Financial YouTube Channels and the Capital Markets*

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January 22, 2024

PRELIMINARY 1st DRAFT
For Discussion at UTS Summer Accounting Conference Only
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* We wish to thank Volkan Muslu, Yuping Zhao, Sanjeev Bhojraj, Sangwoo Sohn, Mei Cheng, Kai Gu, Thien Le, and David Park for their helpful insights and suggestions. We gratefully acknowledge support from our respective institutions. All errors are our own.

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Abstract: A recent Nasdaq study of retail investors revealed that, relative to older investors, younger investors obtain a significant higher portion of their investment information from social media platforms than traditional channels like investment advisors. We examine YouTube as a primary channel for content creators who effectively serve as financial advisers to watchers of their videos ("Financial YouTubers"). We find significant market reactions and declines in information asymmetry on video upload dates, and the effect is stronger for firms with lower institutional ownership. Further, we extract video content and find that market response are associated with the tone of video content. Information asymmetry declines for videos that contain more quantitative information. Market responses are stronger and the information environment improves for Financial YouTubers with more subscribers and viewers. We perform analyses to rule out endogeneity stemming from alternative information releases. Finally, we note that 73% of YouTubers post disclaimers for their videos, and we find moderated market responses to videos with disclaimers. Overall, our evidence is consistent with Financial YouTubers providing investors with investment information.

Financial YouTube Channels and the Capital Market

1. Introduction

There has been a surge of disruptive information and social media platforms used by firms, institutional investors, and retail investors for disclosure and investment research. Academic research has examined many of these platforms, including Twitter (e.g., Blankespoor, Miller, and White 2014; Nekrasov, Teoh and Wu 2022), Seeking Alpha (e.g., Dyer and Kim 2021; Farrell, Green, Jame, and Markov 2022; Drake, Moon, Twedt, and Warren 2023), Yahoo Finance (e.g., Lawrence, Ryans and Sun 2017; Lawrence, Ryans, Sun, and Laptev 2018), Estimize (e.g., Jame, Johnston, Markov, and Wolfe 2016), Reddit (e.g., Bradley, Hanousek Jr., Jame, and Xiao 2021; Chacon, Morillon, and Wang 2023), and others. In response to these new platforms and growing retail investor presence in capital markets, the Nasdaq conducted a study of 2,000 retail investors (Nasdaq 2022), revealing disparate research and investing practices of different generations of investors.[1] Although all generations rate financial advisers as the most reliable source of investment information, younger generations also rely heavily on podcasts, online discussion boards, and social media platforms. Nasdaq specifically highlights that, "for those that use social media [for credible financial advice], YouTube and Facebook were the most popular applications."

In this study, we examine whether YouTube is viewed as a source of financial information for investors and whether content creators on YouTube ('YouTubers') function as financial advisers and affect stock prices. Launched in 2005, YouTube is the predominant video-sharing media platform, is the second most visited website in the world (behind Google), and is watched over one billion hours per day.[2] As of 2023, there are 15 million YouTubers, including an

[1] The four categories included Boomers (born 1946-1964), Gen X (1965-1980), Gen Y (1981-1996) and Gen Z (1997-2012).
[2] See https://www.comparitech.com/tv-streaming/youtube-statistics/.

emergence of financial influencers who provide analyses on specific stocks using videos (also known as 'finfluencers,' but hereafter referred to as "Financial YouTubers"). Finance YouTube channels are among the highest profitability 'niches' on YouTube.[3] Anecdotal evidence suggests that the average salary for YouTubers with just one million subscribers is $60,000 per year and successful Financial YouTubers earn well above $100,000 per year (Measom 2023).

The extent to which Financial YouTubers provide useful information is controversial (e.g., see online commentaries like Fairchok 2023 and Khattar 2023). Further, it is unclear whether Financial YouTubers ought to be formally registered as investment advisers according to SEC and FINRA rules and regulations. To the best of our understanding, there has been no sanctioning of Financial YouTubers for not being registered as an investment adviser, although in 2022 the SEC charged seven social media influencers on Twitter and Discord in a classic pump-and-dump scheme. Thus, the SEC appears to be monitoring social media information regarding investment advice; but so far, there have been no actions against Finance YouTubers as investment advisers.[4] Because regulators and market participants both have expressed concerns about Financial YouTubers circumventing the requirements to be registered investment advisors and may be potentially misleading investors, we examine the role of Financial YouTube influencers in the capital market.

We construct a hand-collected sample of 7,417 videos posted by 79 prominent Financial YouTubers. Because there is no established list of channels, we manually compile the list based on numerous online websites and social media platforms. Our determinants model indicates that

[3] See, for example, https://www.tastyedits.com/most-profitable-youtube-niches/ and https://www.linkedin.com/pulse/7-most-profitable-youtube-niches-2023-majed-khalaf/.
[4] Surprising to us, the SEC has determined that cryptocurrencies do not meet the definition of securities under the Investment Advisers Act of 1940 (see https://corpgov.law.harvard.edu/2022/12/06/why-cryptoassets-are-not-securities/). See Merkley et al. (2023) for a study of 'cryptoinfluencers.'

Financial YouTubers are more likely to cover older and larger firms with lower profitability. Also, Finance YouTubers tend to follow firms with lower leverage, more cash, and higher sales growth. In terms of information environment, Financial YouTubers follow firms with fewer management forecasts and lower institutional ownership, yet with higher sell-side analyst coverage.

Our main analyses relate to impacts of Financial YouTuber video uploads on stock prices. We first examine returns centered on video upload dates. If investors use information presented in videos, we should observe abnormal returns following video uploads. However, the null hypothesis of no association is plausible for several reasons. First, the content in these videos may be piggybacked information from recent information releases from the firm or other sources. Second, Financial YouTubers are generally not licensed investment advisers, so their content may be viewed as entertainment and predominantly uninformative. Third, Financial YouTubers videos may provide limited new information because they are primarily motivated to post videos frequently to support a subscription model. Finally, because the consumers of these YouTube channels, according to Nasdaq, are predominantly younger retail investors, the marginal trades by these investors may not affect market prices.

Using both signed and unsigned cumulative abnormal returns, we document significant market reactions to Financial YouTuber videos. Because of concerns that returns around analyst research might be contaminated by overlapping earnings announcements (Altinkilic and Hansen 2009; Li, Ramesh, Shen, and Wu 2015), we exclude videos posted in the seven days following firm-specific events (e.g., earnings announcements, product announcements, and corporate filings) and continue to document strong market reactions. Further, we apply a one-to-one propensity score matching and continue to find stronger market reactions for firms covered by Financial YouTubers relative to those not covered.

Next, we explore the informational role of Financial YouTubers by examining information asymmetry surrounding video upload dates. Financial YouTubers could impact firms' information environment in two ways. First, because Financial YouTubers are monetarily incentivized to engage viewers through content, the information embedded in their videos could be incremental to other information, consistent with the returns results just described, which could decrease (or increase) information asymmetry. Second, if our efforts to preclude the effects of information piggybacking by Financial YouTubers (previously highlighted) are imperfect, videos may include firm disclosures or other news, resulting in Financial YouTubers serving roles of information dissemination, which may also reduce information asymmetry.

We find that standard measures of information asymmetry decline shortly after video upload dates, consistent with the informational role of Financial YouTubers. When compared with firms matched through one-to-one propensity-scored matching (PSM), firms covered by Financial YouTubers exhibit a differential reduction in information asymmetry. Again, results are robust to excluding firm-specific events within the seven-day window prior to video posting dates.

If Financial YouTubers primarily stimulate retail trading, we would expect market reactions and improvements in information asymmetry to be concentrated among firms that are predominantly held by retail investors. In cross-sectional analysis, we utilize institutional ownership ratio as an inverse proxy for retail ownership and find that the positive (negative) association between returns (information asymmetry) is less prominent for firms with higher institutional ownership (i.e., lower retail investor ownership), consistent with our prediction.

In the second set of analyses, we examine the actual content of videos and test whether variation in content is associated with market outcomes. First, we expect that returns will be associated with the tone of the videos, measured in standard ways using video transcripts. Second, we expect a further reduction in information asymmetry when the video contains more quantitative information. We find that returns are positively associated with the tone of video content. Further, videos with more quantitative information are associated with lower information asymmetry after the video postings. Both findings are consistent with investors reacting to information embedded in Financial YouTuber videos.

We next examine whether more influential Financial YouTubers, captured by number of subscribers or video views, are associated with stronger market outcomes. The rationale is is straightforward given that Financial YouTubers with more subscribers or views are more likely to (i) influence investors and/or (ii) exhibit greater ability and incentives to produce information that is informative. Additionally, given their visibility and the financial rewards associated with such visibility (i.e., deep pockets), these Financial YouTubers may anticipate more monitoring from external parties such as regulators and investors, and mitigate this risk by providing higher quality content. Indeed, we find evidence of a strong positive (negative) association between a Financial YouTuber's visibility and stock market reactions (information asymmetry) surrounding video upload dates.

Lastly, we explore a distinct feature of Financial YouTubers' videos, which involves the occasional inclusion of disclaimers regarding the videos providing investment advice. On one hand, these disclaimers could be interpreted as an attempt by the Financial YouTuber to provide boilerplate risk deflection, and disregard the disclaimers while acting on the video content as investment advice (i.e., results). On the other hand, viewers could interpret videos with such disclaimers as being valid, which would lead to those videos being viewed more as entertainment than actionable investment advice (i.e., attenuated or no results).

We hand-collect data on which Financial YouTubers provide disclaimers, and find that disclaimers are associated with significantly weaker market reactions. Further, the presence of a disclaimer diminishes the influence of tone on returns. These findings indicate that investors act as if they view the disclaimers in a cautionary way and are less inclined to follow investment advice from the associated videos. In contrast, for the subset of Financial YouTubers who include disclaimers but also disclose ownership in covered stocks, unreported results indicate some evidence that market reactions are stronger.

Our study makes several contributions. First, it contributes to the burgeoning literature on social media as an increasingly influential component of information flows in capital markets. We document that investment advice of non-regulated advisers is associated with market prices and information asymmetry. Given the survey results from Nasdaq (2022) that younger investors are more actively managing their money and keener to obtain information from social media outlets like YouTube, these results are important to understand the changing structure of how the next generation of investors obtains investment information.

Second, our study adds to related research on the informativeness of non-professional analyst research. Prior studies examine the impact of non-professional analysts from crowd-sourcing platforms such as Seeking-alpha (e.g., Chen, De, Hu, and Hwang 2014; Dyer and Kim 2021; Farrell et al. 2022), Yahoo Finance (e.g., Lawrence et al. 2017, 2018), Estimize (e.g., Jame et al. 2016), and Reddit (e.g., Chacon et al. 2023). Our study differs from prior literature by focusing on YouTube, a platform that enables multimodal communication and is alleged to primarily cater to less experienced investors.

Third, our results contribute to the literature on capital markets regulation. Accounting research provides mixed evidence on the effectiveness of disclaimers in cautioning investors in other settings, including (i) the required disclosure of conflicts of interest provided by financial analysts (Kelly, Low, Tan, and Tan 2012; Taha and Petrocelli 2014; Liu, Huang, Jiang, Messier 2020), (ii) the cautionary disclaimers provided by managers when making forward-looking statements under the SEC safe harbor provisions (Asay and Hales 2018; Cazier, McMullin, and Treu 2021; Huang, Shen, and Zang 2021), and (iii) warnings about managers' strategic incentives (Koonce, Leitter, and White 2019). In addition to the mixed evidence, a lot of these studies draw conclusions based on experimental methods (e.g., Cain, Loewenstein, and Moore 2005; Church and Kuang 2009). Our findings regarding the moderating effect of disclaimers contribute to this line of research by providing complementary empirical evidence.

2. Background and Hypothesis Development

2.1 Institutional Background

YouTube is a video-sharing media platform launched in 2005. After its launch, it quickly gained popularity among content creators of various topics, such as music, sports, education, news, and comedy. These content creators are commonly known as YouTubers and are characterized by their ability to engage the audience and can generate income by doing so. Specifically, compensation of YouTubers is measured as revenue per mile (RPM), which captures how much revenue per 1,000 views the YouTuber is earning, and includes ads, subscriptions, and other revenue sources.

According to a 2022 survey conducted by Nasdaq, investors of younger generations place significant faith in online discussion boards, podcasts, and social media platforms. Specifically, Nasdaq highlights that, "In particular, for those that use social media [for credible financial advice], YouTube and Facebook were the most popular applications." Thus, among the various topics for which YouTubers develop video content (i.e., "niches"), the stock market is one that gained popularity around 2014, followed by a wave of increasing demand for stock market information on YouTube from younger investors. These content creators, which we refer to as "Financial YouTubers," post video analyses on various stocks and represent one of the highest RPM niches on YouTubex. For example, Social Blade, a social media analytics website, indicates that the daily revenue range for Financial YouTubers is $12 to $193, or $4,380 to $70,445 annually, but the most popular channels generate hundreds of thousands of dollars per year.[5]

Despite significant income earned by Financial YouTubers, the informational role of their video content is unclear (Khattar 2023). Further, it is also unclear how Financial YouTubers are able to avoid being formally registered as investment advisers according to SEC and FINRA regulations. Subsequent to the stock market crash of 1929 and The Great Depression, investment speculation was blamed, and the SEC released the Investment Adviser Act of 1940, which declares:

> "'Investment adviser' means any person who, for compensation, engages in the business of advising others, either directly or through publications or writings, as to the value of securities or as to the advisability of investing in, purchasing, or selling securities, or who, for compensation and as part of a regular business, issues or promulgates analyses or reports concerning securities …." (Section 202(a)(11)(D))

Financial YouTubers seem to be acting as investment advisers, but there are several exclusions to the above definition that may provide safe haven. The most likely basis for Financial YouTubers not being considered investment advisers by the SEC is a "publisher's exclusion." In a 'no action' letter issued by the SEC to an inquiry from a website host of an investment advisory business, the SEC responds,

> "Section 202(a)(11)(D) of the Advisers Act excludes from the definition of an investment adviser a 'publisher of any bona fide newspaper, news magazine or business or financial publication of general and regular circulation.' The United States Supreme Court has interpreted this 'publisher's exclusion' to include publications that offer impersonal

[5] Social Blade indicates that actual revenue may diverge from their estimate range, because factors, such as quality of traffic, source country, niche type of video, price of specific advertisements, adblock, actual click rate, come into play. In our sample, the average number of daily viewers across Financial YouTubers is 49,983. Using the typical RPM of $18 per 1000 views (KreditKarma 2023), this translates to an estimated daily compensation of $899.

> investment advice to the general public on a regular basis. To qualify for the section 202(a)(11)(D) exclusion, the publication must be: (1) of a general and impersonal nature, in that the advice provided is not adapted to any specific portfolio or any client's particular needs; (2) 'bona fide' or genuine, in that it contains disinterested commentary and analysis as opposed to promotional material; and (3) of general and regular circulation, in that it is not timed to specific market activity or to events affecting, or having the ability to affect, the securities industry."

The question, then, is whether the content of Financial YouTuber videos satisfies the above parameters. In the past, the SEC has sanctioned the publisher of an investment newsletter for not being a registered investment adviser. However, in Lowe v SEC 4 72 US 181 (1985), the Supreme Court interpreted the Investment Act of 1940 as being applicable to person-to-person advice, not general advice consistent with the publisher's exclusion. To date, and to the best of our knowledge, there has been no sanctioning of any Financial YouTuber for not being registered as an investment adviser, although in 2022 the SEC charged seven social media influencers on Twitter and Discord in a classic pump-and-dump scheme. Thus, the SEC appears to be monitoring social media information regarding investment advice, but so far, there have been no actions against Finance YouTubers as investment advisers.[6]

Nevertheless, because there remains uncertainty regarding whether social media financial influencers must register as investment advisers, Financial YouTubers frequently include disclaimers with their video analyses. For example, a YouTube channel called "Financial Advice" ironically includes the following, "** Disclaimer ** The information on this video … should not be understood as Financial Advice." [7] Because regulators and market participants both have concerns about Financial YouTubers potentially misleading investors, we examine the role of Financial YouTube influencers in the capital market, and in a later analysis, examine cross-

[6] Surprisingly, the SEC has determined that cryptocurrencies do *not* meet the definition of securities under the Investment Advisers Act of 1940 (see https://corpgov.law.harvard.edu/2022/12/06/why-cryptoassets-are-not-securities/). See Merkley et al. (2023) for a study of crypto influencers.

[7] See Appendix A for additional examples of such disclaimers.

sectional variation in the provision of disclaimers by Financial YouTubers.

2.2 Literature Review

Our study of YouTube is closely related to the recent literature on new, disruptive platforms used by corporate, institutional, and retail investors as information intermediaries for disclosure and investment research. For example, Blankespoor et al. (2014) find that firms use Twitter as an platform to disseminate news and increase market liquidity. Lawrence et al. (2017) document investors' demand for information on Yahoo Finance using page views of analyst estimates, ratings, and target prices. Lawrence et al. (2018) demonstrate how investor attention on social media affects stock prices and information asymmetry by using a field experiment where a random sample of firms with earnings announcements are promoted to one percent of Yahoo Finance users.

Closely related to our study, one line of research examines the role of non-professional analysts from platforms such as Seeking Alpha and Estimize. For example, Farrell et al. (2022) shows that Seeking Alpha research is valuable to retail investors, but Dyer and Kim (2021) demonstrate that investors discount research by anonymous contributors. Drake et al. (2023) show that non-professional analysts on social media could preempt the market reaction to research provided by sell-side analysts. Jame et al. (2016) find that crowdsourced forecasts on Estimize provide useful supplementary information to the market. Finally, Chacon et al. (2023) find that trading strategies following the WallStreetBets subreddit were alpha neutral.

2.3 Main Predictions

2.3.1 YouTube Video Posting, Market Return, and Liquidity

Our baseline analysis is to examine whether Financial YouTubers affect prices or information asymmetry. On one hand, Financial YouTubers are content creators and are monetarily incentivized to engage viewers through content. To the extent valuable insights can draw a larger audience and generate income for the Financial YouTuber, the information in their videos may be incremental to those provided by firms and other market participants. On the other hand, Financial YouTubers may not be informative for at least two reasons. First, they are not licensed investment advisers, and their content may either be uninformative or merely for entertainment. Second, the videos they post may provide limited new information because incentives to post frequently may result in uninformative video content. Finally, as noted above, even if video content is informative, because the consumers of YouTube video analyses are purportedly young retail investors, their marginal trades would seem unlikely to have any observable effect on market prices.

Further, prior research demonstrates the role of information dissemination in mitigating information asymmetry (Blankespoor et al. 2014). If videos posted by Financial YouTubers contain new information, we expect that in addition to impacting prices, the information asymmetry of firms covered may be affected. Alternatively, if Financial YouTubers merely piggy-back or regurgitate previously released information disclosures, such videos would have no impact on (prices or) information asymmetry. We state our all of our hypotheses in alternative form:

> ***H1:*** *Financial YouTuber videos are associated with changes in prices and information asymmetry.*

All remaining hypotheses relate to cross-sectional variation in characteristics of the covered firm, video content or content creator. Given the Nasdaq (2020) findings regarding the demographics of investors who obtain information from social media platforms like YouTube, we predict that any video impact on prices or information asymmetry will be concentrated among firms with a higher proportion of retail traders. We use institutional investor holdings as an inverse measure of retail traders, and examine the following hypothesis.

H2: *Any impact of YouTube videos on prices or information asymmetry is concentrated among firms with a higher proportion of holdings by retail investors.*

2.3.2 Video Content and Market Outcomes

We next examine the content of YouTube videos. If videos posted by Financial YouTubers contain new information and investors use such information, we expect that returns are associated with the content, and examine two well-established measures of the sentiment of content: (i) tone (e.g., Huang, Teoh and Zhang 2014; Allee and DeAngelis 2015; Chen, Nagar and Schoenfeld 2018; Saiwitz and Kida 2018; Zhang, Stone and Xie 2019; Campbell et al. 2020; Elliott, Loftus and Winn 2023; etc.) and (ii) hard information (e.g., Twedt and Rees 2012; Henry and Leone 2016; Bertomeu and Marinovic 2016; Liberti and Petersen 2019; Bradshaw et al. 2021; etc.). We expect tone to be be primarily associated with the sign of market reactions and hard information to be associated with reductions in information asymmetry. The third hypothesis is as follows:

H3: *Video content tone is positively associated with returns, and greater presence of hard information is negatively associated with changes in information asymmetry.*

Finally, we expect the impact of Financial YouTubers in the capital market to be stronger when they are more influential. The two obvious proxies for influence are the number of subscribers and video views. More subscribers should be associated with a larger audience and contagion for video uploads. Further, these proxies may be endogenous with a past history of valuable information production. Likewise, with greater subscribers and views, Financial YouTubers likely experience increased incentive to deliver useful, high-quality information to users. The fourth hypothesis is as follows:

H4: *Market reactions and changes in information asymmetry are concentrated among Financial YouTubers with more subscribers and video views.*

2.3.3 Disclaimers and Market Return

In light of potential regulatory oversight or litigation that is associated with providing investment information (Fisch and Sale 2002), we conclude with an exploratory examination of the use of disclaimers by Financial YouTubers. On one hand, viewers may interpret disclaimers as indicative of entertainment content of videos, rather than actionable investment advice. On the other hand, disclaimers may be viewed as an attempt at a 'safe harbor,' similar to those commonplace in many professional settings (e.g., Deady 2000; Eysenbach and Kohler 2002) and may disregard them as a boilerplate language. In addition, variation in the use of disclaimers may be endogenous to Financial YouTuber approaches to videos (i.e., cautious vs. bombastic), so may capture the 'style' of a Financial YouTuber (e.g., Cain et al. 2005). Because disclaimers may be more strongly, more weakly, or unassociated with market returns, we state our final hypothesis in the null form:

> ***H5:*** *Market reactions to Financial YouTube videos are unrelated to the mitigated by presence of a disclaimer.*

3. Sample Selection and Research Design

3.1 Sample Selection

We identify prominent Financial YouTubers by manually summarizing YouTube channels that provide opinions about specific stocks. Because there is no established list of these channels, we form our initial list based on various websites such as Forbes, Benzinga, Nasdaq, Trade Stocks, and Edge Investments. We also search social media platforms such as Reddit and Quora, because investors are known to visit these platforms (Ostroff 2021).[8] Because this initial list is likely not exhaustive, we supplement it based on a round of extensive searches of random stock names on

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[8] See Appendix B for a summary of sources where we collect the list of Financial YouTuber channels.

YouTube, which simultaneously verified identification of channels in the initial list. We believe our initial list of channels includes the majority of active Financial YouTubers who release information on individual stocks, as well as those who have video content on markets in general, economics, investment history and other related topics.

We filter and retain YouTuber channels that specialize in equity markets. This filtering process is necessary because some channels heavily focus on general financial interest or other assets such as cryptocurrencies. We limit our selection to channels of English-speaking YouTubers for conformity of text extraction and because we are primarily interested in U.S. stocks, for which our primary tests have been applied in prior research. We further restrict the channels to those with a minimum of 50,000 current subscribers, as anecdotal evidence suggests YouTubers with subscriptions at this level tend to succeed in monetizing their content are include mid-tier, macro, or mega-influencers (Wright 2022; West 2022; Williams 2022).[9] Thus, our sample includes channels with large followings, which shines a light on those that are most likely to have impacts on capital markets.

After finalizing the list of YouTuber channels, we scrape the titles and URLs for all the videos within these channels. Our sample period ranges from 2014 to 2021. We start in 2014 because it is earliest date of firm-specific video posted within our YouTube Channels.[10] We require the video title to include the name or ticker for a specific firm. We remove videos that discuss more than one stock (e.g., "Top 5 stocks") because these videos make it difficult to discern the content related to a particular stock.[11] We then hand match the ticker associated with each video. Finally, we obtain video transcripts for each URL using the website, https://youtubetranscript.com.

[9] YouTubers below this threshold are usually referred to as nano or micro influencers.
[10] This does not suggest the earliest year they started career as Financial YouTubers is 2014. It is not unusual for YouTubers to remove their old postings.
[11] In future analyses, we plan to separately examine videos that pertain to multiple tickers.

After the above sample collection process, we obtain 7,917 video observations released by 79 Financial YouTubers. Data requirements for variables in our regression analyses further reduce the sample to 7,350 for our baseline results, and further for additional data requirements.[12]

Table 1 presents descriptive statistics for the Financial YouTube Channels in our YouTube sample. The 79 Financial YouTubers in our sample have an average of 317 video postings on their YouTube channels, each covering 35 unique firms on average. The number of videos they post on average per year, month, and week is 109, 14, 4, respectively. Each video lasts for an average of 13 minutes. Regarding engagement, the average number of cumulative subscribers (viewers) per Financial YouTuber is 281,170 (45,600,000), with an increase of 116 (50,882) additional subscribers (viewers) every day. The average daily revenue corresponding to the daily engagement translates to $104 per YouTuber. Approximately one-third of videos are posted within one week of the YouTuber's previous posting.

Industry coverage of Financial YouTubers appears in Panel B of Table 1, which indicates diverse coverage across industries. Business Services, Motion Pictures, Holding & Other Investment Offices, Electronic & Electrical Equipment, and Industrial & Commercial Machinery are the most frequent subjects of Financial YouTuber videos. Mining & Quarrying, Furniture & Fixtures, Railroad Transportation, Pipelines (Except Natural Gas), as well as Transportation Services are covered the least by Financial YouTubers in our sample.

[Insert Table 1 here]

Table 2 provides descriptive statistics for all variables used in the analyses.[13] The most

[12] For example, the sample is 5,895, 5,495, and 6,154 video-date observations for the regression analyses focuse on video tone, hard information, and video disclaimer analyses, respectively. Table 2 shows this variation in samples.

[13] All variables are defined in Appendix C. For all analyses, we include industry and year fixed effects to account for unobserved time-invariant industry characteristics and time effects. We also supplement the analyses by substituting industry fixed effects with firm fixed effects to account for time-invariant firm characteristics. Standard errors are clustered by firm.

noteworthy results are that only 28.3 percent of the sample reflects firms with high institutional ownership, yet average analyst following is reasonably high at 8.8. Finally, the average (median) three-day abnormal return across the sample (that includes matched firms without YouTube videos) is close to (equal to) zero. Among the 5, 253 firm-year observations for the coverage determinant analysis, 9.8 percent of firm-years are covered by Financial YouTubers. Mean institutional ownership is 47.6%, the average number of analysts following a firm is 8.8, and the frequency of management forecasts is 77.7%. For the actual video postings, the average net video tone, positive video tone, and negative video tone is 0.018, 0.010, and 0.072, respectively. On average, 1.4 percent of the words in video transcripts are classified as hard information per the *MoreThanSentiments* Python library. Finally, 73 percent of video postings include disclaimers either in the video description part or within videos. Among videos with disclaimers, 9 percent are accompanied by Financial YouTubers ownership statements.

[Insert Table 2 here]

Before implementing our main tests, we estimate a descriptive determinants model to provide descriptive evidence on coverage by Financial YouTubers. We begin with the firm-year observations corresponding with the video-date observations in our sample and match them with non-covered firms within the same 2-digit SIC code for industries with at least 5% of firms covered by Financial YouTubers in the same year. This process results in 5,253 firm-year observations. We model the determinants of coverage by Financial YouTubers using the following model:

$$Pr(Video=1) \text{ or } Log(\#Videos) = \beta_0 + Controls + \varepsilon \quad (1)$$

The two dependent variables capture the probability and frequency of a firm being covered by Financial YouTubers. We include firm characteristics as determinants, including firm age (*Log(Firm Age)*), firm size (*Asset*), profitability (*ROA*), the level of advertising expense

(*Advertising*), financial leverage (*Leverage*), cash holdings (*Cash*), sales growth (*Sales Growth*), management's voluntary disclosure frequency of management forecasts (*Mgt. Frequency*), institutional ownership (%*Institutional*), and analyst following (*Analyst Following*). Given that primary viewers on YouTube are purportedly retail investors, one would expect coverage propensity to increase for firms more likely visible to retail investors. For example, Madsen and Niessner (2019) find that advertisements elicit increased retail investor attention. Similarly, firms that are larger and older might be more likely to be subjects of Financial YouTubers.

Table 3 presents the results of the descriptive determinants analysis. The first two columns employ industry- and year- fixed effects, while the latter two columns use firm- and year- fixed effects. We focus our discussion on the first two columns because we are interested in how heterogeneity in firm characteristics affects the likelihood and frequency of coverage by Financial YouTubers. When compared with firms that are not covered by Financial YouTubers in industries where at least 5% of firms are covered, Financial YouTubers cover firms that are older and larger, have higher advertising expenses, lower leverage, higher cash holdings, higher sales growth, and lower profitability. The positive coefficients on advertising are consistent with Madsen and Niessner's (2019) findings. Further, covered firms have significantly lower institutional ownership, consistent with Financial YouTubers communicating primarily to retail investors. Finally, Financial YouTuber coverage is not associated with firm disclosures (*Mgt. Frequency*) but is associated with analyst coverage (*Analyst Following*).

[Insert Table 3 here]

3.2 Research Design

3.2.1 Market Reaction and Information Asymmetry Tests (H1)

We examine whether signed (*CAR*) or unsigned cumulative abnormal return (|*CAR*|) over three-day window [0, +2] around video posting dates are significantly different from zero at the univariate level. We also conduct a regression analysis, where we match YouTube-covered firms with non-covered firms using 1:1 PSM technique (without replacement). We match based on nearest size, return-on-assets, and leverage within the same SIC two-digit industry and fiscal year, allowing the caliper to be 0.25 (Bochkay, Chychyla, Sankaraguruswamy, and Willenborg 2018; Heitzman and Lester 2022). We then estimate the following OLS regression model:

$$\textit{Signed or Unsigned CAR} = \beta_0 + \beta_1 \textit{ YouTube Posting} + \textit{Controls} + \varepsilon, \qquad (2)$$

where the dependent variable is signed (*CAR*) or unsigned cumulative abnormal return (|*CAR*|) over three-day window [0, +2] around the video posting date. For non-covered firms, we assign a pseudo-posting date to the nearest neighbor identical to the posting date of target firm. The main test variable is *YouTube Posting*, which is an indicator variable equal to one if a firm is covered by a Financial YouTuber on date *t*, and zero otherwise. Under H1, we predict β_1 to be positive.

To test whether Financial YouTuber videos are associated with changes in firms' information environments, we first examine the change in information asymmetry surrounding posting dates. We use two alternative measures of information asymmetry common in literature. The first measure is *Bid-Ask Spread*, calculated as the difference between bid and ask price scaled by the average of the two, multiplied by 100. The second measure is *Amihud*, calculated as the ratio of absolute stock return to dollar volume, multiplied by 10.[9] Our focus is on whether there is a significant decrease in these two information asymmetry measures.

We also include PSM-matched sample in our analysis and estimate the following OLS regression model:

$$\textit{Information Asymmetry} = \beta_0 + \beta_1 \textit{ YouTube Posting} + \textit{Controls} + \varepsilon, \quad (3)$$

where *Information Asymmetry* is placeholder for *Bid-Ask Spread* and *Amihud*. The variable of interest continues to be *YouTube Posting*. A negative coefficient on β_1 is evidence consistent with investors consuming information in YouTube videos and an improvement in the information environment.

3.2.2 Cross-Sectional Tests of Firm Investor Clientele (H2)

We use *%Institutional* and an indicator variable *High %Institutional,* which equals one if the firm belongs to top quartile of institutional ownership, and zero otherwise. We interact these variables with *Video Posting* in models (2) and (3). Under H2, we expect the interaction term between *Video Posting* and these two variables, separately, will be more negative (positive) when signed or unsigned CAR (information asymmetry) is dependent variable.

3.2.3 Cross-Sectional Tests of Tone and Hard Information Content (H3)

The analysis of video content tone is based upon the following OLS regression models:

$$\textit{CAR} = \beta_0 + \beta_1 \textit{ Net Video Tone} + \textit{Controls} + \varepsilon, \quad (4a)$$
$$\textit{CAR} = \beta_0 + \beta_{1a} \textit{ Positive Video Tone} + \beta_{1b} \textit{ Negative Video Tone} + \textit{Controls} + \varepsilon, \quad (4b)$$

The main variables of interest are the measures of video tone. While we use a net video tone measure in model (4a), we partition it into positive and negative components in model (4b). We calculate the tone measures based on three commonly used dictionaries provided by Loughran and McDonald (2011), Henry (2008), and Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Francis, and Booth 2001).[14] Because the content and narratives of Financial YouTubers are not

[14] The word list in Loughran and McDonald (2011) was developed to analyze the tone of MD&A section in 10-K filings and is used extensively to measure the tone of corporate filings. Henry (2008)'s word list was developed to examine earnings announcements and is used in financial communication setting such as earnings conference calls

standardized and possibly YouTuber-specific, we use the principal component of tone measures calculated using the three alternative dictionaries.[15] According to H3a, if the market responds to video postings, the coefficients on *Net Video Tone* (β_1) and *Positive Video Tone* (β_{1a}) will be positive, while the coefficient on *Negative Video Tone* (β_{1b}) will be negative.

To control the possibility of piggy-backing, we augment our model by further controlling firms' past stock market performance and information uncertainty (*6-month CAR*, *6-month Ret. Vol,* and *VIX*). To control for the impact of other information sources or events that could affect returns, we include various informational events prior to video postings, such as firms' Edgar filings, earnings announcements earning conference calls, media coverage of firms, optimism of analysts' forecasts, as well as announcements of financial statement restatements (*Edgar Filings*, *Earnings Announcements*, *Earnings Call*, and *News*, *Analyst Optimism*, and *Restatement*).[16]

We estimate the following model to test whether the decrease in information asymmetry following the releases of videos is more pronounced for videos containing more hard information:

$$\textit{Information Asymmetry} = \beta_0 + \beta_1 \,\%\textit{Hard Information} + \textit{Controls} + \varepsilon, \tag{5}$$

%Hard Information, measured as the number of numerical values in the video is based on the *MoreThanSentiments* Python library relative to the length of the video text transcript (Blankespoor 2019).[17] A negative coefficient on β_1 is consistent with an improvement in the information environment.

and press releases. LIWC's word list is more general and can be applied to various settings such as newspaper articles and MD&A disclosures (Mayew, Sethuraman, and Venkatachalam 2015; Loughran and McDonald 2016; Tsileponis, Stathopoulos, and Walker 2020).

[15] We use the separate tone measures in our robustness analyses and find similar results.

[16] We calculate the frequency of all events in the week prior to video postings except for analyst optimism and restatement announcements, where we adopt an annual window. Specifically, we measure analyst forecast optimism in the year prior to video postings since the information environment level variables of analyst forecasts and institutional ownership are also measured in this window. We measure restatement announcements in the annual window since such events are rather infrequent and are indicators of financial reporting quality at the annual level. Our results are robust if alternative windows are used.

[17] We find robust results when an alternative measure of hard information is used, as discussed in the section 5.

3.2.4 Cross-Sectional Tests of Financial YouTuber Influence (H4)

We create indicator variables, *High #Subscribers* and *High #Viewers*, which take the value of one if the number of subscribers and viewers of a Financial YouTuber, respectively, is in the top quartile, and zero otherwise. We separately interact these two indicator variables with the YouTube content variables, *Net Video Tone* and *%Hard Information* in models (4a) and (5). We focus on the coefficients for the interaction terms. If the coefficients on *Net Video Tone*High #Subscribers* and *Net Video Tone*High #Viewers* are positive and the coefficients on *%Hard Information *High #Subscribers* and *%Hard Information *High #Viewers* are negative, this would be consistent with more influential Financial YouTubers being associated with stronger price impact and changes in information asymmetry.

3.2.5 Disclaimers and Market Return (H5)

To investigate whether disclaimers have a moderating impact on our main results, we estimate the following OLS regression model:

$$\textit{Signed or Unsigned CAR} = \beta_0 + \beta_1 \textit{Disclaimer} + \textit{Controls} + \varepsilon, \tag{6a}$$

$$\textit{CAR} = \beta_0 + \beta_1 \textit{Disclaimer} + \beta_2 \textit{Net Video Tone} + \beta_3 \textit{Net Video Tone*Disclaimer} + \varepsilon, \tag{6b}$$

$$\begin{aligned} \textit{CAR} = {} & \beta_0 + \beta_1 \textit{Disclaimer} + \beta_2 \textit{Positive Video Tone} + \beta_3 \textit{Positive Video Tone*Disclaimer} \\ & + \beta_4 \textit{Negative Video Tone} + \beta_5 \textit{Negative Video Tone *Disclaimer} + \varepsilon, \end{aligned} \tag{6c}$$

where *Disclaimer* equals one if a disclaimer exists, and zero otherwise. The coefficients of interest are β_1 in model (6a), β_3 in model (6b), and β_3 and β_5 in model (6c).

4. Empirical Results

4.1 Univariate Results on Market Reactions and Information Asymmetry (H1)

Table 4 presents univariate test results on whether Financial YouTuber videos are associated with short-window market returns. We find the average cumulative abnormal return over the three days following a YouTube video posting is positive and significant, regardless of whether *CAR* is signed or not. For example, the average three-day signed (unsigned) abnormal return is 0.3% (12.3%). To rule out an alternative explanation that these returns are simply piggybacking off of other information events adjacent to the posting of Financial YouTuber videos, we examine reactions for reduced samples that have no information events (i.e., earnings announcements, firm EDGAR filings, and S&P-designated firm-specific events) in the week preceding the video posting dates. We present the market reaction tests in Panels B to D, corresponding to each exclusion.[18] The results are remarkably consistent across partitions, despite significant conservative sample deletions. Overall, the univariate returns are preliminarily consistent with Financial YouTubers provide information content in their videos.

[Insert Table 4 here]

Table 5 presents the univariate analysis for changes in information asymmetry. We find that mean of information asymmetry measures, either *Spread* or *Amihud*, is significant lower in the day following Financial YouTuber videos relative to the day before, consistent with the improvement in information environment for firms covered by Financial YouTubers.

[Insert Table 5 here]

Table 6 presents multivariate results using the propensity matched sample. For the returns regressions in columns (1)-(4), the coefficients on *YouTube Posting* are significant in all specifications. Additionally, coefficients of controls are largely consistent with the prior literature (e.g., Dyer and Kim 2021). Columns (5)-(8) present results for information environment tests. Both bid-ask spreads and the Amihud illiquidity measures decrease significantly following YouTube

[18] S&P Capital IQ provides more than 100 event types of a specific firm in Key Development Database. Event types include earnings announcements, product announcements, EDGAR filings, conference calls, etc.

posting dates. Overall, the evidence is consistent with the first hypothesis that video postings of Financial YouTubers are associated with returns and information asymmetry.

[Insert Table 6 here]

The most obvious validity threat is that returns and information asymmetry analyses are contaminated by market reactions to firm-specific news adjacent to the Financial YouTuber videos. As with the univariate results presented above, we adopt an extreme sensitivity test and exclude all firm-specific events identified in the Key Development database within the seven-day window preceding the video posting dates. This data includes over 100 events, ranging from earnings announcements to events identified with customer or rumors, and excluding all observations with any single event in the 7-day window results in an 81.5% decrease in the sample. With this conservative sample deletion, the coefficients on signed CAR become insignificant, but all other findings remain consistent. Although the signed CAR results might suggest Financial YouTubers could be piggybacking on other news, the results for the other variables suggest otherwise. We rely on the cross-sectional tests discussed next to gain further insight into the association between video uploads and market outcomes.

[Insert Table 7 here]

4.2 Cross-sectional Results of Institutional Investors (H2)

We interact institutional ownership variables with YouTube posting indicator in models (2) and (3). In Panel A of Table 8, we include the continuous measure, *%Institutional* and its interaction with *YouTube Posting.* Market reactions are weaker for firms with higher institutional ownership, and the change in information asymmetry is higher. In Panel B of Table 8, where we use *High %Institutional* indicator, we find similar results. Collectively, these results are consistent with market outcomes surrounding YouTube video uploads being concentrated among stocks with greater retail investor ownership.[19]

We also use NYSE Trade and Quote (TAQ) data and compute three different measures of retail trade percentage (Barber, Odean, and Zhu 2008). *%Retail1* is the ratio of number of retail trades to number of total trades on date *t+1*. *%Retail2* is the ratio of total retail trade volume in shares to total trade volume in shares on date *t+1*. *%Retail3* is the ratio of total retail trade value in dollar to total trade value in dollar on date *t+1*. Panel C of Table 8 indicates that YouTube video postings are significantly associated with percentage of retail trading, providing more direct evidence that retail investors are likely the primary audience of Financial YouTube channels.

[Insert Table 8 here]

4.3 Video Tone and Market Reactions (H3)

To further examine the robustness of the *CAR* results presented above and examine cross-sectional variation in video content, we regress *CAR* on the tone of video content (Models (4a) and (4b)) and report the results in Table 9. Columns (1) and (2) suggest that the market reactions to YouTube postings are positively associated with the net tone of videos (*Net Video Tone*). In columns (3) and (4), we separate the net tone into positive (*Positive Video Tone*) and negative tone (*Negative Video Tone*) and find that returns increase (decrease) with higher positive (negative) tone in video postings, again consistent with investors responding to video content. We also examine whether investors' response to video is symmetric by comparing the absolute coefficients on *Positive Video Tone* and *Negative Video Tone*. The F-statistics of the differences are both significant at the 1% level, suggesting investors respond more strongly to negative relative to positive tone, consistent with a variety of prior research. In Columns (5)-(8), where we augment

[19] Results from Table 6 to 8 are qualitative similar when we match control groups using propensity score matching based on the determinant controls from Table 3.

controls to further mitigate the possibility of piggy-backing, results are similar.

The coefficients on control variables are also largely consistent with prior literature. positive coefficients on analyst following and analyst forecast optimism are consistent with Bradley, Clarke, Lee, and Ornthanalai (2013). Also, the negative coefficients on *Restatement* are consistent with the market responding negatively to restating firms, consistent with Palmrose, Richardson, and Scholz (2004). Overall, the results suggest that markets reactions correspond to the tone of video and we find even stronger reactions for negatively toned videos.

[Insert Table 9 here]

We next explore whether reduction in information asymmetry is driven by the level of hard information contained in YouTube videos, controlling with firm characteristics and other information sources prior to video postings. Table 10 shows that the coefficients on *%Hard Information* are significantly negative in seven of eight columns, with the alternative usage of two information asymmetry measures, two fixed effect structures, and augmented controls. The results are generally consistent with investors responding to information embedded in videos posted by Financial YouTubers.

As with the previous analyses, coefficients on control variables are consistent with prior literature. For example, the negative coefficients on *Asset* and *%Institutional* are consistent with findings that larger firms and firms with more institutional investors have better information environments (Heflin, Kross, and Suk 2012; Balakrishnan, Billing, Kelly, and Ljungqvist 2014). Overall, results in Table 10 are consistent with H3 that predicts declines in information asymmetry are more pronounced for videos containing hard information.

[Insert Table 10 here]

4.4 Cross-Sectional Results of Financial YouTubers Influence (H4)

Next, we predict that Financial YouTubers who are more influential on YouTube will have more impact on stock market and information environments of firms, possibly due to heightened expertise, resources, and/or monitoring from outsiders. We interact our measures of video content (tone and hard information) from our main analyses with two proxies for Financial YouTuber influence, separate indicators for high subscriptions and viewership, and report the results in Table 11. In Panel A, we find that the coefficients on the interaction terms of *Net Video Tone*High #Subscribers* are marginally positive (at the 0.10 level) columns (1) and (2), and the coefficients on and *Net Video Tone*High #Viewers* are positive and more significant (at the 0.05 or 0.01 levels).

In Panel B of Table 11, the coefficients on the interaction terms of *%Hard Information *High #Subscribers* and *%Hard Information *High #Viewers* are only significantly negative in two of eight columns. Thus, the association between hard information and information asymmetry is not moderated by the number of subscribers or viewers.

[Insert Table 11 here]

4.5 Disclaimers and Ownership by Financial YouTubers (H5)

Our final analysis is exploratory, and focuses on disclaimers provided by some Financial YouTubers. We examine whether disclaimers or ownership in covered companies alters the main results. Financial YouTubers in our sample include disclaimers in 73.4% of videos. We estimate model (6a) and present results in Table 12. The coefficients on *Disclaimer* are generally negative at varying levels of significance in three of four columns, consistent with disclaimers moderating investors' perceptions of Financial YouTube postings or these disclaimers proxying for conservatism of the investment advice contained in the videos.[20]

[20] As an alternative measure of *Disclaimer*, we use the textual length of disclaimers as a proxy for severity of disclaimer and find similar results (untabulated).

[Insert Table 12 here]

We augment models (6b) and (6c) by including interactions of *Disclaimer* and video tone and report the results in Table 13. In Columns (1) and (2), where we interact *Net Video Tone* with *Disclaimer,* the coefficients on the interaction terms are again negative and significant, corroborating the attenuation of returns for Financial YouTuber videos with disclaimers. We further break down into positive and negative tone and find that mitigation effect stems primarily from mitigating the impact of positive tone. Overall, these exploratory results suggest investors react less to videos with disclaimers.[21]

[Insert Table 13 here]

6. Conclusion

We provide preliminary evidence on the role of Financial YouTubers as a source of information for market participants. Using a hand-collected sample of videos posted by influential Financial YouTubers, we examine whether these postings are associated with returns and changes in information asymmetry. We find strong market reactions and reductions in information asymmetry following the releases of videos by Financial YouTubers. Both results are concentrated among firms with greater retail investor presence. Returns are positively associated with video tone, and information asymmetry decreases for video postings with more hard information. Both results exhibit some tendency to be stronger with more viewers and subscribers. Finally, disclaimers attenuate the main results. Overall, the findings in our study are consistent with Financial YouTubers serving an informational role in the capital market.

[21] As part of our extraction of disclaimers, we also observed that Financial YouTubers sometimes include disclosures on their ownership in firms covered in videos (9 percent of Financial YouTuber videos containing disclaimers). In unreported analyses, we find some evidence of stronger reactions for stocks the Financial YouTuber discloses ownership.

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Appendix A: Examples of YouTube Video Disclaimers:

Example 1
Name (URL) of YouTube Video: "Tesla WILL be the MOST Valuable company on Earth!!" (https://www.youtube.com/watch?v=i81U-8RlwjI)

Disclaimer: "The information presented herein shall not be construed as financial, investment, tax, legal, or insurance advice. The content is for entertainment purposes only. Please do not make buying or selling decisions based on these videos. If you need financial advice, please contact a qualified financial adviser. The views and opinions expressed by the speaker are their own as of the date of the recording. Any such views and opinions are subject to change without notice. It is your responsibility to verify all information. The speaker can not be held responsible for any direct, indirect, incidental, or consequential losses incurred by applying any of the information provided. Past performance is not indicative of future results. All investments carry risk. The speaker does not guarantee any specific outcome or profit. Please make sure you do your own due diligence".

Example 2
Name (URL) of YouTube Video: "Is It Finally Time To Buy APPLE Stock? - (AAPL Stock Analysis & Review 2019)"

Disclaimer: "Please be advised that I am not giving any financial or investing advice. I am not telling anyone how to spend or invest their money. Take all of my videos as my own opinion, as entertainment, and at your own risk".

Appendix B: List of Information Sources for Data Collection

Source	URL
benzinga.com	https://www.benzinga.com/money/best-stock-trading-youtube-channels
wondershare.com	https://filmora.wondershare.com/youtube/best-youtube-channel-for-stock-market.html
forbes.com	https://www.forbes.com/sites/jrose/2019/02/13/13-must-watch-youtube-channels-for-making-money/?sh=6bf2d3635bf8
mywallst.com	https://mywallst.com/blog/7-best-investing-youtube-channels-to-kickstart-your-2022/
tradestocks.com	https://www.tradestocks.com/trading/the-very-best-youtube-trading-channels/
joywallet.com	https://joywallet.com/article/best-youtube-investing-channels/
nasdaq.com	https://www.nasdaq.com/articles/10-best-youtube-channels-for-finance
feedspot.com	https://videos.feedspot.com/investment_youtube_channels/
beanvest.com	https://beanvest.com/blog/youtube-value-investing
financhill.com	https://financhill.com/blog/investing/best-youtube-stock-traders
edgeinvestments.org	https://edgeinvestments.org/blog/best-investing-youtube-channels
linkedin.com	https://www.linkedin.com/pulse/top-youtube-channels-stock-picking-michael-spencer-/
quora.com	https://www.quora.com/Which-YouTube-channels-are-good-for-learning-the-stock-market-and-real-time-trading
	https://www.quora.com/Which-are-some-of-the-good-channels-on-YouTube-for-understanding-stock-markets
	https://www.quora.com/Which-YouTube-channel-do-you-follow-for-stock-market-learning-or-fundamental-analysis
	https://www.quora.com/What-is-the-best-YouTube-channel-for-trading
	https://www.quora.com/What-are-some-good-YouTube-channels-websites-books-to-learn-about-how-the-stock-market-trades-and-bitcoin-works
	https://www.quora.com/What-is-the-best-YouTube-Channel-to-learn-fundamental-and-technical-analysis-of-stocks-for-beginners
	https://www.quora.com/What-are-the-best-YouTube-channels-for-investment-and-trading
	https://www.quora.com/Which-are-the-genuine-YouTube-channels-and-other-online-platforms-from-where-I-can-learn-about-stock-market-from-zero-to-an-advanced-level
	https://www.quora.com/What-are-the-best-Youtube-channels-podcasts-blogs-to-keep-a-daily-track-of-Indian-stock-markets-online-resources-only-not-TV-shows-printed-media
reddit.com	https://www.reddit.com/r/stocks/comments/juj33r/who_are_the_most_popularbest_youtube_stock/
	https://www.reddit.com/r/stocks/comments/1uky3p/10_best_stock_trading_youtube_channels_to_learn/
	https://www.reddit.com/r/thetagang/comments/qyx2wx/favorite_youtube_channels_for_stock_analysis/
	https://www.reddit.com/r/investing/comments/7opb4n/what_are_some_good_youtube_channels_on_investing/
	https://www.reddit.com/r/trakstocks/comments/nx436n/what_stock_youtubers_do_you_guys_follow_besides/

	https://www.reddit.com/r/stocks/comments/79in0n/favourite_youtubers_that_talk_about_the_stock/
	https://www.reddit.com/r/stocks/comments/j2zs4q/best_investing_youtubers/
	https://www.reddit.com/r/youtubers/comments/j5gshl/question_where_to_get_stock_videos_for_free/
	https://www.reddit.com/r/investing/comments/egrrvd/any_youtube_channels_youd_recommend_for_investing/
	https://www.reddit.com/r/ValueInvesting/comments/q7co7j/top_youtube_channels_about_value_investing/
	https://www.reddit.com/r/Daytrading/comments/mf061b/best_daytrading_youtube_channels/
	https://www.reddit.com/r/Trading/comments/r1mns1/best_youtube_channels_to_learn_how_to_trade/
	https://www.reddit.com/r/stocks/comments/aev417/what_are_good_youtube_channels_to_learn/
	https://www.reddit.com/r/Filmmakers/comments/ceu27n/where_can_i_find_free_stock_footage/
	https://www.reddit.com/r/Daytrading/comments/g2mxhx/best_stock_trading_teachers_on_youtube/
	https://www.reddit.com/r/Daytrading/comments/ngmb0k/what_are_some_of_your_favorite_youtube_traders_to/
	https://www.reddit.com/r/IndiaInvestments/comments/wro4zb/are_there_any_good_youtube_channels_to_learn/
	https://www.reddit.com/r/ValueInvesting/comments/10eq98l/best_and_worst_youtube_channels_and_why/
	https://www.reddit.com/r/dividends/comments/wi8p1k/good_youtube_channels/
	https://www.reddit.com/r/editors/comments/mkoqik/best_stock_video_service_recommendations/
	https://www.reddit.com/r/options/comments/v006rg/best_options_trading_channels_on_youtube/
	https://www.reddit.com/r/Daytrading/comments/ljssv5/a_list_of_helpful_youtube_channels_to_learn_day/
	https://www.reddit.com/r/ValueInvesting/comments/xtsa00/value_investing_focussed_youtube_channels/
	https://www.reddit.com/r/RobinHood/comments/hq2om2/youtube_channels_for_investing_advice/
	https://www.reddit.com/r/stocks/comments/pbtegp/good_youtube_channels_for_macro_updates_stock/
	https://www.reddit.com/r/investing/comments/42cqt9/best_youtube_channels_for_financial_news/
	https://www.reddit.com/r/investing/comments/db4poa/what_are_your_favorite_youtube_channels_for/
	https://www.reddit.com/r/StockMarket/comments/hnks4p/good_youtube_channelspodcasts_to_follow/

Appendix C: Variable Definitions

Variable	Definitions
Pr(Video=1)	Indicator variable set to 1 if a firm is covered by at least one YouTuber during a year, and 0 otherwise.
Log(#Videos)	Natural logarithm of 1 plus the number of videos a firm is covered by YouTubers during a year, and 0 otherwise.
Log(Firm Age)	Natural logarithm of 1 plus the number of years the firm has been on Compustat.
Asset	Natural logarithm of 1 plus total assets.
ROA	Income before extraordinary items, scaled by total assets.
%Institutional	Institutional ownership ratio from 13-F Thomson Reuters database.
High %Institutional	Indicator variable set to 1 if *%Institutional* belongs to top quartile in the distribution, and 0 otherwise.
Advertising	Advertising expense, scaled by capital expenditure.
Leverage	Total debt, scaled by total assets.
Cash	Total cash, scaled by total assets.
Sales Growth	Percentage change in sales revenue from year t-1 to t.
Mgt. Frequency	The number of management frequency during a fiscal year.
Analyst Following	The number of analysts following a firm during a fiscal year.
YouTube Posting	Indicator variable set to 1 if a YouTube post about the firm on date *t*, and zero otherwise.
CAR	Cumulative abnormal returns over three-day window [0,+2] around video posting, where abnormal return is computed as raw return minus the value-weighted market adjusted return.
Net Video Tone	Principal component of Loughran and McDonald's net tone, Henry's net tone, and LIWC's net tone measure. Loughran and McDonald's list has 254 words and 2,329 words associated with positive tone and negative tone, respectively. Henry's list has 105 words and 85 words associated with positive tone and negative tone, respectively. LIWC's list has 1,020 words and 1,530 words associated with positive tone and negative tone, respectively.
Positive Video Tone	Principal component of Loughran and McDonald's positive tone, Henry's positive tone, and LIWC's positive tone measure.
Negative Video Tone	Principal component of Loughran and McDonald's negative tone, Henry's negative tone, and LIWC's negative tone measure.
VIX	7-day average CBOE Volatility Index (VIX) prior to posting.
6-month CAR	6-month past cumulative abnormal return prior to posting.
6-month Ret. Vol.	Standard deviation of 6-month past returns prior to posting.
Edgar Filings	Total number of Edgar filings during a week before posting.
Earnings Announcements	The total number of earnings announcements a firm during the week before posting.
Earnings Call	Natural logarithm of 1 plus the number of conference calls during a week before posting.
News	Natural logarithm of 1 plus the number of media mentioning the firm during a week before posting.
Analyst Optimism	Yearly average of individual annual earnings forecast minus actual earnings, scaled by stock price as of the beginning month of forecast.
Restatement	The total number of restatements announced by a firm during the 365 days before posting.

Bid-Ask Spread	The difference between bid and ask price scaled by the average of the two, multiplied by 100, in date t+1.
Amihud	The ratio of absolute stock return to dollar volume, multiplied with 1,000,000,000.
%Retail1	The ratio of number of retail trades to number of total trades on date *t+1*.
%Retail2	The ratio of total retail trade volume in shares to total trade volume in shares on date *t+1*.
%Retail3	The ratio of total retail trade value in dollar to total trade value in dollar on date *t+1*.
%Hard Information	The number of numerical values against the length of the whole text, based on *MoreThanSentiments* Python library.
High #Subscribers	Indicator variable set to 1 if the number of subscribers of the YouTube Channel belongs to top quartile, and zero otherwise.
High #Viewers	Indicator variable set to 1 if the number of viewers of the YouTube Channel belongs to top quartile, and zero otherwise.
|*CAR*|	Absolute abnormal returns over three-day window [0,+2] around video posting.
Disclaimer	Indicator variable set to 1 if a YouTuber posts a disclaimer, and 0 otherwise.
Stake	Indicator variable set to 1 if a YouTuber states in a disclaimer that (s)he owns a certain stake in the stock, and zero otherwise.

Table 1
YouTube Descriptive

Panel A presents the descriptive statistics of the Financial YouTubers and their videos in our sample. Panel B presents the industry coverage by Financial YouTubers.

Panel A: Descriptives on YouTuber/Video

Item	
Number of YouTubers	79
Average total number of videos per YouTuber	317
Average yearly number of videos per YouTuber	109
Average monthly number of videos per YouTuber	14
Average weekly number of videos per YouTuber	4
Average length of videos	13 minutes
Average number of unique firms covered per YouTuber	35
Average number of cumulative subscribers per YouTuber	281,170
Average number of new daily subscribers per YouTuber	116
Average number of cumulative viewers per YouTuber	45,600,000
Average number of new daily viewers per YouTuber	50,882
Average daily dollar revenue per YouTuber	$104
Percentage of YouTube Videos after one week of posting	33%

Panel B: Industry Coverage by YouTuber

SIC-2 digit	Description	Number of Videos	Percentage
10	Metal Mining	12	0.16%
13	Oil & Gas Extraction	6	0.08%
14	Mining & Quarrying	1	0.01%
15	Construction	3	0.04%
20	Food & Kindred Products	50	0.67%
21	Tobacco Products	11	0.15%
23	Apparel	4	0.05%
25	Furniture & Fixtures	1	0.01%
27	Printing & Publishing	4	0.05%
28	Chemicals	99	1.33%
29	Petroleum Refining	17	0.23%
30	Rubber & Plastic Products	17	0.23%
33	Primary Metal	2	0.03%
34	Fabricated Metral	4	0.05%
35	Industrial & Commercial Machinery	258	3.48%
36	Electronic & Electrical Equipment	278	3.75%
37	Transportation Equipment	85	1.15%
38	Measuring, Photographic, Medical & Optical	32	0.43%
39	Miscellaneous Manufacturing Industries	5	0.07%
40	Railroad Transportation	1	0.01%
41	Local & Suburban Transit	59	0.80%
44	Water Transportation	41	0.55%
45	Transportation by Air	26	0.35%
46	Pipelines, Except Natural Gas	1	0.01%
47	Transportation Services	1	0.01%
48	Communications	102	1.38%
49	Electric, Gas, & Sanitary Services	15	0.20%
50	Wholesale Trade – Durable Goods	27	0.36%

51	Wholesale Trade – Nondurable Goods	9	0.12%
52	Building Materials, Hardware, Garden Supplies	18	0.24%
53	General Merchandise Stores	66	0.89%
54	Food Stores	10	0.13%
55	Automotive Dealers & Gasoline Service Stations	9	0.12%
56	Apparel & Accessory Stores	19	0.26%
57	Home Furniture, Furnishings, & Equipment Stores	21	0.28%
58	Eating & Drinking Places	53	0.71%
59	Miscellaneous Retail	80	1.08%
60	Depositary Institutions	14	0.19%
61	Nondepository Credit Institutions	11	0.15%
62	Brokers, Dealers & Exchanges	21	0.28%
63	Insurance Carriers	72	0.97%
65	Real Estate	7	0.09%
67	Holding & Other Investment Offices	537	7.24%
70	Hotels, Rooming Houses & Camps	5	0.07%
72	Personal Services	2	0.03%
73	Business Services	1,391	18.75%
75	Automotive Repair, Services & Parking	5	0.07%
78	Motion Pictures	776	10.46%
79	Amusement and Recreation Services	84	1.13%
80	Health Services	32	0.43%
82	Educational Services	2	0.03%
87	Engineering, Accounting, & Research Services	60	0.81%
89	Services, Not Elsewhere Classified	6	0.08%
99	Nonclassifiable Establishments	2,945	39.70%
Total		7,417	100.00%

Table 2
Descriptive Statistics

This table presents descriptive statistics for all regression variables. Variables are defined in Appendix C.

	N	Mean	σ	25%	Median	75%
YouTube Posting	7,350	0.501	0.500	0.000	1.000	1.000
High %Institutional	7,350	0.283	0.450	0.000	0.000	0.000
|CAR|	7,350	0.015	0.020	0.004	0.008	0.018
CAR	7,350	0.002	0.038	-0.009	0.000	0.008
Bid-Ask Spread	7,350	0.117	0.191	0.026	0.059	0.118
Amihud	7,350	2.804	4.650	0.380	1.099	3.258
Pr(Video=1)	5,253	0.098	0.297	0.000	0.000	0.000
Log(#Videos)	5,253	0.120	0.439	0.000	0.000	0.000
Log(Firm Age)	5,253	3.137	0.706	2.833	3.258	3.584
Asset	5,253	7.181	2.343	5.646	7.396	8.842
ROA	5,253	-0.066	0.517	-0.058	0.025	0.080
Advertising	5,253	0.125	0.345	0.000	0.000	0.062
Leverage	5,253	0.646	0.625	0.390	0.581	0.759
Cash	5,253	0.167	0.183	0.044	0.106	0.214
Sales Growth	5,253	0.180	0.665	-0.035	0.074	0.230
Mgt. Frequency	5,253	0.777	1.601	0.000	0.000	0.000
%Institutional	5,253	0.476	0.396	0.000	0.566	0.871
Analyst Following	5,253	8.840	9.629	1.000	6.000	13.000
%Retail1	1,205	0.093	0.061	0.044	0.082	0.128
%Retail2	1,205	0.133	0.081	0.063	0.121	0.196
%Retail3	1,205	0.133	0.081	0.063	0.121	0.195
Net Video Tone	5,895	0.018	1.082	-0.591	0.052	0.681
Positive Video Tone	5,895	0.010	1.291	-0.682	-0.007	0.772
Negative Video Tone	5,895	0.072	0.967	-0.440	0.058	0.617
VIX	5,895	22.449	6.304	17.717	21.990	26.191
6-month CAR	5,895	1.195	3.850	-0.178	0.049	0.775
6-month Ret. Vol.	5,895	0.357	0.582	0.092	0.156	0.270
Edgar Filings	5,895	1.243	1.693	0.000	1.000	2.000
Earnings Announcements	5,895	0.247	0.431	0.000	0.000	0.000
Earnings Call	5,895	0.108	0.310	0.000	0.000	0.000
News	5,895	3.460	3.316	1.000	3.000	5.000
Analyst Optimism	5,895	5.868	25.748	-0.339	0.034	0.705
Restatement	5,895	0.056	0.271	0.000	0.000	0.000
%Hard Information	5,895	0.014	0.009	0.008	0.013	0.020
High #Subscribers	5,895	0.205	0.404	0.000	0.000	0.000
High #Viewers	5,895	0.246	0.431	0.000	0.000	0.000
Disclaimer	5,895	0.734	0.442	0.000	1.000	1.000
Stake	4,326	0.092	0.289	0.000	0.000	0.000

Table 3: Which Firms are Covered?

This table reports OLS regression results of video posting on firm characteristics, using the sample of 5,253 firm-year observations from 2014 to 2021. Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. Sample is restricted to SIC two-digit, wherein at least 5% of firms are mentioned by YouTubers. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix C.

	(1)	**(2)**	**(3)**	**(4)**
Dep. Var. =	***Pr(Video=1)***	***Log(#Videos)***	***Pr(Video=1)***	***Log(#Videos)***
Log(Firm Age)	0.018**	0.031***	-0.080	0.102
	2.42	2.69	-0.79	0.44
Asset	0.011***	0.008*	0.060***	0.049**
	4.27	1.81	3.48	2.40
ROA	-0.019**	-0.041***	-0.027	-0.033
	-2.04	-2.51	-1.59	-1.09
Advertising	0.043***	0.033	0.010	0.039
	2.81	1.32	0.33	1.15
Leverage	-0.003	-0.018**	0.017	0.008
	-0.52	-2.02	1.34	0.50
Cash	0.130***	0.116***	0.024	0.020
	4.83	2.45	0.44	0.25
Sales Growth	0.012**	0.015**	-0.007	-0.004
	1.99	2.22	-0.86	-0.41
Mgt. Frequency	-0.011***	-0.028***	-0.012**	-0.021***
	-3.20	-4.68	-1.99	-2.82
%Institutional	-0.045***	-0.109***	0.063	-0.142
	-3.64	-5.27	1.12	-1.21
Analyst Following	0.013***	0.023***	0.007***	0.019***
	13.95	8.96	3.16	4.86
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	5,253	5,253	5,253	5,253
adj. R^2	20.1%	24.5%	42.5%	58.6%

Table 4
Market Reaction around YouTube Posting

This table reports the short window return around YouTube posting. Panel A presents the signed and absolute value of CAR including all firm-specific events. Panel B, C, and D present results excluding earnings announcements, EDGAR filings, and all firm-specific events identified by the Key Development Datasets (e.g., earnings announcements, product announcements, EDGAR filings) in the past seven days.

Panel A: CAR [0,2]

Variable	Obs.	Mean	Std. Err.
CAR	7,417	0.003***	0.001
|*CAR*|	7,417	0.123***	0.002

Panel B: CAR [0,2] excluding earnings announcements in the previous 7 days

Variable	Obs.	Mean	Std. Err.
CAR	5,766	0.004***	0.001
|*CAR*|	5,766	0.126***	0.002

Panel C: CAR [0,2[excluding EDGAR Filings in the previous 7 days

Variable	Obs.	Mean	Std. Err.
CAR	3,221	0.004***	0.001
|*CAR*|	3,221	0.114***	0.003

Panel D: CAR [0,2] excluding S&P Capital IQ Key Developments events in the previous 7 days

Variable	Obs.	Mean	Std. Err.
CAR	1,819	0.002**	0.001
|*CAR*|	1,819	0.133***	0.004

Table 5
Information Asymmetry around YouTube Posting

This table provides means and differences of information asymmetry measures before and after the posting. The first two rows provide results for measures one day before and after the posting. The last two rows provide means of each measure two days surrounding the posting. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix C.

Variable (before)	**Mean of Variable (before) (a)**	**Variable (after)**	**Mean of Variable (after) (b)**	**Difference (b)-(a) (t-stat)**
$Spread_{t-1}$	0.079	$Spread_{t+1}$	0.074	-0.005*** (-4.94)
$Amihud_{t-1}$	0.777	$Amihud_{t+1}$	0.750	-0.027*** (-3.24)
$Spread_{t-2}$	0.078	$Spread_{t+2}$	0.073	-0.004*** (-5.12)
$Amihud_{t-2}$	0.805	$Amihud_{t+2}$	0.758	-0.047*** (-6.30)

Table 6
Short-window Return and Information Asymmetry around YouTube Posting

This table reports the results from estimating short window return and information asymmetry around YouTube Posting using 1:1 propensity score matching technique. Matching is based on the nearest size, ROA, book-to-market, and leverage within the same SIC two-digit and year. We allow the caliper to be 0.25. We use pseudo posting dates for the control groups the same as posting dates of the matched target firms. *YouTube Posting* is an indicator variable equal to one if a YouTube post about the firm on date *t*, and zero otherwise. All variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var. =	***|CAR|***	***CAR***	***|CAR|***	***CAR***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
YouTube Posting	**0.011*****	**0.004****	**0.011*****	**0.002***	**-0.044*****	**-2.700*****	**-0.059*****	**-3.190*****
	11.63	**1.97**	**10.61**	**1.82**	**-3.26**	**-8.00**	**-3.65**	**-7.93**
Log(Firm Age)	-0.002***	0.002*	-0.004***	0.001	0.026**	0.134	0.004	-0.298
	-2.72	1.86	-5.21	1.08	2.32	0.46	0.20	-0.77
Asset	-0.002***	-0.001**	-0.001	-0.001*	-0.035***	-0.805***	-0.036***	-0.749**
	-5.06	-1.93	-1.26	-1.83	-5.34	-5.54	-2.50	-1.96
ROA	-0.013***	-0.011	-0.011***	-0.002	-0.066**	-0.056	-0.081**	0.607
	-3.81	-1.42	-4.13	-0.61	-2.41	-0.09	-2.09	1.14
Advertising	-0.002***	-0.002**	-0.001	-0.001*	-0.032***	-0.096	-0.038***	0.056
	-3.25	-2.35	-1.52	-1.76	-3.85	-0.61	-3.55	0.26
Leverage	0.004***	0.002	0.005***	0.002	0.009	1.633**	-0.003	2.287**
	2.74	0.59	2.47	0.99	0.25	2.06	-0.09	2.04
Cash	-0.000	-0.004	0.000	-0.002	-0.093*	-3.000***	-0.075*	-0.331
	-0.03	-0.59	0.10	-0.47	-1.80	-2.90	-1.81	-0.24
Sales Growth	0.002*	0.003	0.002	0.001	-0.029**	-0.670**	-0.024	-0.498
	1.88	1.49	1.49	0.79	-2.19	-2.35	-1.59	-1.56
Mgt. Frequency	-0.000	0.000	0.000	0.000	-0.015***	-0.428***	-0.008***	-0.207***
	-1.09	0.59	0.48	0.56	-6.71	-6.47	-2.54	-3.04
%Institutional	-0.003***	-0.003**	-0.002	-0.002	-0.102***	-2.304***	-0.081***	-1.714***
	-2.69	-2.06	-1.58	-1.45	-4.30	-4.18	-3.68	-3.25
Analyst Following	-0.000***	-0.000	-0.000***	0.000	-0.000	-0.009	0.000	0.001
	-3.96	-1.11	-5.32	0.03	-0.43	-0.78	0.21	0.14
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	7,350	7,350	7,350	7,350	7,350	7,350	7,350	7,350
adj. R^2	23.3%	1.0%	26.8%	1.2%	33.9%	39.4%	50.3%	55.3%

Table 7
Excluding Firm-Specific Events in Previous 7 days

This table reports the results from estimating short window return and information asymmetry around YouTube Posting using 1:1 propensity score matching technique after excluding all firm-specific events identified by the Key Development Datasets (e.g., earnings announcements, product announcements, EDGAR filings) in the past seven days. Matching is based on the nearest size, ROA, book-to-market, and leverage within the same SIC two-digit and year. We allow the caliper to be 0.25. We use pseudo posting dates for the control groups the same as posting dates of the matched target firms. *YouTube Posting* is an indicator variable equal to one if a YouTube post about the firm on date *t*, and zero otherwise. All variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

	(1)	**(2)**	**(3)**	**(6)**	**(5)**	**(6)**	**(7)**	**(8)**
Dep. Var. =	***|CAR|***	***CAR***	***|CAR|***	***CAR***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
YouTube Posting	**0.010*****	**0.003**	**0.010*****	**0.002**	**-0.039***	**-3.651*****	**-0.063****	**-4.528*****
	4.68	**0.75**	**4.66**	**0.98**	**-1.67**	**-4.12**	**-2.28**	**-3.52**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	1,361	1,361	1,361	1,361	1,361	1,361	1,361	1,361
adj. R^2	22.7%	11.6%	27.0%	2.0%	37.5%	46.5%	49.5%	57.8%

Table 8
Cross-sectional Variation based on Institutional Ownership and Retail Trading

Panels A and B of this table report the regression results of short window return and information asymmetry on YouTube Posting indicator, institutional ownership ratio, and their interaction term, as well as controls using 1:1 propensity score matching technique. Matching is based on the nearest size, ROA, book-to-market, and leverage within the same SIC two-digit and year. We allow the caliper to be 0.25. We use pseudo posting dates for the control groups the same as posting dates of the matched target firms. *YouTube Posting* is an indicator variable equal to one if a YouTube post about the firm on date *t*, and zero otherwise. All variables are described in Appendix C. Two-tailed *p*-values are reported. ****p*<0.01 ***p*<0.05 **p*<0.1.

Panel A: Continuous Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var. =	***|CAR|***	***CAR***	***|CAR|***	***CAR***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
YouTube Posting	0.012***	0.005**	0.013***	0.002*	-0.088***	-4.168***	-0.088***	-4.318***
	9.57	2.26	9.56	1.77	-4.24	-7.56	-2.99	-6.11
YouTube Posting * %Institutional	**-0.002**	**-0.004***	**-0.005****	**-0.002**	**0.126*****	**4.234*****	**0.083***	**3.224*****
	-1.41	**-1.79**	**-2.43**	**-0.94**	**4.16**	**5.09**	**1.89**	**2.88**
%Institutional	-0.002*	-0.002	-0.000	-0.001	-0.155***	-4.083***	-0.117***	-3.146***
	-1.73	-0.98	-0.09	-0.60	-5.32	-6.66	-3.89	-5.48
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	7,350	7,350	7,350	7,350	7,350	7,350	7,350	7,350
adj. R^2	23.4%	1.0%	26.9%	1.2%	35.1%	41.6%	50.7%	56.3%

Panel B: High %Institutional Indicator (Top quartile of institutional ownership in the distribution)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var. =	***|CAR|***	***CAR***	***|CAR|***	***CAR***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
YouTube Posting	0.010***	0.004**	0.010***	0.002**	-0.092***	-4.201***	-0.089***	-4.245***
	10.07	2.22	8.96	1.98	-5.25	-8.44	-4.03	-7.76
YouTube Posting * High %Institutional	**-0.001**	**-0.004****	**-0.003****	**-0.002**	**0.130*****	**4.103*****	**0.084*****	**3.061*****
	-0.72	**-2.25**	**-2.05**	**-1.57**	**5.83**	**6.76**	**2.76**	**4.18**
High %Institutional	-0.002**	-0.001	-0.000	0.001	-0.155***	-4.092***	-0.111***	-2.922***
	-1.98	-0.38	-0.25	0.88	-7.78	-8.04	-4.85	-6.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	7,350	7,350	7,350	7,350	7,350	7,350	7,350	7,350
adj. R^2	22.8%	1.1%	26.3%	1.2%	35.0%	41.1%	50.8%	56.4%

Table 8 (Continued)
Cross-sectional Variation based on Institutional Ownership and Retail Trading

Panel C of this table reports the results from estimating short window return and information asymmetry around YouTube Posting using 1:1 propensity score matching technique from 2018 to 2020. *Retail1* is the ratio of number of retail trades to number of total trades on date *t+1*. *%Retail2* is the ratio of total retail trade volume in shares to total trade volume in shares on date *t+1*. *%Retail3* is the ratio of total retail trade value in dollar to total trade value in dollar on date *t+1*. All retail trading variables are obtained from TAQ. All other variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

Panel C: Retail trading around YouTube Posting

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. =	***%Retail1***	***%Retail2***	***%Retail3***	***%Retail1***	***%Retail2***	***%Retail3***
YouTube Posting	**0.056*****	**0.083*****	**0.083*****	**0.042*****	**0.062*****	**0.062*****
	9.67	**11.95**	**11.93**	**5.67**	**7.51**	**7.48**
Log(Firm Age)	0.004	0.004	0.004	-0.009	-0.007	-0.007
	1.07	0.65	0.65	-1.61	-0.86	-0.86
Asset	-0.001	-0.010***	-0.010***	0.005	-0.018**	-0.018**
	-0.61	-3.67	-3.67	0.99	-2.02	-2.02
ROA	-0.003	-0.000	-0.000	-0.066***	-0.065***	-0.065***
	-0.26	-0.01	-0.01	-4.30	-3.01	-3.01
Advertising	-0.013***	-0.008	-0.008	-0.008	-0.006	-0.006
	-2.73	-1.21	-1.22	-1.16	-0.56	-0.57
Leverage	0.015	0.010	0.010	-0.004	0.022	0.022
	1.58	0.76	0.76	-0.31	1.29	1.29
Cash	0.046**	0.035	0.035	0.037*	0.026	0.026
	2.22	1.46	1.46	1.68	1.12	1.12
Sales Growth	0.037***	0.029***	0.029***	0.009	0.013	0.013
	4.62	3.19	3.19	1.08	0.90	0.90
Mgt. Frequency	-0.001	-0.005***	-0.005***	-0.003	-0.006**	-0.006**
	-1.03	-3.21	-3.21	-1.43	-2.37	-2.37
%Institutional	-0.056***	-0.071***	-0.071***	-0.022	-0.042	-0.042
	-2.49	-3.09	-3.08	-1.28	-1.55	-1.54
Analyst Following	0.000	0.001***	0.001***	0.000	0.001	0.001
	0.47	3.25	3.25	0.17	0.98	0.97
Fixed effects	Ind, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Firm, Year
N	1,205	1,205	1,205	1,205	1,205	1,205
adj. R^2	0.642	0.623	0.623	0.804	0.761	0.761

Table 9

The Association between Video Tone and Short-Window Returns

This table reports the results from estimating short window return around YouTube Posting as a function of video tone as well as firm and market characteristics. The total sample consists of 5,895 observations. *Video Tone* is the principal component of Loughran and McDonald's tone, Henry's tone, and LIWC's tone measure. YouTube videos with disclaimers between 2014 and 2022. All variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep. Var. =	***CAR***	***CAR***	***CAR***	***CAR***	***CAR***	***CAR***	***CAR***	***CAR***
Net Video Tone	**0.002*** **	**0.002*** **	.	.	**0.001*** **	**0.001** **	.	.
	3.44	**3.52**			**2.62**	**2.38**		
Positive Video Tone	.	.	**0.001*** **	**0.001*** **	.	.	**0.001** **	**0.001* **
			3.85	**3.88**			**2.08**	**1.83**
Negative Video Tone	.	.	**-0.003*** **	**-0.003*** **	.	.	**-0.003*** **	**-0.003*** **
			-3.89	**-3.55**			**-4.04**	**-3.53**
Log(Firm Age)	0.003	-0.021	0.003	-0.019	0.005***	-0.034**	0.005***	-0.031**
	1.34	-1.32	1.36	-1.21	2.66	-2.16	2.71	-2.06
Asset	-0.000	-0.001	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001
	-0.36	-0.33	-0.36	-0.26	-1.30	-0.22	-1.27	-0.14
ROA	-0.009	0.006	-0.009	0.006	-0.009	0.008	-0.010	0.008
	-1.38	1.04	-1.41	0.92	-1.54	1.30	-1.60	1.21
Advertising	-0.001	-0.000	-0.001	-0.000	-0.000	-0.002	-0.000	-0.002
	-1.00	-0.17	-0.97	-0.18	-0.33	-0.92	-0.31	-0.95
Leverage	0.005	-0.005	0.005	-0.006	0.004	0.002	0.004	0.002
	0.95	-0.41	0.90	-0.46	1.08	0.21	1.03	0.16
Cash	-0.000	0.019	-0.001	0.018	0.006	0.033***	0.005	0.032***
	-0.00	1.42	-0.07	1.34	1.02	2.80	0.96	2.69
Sales Growth	0.001	-0.003	0.001	-0.004	-0.000	-0.002	-0.000	-0.003
	0.63	-1.33	0.55	-1.36	-0.10	-1.42	-0.21	-1.48
Mgt. Frequency	-0.008***	-0.006**	-0.008***	-0.006*	-0.006*	-0.005	-0.006*	-0.005
	-2.76	-2.01	-2.68	-1.91	-1.92	-1.44	-1.89	-1.42
%Institutional	-0.009***	0.035	-0.009***	0.035	-0.009***	0.013	-0.010***	0.013
	-2.91	1.10	-2.96	1.09	-3.61	0.53	-3.77	0.51
Analyst Following	-0.000	0.000	-0.000	0.000	0.000***	0.000**	0.000***	0.000**
	-0.20	0.37	-0.26	0.31	2.59	2.03	2.59	2.02
VIX	.	.	.	.	0.000	0.000	0.000	0.000
					1.22	1.14	1.21	1.13

6-month CAR	.	.	.	.	-0.001***	-0.002***	-0.001***	-0.002***
					-2.85	-4.98	-2.82	-4.86
6-month Ret. Vol.	.	.	.	.	0.016***	0.006	0.016***	0.006
					2.81	0.55	2.83	0.53
Edgar Filings	.	.	.	.	-0.000	-0.000	-0.000	-0.000
					-0.57	-0.29	-0.57	-0.29
Earnings Announcements	.	.	.	.	-0.001	-0.001	-0.001	-0.001
					-0.41	-0.28	-0.28	-0.18
Earnings Call	.	.	.	.	0.000	0.002	0.000	0.001
					0.15	0.47	0.10	0.44
News	.	.	.	.	0.000	0.000	0.000	0.000
					0.07	0.03	0.01	0.01
Analyst Optimism	.	.	.	.	0.000*	0.000*	0.000*	0.000*
					1.89	1.69	1.85	1.69
Restatement	.	.	.	.	-0.005*	-0.002	-0.005*	-0.002
					-1.88	-0.51	-1.88	-0.47
Fixed effects	Ind, Year	Firm, Year	Ind, Year	Firm, Year	Ind, Year	Firm, Year	Ind, Year	Firm, Year
N	5,895	5,895	5,895	5,895	5,895	5,895	5,895	5,895
adj. R^2	0.041	0.084	0.045	0.087	0.077	0.118	0.080	0.121
Comparison of Absolute Value of Coefficients					**F-stat. (p-val.)**			
Absolute value of coeff. on Positive Video Tone =			5.78	4.74			7.52	6.57
Absolute value of coeff. on Negative Video Tone			(0.017)	(0.030)			(<0.001)	(0.011)

Table 10
The Effect of Hard Information on Information Asymmetry

This table reports OLS regression results of information asymmetry measures on the percentage of hard information using the sample of 5,895 video-date observations from 2014 to 2021. Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. Industry fixed effects are based on SIC two-digit industry. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix C.

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep. Var. =	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
%Hard Information	**-0.325*****	**-2.061****	**-0.163***	**-0.879***	**-0.314*****	**-2.264****	**-0.181****	**-0.860**
	-3.00	**-2.02**	**-1.90**	**-1.78**	**-3.01**	**-2.29**	**-2.23**	**-1.55**
Log(Firm Age)	0.010	-0.143	0.008	0.850*	0.011	-0.094	-0.034	0.588
	1.40	-1.15	0.17	1.89	1.52	-0.95	-0.70	1.36
Asset	-0.018***	-0.353***	-0.008	-0.155*	-0.020***	-0.369***	-0.003	-0.151*
	-7.03	-7.94	-1.16	-1.91	-5.62	-10.61	-0.42	-1.81
ROA	-0.053***	-0.119	-0.007	-0.249*	-0.047***	0.034	0.006	-0.164
	-7.14	-0.66	-0.71	-1.75	-4.02	0.34	0.32	-1.31
Advertising	-0.003	-0.017	-0.009***	-0.075*	-0.003	-0.043	-0.010***	-0.082**
	-1.19	-0.42	-2.90	-1.89	-1.15	-1.29	-2.76	-2.06
Leverage	-0.002	0.326	0.051**	0.392**	-0.004	0.225	0.065***	0.407**
	-0.10	1.46	2.06	2.13	-0.23	1.20	2.59	2.42
Cash	-0.068***	-0.746***	-0.010	-0.365*	-0.068***	-0.795***	-0.020	-0.256
	-4.29	-2.45	-0.48	-1.83	-4.58	-3.91	-0.88	-1.37
Sales Growth	-0.008	-0.214***	-0.009*	-0.021	-0.007	-0.132***	-0.006	-0.035
	-1.45	-3.50	-1.86	-0.30	-1.12	-2.91	-0.86	-0.53
Mgt. Frequency	-0.005	-0.139***	0.001	-0.067**	-0.006	-0.125**	-0.001	-0.053*
	-1.32	-2.79	0.26	-2.39	-1.32	-2.11	-0.31	-1.79
%Institutional	-0.031***	-0.411***	-0.042	1.002	-0.034***	-0.444***	-0.072	0.968
	-3.08	-2.95	-0.69	1.41	-3.08	-3.71	-1.05	1.26
Analyst Following	-0.000	-0.001	0.000	0.006***	-0.000	-0.004	0.000	0.007***
	-1.31	-0.23	0.64	3.05	-0.80	-1.35	0.71	3.49
VIX	.	.	.	.	0.001***	0.003**	0.001***	0.004***
					5.03	2.32	6.89	3.64
6-month CAR	.	.	.	.	0.000	0.002	0.001	-0.004
					0.07	0.60	0.85	-1.54
6-month Ret. Vol.	.	.	.	.	-0.002	-0.452***	-0.054*	-0.056
					-0.13	-5.99	-1.74	-0.70
Edgar Filings	.	.	.	.	0.001	0.004	0.000	-0.008*

					0.62	0.61	0.02	-1.75
Earnings Announcements	.	.	.	.	0.004	-0.031	0.006*	-0.026
					1.22	-0.94	1.89	-0.87
Earnings Call	.	.	.	.	-0.007	-0.002	-0.005	0.057**
					-1.54	-0.07	-1.14	2.00
News	.	.	.	.	0.000	-0.007	0.000	-0.005*
					0.18	-1.56	0.62	-1.80
Analyst Optimism	.	.	.	.	0.000	0.008***	0.001***	0.003**
					1.06	6.70	2.65	2.10
Restatement	.	.	.	.	-0.002	0.376**	0.000	0.260
					-0.18	2.24	0.04	0.86
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	5,895	5,895	5,895	5,895	5,895	5,895	5,895	5,895
adj. R^2	30.7%	52.5%	48.1%	69.9%	31.6%	55.9%	50.8%	70.5%

Table 11
Cross-Sectional Analyses based on Subscribership and Viewership

This table reports OLS regression results of cross-sectional analyses of cumulative abnormal return and information asymmetry measures based on the number of subscribers and viewers of YouTube Channels. Panel A presents cross-sectional results of CAR and Panel B presents cross-sectional results of bid-ask spread and Amihud. Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. Industry fixed effects are based on SIC two-digit industry. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix C.

Panel A: CAR

	(1)	**(2)**	**(3)**	**(4)**
Dep. Var. =	***CAR***	***CAR***	***CAR***	***CAR***
Net Video Tone	0.001*	0.001	0.001	0.001
	1.72	1.47	1.22	0.92
Net Video Tone*High #Subscribers	**0.002***	**0.002***	.	.
	1.79	**1.88**		
High #Subscribers	0.001	0.002*	.	.
	0.58	1.71		
Net Video Tone*High #Viewers	.	.	**0.003****	**0.003*****
			2.34	**2.51**
High #Viewers	.	.	0.001	0.002
			0.59	1.50
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Firm, Year	Ind, Year	Firm, Year
N	5,895	5,895	5,895	5,895
adj. R^2	7.7%	11.8%	7.8%	11.9%

Panel B: Information Asymmetry

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dep. Var. =	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***	***Bid-Ask Spread***	***Amihud***
%Hard Information	-0.250**	-0.222	-0.160*	-0.599	-0.322***	-0.814	-0.208**	-0.807
	-2.26	-0.18	-1.69	-0.92	-2.83	-0.62	-2.16	-1.11
%Hard Information*High #Subscribers	**-0.305**	**-6.150*** **	**-0.097**	**-1.264**	.	.	.	.
	-1.23	**-2.58**	**-0.48**	**-0.92**				
High #Subscribers	0.001	0.027	0.001	0.003	.	.	.	.
	0.32	0.81	0.36	0.17				
%Hard Information*High #Viewers	.	.	.	.	**0.032**	**-4.040***	**0.110**	**-0.317**
					0.12	**-1.69**	**0.57**	**-0.20**
High #Viewers	.	.	.	.	-0.007	-0.019	-0.003	-0.022
					-1.48	-0.59	-1.20	-1.06
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Ind, Year	Firm, Year	Firm, Year	Ind, Year	Ind, Year	Firm, Year	Firm, Year
N	5,895	5,895	5,895	5,895	5,895	5,895	5,895	5,895
adj. R^2	31.6%	51.8%	50.8%	70.5%	31.7%	51.4%	50.8%	70.6%

Table 12
YouTube Disclaimers and Short-Window Returns

This table reports the results from estimating short window return around YouTube Posting as a function of disclaimer indicator as well as firm and market characteristics. The total sample consists of 6,154 YouTube videos between 2014 and 2022. All variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

	(1)	(2)	(3)	(4)
Dep. Var. =	***|CAR|***	***|CAR|***	***CAR***	***CAR***
Disclaimer	**-0.007****	**-0.009*****	**-0.003**	**-0.005***
	-2.28	**-3.32**	**-1.06**	**-1.89**
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind, Year	Firm, Year	Ind, Year	Firm, Year
N	5,895	5,895	5,895	5,895
adj. R^2	36.7%	43.7%	6.8%	9.9%

Table 13
The Effect of Disclaimers on the Association between Video Tone and Short-Window Returns

This table reports the results from estimating short window return around YouTube Posting as a function of video tone, disclaimer, and their interactions as well as firm and market characteristics. The total sample consists of 5,675 YouTube videos with disclaimers between 2014 and 2022. All variables are described in Appendix C. Two-tailed *p*-values are reported. ***p<0.01 **p<0.05 *p<0.1.

	(1)	(2)	(3)	(4)
Dep. Var. =	***CAR***	***CAR***	***CAR***	***CAR***
Disclaimer	-0.001	-0.002**	-0.001	-0.002*
	-0.81	-1.95	-0.71	-1.84
Net Video Tone	0.003***	0.003***	.	.
	3.66	3.73		
Net Video Tone*Disclaimer	**-0.002****	**-0.002****	.	.
	-2.16	**-2.28**		
Positive Video Tone	.	.	0.002***	0.002***
			4.06	4.42
Negative Video Tone	.	.	-0.004***	-0.004***
			-4.89	-5.29
Positive Video Tone*Disclaimer	.	.	**-0.002****	**-0.002****
			-2.11	**-2.40**
Negative Video Tone*Disclaimer	.	.	**0.001**	**0.002****
			1.42	**2.02**
Controls	Yes	Yes		
Fixed effects	Ind, Year	Firm, Year		
N	5,895	5,895		
adj. R^2	7.7%	11.8%		
	F-stat. (p-val.)			
*Net Video Tone+ Net Video Tone*Disclaimer*	2.00	1.62		
	(0.158)	(0.204)		
*Positive Video Tone+Positive Video Tone*Disclaimer*			0.97	0.70
			(0.324)	(0.405)
*Negative Video Tone+Negative Video Tone*Disclaimer*			8.13	5.69
			(0.004)	(0.018)