FinTechs and the Market for Financial Analysis[*]

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ABSTRACT

We examine if FinTechs disrupt incumbents (i.e., sell-side research analysts) in the market for financial analysis. FinTechs aggregate and synthesize investment analysis which may change how investors discover such advice. FinTechs could serve as substitutes to analysts if investors forgo reviewing original content. Or, FinTechs could serve as complements if it is easier to discover the best analysis. This economic tension, in turn, could impact the quality of the original research. Data on investor's internet use suggests FinTechs and analysts are substitutes. Thereby, the contents of analysts' reports are read less. In response, we find analysts produce more optimistic, less accurate analysis where FinTechs concentrate. The change in reporting quality is greatest for stocks where analysts' conflicts of interest are strongest. This suggests FinTechs alter market efficiency but not like traditional competitors do.

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

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I. Introduction

Technology is changing how information is produced and discovered in financial markets. To assess the value of a stock, modern investors can easily obtain financial analysis online and trade upon that information. Yet the sheer quantity of financial information available is making it more difficult for investors to extract what matters most. Seeing an opportunity, financial technology firms or "FinTechs"[1] have begun to streamline and synthesize the abundance of financial information. In some cases, the FinTechs extract signals from the financial data and provide it to investors. In other cases, they simply aggregate the analysis providing snippets of the best analysis. In this paper, we attempt to quantify the impact FinTechs have on the professionals in the financial services industry who traditionally provide financial analysis (i.e., equity analysts).

This question is important because an ideal financial market is one in which prices fully reflect available analysis and information; and thereby, the prices provide accurate signals for investors to allocate capital (Fama (1970); Bond, Edmans, Goldstein (2012)). While efficient outcomes depend on the accuracy of information, equity research may exhibit substantial bias because of conflicts of interest (Michaely and Womack (1999)). While policymakers try to limit such distortions through regulation (Bailey et al. (2003)), gains to informational efficiency since 1960 have been modest (Bai, Philippon, and Savov (2016)). FinTechs have the potential to significantly disrupt the status quo in this market and create positive change, yet their function as "aggregators" may in fact create negative change.

FinTechs business model in the market for financial analysis is not to provide original financial analysis but to aggregate existent analysis. Since the advent of the internet, many users have provided their own financial analysis for free. For example, the information posted on financial blogs is often forward-looking and similar in nature to analyst reports. But these non-traditional sources of analysis such as blogs and twitter offer inconsistent advice (Tumarkin and Whitelaw (2001); Antweiler and Frank (2004); Das and Chen (2007); Cookson, Niessner (2017)). In contrast, Fin-

[1] FinTech covers digital innovations and technology-enabled business model innovations in the financial sector. FinTech innovations have the potential to disrupt existing industry structures, facilitate strategic disintermediation, revolutionize how existing firms create and deliver products and services, provide new gateways for entrepreneurship, democratize access to financial services (Philippon (2016)).

Techs use machine learning algorithms to aggregate, streamline, and synthesize the vastly expanded set of financial analysis available to help investors to find and consume the best financial analysis. As an example, consider TipRanks; they provide a platform that allows investors to see a ranking of the historical performance of anyone who provides financial advice (i.e., bloggers, analysts, corporate insiders). As another example consider FirstAccess; they "turn big data into smart data, by separating the signal from the noise and delivering simple, reliable investment recommendations."

Aggregation is important because it is unclear if it decreases or increases the attention paid to the underlying financial analysis. If FinTechs serve as substitutes for the readership of original-content financial analysis, an investor will spend less time at an original-content website after visiting a FinTech website. Instead, the investor will rely more on the aggregated analysis rather than any individual piece of financial analysis. But the diverted attention may, in turn, generate changes in the production of financial information. Specifically, analysts may respond by decreasing their reporting quality (i.e., accuracy and bias) when FinTechs serve as substitutes. Thus, the entry of FinTechs could reduce the disciplinary forces that analysts endure for providing inaccurate analysis. This implies the competition brought about by FinTechs has the opposite effect as competition brought about by increasing the supply of analysts.

Under the complements view incumbents' responses will be polarized. On one hand, the average quality of any individual creating financial analysis is more salient, this increases market discipline from inaccurate analysis. The increase in discipline suggests the effect of FinTechs on incumbents will be an increase in analyst accuracy and a decrease analyst bias. On the other hand, investors' exposure to different types of financial analysis means that investors can more easily find financial analysis that conforms to their priors. Hence, through a preference for like-minded financial analysis, investors may increase the incentives for less well-known analysts to increase their bias and decrease their accuracy. We note these empirical predictions assume the incumbents are not changing for other reasons. For example, if the sell-side analyst industry is also becoming less profitable as a result of the FinTechs entry, then the financial analysis of analysts may be done by less qualified people since they are being paid less. Hence, FinTechs may prompt both a direct and indirect response from incumbents.

To enhance our understanding of financial analysis online, we collect data on financial bloggers and FinTechs. For a blog or FinTech to be included in our analysis, at least one internet user in ComScore's rotating monthly sample of 50,000 representative U.S. households must visit their website between 2010 and 2017. We observe that 90% of financial blogs that internet users read do not make buy or sell recommendations. Instead, the financial bloggers provide commentary on the information that moves markets. Internet users, however, 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. Internet users want to consume financial analysis quickly. While the typical blog post can be several paragraphs long and similar in nature to an equity analysts' report, the average internet user views 16 pages on the financial blog spending 6.6 minutes reading those pages in a given month. Part of the problem with low dwell time per page may be the noisy nature of the analysis provided by bloggers. Analyzing 1.3 million blog posts across 20 financial blogs, we find 90% of the time, the market-adjusted returns to bloggers recommendations were negative at an investment horizon of 6 or 12 months. Hence, the need for FinTechs that sift through the noise to detect any potentially useful financial analysis.

Turning to the data we collected on FinTechs, we observe 290 FinTechs with a mean founding year of 2008. 72% of the FinTechs target retail investors and 60% target professional investors with some targeting both. We observe that the most common capabilities 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 bloggers and analyst (11% do this). Overall, our review of the FinTech webistes confirms that aggregating and streamline pre-existing financial analysis rather than producing their own content is pervasive.

To assess whether FinTech's role as aggregators leads them to be substitutes or complements for original-content financial analysis, we examine internet traffic data to detect changes in how investors find financial analysis online. We assess whether investors increase or decrease their visits, pages views, and time spent at original-content websites after visiting a FinTech website. We find that investors are 57 percentage points less likely to visit an original-content website. And among those who do visit an original content website, they cut their page views in half and spend one-third less time on those websites. This finding is robust to a myriad of controls including income, education, race, age, and time. Overall, the evidence suggests that investors use FinTechs as a substitute for reading traditional financial analysis. A natural corollary is that the reduction in time spent on primary source websites reduces the saliency of any individual analyst's report.

Next, we examine if the diversion of attention from incumbents brought about by FinTechs entering the market for financial analysis leads them to respond. To operationalize this test, we examine two important attributes of analyst reports: (1) aggregate earnings forecast accuracy and (2) aggregate optimism bias. We use an instrumental variable (IV) approach to test the analysts response. We proxy for the diverted attention using the quantity of non-traditional data sources that also providing financial analysis on that stock. The IV approach helps to address the challenge that a concentration of non-traditional financial analysis is not randomly assigned.[2] To overcome this bias and other empirical challenges, we use a linguistic-based instrument that provides variation in the concentration of financial bloggers covering an equity. We match daily financial blog entries with Buy/Sell recommendations for an equity to daily newspaper headlines for that same equity. We use a text-based algorithm to identify if the newspaper headlines use a psychological trick for increasing in attention. The psychological tricks include: surprise, questions, curiosity gap, tone, "how to," precision, audience reference, and length (Andrews et al. (2014)). For example, surprising headlines work because novelty releases additional endorphins in the brain and stimulates attention. These techniques satisfy the relevance condition because they increase the frequency of blogging, and, they plausibly satisfy the exclusion restriction because headlines are assigned by an editor in a way that is independent of an analyst' bias.

Our empirical tests lead to a number of findings. First, we find analysts respond to the diverted attention stemming from FinTechs by reducing their reporting quality. We find higher aggregate

[2] As an example, suppose a firm's latent investment opportunities were going to change. If bloggers like to speculate about such changes, but analysts' through their access to management knew the latent investment opportunities were going to improve, we would observe both an increase in financial blogging and a decrease in analyst accuracy. Yet in this hypothetical setting, any claims that increases in financial blogging lead to decreases in accuracy would be spurious, because the observed negative interrelation is through latent investment opportunities rather than through a direct effect.

absolute forecast errors and more optimistic bias for analysts where FinTechs concentrate. A one standard deviation increase in the number of blog posts written about a firm are associated with a 0.30 standard deviation increase in aggregate optimistic bias and a 0.22 standard deviation increase in aggregate absolute forecast error. Respectively, these represent a 24% increase in aggregate optimistic bias and a 17% increase in aggregate absolute forecast error. Overall, these results provide a consistent message that increases in coverage by financial bloggers adversely affect the overall quality of analysts' reports.

Second, we find that the effect on quality of analyst reports is strongest when we focus on blog entries by the financial bloggers FinTechs identify as having the highest quality recommendations. Specifically, we find a 0.37 and 0.26 standard deviation increase in aggregate optimistic bias and aggregate absolute forecast error, respectively. These represent a 30% increase in aggregate optimistic bias and a 20% increase in aggregate absolute forecast error. The results are similar when we focus on bloggers ranked as having high quality recommendations in the short-term (investments under one year) and in the long-term (investments over a year). Overall, these results suggest that the signals and rankings generated by FinTechs that incorporate non-traditional financial analysis are part of the reason incumbent analysts are changing.

The response by analysts to change the financial information they produce suggests that the competition from FinTechs is not traditional competition. In theory, competition from additional suppliers of financial analysis should make it more difficult for any single analyst to suppress information (Gentzkow and Shapiro (2008)). The logic being that the more people supplying information about an equity, the more costly it will be for the analysts' reputation and career advancement to keep unfavorable news suppressed. In our case, it appears FinTechs by diverting attention from analysts reports have changed the economic incentives encouraging them to produce unbiased and accuracte financial analysis. Next, we use the heterogeneity in our data to understand what economic forces are driving analysts response.

We find evidence to suggest that analysts' changes in reporting quality vary as a function of their existing conflicts of interest and outside options. We find analyst's reports for affiliated stocks (ones where their employer has served as an underwriter for that stocks' initial public offering, a seasoned equity offering or as an advisor on an M&A deal) are more biased in response to FinTech concentration than are their reports for non-affiliated stocks. Similarly, we find independent analysts exhibit less bias in response to FinTech concentration than non-independent analysts. And finally, we observe the bias is stronger among less experienced, unranked analysts suggesting at least part of the story stems from changes in the composition of those who choose to be research analysts.

Our research relates to a number of strands in the literature. First, it relates to the literature on FinTechs (Philippon (2016); Yermack (2017)) and in particular, on new businesses that serve as intermediaries by aggregating information (Chiou and Tucker (2015); Calzada and Gil (2016)). Our examination of innovation in the market for financial analysis adds to a literature that studies finance's total contribution to economic efficiency (Philippon (2015); Zingales (2015)). Our research helps to explain the forces shaping analyst recommendations (Hong and Kubik (2003); Barber, Lehavy, and Trueman (2007); Fang and Yasuda (2009); Merkley, Michaley, and Pacelli (2017)) and market efficiency (Bai, Philippon, and Savov (2016)). The relationship between technology and bias is related more to research on digitization (Greenstein, Lerner, and Stern (2011), media markets (Mullainathan and Shleifer (2005); Tetlock (2007)), and social media (Greenstein and Zhu (2012); Chen et al. (2014)).

II. Hypotheses Development

In this section we present a stylized model that considers how investors access financial analysis online now that FinTechs aggregate and synthesize such analysis. The goal of the stylized model is to motivate our empirical hypotheses. In particular, we consider the ways in which the introduction of FinTechs may make the analysis provided by incumbents in this market (i.e., sell-side research analyst) more or less salient. First, we characterize how investors find online financial analysis. Next, we consider how FinTechs may alter the process by which investors discover financial analysis. This reveals that FinTechs may act as compliments or substitutes for the reading of incumbents' financial reports. We conclude by considering the economic forces that influence incumbents' responses to the entry of FinTechs in the case where they are compliments and where they are substitutes.

A. *How Investors Find Online Financial Analysis*

To characterize an individual investor's preferences for online financial analysis, let investor i have one unit of time t that he can allocate between reading financial analysis online and other activities. Every piece of financial analysis that he reads online has characteristics c, which are indexed as $d = 1, \ldots, D$. Characteristics such as the supplier of the information, the sentiment of the analysis, the stock covered, and/or the recommended investment horizon would be typical. The characteristic space is the set $C = \prod_{d=1,\ldots,D} C_d$. We denote investor i's reading of financial advice with characteristics c at time t by $A_{i,c}^t$ and if he reads many pieces of financial analysis, we denote his overall consumption of financial analysis as A_i^t.

Given that reading financial analysis online is one of many ways an investor can spend his time, let L_i^t denote his overall consumption of other leisure activities, L_i^t. Next, we assume the investor's utility from consuming the bundle $\left(A_i^t, L_i^t\right)$ follows a Cobb-Douglas utility function:

$$U_{it} = \left[\prod_{c \epsilon C} \left(A_{i,c}^t\right)^{a_{i,c}}\right]^{\tau^t \tau^i} L^{1-\tau^t \tau^i} \tag{1}$$

We use the Cobb-Douglas functional form to obtain two main implications. First, that the investors' share of time spent reading financial advice online can be broken down into a date effect $\left(\tau^t\right)$ and a person effect $\left(\tau^i\right)$. For example, the date effect includes seasonal preferences for reading online financial advice while the person effect captures preferences for reading online financial advice as opposed to getting it from a financial advisor. Second, a utility maximizing individual will consume a constant share of online financial advice with a particular set of characteristics, so long as the cost of finding online financial advice with different characteristics does not change.

To characterize how an investor finds online financial analysis, we consider two cases: without access to FinTech websites that aggregate financial advice and with access to such websites. In both cases, we assume the investor does not directly know what analysis is available to read. FinTech websites will serve to speed up the discovery of financial analysis with a particular characteristic set.

First, consider the case without FinTech websites that aggregate and synthesize financial analysis. To discover financial analysis, the investor must use an internet search engine or search after they've navigated to a financial blog. For each piece of financial analysis with characteristics c, the investor translates 1 unit of time into reading a quantity of financial analysis, denoted π_c. Let this process for finding online financial analysis have constant returns to scale so that allocating more or less time results in a proportional increase or decrease in the quantity of financial analysis found.

Second, consider the case with FinTech websites that aggregate financial analysis. These FinTech websites change the amount of financial analysis an investor can consume per unit of time in two ways. First, FinTech websites change the quantity of analysis with a given set of characteristics that can be found. Second, 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. This introduces three different ways an investor can use his time to find and read financial analysis: (1) finding and reading original-content financial analysis from traditional search (π_c^{search}), (2) clicking-through to original-content financial analysis from a FinTech website ($\pi_c^{click-through}$), and (3) partially reading financial analysis via the FinTech website itself ($\pi_c^{fintech}$).

Given that the FinTech websites speed up the discovery of financial analysis, by definition they are more productive than traditional search alone for a given unit of time. That is, $\pi_c^{search} < \pi_c^{search} + \pi_c^{click-through} + \pi_c^{fintech}$. Even though the use of FinTech websites always weakly increases total financial analysis consumed per unit of time, it may actually decrease the quantity of financial analysis that is consumed directly from the original sources. This is the case when investors rely on $\pi_c^{fintech}$ rather than $\pi_c^{click-through}$. This explains how FinTech websites may make the original content of financial analysis more or less salient.

Formally, the FinTech websites serve as substitutes for the reading of original-content financial analysis when they produce fewer click-through than with search. That is, $\pi_c^{fintech} + \pi_c^{search} < \pi_c$. Conversely, the FinTech websites serve as complements for the reading of original-content financial analysis when they generate more click-throughs than search alone. That is, $\pi_c^{fintech} + \pi_c^{search} \geq$

π_c^{search}. And utility maximization suggests an investors demand for financial analysis of type c with FinTech websites will be:

$$A_{i,c}^{t} = \tau^{t}\tau^{i}\alpha_{i,c}\left(\pi_c^{search} + \pi_c^{click-through} + \pi_c^{fintech}\right) \tag{2}$$

So far, we assume a characteristic c of an investor's search is if the financial analysis comes from a traditional or non-traditional source. In reality, when FinTechs aggregate and synthesize financial analysis, they make independent yet valuable analysis from non-traditional sources such as that from financial bloggers easier to discover. We explore how excluding the source of the analysis from the characteristic set C may decrease (increase) the reading of original-content financial analysis from sell-side research analysts even if FinTechs serve as complements (substitutes) for the reading of original analysis overall.

Consider the case where FinTechs in their effort to display the best analysis routinely display analysis from financial bloggers rather than financial analysts more prominently on their website. Let β denote the portion of the FinTech's website that displays financial analysis from non-traditional sources such as bloggers. Just as before the FinTech's website will always weakly increase total financial analysis consumed per unit of time but may in fact decrease the total financial analysis consumed from traditional sources. That is, $\pi_c^{search} < \pi_c^{search} + \beta\left(\pi_c^{click-through} + \pi_c^{fintech}\right) + (1-\beta)\left(\pi_c^{click-through} + \pi_c^{fintech}\right)$.

Even if FinTechs serve as complements to the reading of original-content financial analysis they may still be directing readership away from incumbents in this market. In this way, the FinTechs serve as complements to non-traditional sources of financial analysis and substitutes for traditional sources of financial analysis. More formally, the FinTech websites serve as substitutes for the reading of original-content financial analysis from traditional sources when they produce fewer click-throughs than with search. That is, $(1-\beta)\left(\pi_c^{click-through}\right) < \pi_c^{search}$. Conversely, the FinTech websites serve as complements for the reading of original-content financial analysis from traditional searches when they generate more click-throughs than search alone. That is, $(1-\beta)\left(\pi_c^{click-through}\right) \geq \pi_c^{search}$.

B. FinTech Entry and Incumbents' Incentives

Having characterized how FinTechs may serve as substitutes or complements for the reading of original-content financial analysis form incumbents, we now turn to the economic incentives for incumbents that the FinTech websites change. In particular, we consider the role played by competition, outside employment options, and conflicts of interest. If FinTechs divert attention from original-content financial analysis for incumbents (substitutes view), then they produce anti-competitive effects that reduce effort, encourage catering to conflicts of interest, and incentivize alternative employment options. If FinTechs focus attention on incumbent's original-content financial analysis (complements view), then they produce competitive effects that increase effort, reduce catering to conflicts of interest, and discourage seeking alternative employment.

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, theory suggests this will discipline analysts.

But as we saw above, when FinTechs make non-traditional analysis easier to discover, this competition may influence analysts but not in a disciplinary way. This occurs when FinTechs through their placement of non-traditional financial analysis serve as a substitute for the readership of traditional analysis. A reduction in readership for the same quality of report may encourage an analyst to reduce his effort to provide quality financial analysis. It may also lead to a change in the composition of those who choose to be sell-side analysts (Merkley, Michaley, and Pacelli (2017)). It could encourage some more experienced analysts to leave their institutions given their reduced position of prominence and prestige. In this case, the whole pool of analysts may be younger and less qualified compared to previous generations. In other cases, it may depend on the relationships the analyst has if they choose to stay. For example, the unaffiliated analysts may leave and the ones who stay are the affiliated analysts.

Perhaps the most prominent change when FinTechs substitute for traditional readership is the incentives discouraging analysts from catering to conflicts of interest are lower. Potential conflicts of interest come from the analysts employer from its investment banking and/or brokerage business. When investment banking is an important source of revenue for the analysts employer, then the analyst may face pressure to inflate his recommendation. This pressure is due to the fact that the firm would like to sell investment banking services to accompany that the analyst tracks. The company, in turn, would like the analyst to support its stock with a favorable opinion. Similarly, analysts face conflicts from their employers' brokerage businesses. Here, the pressure on analysts originates not from the companies that they follow but from within their employing firms. Brokerage business generates a large portion of most securities firm's revenues, and analyst compensation schemes may be related to trading commissions. Thus, analysts have incentives to increase trading volumes which are more likely to increase with bullish recommendations as institutional investors often face short sale constraints.

The discussion above provides several empirical implications. First, when FinTechs are substitutes (complements) for the readership of original-content financial analysis, an investor will spend less (more) time at an original-content website after visiting a FinTech website. Second, analysts will respond by decreasing (increasing) their reporting quality (i.e., accuracy and bias) when FinTechs serve as substitutes (complements). And third, analysts' changes in reporting quality will vary as a function of their existing conflicts of interest and outside options.

III. Characterizing Financial Analysis Online

In this section we present descriptive statistics for the type of financial analysis investors have access to online now that there are FinTech websites that aggregate and synthesize such analysis. We begin by summarizing the financial blog data. The best characterization of the financial blog data is that it is ubiquitous, free, and very noisy. Hence, the need for FinTechs that sift through the noise to detect potentially useful analysis. We end this section by detailing the business plans of the FinTechs that are operating in this market and the ways in which they attempt to elevate the prominence of more accurate, higher quality financial analysis.

Table I summarize data from financial blog websites that make buy and sell recommendations. Our data include blog posts from 20 different financial blogs where bloggers make buy or sell recommendations on stocks. Our data on the contents of financial blog posts comes from TipRanks, a FinTech firm operating in this market. 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. 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 explicit permission to confidentially capture their detailed browsing behavior at the website level. User sessions are recorded with date and time stamps as well as clickstream data to show within an internet users session the number of pages viewed on a particular website. The sample of internet users changes on a monthly basis. Each month, we calculate the total number of pages views and seconds spent on each website. We, then, calculate the relative percentile for the financial blog websites among all websites. Percentiles allow for comparison over time as the total number of websites on the internet fluctuates.

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 I 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. Almost all financial blogs earn negative market-adjusted returns, on average, over time. Moreover, the performance appears to be worst, on average, over longer horizons.

Table II 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 blogs, on average, and have a total of 268 posts. These bloggers write 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.

Table III characterizes the online market for financial analysis more broadly by describing a large sample of financial blogs and FinTechs in the market for financial analysis. To generate a comprehensive list of financial blogs and FinTechs, we use three different techniques. First, we search for relevant business descriptions on Crunchbase, a public database of company information about early-stage startups to Fortune 500 firms. Second, we search the internet for “Best of” FinTech and financial blog lists. Third, we use Google search to identify potentially relevant firms and blogs. Based on our initial list of FinTechs and blogs, we then examine each website to gather additional information and confirm that the website is in fact a financial blog or FinTech. To reduce survivorship bias, we use Wayback Machine to examine earlier versions of the website if the firm or blog stopped operating. For the financial blogs, the additional information we gather includes if the bloggers made equity recommendations or not and the general theme of the website. For the FinTech websites, the additional information we gather includes business plan attributes such as what the firm does and its intended user.

Panel A of Table III describes our sample of financial blogs and Panel B describes our sample of FinTechs. To be part of the final sample of financial blogs or FinTechs, at least one internet user from the comScore sample of nationally representative U.S. households must visit the website between 2010 and 2017. The statistics in Panel A 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.

Panel B of Table III describes our sample of FinTechs and their business plans. We observe 290 FinTechs operating in the market for financial analysis. We categorize the business operations of these FinTechs into: (1) those that aggregate data from financial experts (e.g., sell-side research analysts and/or bloggers), (2) those that aggregate financial news, (3) those that crowdsource financial advice, (4) those that datamine financial analysis and news for investment signals, and (5) those that rank and evaluate existing financial advice. These categories are not mutually exclusive. To be included in our sample, a FinTech's capabilities must include at least one of these functions. The most common capabilities are aggregating financial news (83% do this), datamining for investment signals (57% do this), and evaluating and ranking existent financial advice (27% do this). Overall, the business plan analysis shows that these firms aggregate and streamline pre-existing financial analysis rather than produce their own original-content.

Column (2) of Panel B shows the mean founding year of FinTechs in our sample is 2008. 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.

IV. Empirical Strategy

A. *Investor Discovery of Financial Analysis*

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

$$OriginalAnalysis_{it} = \alpha + \beta FinTechVisit_{it} + \theta X_{it} + f_i + \delta_t + \epsilon_{it} \tag{3}$$

where $OriginaAnalysis_{it}$ represents a visit to the website containing original-content financial analysis in month t for household i, $FinTechVisit_{it}$ indicates if the household visited a FinTech website in that month, X_{it} is a vector of observables (income, race, age, education, census region, internet connection speed, and number of children), f_i is a household fixed effect, δ_t is a quarter fixed effect, and ϵ_{it} is the unobservable error component. We also consider variations on the definition of $OriginalAnalysis_{it}$ including the number of pages viewed on an original-content website as well as the time spent on the original-content website.

B. Analyst Response to FinTechs

To test the hypothesis that incumbents respond to FinTechs in the market for financial analysis, 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 concerntation 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. 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 instrumental variable approach.

Specifically, we use a linguistic-based instrument to generate variation in the concentration of financial bloggers covering an equity. The relevance of the instrument comes from sources of inspiration for financial bloggers. Namely, current financial news. We match daily blog postings for an equity to daily news headlines for that same equity. We focus on newspaper headlines that use a psychological trick for increasing in attention. The psychological tricks include: surprise, questions, curiosity gap, tone, "how to," precision, audience reference, and length. For example, surprises in headlines work because novelty releases additional endorphins in the brain. Compared to expected pleasant news, unpredicted pleasant news turns on the pleasure centers of the brain even more. Thus, surprises stimulate and grab attention more than other headlines. We use a text-based algorithm to identify if the headline uses a psychological trick for increasing in attention. Prior finance research has focused on some of these tricks (e.g., Loughran and McDonald (2011) examine tone and Umar (2017) examines length), while an extensive psychology literature documents them (Andrews et al. (2014)).

The exclusion restriction for instrumental variable identification requires the attention-grabbing financial news headlines only alter an analyst' bias via their effect on financial blog concentration. Given that the restriction relates quantities I cannot observe together, I cannot test it. Rather arguments must support the plausibility of satisfying the restriction. In this case, the main argument is financial news headlines are quasi-random since they are selected at the discretion of the editor.

The instrumental variable specification is as follows:

$$ReportQuality_{it} = \alpha + \beta BlogCoverage_{it} + \theta X_{it} + f_i + \delta_t + \epsilon_{it} \tag{4}$$

where $ReportQuality_{it}$ represents characterizes the analysts' report quality in terms of optimism bias and accuracy in quarter t for equity i, $BlogCoverage_{it}$ measures the quantity of financial blog posts in quarter t that discuss equity i covers, X_{it} is a vector of observables (analyst coverage, firm size, daily return volatility, mean monthly return, log market-to-book ration, 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.

V. Results

Table IV examines how investors discover financial analysis online. Column (1) describes who reads financial analysis online. Unsurprisingly, the data indicate older investors with higher income and a college degree are more likely to read financial analysis online. Columns (2) through (4) examine if FinTechs serve as substitutes or complements for the reading of original-content financial analysis. Column (2) reveals investors are 57 percentage points less likely to visit an original-content website if they visit a FinTech website. This correlation is highly statistically significant. The variation explained by the regression is 55% which suggests these variables meaningfully explain investors visits to websites with original-content financial analysis. Overall, this first piece of evidence suggest that FinTechs serve as substitutes. That is, people read the snippets of analysis on the FinTech websites rather than clicking-through to the original content.

Column (3) and (4) further support the view that FinTechs serve as substitutes. Column (3) shows that the page views at original-content websites are reduced by 55% and Column (4) shows that the time spent at the original-content website is reduced by 33% when an investor visits a FinTech website. These results are statistically significant and these findings are robust to controls for income, race, age, education, census region, internet connection speed, number of children. Further, monthly fixed effects help to rule out changes in preference over time as driving these results. Taken together, the internet traffic data suggests that investors use FinTechs as a substitute for traditional financial analysis.

Next, we turn to the financial analyst sample to understand if analysts respond to the changes stemming from FinTechs. Table V summarizes our sample of data on financial analysts. It displays the analyst coverage, firm size, daily return volatility, mean monthly return, the log of market-to-book, volatility of ROE, profitability, and inclusion in the S&P 500. We note these are the exact same controls used by Hong and Kacperczyk (2010). We explore both cross-sectional and within-equity variation. If financial blog coverage is fairly persistent over time, then focusing on within-equity variation (i.e., with firm fixed-effects) may be too restrictive.

We begin by running OLS regressions and present these results in Table VI. We first present the results with just time fixed effects in Columns (1), (3), (5), and (7), while we present the results with time and firm-fixed effects in Columns (2), (4), (6), and (8). The results show a small positive partial correlation between financial blog coverage and analysts' aggregate optimism bias and aggregate absolute forecast error. Note this is absolute forecast error, so a bigger value means the analysts report is less accurate. In general, we see a small positive increase in bias and reduction in accuracy both in the cross-section and within-equity over time.

Next, we estimate IV regressions and present those results in Table VII. We find that an increase in financial blog coverage for a stock is associated with higher aggregate absolute forecast errors and more optimistic bias for analysts that cover that firm. A one standard deviation increase in the number of blog posts written about a firm are associated with a 0.30 standard deviation increase in aggregate optimistic bias and a 0.22 standard deviation increase in aggregate absolute forecast error. Respectively, these represent a 24% increase in aggregate optimistic bias and a 17% increase in aggregate absolute forecast error.

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 204.2, which exceeds the requisite 10 to ensure minimal bias of the point estimate. The instrumental variable specification includes controls for 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 as well as firm and industry-by-time fixed effects. These controls help to account for other industry dynamics that may cause analysts reporting quality to deteriorate.

In Table VIII, we focus on blog entries by the financial bloggers FinTechs firms identify as having the highest quality recommendations. We find that the effect on quality of analyst reports is strongest when we focus on blog entries by the financial bloggers FinTechs firms identify as having the highest quality recommendations. Specifically, we find a 0.37 and 0.26 standard deviation increase in aggregate optimistic bias and aggregate absolute forecast error, respectively. These represent a 30% increase in aggregate optimistic bias and a 20% increase in aggregate absolute forecast error. The results are similar when we bloggers ranked as having high quality recommendations in the short-term (investments under one year) and in the long-term (investments over a year). Overall, the instrumental variable results provide a consistent message that increases in coverage by financial bloggers adversely affect the overall quality of analyst reports.

In Table IX, we change our analysis to the analyst-equity-quarter level. This allows to explore what characteristics of analysts and their employers may be associated with more or less response to FinTech concentration. Column (1) repeats the previous analysis where the dependent variable is optimism bias. As with before, we see an increase in optimism bias where FinTechs concentrate at this more disaggregated analyst-level. The disaggregation allows us to include many additional controls for analyst and brokerage characteristics. Specifically, we control for analyst experience, their experience covering that equity, the number of equities they cover, the number of industries they cover, their average forecast frequency, forecast horizon, and days since last forecast, whether the stock they are covering is an affiliated stocks (ones where their employer has served as an underwriter for that stocks' initial public offering, a seasoned equity offering or as an advisor on an M&A deal), the brokerage size, and if the brokerage is independent.

Next, we analyze sub-samples of the data to understand which economic incentives are influencing analysts to change. Specifically, Columns (2) and (3) focus on affiliated vs. non-affiliated stocks. We see the analysts reports for affiliated stocks exhibit 0.13 standard deviation higher increase in optimism bias in response to FinTech concentration. This supports the notion that investment banking conflicts of interest may be inducing analysts to cater to those clients when FinTechs divert attention from their research. It could also support the notion that the composition of analysts is changing in response to FinTechs. This would be the case if some analysts, especially the unaffiliated analysts leave the profession, and the ones who stay are the affiliated analysts whose forecast are more biased and less accurate.

As an alternative cut on the data, Columns (4) and (5) focus on independent and non-independent brokerage houses. Again, we see the analysts' reports for from non-independent brokerage houses exhibit more increase in optimism bias (0.08 standard deviations) in response to FinTech concentration. This is consistent with a story of analysts catering to their conflicts of interest after attention has been diverted from their research. Finally, in Columns (6) and (7) we elaborate on the change in composition of the analyst workforce argument. Our evidence indicates that inexperienced analysts show more increase in optimism bias (0.17 standard deviations) in response to FinTech concentration. Overall, our evidence suggests both catering to conflicts of interest and changes in the attractiveness of outside employment opportunities are driving analysts response.

VI. Conclusion

With advances in technology, the relationship that investors have with those who traditionally provide financial analysis (i.e., sell-side analysts) is changing. Investors have new options for discovering financial analysis brought about by the entry of FinTechs. The services provides 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, tweets, etc.). Given that investors are attracted to equities where they get a lot of information, being able to quickly incorporate all the relevant analysis has helped these new FinTechs to expand rapidly in recent years.

Our paper evaluates how incumbents are responding to these changes in the market for financial analysis. FinTechs could serve as traditional competition for analysts causing them to reduce their bias and increase their accuracy as in Hong and Kacperczyk (2010). Alternatively, FinTechs could serve as intermediaries that funnel investors away from the primary sources to instead focus on derived signals. In this case, attention could be diverted from the original content of the analysts' reports, which in turn, could lead analysts to change how the report financial information. Given that equity analysts still have the best corporate access for assessing financial information and connecting companies with investors, understanding their response is critical.

Using an instrumental variable strategy and novel data, we find that FinTechs serve as a substitute for reading analysts' reports. In particular, we find investors view fewer webpages with original-content financial analysis and spend less time on original-content financial analysis websites. In turn, the reduced saliency on analysts leads them to cater to their conflicts of interest. When FinTechs enter the market for financial analysis, we observe significant decreases in analysts' accuracy and increases in optimism bias for the equities where the FinTechs concentrate. The change in reporting quality is greatest for equities where analysts' conflicts of interest are strongest. This suggests significant disruption in the market for financial analysis and has important implications for market efficiency. Most notably that FinTech entry should not be viewed in the same manner as traditional increase in supply of financial analysis.

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Table I. Financial Blogs with Stock Recommendations

This table presents summary statistics for our sample of financial blog sites 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 A.

Blog Site	Page View Percentile	Minutes on Site Percentile	Monthly Visits per User	Page Views per Visit	Minutes per Visit	Pct. of Tot. Blog Posts	Pct. of Posts with Rec.	Num. of Unique Bloggers	Num. of Stocks Covered	Market-adjusted 1-month Returns	Market-adjusted 6-month Returns	Market-adjusted 12-month Returns
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(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 II. Characterizing Financial Blog Posts

This table presents summary statistics for our sample of financial blog sites 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 A.

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 III. Financial Blogs and FinTechs

This table presents summary statistics for a broader sample of financial blogs and FinTechs in the market for financial analysis. Panel A describes our sample of financial blogs and Panel B describes our sample of FinTechs. To be part of the sample of financial blogs or FinTechs, at least one internet user from the comScore sample of nationally representative U.S. households must visit the website between 2010 and 2017. Columns (1) through (4) of Panel A describe the mean internet traffic at all financial blogs with stock recommendations and columns (5) through (8) for those without stock recommendations. Panel B describes the business operations of the FinTechs and their progress as a business. For a detailed description of each variable, see the definitions in Appendix A.

	Financial blogs with stock recs.				Financial blogs without stock recs.			
	Mean	Std. Dev.	Median	Max	Mean	Std. Dev.	Median	Max
Panel A. Characteristics of financial blogs	(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	36				448			

	Obs.	Mean Year Founded	Targets Retail Investors	Targets Prof. Investors	Covers Specific Stocks	Mean Num. of Investors	Mean Funding ($mil)	Mean Num. of Workers
Panel B. Characteristics of FinTechs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All FinTechs	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 IV. Are FinTechs and Financial Analysis Substitutes or Complements?

This table presents OLS estimates of investors discovery of original-content financial analysis when using FinTech websites. Column (1) examines the binary choice to visit a financial blog or FinTech website. Column (2) through (4) examine how visiting a FinTech website changes readership of financial blogs. The dependent variable in Column (2) is an indicator variable for visiting a financial blog. The dependent variable in Column (3) is the percent of page views at the financial blog and Column (4) is the percent of the internet users time spent at the financial blog. Coefficients on demographic variables should be interpreted as relative to the excluded category. For income, less than 50k is excluded. For race, other is excluded. For age, 18-29 is excluded. For education, high school degree or less is excluded. Additional control variables include census region, internet connection speed, and number of children. 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 A.

	Dependent Variable =			
	Internet user visits a financial blog or FinTech website	Internet user visits a financial blog	Log of internet users page views at financial blogs	Log of internet users time spent at financial blogs
Determinants of financial blog use	(1)	(2)	(3)	(4)
FinTech Use				
Visits a FinTech website		-57.4***	-0.55***	-0.33***
		(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	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
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 V. Summary Statistics for Financial Analysts

This table presents summary statistics for the financial analyst sample. The sample is drawn from Zacks Investment Research. For a detailed description of each variable, see the definitions in Appendix A.

	Mean (1)	Median (2)	Std. Dev. (3)	Obs. (4)
Mean Bias (As % of the Absolute Value of Consensus EPS)	37.6%	5.6%	80.9%	91,871
Median Bias	36.5%	3.4%	85.2%	91,871
Mean Accuracy	61.9%	25.0%	77.6%	91,871
Median Accuracy	58.4%	20.2%	81.2%	91,871
Mean Bias (As % of the Previous Quarter's Stock Price)	1.6%	0.5%	3.6%	91,871
Median Bias	1.1%	0.2%	3.7%	91,871
Mean Accuracy	3.1%	1.4%	4.6%	91,871
Median Accuracy	2.2%	0.8%	4.6%	91,871
Analyst Coverage	7.0	5.3	5.6	91,871
Forecast Dispersion	0.7	0.5	0.7	91,871
Firm Size	13.9	13.8	1.8	91,871
Daily Return Volatility	40.5%	34.2%	23.9%	91,871
Mean Monthly Return	1.5%	1.4%	7.1%	91,871
Log Market-to-Book	0.81	0.74	0.44	91,871
Volatility of ROE	23.6%	0.2%	102.7%	91,871
Profitability	1.85%	2.27%	4.43%	91,871
Member of S&P 500	15.2%	0.0%	35.9%	91,871
Institutional Ownership	60.8%	67.8%	30.1%	91,871
Hedge Fund Ownership	9.7%	6.3%	10.1%	52,395

Table VI. OLS Regression of Consensus Analyst Bias and Accuracy

This table presents OLS estimates at the equity-quarter level for analysts' responses when financial bloggers concentrate in the equities they cover. 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. 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 A.

	Bias (As % of EPS)				Accuracy (As % of EPS)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Blog Coverage	0.05***	0.01***	0.05***	0.01***	0.06***	0.01***	0.06***	0.01***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Analyst Coverage	0.01*	0.09***	0.01*	0.08***	-0.02**	0.02*	-0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm Size	-0.23***	-0.14***	-0.22***	-0.14***	-0.22***	-0.47***	-0.22***	-0.45***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Daily Return Volatility	0.23***	0.06***	0.23***	0.06***	0.27***	0.04***	0.27***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean Monthly Return	-0.03***	-0.02***	-0.03***	-0.02***	-0.00**	0.00***	-0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Market-to-Book	0.12***	0.03*	0.12***	0.02*	0.07***	-0.00	0.08***	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Volatility of ROE	0.01*	-0.01	0.01	-0.02*	0.01*	-0.01	0.01*	-0.02
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Profitability	-0.42***	-0.15***	-0.40***	-0.14***	-0.40***	-0.17***	-0.38***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	0.02***	0.01	0.02***	0.01	0.01	0.02*	0.01**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R-squared	36.2%	72.6%	33.6%	68.3%	38.7%	75.3%	36.4%	71.3%
Observations	91,871	91,871	91,871	91,871	91,871	91,871	91,871	91,871

Table VII. IV Regression of Consensus Analyst Bias and Accuracy

This table presents instrumental variable (IV) estimates at the equity-quarter level for analysts' responses when financial bloggers concentrate in the equities they cover. 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. 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 A.

	Bias (As % of EPS)				Accuracy (As % of EPS)			
	Mean		Median		Mean		Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Blog Coverage	0.52***	0.30***	0.50***	0.29***	0.64***	0.22***	0.62***	0.24***
	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.06)	(0.10)	(0.06)
Analyst Coverage	-0.08***	-0.02	-0.08***	-0.02	-0.15***	-0.05**	-0.14***	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Firm Size	-0.36***	-0.14***	-0.35***	-0.14***	-0.38***	-0.47***	-0.38***	-0.45***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Daily Return Volatility	0.15***	0.04***	0.15***	0.04***	0.18***	0.03***	0.17***	0.03***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Mean Monthly Return	-0.03***	-0.02***	-0.03***	-0.02***	-0.00	0.00***	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Market-to-Book	0.10***	0.00	0.09***	0.00	0.05***	-0.02	0.05***	-0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Volatility of ROE	0.00	-0.02*	0.00	-0.03**	0.00	-0.02	0.00	-0.02*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Profitability	-0.42***	-0.15***	-0.40***	-0.15***	-0.40***	-0.17***	-0.39***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	-0.04**	-0.01	-0.03**	-0.01	-0.07***	-0.00	-0.06***	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
First Stage F-Stat	182.5	222.5	182.5	222.5	182.5	222.5	182.5	222.5
T-Stat on Instrument	13.51	13.51	13.51	13.51	13.51	13.51	13.51	13.51
Adjusted R^2	36.2%	72.6%	33.6%	68.3%	38.7%	75.3%	36.4%	71.3%
Observations	91,871	91,871	91,871	91,871	91,871	91,871	91,871	91,871

Table VIII. Analysts Reaction to High Quality Bloggers

This table presents instrumental variable (IV) estimates at the equity-quarter level for analysts' responses when high quality financial bloggers concentrate in the equities they cover. 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 exact specification is: $ReportQuality_{it} = \alpha + \beta QualityBlogCoverage_{it} + \theta X_{it} + f_i + \delta_t + \epsilon_{it}$. The primary independent variable of interest is $QualityBlogCoverage_{it}$ which measures the quantity of financial blog posts identified by FinTechs as high quality in quarter t that discuss equity i. In Columns (1) and (3), quality is defined by short-term investment performance (i.e., less than six months) and in Columns (2) and (4) quality is defined by long-term investment performance (i.e., one year or more). We instrument for $QualityBlogCoverage_{it}$ using $PsychTrick_{it}$ which indicates the percent of newspaper headlines that covered equity i in quarter t that relied on psychological tricks for increasing attention. 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 A.

	Mean Bias (As % of EPS)		Mean Accuracy (As % of EPS)	
	Short-Term Positive Return Bloggers	Long-Term Positive Return Bloggers	Short-Term Positive Return Bloggers	Long-Term Positive Return Bloggers
	(1)	(2)	(3)	(4)
Financial Blog Coverage	0.33***	0.37***	0.24***	0.26***
	(0.07)	(0.08)	(0.07)	(0.08)
Analyst Coverage	-0.02	-0.00	-0.05**	-0.04*
	(0.03)	(0.03)	(0.03)	(0.02)
Firm Size	-0.11***	-0.13***	-0.45***	-0.46***
	(0.03)	(0.03)	(0.03)	(0.03)
Daily Return Volatility	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Mean Monthly Return	-0.03***	-0.02***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Log Market-to-Book	0.00	0.00	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Volatility of ROE	-0.03*	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Profitability	-0.15***	-0.16***	-0.17***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)
Member of S&P 500	-0.01	-0.02	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat	204.2	178.6	204.2	178.6
T-Stat on Instrument	13.76	11.97	13.76	11.97
Adjusted R^2	72.6%	72.6%	75.3%	75.3%
Observations	91,871	91,871	91,871	91,871

Table IX. What Economic Forces Drive Analysts' Responses to FinTechs?

This table presents instrumental variable (IV) estimates at the analyst-equity-quarter level. Column (1) repeats the previous anlaysis where the dependent variable is forecast bias 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, respecitvely. Additional equity-level controls include firm size, daily return volatility, mean monthly returns, market-to-book, volatility of ROE, profitability, membership in the S&P 500, momentum, institutional ownership. 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 A.

	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)
Financial Blog Coverage	0.32***	0.42***	0.29***	0.24***	0.32***	0.38***	0.21***
	(0.03)	(0.11)	(0.03)	(0.08)	(0.04)	(0.04)	(0.05)
Analyst Coverage	-0.06***	-0.08***	-0.05***	-0.04	-0.06***	-0.08***	-0.02
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)
General Experience	-0.00**	-0.00	-0.00**	-0.00	-0.00	-0.00	-0.00**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Firm Experience	-0.00***	-0.00	-0.00***	-0.00	-0.00***	0.002	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Firms Covered	0.00***	-0.00	0.00***	0.01**	0.00**	0.01***	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Industries Covered	-0.00**	0.006	-0.00*	-0.01**	-0.00*	-0.02***	0.00**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Forecast Frequency	0.00	-0.00	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	0.00*	0.00**	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Days Since Last Forecast	0.01***	0.00*	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Affiliated with Firm	0.00	N.A.	N.A.	0.02	0.00	0.01**	-0.0**
	(0.00)	N.A.	N.A.	(0.06)	(0.00)	(0.00)	(0.01)
Brokerage Size	0.00***	0.00*	0.00***	0.01***	0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Independent Brokerage	0.01***	0.09*	0.00***	N.A.	N.A.	0.01***	0.02***
	(0.00)	(0.05)	(0.00)	N.A.	N.A.	(0.00)	(0.01)
Additional Equity-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat	820.8	98.6	730.9	78.9	733.5	516.6	234.1
T-Stat on Instrument	29.88	11.66	27.31	9.30	27.90	23.60	16.97
Adjusted R^2	68.2%	76.2%	67.0%	75.1%	68.1%	68.5%	70.0%
Observations	296,743	45,357	251,264	40,505	255,964	189,550	106,927

Appendix A. Variable Definitions

We use data from IBES, 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.

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 Zacks 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 2-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.

To construct our dataset of FinTech firms and financial blogs, 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.