Video Sentiment and Stock Returns Around the World*

Ran Chang[†] and Lin Peng[‡]

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Abstract

We introduce a novel video-based stock market sentiment index (VSI) created from over nine billion popular videos generated by users on social media across 48 countries. The VSI index is significantly associated with mood proxies such as those induced by seasonal factors, cloud coverage, and COVID-related restrictions. VSI is positively correlated with contemporaneous market returns and strongly predicts future market declines. The pattern holds across countries and is more pronounced in countries with higher arbitrage costs, for markets with greater retail investor participation, and for sentiment extracted from more viral videos. A higher VSI predicts net inflows (outflows) to equity (bond) mutual funds and lower government bond returns. Our results are consistent with popular videos on social media reflecting investor sentiment and are associated with short-term mispricing.

JEL Classification: G02, G12, G13.

Keywords: Social media, social network, social interaction, user-generated videos, sentiment, market returns, TikTok, mutual funds, government bonds.

Preliminary; Please do not circulate.

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[†] Antai College of Economics & Management, Shanghai Jiao Tong University, China. Email: r.zhang@sjtu.edu.cn

[‡] Zicklin School of Business, Baruch College, City University of New York and Economics Faculty, University of Cambridge. Email: lin.peng@baruch.cuny.edu and lp604@cam.ac.uk.

The Sentiment of Short Videos and Stock Returns Around the World

Abstract

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JEL Classification: G02, G12, G13.

Keywords: Short video, TikTok, sentiment, market returns, mutual funds, government bonds.

1 Introduction

Extensive literature has been devoted to the prediction of aggregate stock market returns. While most papers focusing on macroeconomic variables,[1] a growing literature shows that investor sentiment generates temporary marketwide overvaluation and is followed by subsequent reversals (see, for example, De Long et al. 1990; Baker and Wurgler 2006, 2007). The investor sentiment proxies used in previous studies include market-based variables, internet searches, exogenous shocks related to seasonal factors, weather, or sporting events, or information from venues such as popular songs or news photos.[2]

Our paper proposes a novel measure of investor sentiment (VSI), based on popular short videos generated by users on TikTok, the world's #1 video-sharing social media app owned by the tech company ByteDance. With a simple Mobile app, the platform allows user to create, edit, and share short-form video clips, which have durations ranging from 15 seconds to three minutes and are often jazzed up with filters and accompanied by the latest music trends. Launched in 2017, TikTok quickly rose to global popularity. As of January 2022, TikToc (together with Douyin, the popular sister app in the chinese market) is the fourth most popular social networks worldwide, with 1.6 billion monthly active users. TikToc is also ranked #2 among the social media and communication apps worldwide in user engagement, with an average user spending 19.6 hours per month.[3]

Given that a substantial fraction of a country's population spends a considerable amount of time creating and viewing the videos, the popular videos featured on the platform reflect the mood of a sizable share of the country's population. A 2021 survey further shows that 75% of TikToc users in the United States were above 20 years old, with 53% above 30 and more than 30% above

[1]See, for example, Ang and Bekaert (2006), Campbell and Yogo (2006), Cochrane (2007), and Goyal and Welch (2008). See Rapach and Zhou (2013) for a comprehensive overview.

[2]For example, the sentiment index of Baker and Wurgler (2006) is a composite measure that includes information from trading volume, the dividend premium, the closed-end fund discount, the number and returns of IPOs, and the equity share in new issues and Ben-Rephael et al. (2012) measure sentiment with mutual fund flows. Da et al. (2015) and Gao et al. (2020) measure sentiment using Google search volume related to selected keywords. Hirshleifer and Shumway (2003) use seasonal factors and weather to proxy for investor mood and Edmans et al. (2007) examines international sports results as exogenous shocks to investor sentiment. Edmans et al. (2021) and Obaid and Pukthuanthong (2021)) extract sentiment from popular songs and news photos, respectively.

[3]The top three social networks by number of monthly active users are Facebook, YouTube, and WhatsApp, with average monthly users of 2.9, 2.6, and 2.0 billion. TikTok is ranked #1 in terms of number of apps downloaded in 2021, at 656 million, followed by Instagram, Facebook, WhatsApp, at 545, 416, and 395, respectively. As of April 2022, the countries with the largest TikTok users are the United States, Indonesia, Brazil, Russia, and Mexico, at 136.4, 99.1, 73.6, 51.3, and 50.5 millions of users. In 2021, the top social medias in the average number of hours users spend per month worldwide (excluding China) are: YouTube (23.7), TikTok (19.6), Facebook (19.6), WhatApp (18.6), and LINE (11.6). The top five countries in the average number of hours users spend per month on TikToc are: UK (27.3), Russia (26.3), US (25.6), Germany (23.6) and Australia (23.4). The most-used hashtags on TikTok as of January 2022 are: fyp, viral, tiktok, duet, trending, funny, comedy, humor, love, stitch, like, dance, meme, football, and explore. The statistics were obtained from https://www.statista.com/study/70013/tiktok/.

40. Hence, there is likely a sizable overlap between TikTok users and participants in financial markets.[4] An open question is whether the mood reflected in these popular short videos contain valuable information about the mood of investors in a country's financial market and whether the video-related mood measure helps us better understand what drives the movements of securities prices.

This paper addresses the question using data from popular short videos created and shared by users on TikToc. We collect daily data on the 500 most popular short videos on TikToc, as well as statistics including views, likes, comments, and forwards for each video. Our sample consists of over 9.3 billion unique short videos for 48 countries over the period of July 1, 2017, to June 30, 2021. The videos together generated over 22 trillion views, with an average of 193.86 million videos per country and around 2,443 views per video. We extract the emotions associated with each video by applying a machine learning technique, the deep Visual Audio Attention Network (VAANet, Zhao et al. 2020). We then construct a views-weighted average sentiment index for each country, with a higher value indicating a more positive sentiment.

We first validate that the VSI measure is associated with mood proxies established in the prior literature. Studies have shown that investors' mood is influenced by seasonal factors (e.g., Thaler (1987); Kamstra et al. (2017); Birru (2018); Hirshleifer et al. (2020)), cloud cover (e.g., Hirshleifer and Shumway (2003); Goetzmann et al. (2015)), and COVID-related restrictions imposed by the government (e.g., Terry et al. (2020); Bueno-Notivol et al. (2021)). We show that the VSI index is positively correlated with the seasonal factors, negatively associated with cloud cover, and negatively associated with the stringency of COVID-related restrictions.

We then investigate the relation between short video sentiment and stock market returns. We find that VSI is strongly and positively associated with the contemporaneous market returns whereas the association between VSI and the one-week-ahead market returns is strongly negative. The effects are also economically large. A one standard deviation increase in market sentiment predicts a decline in weekly returns of 55 basis points. The results are robust for both the US-dollar-measured market returns and returns based on local currencies and remain significant for both developed markets and emerging markets. Consistent with this, the coefficient on VSI is negative for 46 of the 48 countries in our sample and are negative and significant for 31. The results suggest that VSI captures sentiment-induced temporary overvalution, which is followed by subsequent reversals.

[4]Source: https://www.statista.com/statistics/1095186/tiktok-us-users-age/

We next explore heterogeneity in video sentiment by exploring the characteristics of videos by the topic that a video is affiliated with or the video's popularity. Videos featuring economics-related themes may reflect fundamental shocks to the economy, whereas those that are unrelated are less likely to be directly impacted by the underlying economic conditions. We thus classify videos into two categories, those contain hashtags featuring economics-related keywords and those that are unrelated to economics.[5] We show that both the economic-related and the unrelated VSI indexes negatively predicts returns, with the predictability actually greater for the unrelated VSI. The results therefore suggests that a meaningful portion of VSI's return predictability is not driven by fundamental factors such as macroeconomic conditions or business cycle.

Similarly, we classify videos by their popularity, measured by the number of followers the creator has, the number of times the video was forwarded, or the number of comments the video received. We find that the VSI constructed using the more popular videos has a stronger ability to predict future market returns. The result suggests that the more popular videos either are more representative of the mood of the platform users or such videos have a stronger influence on the mood of a large number of people.

We perform additional analyses to gain further insight into what influences the return predictability of VSI. First, retail investors are more susceptible to sentiment effects hence we expect the effect of sentiment to be larger in markets with a greater retail investor participation. Consistent with this, we find that the return predictability of VSI is stronger in countries with high retail ownership. Second, when arbitrage is more limited (Baker and Wurgler 2006, 2007), sentiment should have stronger predictive power. During our sample period, some countries imposed trading restrictions such as short-selling bans, thereby limiting arbitrage opportunities. We conduct difference-in-differences analyses around such exogenous shocks and find that the predictability of VSI on future market returns becomes stronger during periods with more trading restrictions. Third, prior theoretical and empirical literature suggests an association between investor sentiment and volatility as well as the level of asset prices (e.g., Black (1986); De Long et al. (1990); Da et al. (2015)). The results show a significant contemporaneous correlation between absolute short video sentiment and stock market volatility.

We further analyze whether the VSI index is related to investment flows to equity mutual funds and influences government bond prices. Prior literature shows that mutual fund flows are

[5] Hashtags related to economics and finance include *****. Examples of the popular hashtags for noneconomics-related videos are weather, disaster, pollution, holidays, and sports. On average, ***% of the top 500 most popular video is classified as economics-related.

affected by investor sentiment (e.g., Ben-Rephael et al. 2011, 2012). We indeed find a significant positive association between short video sentiment and net equity fund flows. In addition, we find a significant negative association between short video sentiment and government bond index returns, consistent with a "flight to safety" (see also Baker and Wurgler 2012; Laborda and Olmo 2014; Da et al. 2015).

Our study contributes to the literature on the effect of investor sentiment on the stock market. A series of sentiment measures have been proposed in prior studies. For example the sentiment index of Baker and Wurgler (2006) is constructed using market variables and may be influenced by factors other than investor sentiment (Qiu and Welch (2004)). Sentiment measures constructed using weather (Hirshleifer and Shumway (2003)) and sporting events (Edmans et al. (2007)) focus on exogenous shocks to investors' mood is restrictive in that the pre-specified drivers are biased and discrete. Proxies extracted with Google Search data (Da et al. (2015)) and Twitter data (Chen et al. (2014)) require prespecified keywords to identify positive and negative emotions, but the usage of words varies a lot across cultures and regions, making it difficult to use in an international context. Some papers use news photos (Obaid and Pukthuanthong (2021)) and top songs from streaming services (Edmans et al. (2021)) to develop indices of investor sentiment. Our paper uses user-generated videos to construct a new sentiment measure. The advantage of our measure lies in that it does not require any specific word dictionaries, which makes the measure suitable for the analysis of return predictability across different markets. Further, our measure is proactive, given that all short videos are generated by users themselves. Therefore the measure provides complementary information to the sentiment measures used in previous studies. We show that the measure contains incremental power in predicting future market returns and has important implications in corporate finance and asset pricing. Together, our results highlight the multifaceted ways in which investor sentiment can be manifested and captured.

The rest of the paper is organized into four sections. In Section 1, we discuss and validate the short video sentiment measure. Section 2 reports our main results. Section 3 presents additional analyses. Section 4 concludes.

2 Data and Variables

2.1 Short video sentiment

To measure short video sentiment, we download the daily top 500 short videos in each country based on the ranking of the number of views from TikTok and Douyin.[6] For each video, we also collect data on daily statistics including views, likes, comments, and forwards of each short video. We obtain a total sample of 48 countries over the sample period of July 1, 2017, to June 30, 2021. Our sample consists of over 9,305 million unique short videos with over 22 trillion views, with an average of 193.86 million videos per country and around 2,443 views per video.

We use the Zhao et al. (2020) method to measure short video sentiment. The methodology recognizes video emotions in an end-to-end manner based on convolutional neural networks (CNNs). Specifically, their deep Visual-Audio Attention Network (VAANet) integrates spatial, channel-wise, and temporal attention into a visual 3D CNN and temporal attention into an audio 2D CNN. Zhao et al. (2020) show that the method achieves high accuracy on the sentiment analysis of short videos and outperforms the state-of-the-art methods for video emotion recognition.[7]

We fine-tune the model for our specific application using the VideoEmotion-8 (Jiang et al. (2014)) training dataset designed specifically for video emotion recognition. The dataset consists of 1,101 videos collected from YouTube and Flickr with an average duration of 107 seconds. The VAANet algorithm assigns probabilities that a video belongs to the eight basic categories (Plutchik and Kellerman (1980)), with anger, disgust, fear, and sadness reflecting negative sentiment and anticipation, joy, surprise, and trust conveying positive sentiment.[8] We define the sentiment of a video as $0.5 \times (\text{positive sentiment probability} - \text{negative sentiment probability}) + 0.5$, such that the variable range from 0 to 1. We then compute a daily views-weighted average sentiment across the top 500 videos for each country and aggregate the measure to weekly frequencies. Our key variable of interest, the country-level VSI index, is the weekly change in the views-weighted video sentiment for a country.[9]

[6] Douyin is the Chinese version of TikTok. We collect short videos from 47 countries from TikTok and short videos from China from Douyin.

[7] Source code is available at: https://github.com/maysonma/VAANe.

[8] In each category, there are at least 100 videos. The VAANet aggregates the visual and audio features of different segments from a video weighted by temporal attention to obtain the whole video's feature representation, which is followed by a fully connected layer. It designs a polarity-consistent cross-entropy loss that can provide the probabilities that a given short video belongs to each emotion category, with all eight probabilities adding up to 1.

[9] The weekly frequency mitigates the nonsynchronicity trading across different markets and issues related to the different times that video statistics are collected. Taking the first difference allows us to capture innovations in sentiment and at the same time controlling for country-specific factors that influences the sentiment measures.

2.2 Sample and summary statistics

We obtain country-level MSCI total return indices from Refinitiv. Table 1 reports the summary statistics by country on our short video-based sentiment measure, stock market returns, and volatility. We winsorize all continuous variables in our study at the 2.5% and 97.5% levels. The mean VSI across the countries is close to zero, at 0.02%, as one would expect for a de-meaned measure. The sample average for the standard deviation of VSI is 1.656%, suggesting a considerable amount of time-series variations. The AR(1) coefficient for VSI is negative, at -0.241, suggesting that shocks to video sentiment tend to be transitory. We normalize VSI to a mean of zero and a standard deviation of one so that the regression coefficient is easy to interpret. Weekly average stock market returns for our sample is 0.26% and the weekly market return volatility is 1.383%.

2.3 Validation of the video-based sentiment measure

We first assess the extent to which our video-based sentiment index is associated measures that previous studies has shown to reflect investors mood. We first identify seasonal factors (e.g., Thaler (1987); Kamstra et al. (2017); Birru (2018); Hirshleifer et al. (2020)). During certain months, individuals' mood has a clear tendency of upswing or downswing. The monthly difference in mood is mainly associated with holidays and length of daylight. In January, both the Northern Hemisphere countries and the Southern Hemisphere countries exhibit an uplifting mood because of the New Year period. In March, September and October for the Northern Hemisphere, a condition called seasonal affective disorder (SAD) exerts great influence on people. SAD, widely observed across countries with obvious seasonal shifts, is estimated to affect approximately 5 percent of people in the United States and 4 to 14 percent of people in Europe depending on latitude, composing a significant part of the sentiment changes. In September and October, an increase in the exposure to darkness as the days grow shorter causes people susceptible to SAD to develop atypical depressive symptoms, bringing about a low overall mood, while in March, there is a distinct recovery from these symptoms and people's mood improves again. For the Southern Hemisphere, the effect is also observable, only with six months out of phase.

Second, we test whether our short video sentiment is related to weather conditions, as prior literature finds that cloud cover also affects mood (see, e.g., Hirshleifer and Shumway (2003); Goetzmann et al. (2015)). Local climatological data is collected from the National Oceanic and Atmospheric Administration website, which contains hourly weather observations from over 20,000 weather stations worldwide. It provides the degree of cloud cover in the country observed by each station, given by an integer value from 0 (clear sky) to 8 (overcast sky). Following the calculation of Goetzmann et al. (2015), we obtain the average daily cloud cover per country by using hourly values from 6am to 12pm across all of the weather stations in the country. And we deseasonalize the daily cloud cover by subtracting each week's mean cloudiness from the time-series mean to avoid seasonality in cloud cover. We call this measure deseasonalized cloud cover (DCC). Because our sentiment measure is based on the change in sentiment, we use the average daily change in deseasonalized cloud cover within a week ($\overline{\Delta DCC}$) in our validation test.

Finally, recent studies find that government restrictions toward COVID-19 are negatively related to citizens' mood (e.g., Terry et al. (2020); Bueno-Notivol et al. (2021)). So we expect our short video based sentiment to be lower when COVID restrictions are stronger. We construct an index based on lockdown restrictions compiled by the University of Oxford's COVID-19 government response tracker, which includes school closures, workplace closures, cancellations of public events, restrictions on gathering sizes, closures of public transport, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel. (We do not include other government responses contained in the tracker, such as vaccination requirements and testing policy, that do not lead to closures or containment).

We test how VSI is related to the above measures of investor mood by estimating the following panel regression:

$$\text{VSI}_{i,t} = \alpha + \beta_1 * \text{Positive Months}_{i,t} + \beta_2 * \text{Negative Months}_{i,t} + \beta_3 * \overline{\Delta DCC}_{i,t} + \beta_4 * \Delta COVID_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where Positive Months is an indicator variable that equals 1 for January and March for Northern Hemisphere countries (January and September for Southern Hemisphere countries) and 0 otherwise, Negative Months is an indicator variable that equals 1 in September and October for Northern Hemisphere countries (March and April for Southern Hemisphere countries) and 0 otherwise, $\overline{\Delta DCC}_{i,t}$is the average daily change in deseasonalized cloud cover within week t, and is the weekly change in the stringency of a government's response to COVID. We estimate the equation using ordinary least squares (OLS) and report White-corrected t-statistics, which are robust to heteroscedasticity.

Table 2 reports the regression estimates in the world market, developed market, and emerging market respectively. Column 1 includes the month dummies and country and year fixed effects. It shows that decreasing mood periods (Negative Months) are significantly negatively associated with short video based sentiment, but there's no significant effect in increasing mood periods (Positive Months). Column 2 includes the change in cloudiness and country and month fixed effects and shows that an increase in cloudiness is associated with a significant decrease in short video sentiment (at the 1% level). Column 3 shows that more stringent lockdown restrictions are associated with a decrease in short video sentiment at the 5% level. Column 4 integrates all of the above explanatory variables together and shows that the aforementioned associations hold. These results show that our sentiment measure based on short videos can capture the emotion fluctuations of individuals in a country caused by recognized emotional factors. Besides, the stronger results for decreasing mood periods are consistent with prior research that negative sentiment has greater effects than positive sentiment (e.g., Edmans et al. (2007)).

3 Results

3.1 Video-based sentiment and stock market returns

We study the relation between our short video sentiment and stock market returns across countries. Studies in the theoretical field of behavioral finance find that investor sentiment clearly affects stock market activity including noise trading, overreaction, and limits of arbitrage. These anomalies drive asset prices away from economic fundamentals, which is followed by subsequent price reversals. Accordingly, we expect a positive association between investor sentiment and contemporaneous market returns and a negative association between sentiment and future market returns.

In our main analysis, we investigate the relation between short video sentiment and stock market returns. We use all 48 countries to construct the panel. The sample period is from July 1, 2017, to June 30, 2021. We estimate the following baseline panel regression:

$$RET_{i,t+1} = \alpha + \beta_1 * VSI_t + \sum \Gamma Controls_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $RET_{i,t+1}$ is the weekly return of country i's stock market index, and is an array of control variables that include the five lagged weekly returns for country i($RET_{i,t}$,$RET_{i,t-1}$,...,$RET_{i,t-4}$) , lagged implied volatility(VIX_t, weekly change in economic policy uncertainty(ΔEPU_t, weekly change in macroeconomic activity(ΔADS_t, and the average daily change in deseasonalized cloud cover over the week(ΔDCC_t).

All of these regressions include country fixed effects, and standard errors are clustered at the country and year-week levels. Columns 1 and 2 of Table 4 show the return prediction of sentiment for all countries in our sample. We find a negative relation between change in short video sentiment and future market returns. As shown, a 1-standard-deviation increase in market sentiment predicts a decline in weekly returns of 55 bps. In addition, we run panel regressions separately for subsamples of emerging and developed countries. Columns 3 and 4 report the results for developed markets and columns 5 and 6 for emerging markets. Comparing the coefficients, we find that sentiment indices provide a stronger prediction for future returns in developed markets than in emerging markets: As shown in column 6, the coefficient of the sentiment indices is -0.44 for emerging markets and -0.59 for developed markets, which indicates the notable economic difference: A 1-standard-deviation increase in sentiment leads to a decrease in the market return in the following week of 44 bps in emerging markets. The magnitude is smaller than the 59 bps decrease in developed markets.

Table 5 provides additional regression results of a battery of subsample tests. Panel A reports the results for our sentiment indices based on either economics- and finance-related short videos or short videos unrelated to economics and finance. Both indices demonstrate significant predictive power for future stock market returns. A 1-standard-deviation increase in Economics VSI (Non-economics VSI) leads to a decrease in the market return in the following week of 24 (34) bps, which suggests that the non-economics-related sentiment index provides stronger predictive power.

Panel B provides additional regression results for our sentiment indices based on number of fans the short video creator has. Short video creators with more followers usually have the motivation to cater to the overall sentiment for their videos to arouse sympathy and spread widely, which should supposedly provide a more outstanding effect in measuring the investors' sentiment across the market. The results show that both coefficients are significant using the new measure. A 1-standard-deviation increase in High number of fans VSI (Low number of fans VSI) leads to a decrease in the market return in the following week of 35 (20) bps, suggesting that the sentiment index based on short videos created by creators with high number of fans provides stronger predictive power. Similarly, we reconstruct sentiment indices based on the number of forward, comments and number of likes the short videos have. As more forward, comments and likes suggest a better user reception and user reception are closely related to user sentiment, a higher ability of the index to proxy for investors' sentiment is expected.

Panel C shows that both coefficients are significant using the indices based on number of forward. But the sentiment index based on short videos with more forward exhibits stronger predicative power, as a 1-standard-deviation increase in High number of forward VSI (Low number of forward

VSI) leads to a decrease in the market return in the following week of 36 (18) bps. Panel D reports the result for indices based on number of comments. With control variables, the index constructed on short videos with low number of comments is significant on a 5% level, while the index constructed on short videos with high number of comments is significant on a 1% level. A 1-standard-deviation increase in High number of comments VSI (Low number of comments VSI) leads to a decrease in the market return in the following week of 40 (16) bps, suggesting that the sentiment index based on short videos with more comments provides stronger predictive power.

Panel E reports the result for indices based on number of likes the short videos get. With control variables, the index constructed on short videos with low number of likes is significant on a 5% level, while the index constructed on short videos with high number of likes is significant on a 1% level. A 1-standard-deviation increase in High number of likes VSI (Low number of likes VSI) leads to a decrease in the market return in the following week of 42 (14) bps, suggesting that the sentiment index based on short videos with more likes provides stronger predictive power.

In Table 6, we perform the same analysis as in Table 4 by country. The results indicate that all countries except Israel and Norway exhibit a negative relation between VSI_t and market returns for the week that follows. 31 of the 48 countries display a pattern that is significant at the 5% level and 17 of 48 at the 1% level. Based on their economic significance, we rank the sample countries in the last column. Among all these countries, Brazil has the strongest reversal pattern, where a 1-standard-deviation increase in sentiment predicts a decrease in weekly market returns of 85 bps.

Table 7 confirms the hypothesis that our sentiment measure has stronger predictability in countries with larger retail holdings. The retail holdings are 1 minus the sum of country i 's total institution holdings scaled by its total stock market capitalization at the end of last year. After computing the time-series average of retail ownership for each country, we define countries whose average retail holdings ranks in the top 10% in our sample as high-retail-ownership countries and countries in the bottom 10% as low-retail-ownership countries. We then conduct sentiment prediction analyses for these 2 groups. Similarly, we expand the scope to countries ranking top and bottom 20% and countries ranking top and bottom 30% respectively and conduct the same analyses. In each column, the coefficient for VSI_t is significant, which suggests that our sentiment index has significantly stronger power to predict returns in high- versus low-retail-ownership countries. The higher the country ranks in retail holdings, the stronger the reversal pattern is.

4 Additional Analyses

4.1 Limits of arbitrage

4.1.1 Trading restrictions

Limits of arbitrage (Shleifer and Vishny, 1997), among multiple factors that cause price deviations, can amplify the effect of investor sentiment on mispricing. Trading restrictions, among which short-selling ban is a principal means, are shock that will increase limits of arbitrage. As prior studies find that prices incorporate negative information more slowly (Bris et al. (2007)) and option prices have greater deviations from put-call parity (Ofek et al. (2004)) where short sales are allowed, we draw on trading restrictions with short-selling bans in particular to conduct difference-in-differences analyses on trading restrictions in our sample countries during the COVID-19. To test the hypothesis that limits of arbitrage exacerbate the effect of investor sentiment on asset prices, we estimate the following difference-in-differences regression:

$$RET_{i,t} = \alpha + \beta_1 * VSI_t + \beta_2 * VSI_{i,t} \times BAN_{i,t} + \beta_3 * BAN_{i,t} + \Sigma\Gamma Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

where BAN is a dummy variable equal to 1 if a country i's stock market is subject to a trading restriction for the full week t, and 0 otherwise, and are the control variables from Table 4. We expect β_2 to be negative for lagged change in short video sentiment, suggesting a higher sensitivity in stock market under trading restrictions. Table 8 reports the estimation results of the regression for one week-lagged change in short video sentiment in different markets. We find that coefficients of the interaction term are significantly negative for future returns in all three models, suggesting that short video sentiment is associated with greater subsequent reversals under trading restrictions. Specifically, a one-standard-deviation increase in short video sentiment is associated with a 69 bps greater decrease in future returns in ban weeks versus non-ban weeks in the world market. The results hold in developed market and emerging market, with a decrease of 74 bps and 55bps respectively. In sum, the effect of short video sentiment on market returns is significantly stronger when a country's stock market is subject to trading restriction.

4.2 Global sentiment and sentiment comovement

We next delve into the effect of investor sentiment across countries. In this section, we construct a global sentiment index by using the simple average of our sentiment index of all 48 sample countries and examine whether global sentiment predicts future market returns. We estimate the following regression:

$$VSI_{i,t} = a + bVSIG_t + Controls_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $VSI_{i,t}$ is the change in country i's sentiment in week t, and $VSIG_t$ is the simple average of $VSI_{i,t}$ for our 48 sample countries, except country i, in week t. Table 9 reports the results. First, results from world market reveal that on average, 3.33% of the variation in a country's sentiment is driven by global sentiment. Second, we find a significant difference between developed and emerging countries: Investor sentiment has a higher correlation with global sentiment in developed countries than in emerging countries, as developed countries are more integrated into the global market. In terms of economic significance, a 1-standard-deviation change in global sentiment is associated with a 0.73-standard-deviation change in sentiment in developed markets and a 0.56-standard-deviation change in sentiment in emerging markets.

4.3 Stock market volatility

As is suggested in prior literature, investors' sentiment exacerbates market volatility by misleading prices to incorrectly adjust to it and then restore to fundamentals. To further delve into the effect, we conduct analysis on the relationship between weekly stock market volatility and weekly change in short video sentiment. We estimate the following regression:

$$VOL_{i,t} = \alpha + \beta_1 \cdot |VSI_{i,t}| + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t}, \tag{5}$$

where Controls include the previous control variables and month and country fixed effects,. Panel A of Table 10 reports the estimation results. We document a strong correlation between absolute change in short video sentiment and stock market volatility in the same week. A one-standard-deviation increase in absolute change of short video sentiment is associated with a contemporaneous 0.19 bps increase in stock market volatility. These findings help explain the stock price deviations induced by investors' sentiment.

4.4 Net equity fund flows

We expect that trading of mutual fund would also be affected by investor sentiment. In fact, studies have found that there is a significant relation between individual investor sentiment and mutual fund flows (Ben-Rephael et al. (2011), Ben-Rephael et al. (2012)). This can be explained by investors' confidence in equity market when making decisions regarding funds.

We collect information on daily net fund flows from Morningstar, focusing on open-end equity mutual funds denominated in local currency, and convert these flows to U.S. dollars. We remove duplicates (funds with the exact same time series of net flows and size) and funds with fewer than one observation per week on average. We also drop funds that started after the beginning of our sample period (July 1, 2017) and fund-week observations with less than $15 million of assets under management, following Pástor and Vorsatz (2020). The latter is because, for small funds, modest dollar flows can translate into extreme percentage flows; the results are similar when we use alternative cut-off points such as $20 million of assets under management. This screening process results in 9001 equity funds from 35 different countries and around 1,682,000 fund-week observations.

We expect a positive relation between short video sentiment and mutual fund net inflows. For each fund, we summarize the daily net fund flows within the week and scale the weekly net fund flows by the fund's total assets under management at the end of the previous week (e.g., Kamstra et al. (2017)). Then we estimate the following panel regression:

$$NetFlows_{f,i,t} = \alpha + \sum \beta_j \cdot VSI_{i,t} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{f,i,t}, \tag{6}$$

where $NetFlows_{f,i,t}$ is the weekly scaled net flow of fund f, in country i, in week t. Controls are our previous controls, including month and fund fixed effects. Panel B of Table 10 reports the results of the estimation. We find that change in short video sentiment is positively related to mutual fund flows in the same week, significant at the 1% level. A one-standard-deviation increase in change of short video sentiment corresponds to an average increase of 0.01 bps in net fund flows in the same week. Our results suggest that increases in short video sentiment are associated with marked inflows to the equity market.

4.5 Government bonds

There have been an active literature studying "flight to safety," whereby investors' risk aversion increases when the sentiment is low (e.g., Baker and Wurgler (2012); Laborda and Olmo (2014); Da et al. (2015)). A flight to safety is often accompanied by a flight to liquidity, that is , investors demand higher safety and liquidity, and exhibit a preference for assets such as government bonds. Thus, we predict that low sentiment causes investors to move into government bonds. We test this hypothesis by studying the returns of the Refinitiv Datastream Benchmark Government Bond Index. We use the returns of the five-year bond index because this maturity has the greatest data availability (Pitkäjärvi et al. (2020)). In Panel C of Table 10 the same analysis as in Table 4 is performed but with equity index returns replaced by government bond index returns. We document a significant negative association between short video sentiment and government bond index returns. In terms of economic significance, a one-standard-deviation increase in short video sentiment is associated with a contemporaneous decrease in government bond returns of 0.05 bps per week, or -2.8% per year, which is economically large.

5 Conclusion

In this article, we introduce a novel measure of investor sentiment constructed on popular user-generated short videos on the world's largest video sharing platform. We show that our short video based sentiment (VSI) is correlated with mood proxies induced seasonal factors, cloud coverage, and COVID-related restrictions that previous literature suggests. We find that VSI is strongly and positively associated with next-week market returns, and VSI also strongly predict future market returners. The pattern holds across country and is more concentrated in countries when arbitrage is more costly or in markets for which retail investors play a bigger role. A higher short video sentiment also predicts increases in net mutual fund flows and decreases in government bond returns, and an increase in absolute VSI is followed by a higher stock market volatility in the future. Overall, the results suggest that our short video sentiment captures investor sentiment about the economy and contributes significantly to asset prices. We further show that the country-level VSI comove with each other and a common global component also predicts the returns of the world equity index.

Moreover, we identify the predictive power of global sentiment in market returns in each country. Videos are a source of abundant information. With the development on machine learning and video analysis techniques, the index expects considerable room for optimization. Our measure provides future research with a broader context to continue studies in the field of behavioral finance as well as investor sentiment.

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Figure 1: Time series of VSI indices

This figure plots the time series of VSI indices in top 4 short video countries, China, USA, Indonesia, and Russia. All indices are standardized to mean zero and standard deviation one. The sample spans the period from July 2017 to June 2021.

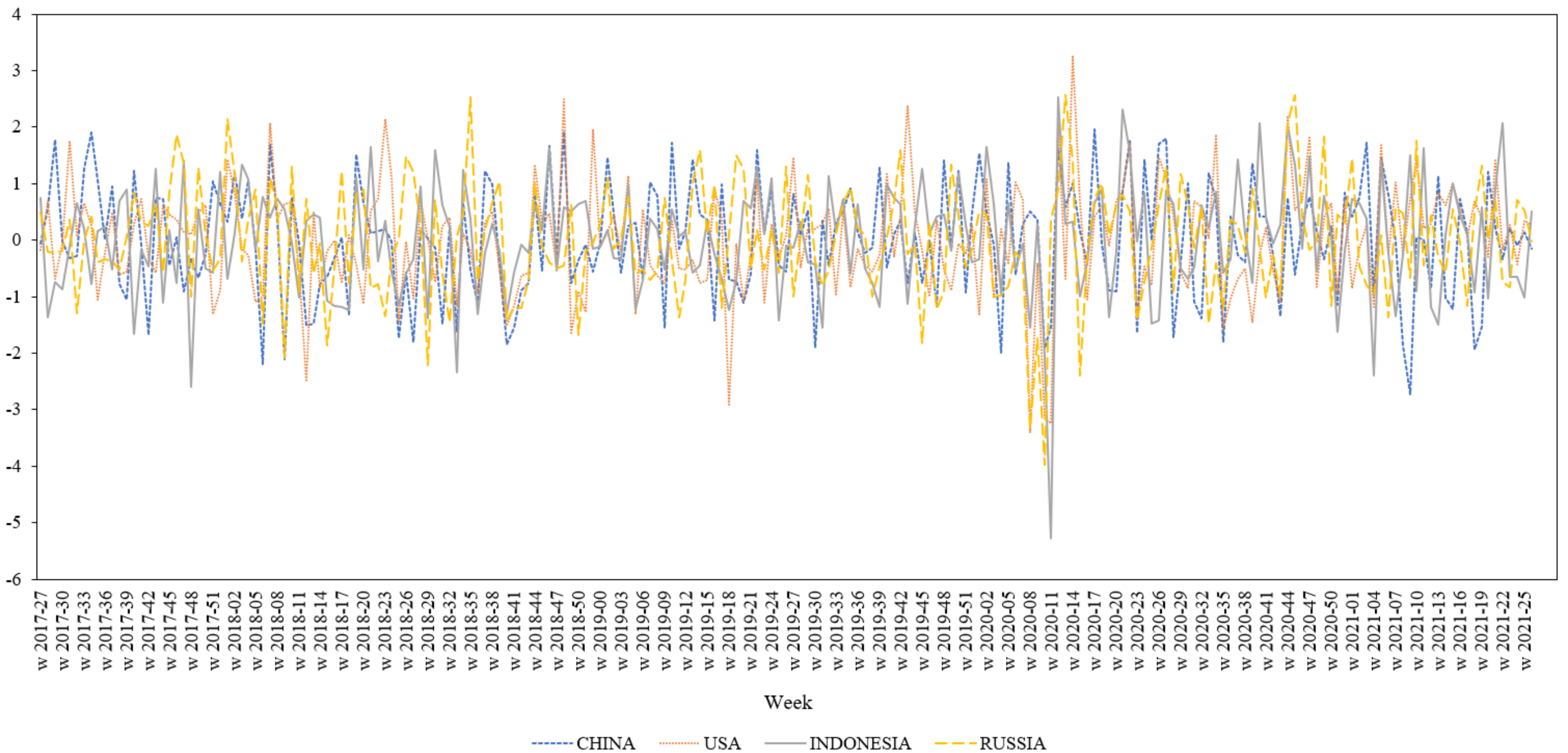


Table 1: Summary Statistics

This table reports summary statistics (full sample average) on our main variables. VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos played for a country (multiplied by 100). RET is the weekly stock market return. VOL is the standard deviation of daily stock market returns within the week. SD is the standard deviation. AR(1) is the first coefficient of autocorrelation. The sample period is from July 1, 2017, to June 30, 2021.

Country	Market	Region	VSI			RET (%)	VOL (%)
			Mean	SD	AR(1)	Mean	Mean
Argentina	EM	Americas	0.003	1.124	-0.111	0.275	2.473
Australia	DM	Asia-Pacific	0.096	1.969	-0.453	0.434	1.491
Austria	DM	EMEA	0.030	1.083	-0.037	0.351	1.928
Belgium	DM	EMEA	0.040	1.477	-0.364	0.233	1.212
Brazil	EM	Americas	-0.050	1.504	-0.339	0.358	1.022
Canada	DM	Americas	-0.020	2.246	-0.440	0.023	0.967
Chile	EM	Americas	-0.042	0.615	-0.463	0.380	1.899
China	EM	Asia-Pacific	0.003	2.446	-0.022	0.218	1.602
Colombia	EM	Americas	0.045	0.932	-0.254	0.318	1.709
Czech	EM	EMEA	0.048	0.943	-0.102	0.113	0.990
Denmark	DM	EMEA	0.067	2.382	-0.085	0.223	1.920
Egypt	EM	EMEA	0.068	1.751	-0.296	0.217	1.094
Finland	DM	EMEA	-0.031	2.203	-0.042	0.021	1.153
France	DM	EMEA	-0.022	0.784	-0.296	0.115	1.068
Germany	DM	EMEA	0.048	1.194	-0.393	0.148	1.491
Greece	EM	EMEA	0.058	1.738	-0.191	0.456	0.554
Hong Kong, China	DM	Asia-Pacific	0.051	1.745	-0.005	0.063	0.936
Hungary	EM	EMEA	0.019	2.048	-0.057	0.202	1.885
Indonesia	EM	Asia-Pacific	0.031	0.719	-0.210	0.420	2.130
Ireland	DM	EMEA	0.079	1.375	-0.138	0.488	1.238
Israel	DM	EMEA	-0.036	2.475	-0.267	0.089	1.125
Italy	DM	EMEA	0.077	0.967	-0.309	0.225	2.385
Japan	DM	Asia-Pacific	0.015	2.162	-0.442	0.146	1.712
Korea	EM	Asia-Pacific	0.003	1.981	-0.097	0.499	1.863
Kuwait	EM	EMEA	-0.019	2.433	-0.249	0.493	0.695
Malaysia	EM	Asia-Pacific	0.002	1.653	-0.006	0.114	0.821
Mexico	EM	Americas	0.093	1.842	-0.316	0.177	0.594
Netherlands	DM	EMEA	-0.006	0.785	-0.123	0.228	1.252
New Zealand	DM	Asia-Pacific	-0.021	2.002	-0.461	0.035	1.785
Norway	DM	EMEA	0.044	2.455	-0.438	0.408	2.261
Peru	EM	Americas	-0.016	1.203	-0.103	0.186	0.928
Philippines	EM	Asia-Pacific	0.006	0.689	-0.286	0.135	1.729
Poland	EM	EMEA	0.097	2.350	-0.075	0.337	1.199
Portugal	DM	EMEA	0.049	2.464	-0.118	0.455	0.597
Qatar	EM	EMEA	0.019	1.879	-0.170	0.058	1.438

Country	Market	Region	VSI			RET (%)	VOL (%)
			Mean	SD	AR(1)	Mean	Mean
Russia	EM	EMEA	0.026	0.807	-0.375	0.056	1.747
Saudi Arabia	EM	EMEA	0.066	2.384	-0.299	0.383	1.385
Singapore	DM	Asia-Pacific	0.035	1.694	-0.104	0.420	1.015
South Africa	EM	EMEA	-0.021	2.319	-0.306	0.222	1.938
Spain	DM	EMEA	-0.007	1.045	-0.420	0.403	0.509
Sweden	DM	EMEA	0.029	1.599	-0.315	0.441	0.857
Switzerland	DM	EMEA	-0.009	1.145	-0.330	0.257	1.174
Taiwan, China	EM	Asia-Pacific	-0.006	1.828	-0.291	0.246	2.404
Thailand	EM	Asia-Pacific	0.014	0.732	-0.252	0.232	1.122
Turkey	EM	EMEA	0.038	2.149	-0.474	0.126	1.679
UAE	EM	EMEA	-0.046	2.238	-0.235	0.305	0.605
UK	DM	EMEA	-0.013	2.280	-0.149	0.491	1.408
US	DM	Americas	0.036	2.148	-0.095	0.182	1.862
Sample average			0.020	1.656	-0.241	0.260	1.383

Table 2: Validation of the Video Sentiment Index

This table reports the validation of the video sentiment measure. We estimate a panel regression of Eq. 1 and report the estimates. The dependent variable, VSI, is the weekly change in the views-weighted sentiment of the top-500 TikToc videos played for a country (multiplied by 100). Positive months is an indicator variable that equals 1 in January and March (January and September) for Northern (Southern) Hemisphere countries, and 0 otherwise. Negative months is an indicator variable that equals 1 in September and October (March and April) for Northern (Southern) Hemisphere countries, and 0 otherwise. ΔDCC is the average daily change in deseasonalized cloud cover over the week. ΔCOVID is the weekly change in the containment and closure index. Market Ret is the monthly stock market returns in each country. In columns (1), (4), and (5), the regressions include country and year fixed effects. In columns (2) and (3), the regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

World market	VSI	VSI	VSI	VSI	VSI
Positive months	-0.006				-0.003
	(-1.07)				(-0.43)
Negative months	-0.019***				-0.012***
	(-3.92)				(-3.34)
ΔDCC		-0.030***			-0.029***
		(-3.82)			(-3.72)
ΔCOVID			-0.003**		-0.002*
			(-2.03)		(-1.69)
Market Ret				0.005	0.004
				(0.84)	(0.75)
Fixed Effects	Country, year	Country, month	Country, month	Country, year	Country, year
R^2	1.56%	2.20%	2.31%	1.09%	3.59%
N	7,738	8,935	9,936	9,936	7,660

Developed market	VSI	VSI	VSI	VSI	VSI
Positive months	-0.007				-0.003
	(-1.02)				(-0.42)
Negative months	-0.021***				-0.012***
	(-3.43)				(-3.22)
ΔDCC		-0.034***			-0.028***
		(-3.27)			(-3.34)
ΔCOVID			-0.003*		-0.003*
			(-1.77)		(-1.68)
Market Ret				0.007	0.005
				(1.01)	(0.81)
Fixed Effects	Country, year	Country, month	Country, month	Country, year	Country, year
R^2	1.71%	2.42%	2.55%	1.20%	4.05%
N	3,708	4,281	4,761	4,761	3,670

Emerging market	VSI	VSI	VSI	VSI	VSI
Positive months	-0.005				-0.003
	(-0.90)				(-0.34)
Negative months	-0.017***				-0.010***
	(-3.02)				(-2.77)
ΔDCC		-0.029***			-0.025***
		(-3.05)			(-3.08)
ΔCOVID			-0.003*		-0.002
			(-1.71)		(-1.36)
Market Ret				0.004	0.003
				(0.67)	(0.54)
Fixed Effects	Country, year	Country, month	Country, month	Country, year	Country, year
R^2	1.40%	1.98%	2.08%	0.98%	3.11%
N	4,030	4,654	5,175	5,175	3,989

Table 3: Video Sentiment and Contemporaneous Stock Market Returns

This table reports the regression estimates of stock market returns on contemporaneous short-video sentiment. The dependent variable is the weekly stock market return for a country (RET), with Panels A and B correspond to US-dollar and local-currency-based market returns, respectively. VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos played for a country (multiplied by 100). The control variables include the four lagged weekly returns for country i (RET_{t-1}, ..., RET_{t-4}), implied volatility (VIX), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), and the average daily change in deseasonalized cloud cover over the week (ΔDCC). In columns 1 and 2, we use all 48 countries to run the regression; in columns 3 and 4, we use only developed countries; and in columns 5 and 6, we use only developing countries. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 2017 to June 2021.

Panel A: US-dollar market returns

	World market		Developed market		Emerging market	
	RET_t	RET_t	RET_t	RET_t	RET_t	RET_t
VSI_t	0.73***	0.71***	0.79***	0.73***	0.60***	0.56***
	(10.18)	(9.41)	(8.60)	(6.64)	(7.81)	(7.66)
ΔEPU_t		-2.76		-2.99*		-2.68
		(-1.54)		(-1.89)		(-1.65)
VIX_t		4.74**		5.14***		3.68**
		(2.46)		(2.60)		(2.45)
ΔADS_t		0.33**		0.37***		0.30***
		(2.41)		(2.80)		(2.76)
ΔDCC_t		-0.98*		-1.38		-0.83
		(-1.70)		(-1.55)		(-1.43)
RET_{t-1}		0.06		0.05		0.08*
		(1.41)		(0.93)		(1.73)
RET_{t-2}		0.00		0.00		-0.01
		(-0.12)		(-0.07)		(-0.17)
RET_{t-3}		0.01		0.00		0.02
		(0.31)		(-0.04)		(0.58)
RET_{t-4}		-0.02		-0.02		-0.03
		(-0.67)		(-0.46)		(-0.74)
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month
R^2	0.82%	3.69%	1.23%	5.05%	0.55%	3.14%
N	9,986	9,547	4,785	4,574	5,201	4,972

Part B:Local-currency market returns						
	World market		Developed market		Emerging market	
	RET_t	RET_t	RET_t	RET_t	RET_t	RET_t
VSI_t	0.59***	0.49***	0.66***	0.56***	0.5***	0.45***
	(7.83)	(7.01)	(6.66)	(5.37)	(5.63)	(5.34)
ΔEPU_t		-2.35		-2.27		-1.98
		(-1.21)		(-1.45)		(-1.35)
VIX_t		3.60*		3.96*		2.89**
		(1.83)		(1.70)		(2.02)
ΔADS_t		0.20**		0.25*		0.19*
		(1.97)		(1.86)		(1.94)
ΔDCC_t		-0.75		-1.05		-0.62
		(-1.40)		(-1.22)		(-1.20)
RET_{t-1}		0.04		0.04		0.05
		(0.97)		(0.63)		(1.50)
RET_{t-2}		0.00		0.00		-0.01
		(-0.09)		(-0.04)		(-0.13)
RET_{t-3}		0.01		0.00		0.02
		(0.25)		(-0.03)		(0.46)
RET_{t-4}		-0.02		-0.02		-0.02
		(-0.54)		(-0.33)		(-0.56)
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month
R^2	0.69%	3.12%	1.04%	4.27%	0.46%	2.66%
N	9,986	9,547	4,785	4,574	5,201	4,972

Table 4: Video Sentiment and Future Stock Market Returns

This table reports the regression estimates of stock market returns on lagged short-video sentiment. The dependent variable is the weekly stock market return for a country (RET), with Panels A and B correspond to US-dollar and local-currency-based market returns, respectively. VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos played for a country (multiplied by 100). The control variables include the five lagged weekly returns for country i (RET_t, RET_{t-1}, ..., RET_{t-4}), lagged implied volatility (VIX), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), and the average daily change in deseasonalized cloud cover over the week (ΔDCC). In columns 1 and 2, we use all 48 countries to run the regression; in columns 3 and 4, we use only developed countries; and in columns 5 and 6, we use only developing countries.VSI is the weekly change in the views-weighted video sentiment for a country. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

Panel A: US-dollar market returns

	World market		Developed market		Emerging market	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-0.57***	-0.55***	-0.65***	-0.59***	-0.47***	-0.44***
	(-8.23)	(-7.67)	(-6.65)	(-5.31)	(-6.03)	(-5.93)
ΔEPU_t		-2.44		-2.51*		-2.28
		(-1.38)		(-1.58)		(-1.44)
VIX_t		4.10**		4.42**		3.10**
		(2.16)		(2.34)		(2.15)
ΔADS_t		0.29**		0.32**		0.26**
		(2.08)		(2.35)		(2.32)
ΔDCC_t		-0.86		-1.16		-0.69
		(-1.48)		(-1.37)		(-1.29)
RET_t		0.01		-0.01		0.01
		(0.15)		(-0.19)		(0.44)
RET_{t-1}		0.05		0.05		0.07
		(1.22)		(0.77)		(1.56)
RET_{t-2}		0.00		0.00		-0.01
		(-0.11)		(-0.06)		(-0.15)
RET_{t-3}		0.01		0.00		0.02
		(0.27)		(-0.03)		(0.52)
RET_{t-4}		-0.02		-0.02		-0.02
		(-0.57)		(-0.41)		(-0.66)
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month
R^2	0.78%	3.51%	1.17%	4.81%	0.52%	2.99%
N	9,936	9,499	4,761	4,552	5,175	4,948

Part B:Local-currency market returns

	World market		Developed market		Emerging market	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-0.46***	-0.39***	-0.53***	-0.46 ***	-0.36***	-0.35 ***
	(-6.50)	(-5.62)	(-5.14)	(-4.21)	(-4.69)	(-4.14)
ΔEPU_t		-2.01		-1.99		-1.70
		(-1.08)		(-1.24)		(-1.19)
VIX_t		3.19		3.49		2.45*
		(1.54)		(1.50)		(1.71)
ΔADS_t		0.18*		0.21		0.16
		(1.78)		(1.58)		(1.62)
ΔDCC_t		-0.64		-0.92		-0.55
		(-1.0)		(-1.10)		(-1.07)
RET_t		0.00		-0.01		0.01
		(0.12)		(-0.15)		(0.34)
RET_{t-1}		0.04		0.03		0.05
		(0.84)		(0.54)		(1.26)
RET_{t-2}		0.00		0.00		0.00
		(-0.08)		(-0.04)		(-0.12)
RET_{t-3}		0.01		0.00		0.02
		(0.21)		(-0.02)		(0.41)
RET_{t-4}		-0.01		-0.02		-0.01
		(-0.46)		(-0.28)		(-0.50)
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month
R^2	0.66%	2.97%	0.99%	4.07%	0.44%	2.53%
N	9,936	9,499	4,761	4,552	5,175	4,948

Table 5: Video Sentiment and Future Stock Market Returns, by Video Heterogeneity

This table reports the regression estimates of stock market returns on lagged short-video sentiment, exploring heterogeneity of the videos. The dependent variable is the weekly stock market return for a country (RET). VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). The control variables are the same as those in Table 4. Panel A considers VSI indexes constructed with videos associated with economics and non economics hashtags, respectively. Panel B studies VSI indexes constructed using videos with high number of fans and low number of fans, respectively. similarly, panels C, D, and E consider VSI indexes constructed with videos that experienced high/low numbers of forwards, comments, and likes, respectively. All regressions include country and week fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

Panel A: Economics VSI and Non-economics VSI

	Economics SVS		Non-economics SVS		Diff(Nonecon−Econ)	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	[p-value]	
VSI_t	-0.24***	-0.24***	-0.35***	-0.34***	-0.11*	-0.10*
	(-6.26)	(-5.87)	(-6.58)	(-5.8)	[0.075]	[0.088]
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country, month	Country, month	Country, month	Country, month		
R^2	0.31%	1.37%	0.49%	2.15%		
N	9,936	9,499	9,936	9,499		

Panel B: VSI by high/low numbers of fans

	High number of fans		Low number of fans		Diff(High−Low)	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	[p-value]	
VSI_t	-0.36***	-0.35***	-0.21 ***	-0.20 ***	0.16*	0.15*
	(-5.59)	(-5.21)	(-3.6)	(-3.14)	[0.056]	[0.062]
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country, month	Country, month	Country, month	Country, month		
R^2	0.48%	2.17%	0.28%	1.24%		
N	9,936	9,499	9,936	9,499		

Panel C: VSI by high/low numbers of forwards

	High number of forward		Low number of forward		Diff(High−Low)	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	[p-value]	
VSI_t	-0.39***	-0.36***	-0.18***	-0.18***	0.21**	0.18**
	(-5.94)	(-5.69)	(-3.26)	(-3.02)	[0.037]	[0.042]
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country, month	Country, month	Country, month	Country, month		
R^2	0.53%	2.38%	0.24%	1.08%		
N	9,936	9,499	9,936	9,499		

Panel D: VSI by high/low numbers of comments						
	High number of comments		Low number of comments		Diff(High−Low	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	[p-value]	
VSI_t	-0.41***	-0.40***	-0.17***	-0.16**	0.24**	0.24**
	(-6.29)	(-5.82)	(-2.66)	(-2.55)	[0.019]	[0.022]
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country, month	Country, month	Country, month	Country, month		
R^2	0.58%	2.49%	0.21%	0.99%		
N	9,936	9,499	9,936	9,499		

Panel E: VSI by high/low numbers of likes						
	High number of likes		Low number of likes		Diff(High−Low	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	[p-value]	
VSI_t	-0.44***	-0.42 ***	-0.14**	-0.14 **	0.30***	0.28***
	(-6.92)	(-6.38)	(-2.24)	(-2.21)	[0.006]	[0.008]
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country, month	Country, month	Country, month	Country, month		
R^2	0.59%	2.66%	0.18%	0.78%		
N	9,936	9,499	9,936	9,499		

Table 6: VSI and Future Stock Returns, by Country

This table reports the regression estimates of stock market returns on lagged short-video sentiment for individual countries. The dependent variable is the weekly stock market return for a country (RET). VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). The control variables are the same as those in Table 4. EM and DM refer to emerging and developed market, respectively. Columns b, t-stat and R^2 report the the coefficient estimates and t-statistics of VSI, and the regression R^2. Eco Sig reports the economic significance of the coefficient, which is the changes in weekly market returns with a 1-standard-deviation increase in VSI.

Country	Market	b	t-stat	R^2	Eco Sig
Argentina	EM	-0.75	-3.18	4.00%	-0.31%
Australia	DM	-0.30	-0.99	2.68%	-0.15%
Austria	DM	-0.64	-2.68	9.17%	-0.48%
Belgium	DM	-0.91	-2.08	5.78%	-0.43%
Brazil	DM	-1.63	-4.95	5.85%	-0.85%
Canada	DM	-0.40	-1.85	5.51%	-0.29%
Chile	EM	-0.63	-2.41	8.62%	-0.34%
China	EM	-1.38	-3.40	6.58%	-0.56%
Colombia	EM	-0.17	-0.58	7.97%	-0.10%
Czech	EM	-0.51	-1.63	5.50%	-0.27%
Denmark	DM	-0.56	-2.19	6.60%	-0.34%
Egypt	EM	-0.50	-1.91	6.99%	-0.33%
Finland	DM	-0.53	-2.05	6.79%	-0.34%
France	DM	-1.01	-3.04	7.88%	-0.52%
Germany	DM	-0.85	-2.43	8.43%	-0.31%
Greece	EM	-0.51	-1.68	4.72%	-0.26%
Hong Kong, China	DM	-0.18	-0.74	3.85%	-0.10%
Hungary	EM	-0.38	-1.08	5.71%	-0.21%
Indonesia	EM	-1.35	-2.77	7.75%	-0.61%
Ireland	DM	-0.76	-1.90	5.55%	-0.37%
Israel	DM	0.01	0.04	3.36%	0.00%
Italy	DM	-0.81	-2.61	11.07%	-0.29%
Japan	DM	-1.01	-2.77	7.51%	-0.43%
Korea	EM	-0.47	-1.54	4.74%	-0.30%
Kuwait	EM	-0.61	-2.36	4.37%	-0.31%
Malaysia	EM	-0.28	-1.74	3.90%	-0.19%
Mexico	EM	-1.06	-3.18	5.35%	-0.57%
Netherlands	DM	-0.61	-1.51	3.93%	-0.23%
New Zealand	DM	-0.52	-2.76	3.56%	-0.32%
Norway	DM	0.19	0.59	8.86%	0.10%
Peru	EM	-0.45	-2.15	5.94%	-0.24%
Philippines	EM	-0.72	-2.48	2.38%	-0.37%
Poland	EM	-0.77	-2.01	4.63%	-0.41%
Portugal	DM	-0.15	-0.76	2.97%	-0.10%
Qatar	EM	-0.46	-1.39	3.80%	-0.25%
Russia	EM	-1.13	-2.73	5.38%	-0.53%

Country	Market	b	t-stat	R^2	Eco Sig
Saudi Arabia	EM	-0.89	-2.24	5.80%	-0.33%
Singapore	DM	-0.76	-3.24	8.52%	-0.40%
South Africa	EM	-0.80	-2.54	10.10%	-0.49%
Spain	DM	-0.63	-2.64	7.99%	-0.39%
Sweden	DM	-0.04	-0.15	4.62%	-0.02%
Switzerland	DM	-0.33	-2.66	6.66%	-0.28%
Taiwan, China	EM	-0.40	-2.08	4.84%	-0.24%
Thailand	EM	-0.71	-2.47	5.45%	-0.35%
Turkey	EM	-0.55	-2.28	5.14%	-0.30%
UAE	EM	-0.85	-2.69	3.03%	-0.43%
United Kingdom	DM	-0.82	-2.83	7.16%	-0.46%
United States	EM	-1.39	-3.14	6.41%	-0.53%
United States	EM	-1.39	-3.14	6.41%	-0.53%

Table 7: Video Sentiment and Future Stock Market Returns, by Retail Ownership

This table reports the regression estimates of stock market returns on lagged short-video sentiment for individual countries, for subsamples sorted by the average retail ownership of a country. The dependent variable is the weekly stock market return for a country (RET). VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). The control variables are the same as those in Table 4. We compute the time-series averages of retail holdings for each country and classify countries into top and bottom 10%, 20%, and 30% groups respectively based on the country's retail holding among the 48 countries in our sample. We perform regression analysis for each of the retail ownership subsamples. Control variables are defined in Table 4. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

	Top 10% retail	Bottom 10% retail	Top 20% retail	Bottom 20% retail	Top 30% retail	Bottom 30% retail
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-0.69***	-0.39***	-0.61***	-0.42***	-0.58***	-0.43***
	(-9.53)	(-4.33)	(-8.16)	(-5.17)	(-7.86)	(-5.60)
Diff (Top−bottom)	0.30***		0.19**		0.14**	
[p-value]	[0.007]		[0.029]		[0.038]	
ΔEPU_t	-2.03***	-2.65***	-2.37***	-3.10***	-2.43***	-3.26***
	(-5.13)	(-6.72)	(-7.16)	(-7.80)	(-6.83)	(-7.91)
VIX_t	3.60***	6.03***	3.41***	5.46***	3.33***	5.27***
	(8.42)	(11.03)	(12.09)	(12.32)	(12.30)	(12.64)
ΔADS_t	0.20***	0.30***	0.21***	0.28***	0.20***	0.28***
	(6.37)	(8.47)	(10.42)	(9.97)	(10.28)	(9.65)
ΔDCC_t	-0.72***	-1.82***	-0.65***	-1.70***	-0.67***	-1.70***
	(-3.05)	(-7.16)	(-4.01)	(-6.70)	(-3.93)	(-6.49)
RET_t	0.00	-0.02**	0.02**	-0.02*	0.02**	-0.02*
	(0.45)	(-2.38)	(2.14)	(-1.75)	(2.23)	(-1.81)
RET_{t-1}	0.06***	0.04**	0.06***	0.04***	0.06***	0.04***
	(4.11)	(2.56)	(6.90)	(2.81)	(6.72)	(2.69)
RET_{t-2}	0.01	-0.02*	0.00	-0.02*	0.00	-0.02*
	(0.88)	(-1.67)	(0.57)	(-1.89)	(0.58)	(-1.94)
RET_{t-3}	0.02*	0.01	0.01	0.02	0.01	0.02
	(1.78)	(0.75)	(0.72)	(1.37)	(0.70)	(1.36)
RET_{t-4}	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.18)	(-0.91)	(-1.09)	(-0.41)	(-1.08)	(-0.40)
Fixed Effects	Country,month	Country,month	Country,month	Country,month	Country,month	Country,month
R^2	4.45%	2.38%	3.80%	2.80%	3.88%	2.84%
N	792	792	1,781	1,781	2,771	2,771

Table 8: Video Sentiment and Future Stock Market Returns, Short-sale Bans

This table reports the regression estimates of stock market returns on lagged short-video sentiment for individual countries, condition on trading restrictions that bans short sale. The dependent variable is the weekly stock market return for a country (RET). VSI is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). BAN is a dummy variable equal to 1 for country-week observations associated with short-sale bans, and 0 otherwise. The control variables are the same as those in Table 4. All regressions include country and week fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

	World market		Developed market		Emerging market	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-0.50***	-0.40***	-0.57***	-0.43***	-0.41***	-0.33***
	(-7.22)	(-5.70)	(-5.84)	(-3.95)	(-5.29)	(-4.41)
$VSI_t \times BAN_t$	-0.33***	-0.69***	-0.38***	-0.74***	-0.27***	-0.55***
	(-5.87)	(-9.29)	(-4.75)	(-6.43)	(-4.30)	(-7.19)
BAN_t	0.01	-0.03	0.01	-0.03	0.01	-0.02
	(0.13)	(-0.30)	(0.10)	(-0.21)	(0.09)	(-0.23)
Controls	N	Y	N	Y	N	Y
Fixed Effects	Country,month	Country,month	Country,month	Country,month	Country,month	Country,month
R^2	0.83%	3.79%	1.28%	5.26%	0.55%	3.22%
N	9,936	9,499	4,761	4,552	5,175	4,948

Table 9: Sentiment comovement

The table examines how video sentiment of a country comoves with the global video sentiment and report the estimates for Equation 4. The dependent variable VSI_i is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). VSIG_{-i} is the corresponding global video sentiment, defined as the average VSI across all countries in our sample except for country i. Columns 1 and 2 use all 48 countries, Columns 3 and 4 use developed countries, and Columns 5 and 6 use emerging countries, respectively. The control variables are from Table 4. All regressions include country and week fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

	World market		Developed market		Emerging market			
	(1)	(2)	(3)	(4)	(5)	(6)	Diff(DM−EM)	
	$VSI_{i,t}$	$VSI_{i,t}$	$VSI_{i,t}$	$VSI_{i,t}$	$VSI_{i,t}$	$VSI_{i,t}$	[p-value]	
$VSIG_{-i,t}$	0.66***	0.63***	0.77***	0.73***	0.59***	0.56***	0.18***	0.17**
	(14.51)	(13.25)	(12.43)	(11.84)	(9.48)	(9.03)	[0.009]	[0.011]
ΔEPU_t		0.02		-0.01		0.04	No Controls	Yes Controls
		(1.22)		(-0.35)		(1.41)		
VIX_t		-0.06***		-0.13***		-0.03		
		(-2.92)		(-2.67)		(-0.84)		
ΔADS_t		0.00**		-0.01**		0.00		
		(-2.33)		(-2.36)		(-0.33)		
ΔDCC_t		-0.03		-0.03		-0.03		
		(-1.44)		(-0.67)		(-1.01)		
RET_{t-1}		-0.01***		-0.01***		-0.01***		
		(-5.70)		(-3.68)		(-4.04)		
RET_{t-2}		0.00		0.00		0.00		
		(-0.08)		(-1.42)		(1.42)		
RET_{t-3}		0.00		0.00		0.00**		
		(-1.57)		(-0.21)		(-2.05)		
RET_{t-4}		0.00		0.00		0.00		
		(-0.22)		(-1.11)		(-0.67)		
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month		
R^2	2.84%	3.33%	3.62%	4.21%	2.17%	2.58%		
N	9,984	9,545	4,784	4,574	5,200	4,971		

Table 10: Volatility, Net flows, and Government bonds

This table examines the relationship between lagged video sentiment and stock market variables and reports the panel regression estimates. VSI_i is the weekly change in the views-weighted sentiment of the top-500 TikToc videos for a country (multiplied by 100). The dependent variables are: stock market volatility (Panel A), net flows to equity, fixed-income, and hybrid funds respectively (Panels B through D), and government bond returns (Panel E). Stock market volatility (VOL) is the standard deviation of a country's daily stock market returns for a given week. Net Equity Fund Flows is the net equity fund flow to a country for a given week, scaled by the country's equity fund's assets under management at the end of the previous week. Net Fixed income Fund Flows is the net fixed income fund flow to a country for a given week scaled by the country's fixed income fund's assets under management at the end of the previous week. Net Hybrid Fund Flows is the net hybrid fund flow to a country for a given week scaled by the country's hybrid fund's assets under management at the end of the previous week. Gov Bond RET is the weekly government bond index return for a country. The regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

Panel A	VOL_t	VOL_t
VSI_{t-1}	0.14***	0.12***
	(4.97)	(3.74)
Controls	N	Y
Fixed Effects	Country, month	Country, month
R^2	12.86%	24.58%
N	9,986	9,547

Panel B	Net Equity Fund Flows_t	Net Equity Fund Flows_t
VSI_{t-1}	0.12***	0.09**
	(3.84)	(2.56)
Controls	N	Y
Fixed Effects	Country, month	Country, month
R^2	3.71%	5.81%
N	9,986	9,547

Panel C	Net Fixed income Fund Flows_t	Net Fixed income Fund Flows_t
VSI_{t-1}	-0.04***	-0.02**
	(-2.96)	(-2.10)
Controls	N	Y
Fixed Effects	Country, month	Country, month
R^2	2.27%	3.63%
N	9,986	9,547

Panel D	Net Hybrid Fund Flows$_t$	Net Hybrid Fund Flows$_t$
VSI_{t-1}	0.05***	0.04***
	(4.22)	(2.81)
Controls	N	Y
Fixed Effects	Country, month	Country, month
R^2	2.99%	4.72%
N	9,986	9,547

Panel E	Gov Bond RET$_t$	Gov Bond RET$_t$
VSI_{t-1}	-0.04***	-0.03***
	(-3.58)	(-2.64)
Controls	N	Y
Fixed Effects	Country, month	Country, month
R^2	1.89%	3.02%
N	6,240	5,962

Table 11: Factors that influence videos and views

This table reports which factors that influence videos and views. The dependent variable in Panel A is the Log (No. Videos) and the dependent variable in Panel B is the Log (No. Views) are the number of short videos and the number of views for a country. In column (1), the day-of-week (from Monday to Sunday except Wednesday) is an indicator variable that equals 1 in the day-of-week. For example, the Monday is an indicator variable that equals 1 on Monday. In column (2), EPU is the weekly economic policy uncertainty, VIX is the weekly implied volatility, ADS is the weekly macroeconomic activity, and RET is the weekly stock market returns. In column (3), DCC is the average daily deseasonalized cloud cover over the week, and COVID is the weekly containment and closure index. In column (4), $Loss_{i,t}$ equals one if country i loses a match in week t and zero otherwise. $Win_{i,t}$ equals one if country i wins a match in week t and zero otherwise. We collect the results of the knockout stage games played by our sample countries in World Cup 2018; European Championship 2020; Copa América 2019 and 2021; and Asian Cup 2019. In columns (1), the regressions include country and week fixed effects. In columns (2), (3), and (4), the regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

Panel A: Factors that influence the number of videos

World market	log (No. Videos)	log (No. Videos)	log (No. Videos)	log (No. Videos)
Monday	-0.07***			
	(-2.98)			
Tuesday	0.01			
	(0.26)			
Thursday	0.01			
	(0.73)			
Friday	0.09***			
	(2.88)			
Saturday	-0.01			
	(-0.18)			
Sunday	0.03			
	(1.78)			
EPU		0.08		
		(3.70)		
VIX		-0.02		
		(-0.83)		
ADS		0.03		
		(1.18)		
RET		0.04		
		(1.38)		
DCC			-0.08***	
			(-3.13)	
Covid			-0.03***	
			(-2.76)	
$Loss_{i,t}$				-0.10***
				(-3.17)
$Win_{i,t}$				0.06*
				(1.92)
Fixed Effects	Country, week	Country, month	Country, month	Country, month
R^2	0.97%	5.29%	2.83%	2.08%
N	70,081	9,984	9,984	9,984

Panel B: factors that influence the number of views				
World market	log (No. Views)	log (No. Views)	log (No. Views)	log (No. Views)
Monday	-0.25***			
	(-3.40)			
Tuesday	-0.02			
	(-0.22)			
Thursday	0.05			
	(0.75)			
Friday	0.22***			
	(2.76)			
Saturday	0.10**			
	(2.09)			
Sunday	0.11**			
	(1.98)			
EPU		0.34***		
		(3.52)		
VIX		-0.08		
		(-0.86)		
ADS		0.11		
		(1.13)		
RET		-0.13		
		(-1.40)		
DCC			-0.25***	
			(-3.03)	
Covid			-0.15***	
			(-2.98)	
$Loss_{i,t}$				-0.39***
				(-2.84)
$Win_{i,t}$				0.19*
				(1.82)
Fixed Effects	Country, week	Country, month	Country, month	Country, month
R^2	1.13%	5.65%	3.03%	2.76%
N	70,081	9,984	9,984	9,984

Table 12: VSI and MSI

This table reports the relation between weekly stock returns and VSI and MSI[1]. The dependent variable is the weekly stock market return (RET). In columns 1 and 2, we use 38 countries to run the regression; in columns 3 and 4, we use only developed countries; and in columns 5 and 6, we use only developing countries. The independent variable of interest, VSI is weekly change in the equal-weighted of short videos' sentiment in a week for a country. The control variables include the five lagged weekly returns for country i (RET_t, RET_{t-1}, …, RET_{t-4}), lagged implied volatility (VIX), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), the average daily change in deseasonalized cloud cover over the week (ΔDCC), and the weekly music sentiment index (MSI). The dependent variable is US-dollar market returns. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. There are 38 countries in the sample. The sample period is from July 1, 2017, to December 31, 2020.

	World market		Developed market		Emerging market	
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-0.89***	-0.78***	-1.04***	-0.86***	-0.76***	-0.68***
	(-9.09)	(-8.82)	(-7.94)	(-6.01)	(-6.76)	(-6.90)
ΔEPU_t		-2.43		-2.61		-1.94
		(-1.38)		(-1.27)		(-1.60)
VIX_t		4.61**		4.34**		2.51**
		(2.34)		(2.41)		(2.34)
ΔADS_t		0.34**		0.36**		0.26*
		(2.00)		(2.07)		(1.87)
ΔDCC_t		-0.86		-1.13		-0.74
		(-1.29)		(-1.57)		(-1.30)
RET_t		0.01		-0.01		0.01
		(0.17)		(-0.22)		(0.41)
RET_{t-1}		0.04		0.05		0.05
		(1.42)		(0.85)		(1.46)
RET_{t-2}		0.00		0.00		0.00
		(-0.10)		(-0.05)		(-0.18)
RET_{t-3}		0.01		0.00		0.02
		(0.23)		(-0.03)		(0.48)
RET_{t-4}		-0.02		-0.02		-0.03
		(-0.59)		(-0.48)		(-0.74)
MSI_t	-4.13***	-4.37***	-4.55***	-4.50***	-3.83***	-3.31***
	(-3.61)	(-2.74)	(-4.30)	(-3.66)	(-3.27)	(-2.72)
Fixed Effects	Country, month	Country, month	Country, month	Country, month	Country, month	Country, month
R^2	5.03%	8.90%	5.61%	10.34%	4.69%	8.14%
N	6,883	6,580	3,298	3,153	3,585	3,427

[1] We thank Alex Edmans to provide the music sentiment index (MSI) data.

Table 13: VSI and stock market returns: U.S. sample

This table reports the relation between U.S. stock market returns and monthly VSI. The dependent variable is the weekly stock market return (RET). VSI is the monthly video sentiment index. The control variables are: BW_{Sent}[2], the Baker and Wurgler (2006) sentiment index; PLS_{Sent}[3], the Huang et al. (2015) PLS sentiment index; the short interest index of Rapach et al. (2016), the PLS anomalies index of Dong et al. (2022), and PLS ESG index[4] of Chang et al. (2022). Newey and West (1987) corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: USA market return prediction

USA index	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
VSI_t	-1.02***	-1.01***	-1.05***	-1.09***	-1.11***	-0.99***	-0.90***
	(-3.64)	(-3.47)	(-3.58)	(-3.51)	(-3.45)	(-3.69)	(-3.06)
BW_{Sent}	-0.15						-0.14
	(-0.60)						(-0.39)
PLS_{Sent}		-0.38					-0.30
		(-1.29)					(-1.15)
Short interest			-0.31				-0.27
			(-1.12)				(-0.84)
PLS anomalies				-0.50			-0.42
				(-1.26)			(-0.86)
MSI					-3.10***		-2.50**
					(-2.71)		(-2.19)
PLS ESG						0.82***	0.66***
						(3.97)	(3.42)
R^2	7.18%	7.44%	7.31%	7.56%	7.65%	7.69%	8.41%

Panel B: Two-Stage Least Squares in USA market

	First stage (VSI)	Second Stage (RET_{t+1})
Predicted VSI		-2.87**
		(-2.08)
I_Dist	-0.52***	
	(-3.37)	
First-stage F-statistic	5.93	
R^2	2.18%	1.35%

Panel C: Two-Stage Least Squares in world market

	First stage (VSI)	Second Stage (RET_{t+1})
Predicted VSI		-1.96***
		(-2.77)
ΔDCC	-0.03***	
	(-3.82)	
First-stage F-statistic	8.44	
R^2	2.20%	1.08%

[2]We thank Jeffrey Wurgler to provide the BW sentiment data.

[3]We thank Guofu Zhou to provide the aggregate PLS sentiment data, the aggregate short interest data, and the aggregate PLS anomalies data.

[4]Ran Chang has the aggregate PLS ESG data.

Table 14: VSI and Long-term Stock Market Return

This table reports the regression estimates of long-term stock market returns on lagged short-video sentiment. The dependent variable includes one-week returns, two-week returns, one-month returns, two-month returns, and three-month returns. Panel A-C reports regression results of world market, developed market, and emerging markets. We include control variables of Table 4. VSI is the weekly change in the views-weighted video sentiment for a country. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from July 1, 2017, to June 30, 2021.

Panel A: World market					
	h = 1w	h = 2w	h = 1m	h = 2m	h = 3m
VSI	-0.55***	-0.94***	-1.59***	-2.70***	-3.45***
	(-7.67)	(-8.34)	(-6.13)	(-4.91)	(-3.92)
Controls	Y	Y	Y	Y	Y
Panel B: Developed market					
	h = 1w	h = 2w	h = 1m	h = 2m	h = 3m
VSI	-0.59***	-1.08***	-1.83***	-3.11***	-3.96***
	(-5.31)	(-9.46)	(-7.05)	(-5.64)	(-4.51)
Controls	Y	Y	Y	Y	Y
Panel C: Emerging market					
	h = 1w	h = 2w	h = 1m	h = 2m	h = 3m
VSI	-0.44***	-0.79***	-1.35***	-2.30***	-2.93***
	(-5.93)	(-6.99)	(-5.21)	(-4.17)	(-3.34)
Controls	Y	Y	Y	Y	Y

Table 15: VSI and Out-of-sample Forecasting Results

This table reports the out-of-sample R^2_{os}'s and MSFE-adjusted statistics for predicting the average stock market returns over the prediction horizon h based on the VSI. h = 1 week, 2 weeks, 1 month, 2 months, and 3 months. Panel A shows results of using GDP average of each country. Panel B shows results of using simple average of each country. All of the predictors and regression slopes are estimated recursively using the data available at the forecast formation time t. The out-of-sample period is from January 1, 2019 to June 30, 2021. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: GDP average of each country						
	World market		Developed market		Emerging market	
	R^2_{os} (%)	MSFE-adjusted	R^2_{os} (%)	MSFE-adjusted	R^2_{os} (%)	MSFE-adjusted
h = 1w	2.07	3.01	2.48	3.77	1.63	2.48
h = 2w	3.02	3.27	3.76	4.26	2.42	2.66
h = 1m	4.63	3.92	5.40	4.24	3.69	2.99
h = 2m	6.96	3.93	8.12	4.74	5.56	3.24
h = 3m	7.93	4.51	9.43	5.42	6.32	3.71
Panel B: Simple average of each country						
	World market		Developed market		Emerging market	
	R^2_{os} (%)	MSFE-adjusted	R^2_{os} (%)	MSFE-adjusted	R^2_{os} (%)	MSFE-adjusted
h = 1w	1.92	2.77	2.27	3.40	1.49	2.26
h = 2w	2.81	3.04	3.33	4.00	2.22	2.47
h = 1m	4.18	3.38	4.61	3.78	3.42	2.66
h = 2m	6.42	3.72	7.61	4.28	5.05	2.96
h = 3m	6.83	3.94	8.78	4.70	5.89	3.28

Table 16: VSI and Asset Allocation Performance

This table reports the annualized CER gains (in percentage) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of five, who allocates assets between the market and risk-free bills using the out-of-sample forecasts based on VSI over the prediction horizon h. h = 1 week, 2 weeks, 1 month, 2 months, and 3 months. Panel A shows results of using GDP average of each country. Panel B shows results of using simple average of each country. We consider three scenarios: zero transaction cost, 25 basis points, and 50 basis points transaction cost per transaction. The out-of-sample period is from January 1, 2019 to June 30, 2021.

Panel A: GDP average of each country

	World market		Developed market		Emerging market	
	CER Gain (%)	Sharpe Ratio	CER Gain (%)	Sharpe Ratio	CER Gain (%)	Sharpe Ratio
No transsaction cost	3.00	0.88	3.56	1.00	2.55	0.72
25bps transsaction cost	2.79	0.80	3.30	0.90	2.37	0.65
50bps transsaction cost	2.52	0.71	3.02	0.81	2.10	0.60

Panel B: Simple average of each country

	World market		Developed market		Emerging market	
	CER Gain (%)	Sharpe Ratio	CER Gain (%)	Sharpe Ratio	CER Gain (%)	Sharpe Ratio
No transsaction cost	2.62	0.75	3.15	0.86	2.20	0.62
25bps transsaction cost	2.39	0.71	2.94	0.78	2.04	0.57
50bps transsaction cost	2.15	0.63	2.70	0.70	1.85	0.53

Table 17: Global Sentiment and Stock Returns

This table reports the regressions of the next week's market returns on global VSI and local VSI. We run the following regression: $RET_{i,t+1} = a + bGVSI_t + cLVSI_i, t + CONTROLS$, where global short video sentiment ($GVSI_t$) is the simple average of market sentiment ($VSI_{i,t}$) of the 48 countries, except country i, in week t. Local sentiment ($LVSI_{i,t}$) of country i is the regression residual of country i's market sentiment ($VSI_{i,t}$) on global sentiment ($GVSI_t$). The sample period is from July 1, 2017, to June 30, 2021. World market uses all the 48 countries. Developed market and emerging market focus on developed and emerging countries, respectively. We also report the difference in coefficients on global and local VSI between developed and emerging countries. Standard errors are clustered at the country and month levels. t-statistics are reported in parentheses.

	World market		Developed market	Emerging market
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
GVSI	-4.28***	-4.13***	-4.42***	-3.32***
	(-6.27)	(-5.65)	(-3.91)	(-4.33)
LVSI	-0.46***	-0.44***	-0.47***	-0.35***
	(-7.31)	(-6.59)	(-4.45)	(-5.05)
Diff in GVSI			-1.10*	
[p-value]			[0.08]	
Diff in LVSI			0.12	
[p-value]			[0.17]	
ΔEPU_t		-2.48	-2.40	-2.29
		(-1.31)	(-1.64)	(-1.44)
VIX_t		4.15**	4.48**	3.01**
		(2.20)	(2.23)	(2.20)
ΔADS_t		0.28**	0.31**	0.27**
		(2.11)	(2.30)	(2.28)
ΔDCC_t		-0.85	-1.18	-0.66
		(-1.43)	(-1.39)	(-1.32)
RET_t		0.01	-0.01	0.01
		(0.16)	(-0.19)	(0.44)
RET_{t-1}		0.06	0.05	0.07
		(1.19)	(0.75)	(1.60)
RET_{t-2}		0.00	0.00	-0.01
		(-0.11)	(-0.06)	(-0.15)
RET_{t-3}		0.01	0.00	0.02
		(0.27)	(-0.03)	(0.53)
RET_{t-4}		-0.02	-0.02	-0.02
		(-0.56)	(-0.41)	(-0.66)
Fixed Effects	Country, month	Country, month	Country, month	Country, month
R^2	2.73%	5.59%	8.58%	4.16%
N	9,936	9,499	4,552	4,948

Table 18: Global Sentiment and Global returns

This table reports the regressions of the next week's global market returns on global VSI. We run the following regression: $GRET_{i,t+1} = a + bGVSI_t + CONTROLS$, where global short video sentiment ($GVSI_t$) is the simple average of market sentiment ($VSI_{i,t}$) of the 48 countries. Global returns ($GRET_{i,t+1}$) is the simple average of market returns ($RET_{i,t}$) of the 48 countries. Brackets below the slope estimates report the t-statistics based on the Newey and West (1987) standard errors. The sample period is from July 1, 2017, to June 30, 2021.

	Glocal market returns	
	$GRET_{t+1}$	$GRET_{t+1}$
$GVSI_t$	-0.91***	-0.83***
	(-5.76)	(-4.98)
ΔEPU_t		-2.67
		(-1.34)
VIX_t		2.08
		(1.20)
ΔADS_t		0.35***
		(2.89)
ΔDCC_t		-1.15
		(-0.86)
RET_t		0.01
		(0.11)
RET_{t-1}		0.05
		(1.53)
RET_{t-2}		-0.01
		(-0.14)
RET_{t-3}		0.01
		(0.20)
RET_{t-4}		-0.01
		(-0.55)
R^2	6.34%	8.78%
N	208	208

Appendix

Figure A1: Category of short videos

Figure A1 shows the number of videos and views in each category of short videos in second quarter of 2021. The vertical axis represents the number of videos and views. The horizontal axis represents each category of short videos.

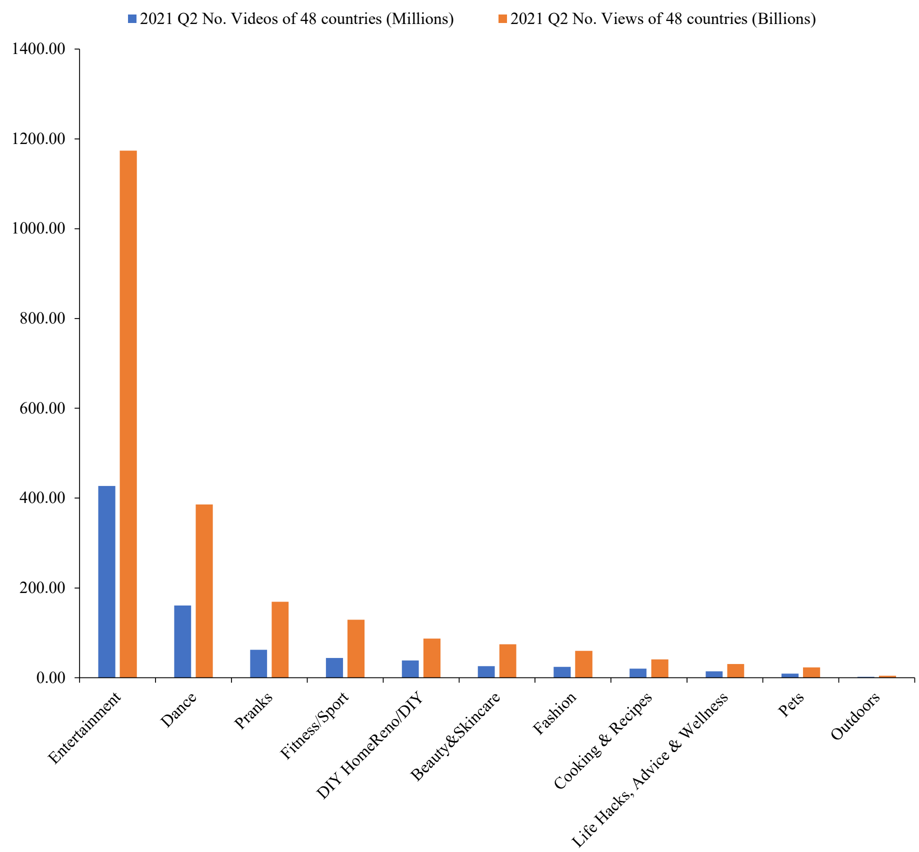
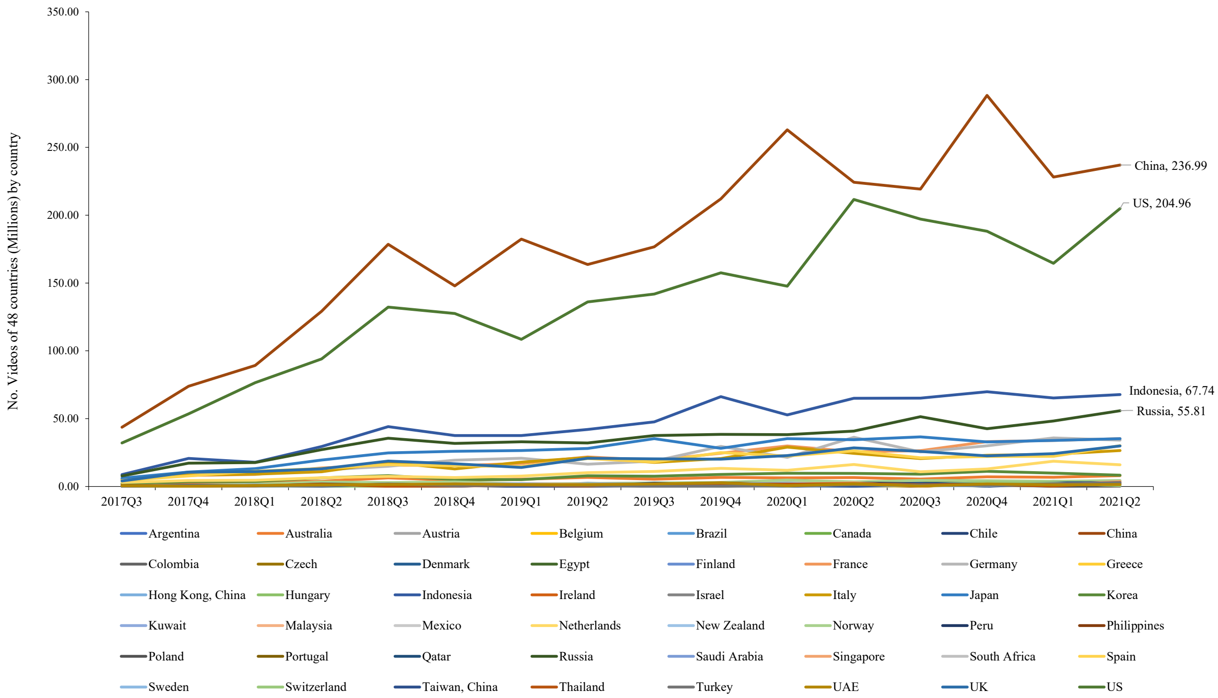


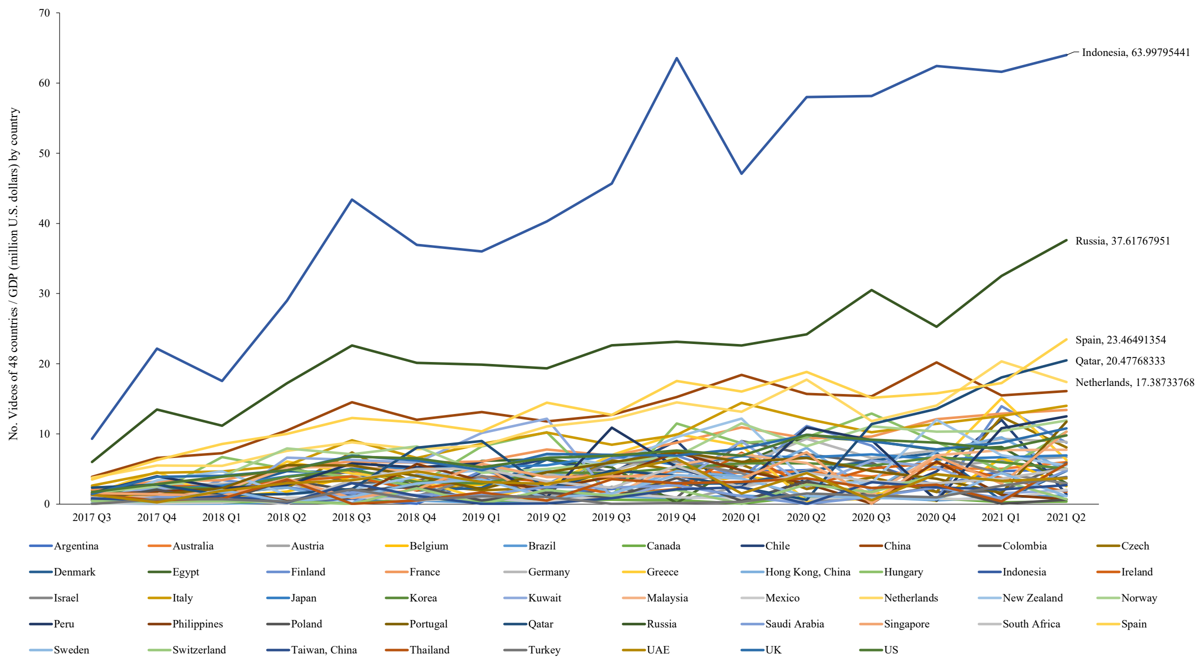
Figure A2: Number of videos by country

Panel A shows the number of videos each quarter by country. Panel B shows the number of videos over the GDP each quarter by country. Panel C shows the number of videos over the population each quarter by country. The horizontal axis represents each quarter in the sample period.

Panel A



Panel B



Panel C

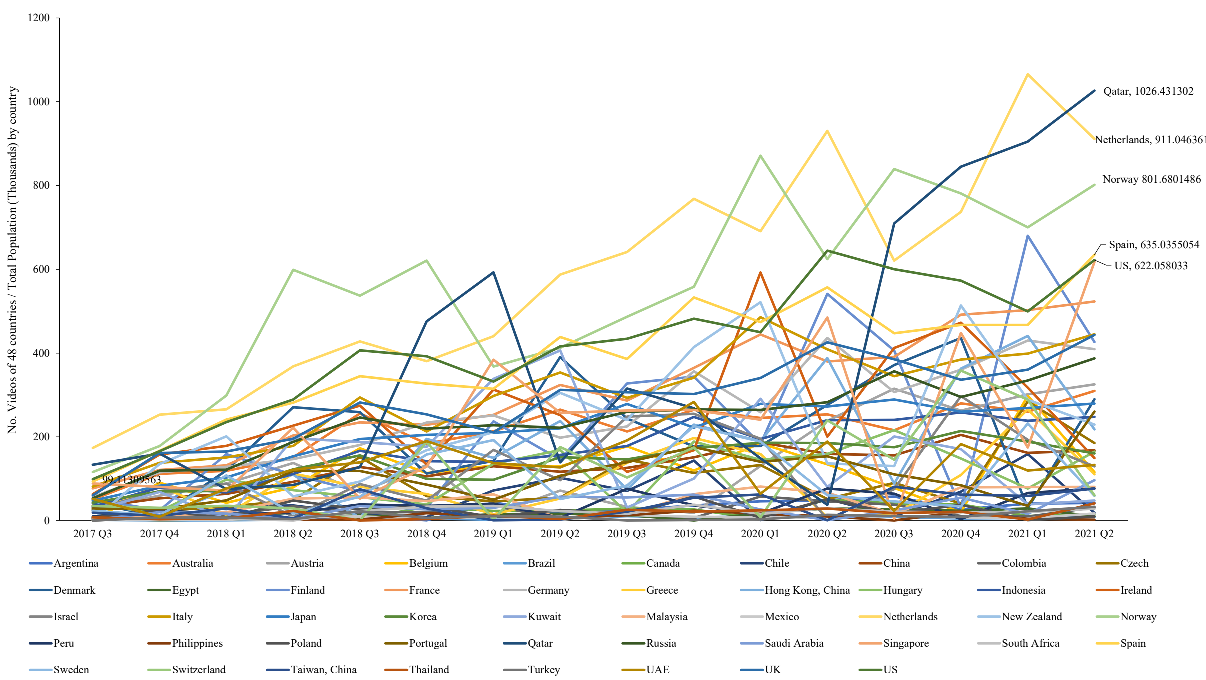
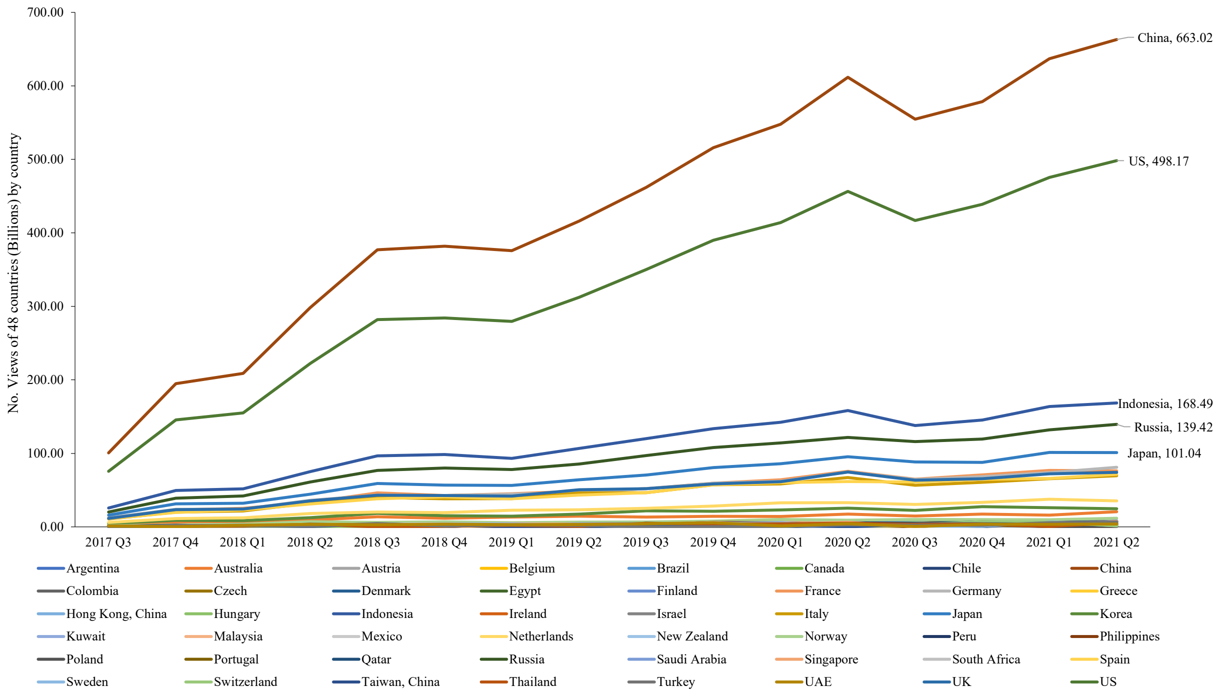


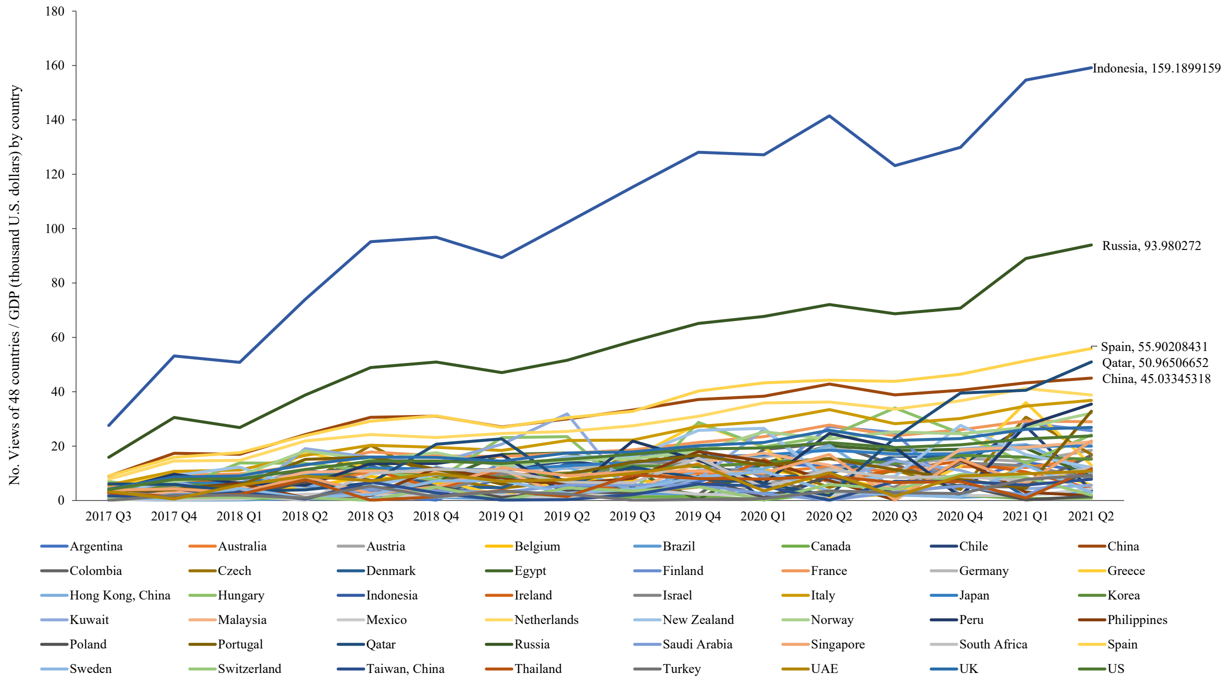
Figure A3: Number of views by country

Panel A shows the number of views each quarter by country. Panel B shows the number of views over the GDP each quarter by country. Panel C shows the number of views over the population each quarter by country. The horizontal axis represents each quarter in the sample period.

Panel A



Panel B



Panel C