,532	69,532	69,532	69,532

Table CIX. Robustness: Analyst Response (Alt. Unit of Observation)

This table presents IV estimates at the analyst-equity-quarter level rather than the equity-quarter level. Column (1) repeats the main anlaysis from Table VIII where the dependent variable is mean forecast bias but at this more disaggregated analyst-level of the data. The remaining Columns repeat the analysis for various subsamples of the data: Columns (2) and (3) focus on affiliated and non-affiliated stocks, Columns (4) and (5) focus on independent and non-independent brokerage houses, and Columns (6) and (7) focus on inexperienced and experienced analysts, respectively. Additional controls include newspaper coverage, analyst coverage, firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, membership in the S&P 500, momentum, and institutional ownership. The primary independent variable of interest, FinTech Coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. The instrument for FinTech Coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Dependent Variable = Mean Bias (As a % of EPS)						
	All	Affiliated Stock	Not Aff. Stock	Indep. Broker	Not Indep.	Inexp. Analyst	Exp. Analyst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FinTech Coverage	0.67***	1.12***	0.59***	0.99***	0.62***	0.78***	0.47***
	(0.08)	(0.36)	(0.08)	(0.28)	(0.09)	(0.11)	(0.12)
General Experience	-0.01***	-0.00	-0.01***	-0.02*	-0.00***	0.00	-0.01***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)
Firm Experience	-0.00***	-0.01	-0.00***	-0.00	-0.00*	-0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Firms Covered	0.01***	-0.00	0.01***	0.02**	0.00***	0.02***	0.01***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Industries Covered	-0.00***	-0.00	-0.00***	-0.02*	-0.01***	-0.03***	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Forecast Frequency	-0.0***	-0.01**	-0.00**	0.00	-0.00**	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Forecast Horizon	0.00***	0.01***	0.00*	0.01**	0.00***	0.00	0.00***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Days Since Last Forecast	0.01***	0.01*	0.01***	0.03***	0.01***	0.01***	0.01***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Affiliated with Firm	-0.00	-	-	0.03	-0.00	-0.00	-0.02***
	(0.00)	-	-	(0.10)	(0.00)	(0.01)	(0.01)
Brokerage Size	0.00***	0.00	0.00*	0.04***	0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Independent Brokerage	0.01***	0.05	0.01***	-	-	0.01***	0.04***
	(0.00)	(0.07)	(0.00)	-	-	(0.01)	(0.01)
Additional Controls	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y
T-Stat on Instrument	14.0	4.6	13.0	4.3	13.1	11.0	8.5
Adjusted R^2	53%	59%	53%	28%	56%	50%	61%
Observations	296,744	45,362	251,265	40,510	255,965	189,551	106,928

Table CX. Robustness: Analyst Response (Alt. Definition)

This table presents IV estimates at the equity-quarter level for analysts' responses to FinTechs coverage of the equities the analysts cover. This table contrasts with Table VIII in the definition of analyst bias and accuracy. In Columns (1) through (4), the dependent variable is analyst bias, defined as a consensus forecast bias of all analysts tracking stock i in quarter t. Forecast bias is the difference between the forecast of analyst j in quarter t and the actual EPS, expressed as a percentage of the previous period's stock price. The consensus is obtained either as a mean as in Columns (1) and (2) or median as in Columns (3) and (4). In Columns (5) through (8), the dependent variable is analyst accuracy, defined as a consensus absolute forecast error of all analysts tracking stock i in quarter t again expressed as a percentage of the previous period's stock price. The primary independent variable of interest, FinTech Coverage, measures the quantity of financial blog posts analyzed by FinTechs in quarter t that discuss equity i. The instrument for FinTech Coverage is headline length which indicates if newspaper headlines about equity i in quarter t were shorter than the median headline length. Below the coefficient estimates are robust standard errors clustered at the equity-level. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Bias (As % of Share Price)				Accuracy (As % of Share Price)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FinTech Coverage	0.22***	0.20	0.17***	0.10	-0.32***	-0.15	-0.27***	-0.16
	(0.04)	(0.20)	(0.04)	(0.19)	(0.04)	(0.17)	(0.04)	(0.16)
Newspaper Coverage	-0.06***	-0.00	-0.04***	0.00	0.08***	-0.00	0.06***	-0.00
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Analyst Coverage	0.02*	0.05	0.01	0.05	0.02*	-0.03	0.03**	0.00
	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.06)	(0.01)	(0.06)
Firm Size	-0.17***	0.16***	-0.12***	-0.04	0.21***	0.41***	0.17***	0.53***
	(0.02)	(0.05)	(0.02)	(0.06)	(0.02)	(0.04)	(0.02)	(0.05)
Daily Return Volatility	0.29***	0.04**	0.24***	0.05**	-0.35***	-0.08***	-0.29***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mean Monthly Return	-0.12***	-0.05***	-0.10***	-0.04***	0.11***	0.03***	0.10***	0.02***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Log Market-to-Book	-0.13***	-0.16***	0.00	-0.09***	0.15***	0.06**	0.12***	0.02
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
Volatility of ROE	0.00	-0.05*	0.00	-0.05*	-0.01	0.06***	-0.01	0.05*
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
Profitability	0.02**	-0.09***	0.03***	-0.08***	0.08***	0.10***	0.07***	0.09***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	-0.04***	-0.04	-0.02**	-0.01	0.02**	-0.00	0.01	-0.01
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	N	Y	N	Y	N	Y	N	Y
First Stage F-Stat	195.9	38.9	195.9	38.9	195.9	38.9	195.9	38.9
T-Stat on Instrument	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0
Adjusted R-squared	13.9%	61.7%	9.7%	51.8%	25.2%	72.6%	18.7%	65.0%
Observations	81,597	81,597	81,597	81,597	81,597	81,597	81,597	81,597

Table CXI. Robustness: Prince Informativeness (Subsample Test)

This table presents estimates of the change in price informativeness for stocks where FinTechs concentrate as in Table XI for two different subsamples of the main dataset. In Panel A, the subsample includes observations with an above median price jump ratio. For this subsample of equities, distortions to price informativeness from algorithmic trading are limited. In Panel B, the subsample includes observations with a below median price jump ratio. For this subsample of equities, distortions to price informativeness from algorithmic trading are stronger. The subsamples are derived from a smaller set of observations because each observation must have a valid jump and have coverage in the MIDAS data used by Weller (2018). In Column (1), the independent variable of interest is FinTech coverage. In Column (2), the independent variable of interest is high quality FinTech coverage. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively. For a detailed description of each variable, see the definitions in Appendix B.

	Dep. Var. = Price Informativeness	
Panel A. High Price Jump Ratio Sample	(1)	(2)
FinTech Coverage	0.203***	
	(0.048)	
High Quality FinTech Coverage		0.189***
		(0.045)
Additional Controls	Y	Y
Time Fixed Effects	Y	Y
First Stage F-Stat	82.2	54.5
T-Stat on Instrument	12.1	12.0
Adjusted R-squared	39%	39%
Observations	9,954	9,954

	Dep. Var. = Price Informativeness	
Panel B. Low Price Jump Ratio Sample	(1)	(2)
FinTech Coverage	0.347***	
	(0.048)	
High Quality FinTech Coverage		0.333***
		(0.046)
Additional Controls	Y	Y
Time Fixed Effects	Y	Y
First Stage F-Stat	108.4	74.2
T-Stat on Instrument	12.7	12.6
Adjusted R-squared	46%	46%
Observations	10,054	10,054