Information Demand during the COVID-19 Pandemic

Hang Dong[a], Javier Gil-Bazo[b,c], Raluca Ratiu[a]

[a] IE Business School, IE University, Spain;

[b] Universitat Pompeu Fabra; [c] Barcelona School of Economics, Spain

Abstract

We investigate the demand for financial information during the initial months of the COVID-19 pandemic. Using Google search data for individual stocks, we show that the Abnormal Search Volume Index declined significantly between March and June of 2020. We find a similar effect around earnings announcements dates, which confirms that the demand for financial information by retail investors declined during the pandemic. Our results are indicative of potentially important consequences for information diffusion, price discovery and market efficiency under extreme uncertainty. We discuss possible explanations for these results.

Keywords: Information Demand; Google Search; COVID-19.

Information Demand during the COVID-19 Pandemic

1. Introduction

The COVID-19 pandemic (henceforth, the pandemic) caused an array of changes in financial markets around the world. No individuals, companies or countries remained immune to the uncertainty created by the pandemic. Greater uncertainty about future company earnings was best reflected by the VIX index reaching in March 2020 its highest level in more than a decade. In this paper, we ask whether and how the pandemic impacted retail investors' demand for financial information in these times of extreme uncertainty. To answer this question, we use Google search data for individual stocks to explore the link between the pandemic, and more specifically its severity in the US, and the demand for financial information.

The pandemic affected both the willingness and ability of retail investors to collect and process financial information. On the one hand, greater uncertainty provided investors with stronger incentives to gather information. Indeed, financial information can help investors identify which firms are more vulnerable to the pandemic, as well as which firms may benefit from the opportunities created by the new situation. This information includes exposure to the effects of lockdowns and travel restrictions, as well as the financial conditions that firms experienced prior to the pandemic. On the other hand, the pandemic had a profound and direct impact on individuals' personal lives. Adapting to the new circumstances (school closures, work-from-home, lockdowns, new health practices) imposed large demands on individuals' time and attention, which may have reduced their commitment to other, less essential, activities. Moreover, social isolation and uncertainty about the future resulted in increased levels of anxiety and depression, which are likely to alter individuals' ability to make important decisions (Brodeur et al., 2021). Whether the net impact of the pandemic on the demand for financial information was positive or negative is ultimately an empirical question.

To answer this question, we follow previous studies on information demand (Da et al., 2011; Drake et al., 2012, 2017) , and use the Abnormal Google Search Volume Index (ASVI) as a proxy for financial information demand. In particular, we study how stock-specific ASVI changed during the initial months of the COVID-19 pandemic, i.e., March to June 2020. To proxy for the severity of the pandemic, we use four different variables: Number of confirmed cases; Stringency index; Infection Index; and the COVID-19 time dummy. We define these variables in section 2.2.

In our empirical analysis, we first study how ASVI changes during the pandemic controlling for stock characteristics, and particularly characteristics related to the supply of information and trading activity. We find that ASVI decreases in the initial months of the pandemic: abnormal weekly searches of a given stock are 0.37 standard deviations lower in the pandemic months than in the pre-pandemic period. Second, we follow Drake et al. (2012) and compare ASVI around earnings announcements before and during the pandemic. We find that ASVI around earnings announcements decreases during the pandemic, consistent with a decline in the demand for financial information. We also test for potential heterogeneity in the evolution of searches across stocks. Finally, we discuss several possible explanations for our results in section 4. Based on previous literature and available empirical evidence, we argue that individuals shifted their search interests from financial information to information related to the pandemic and its direct effects on their personal lives.

Our results are of special interest to regulators and policy makers. In particular, our results suggest that, despite the strong benefits of reducing asymmetric information in times of uncertainty, investors may not be able to collect and process financial information when extreme circumstances affect not only financial markets but also their personal lives. Regulators and policy makers should therefore acknowledge that investors' limitations are aggravated during such times and consider alternatives to the traditional ways of disseminating information aimed at overcoming investors' difficulties in using financial information when it is most needed.

2. Data

2.1 Dependent Variable: ASVI

We obtain the Google Search Volume Index (SVI) from Google Trends following the procedure of Da et al. (2011) and Drake et al. (2012). We focus on S&P 500 companies and use stock tickers as the search keywords. The original SVI data includes weekly SVI covering S&P 500 constituents, at the national level, spreading from July 2019 to June 2020.[1] We remove 32 tickers that

[1] The data was downloaded for the period of January 2018 to June 2020 to calculate moving averages.

potentially have alternative meanings. We also require all observations to appear in other data sources, i.e., Thomson Reuters' Refinitiv Eikon and I/B/E/S. The clearing data process leaves us with 16,268 observations covering 459 stocks and 48 weeks. Similar to other studies using Google search data, our variable of interest is the abnormal search volume (ASVI), that is, the increase in SVI relative to expected SVI. More specifically, we define ASVI for a given stock and week as the natural logarithm of SVI for that stock and week minus the natural logarithm of the average SVI in the previous 10 weeks.[2] That is,

$$ASVI_{i,w} = ln(SVI_{i,w}) - ln(\overline{SVI_{i,w}}) \quad (1)$$

Where $ASVI_{i,w}$ denotes the abnormal search volume for stock i in week w; $SVI_{i,w}$ is the raw Google Search Volume Index for stock i in week w, and $\overline{SVI_{i,w}}$ is the average of the raw SVI during the previous 10 weeks. Using the detrended ASVI measure instead of the raw SVI data allows us to disentangle the effect of the pandemic on searches from that of pre-pandemic trends.

2.2 Independent Variables

We use four variables to proxy for the severity of the pandemic in the US. The first one is the number of confirmed cases, as reported by the Oxford COVID-19 Government Response Tracker. Following Hale et al., (2021) and Baker et al., (2020), we also collect data on the Stringency Index and the Infectious Disease Equity Market Volatility. The stringency index measures how the government responds to the pandemic, including school closures, workplace closures and travel bans. This information is available from the same database. The Infectious Disease Equity Market Volatility quantifies the role of the pandemic and other infectious diseases in U.S. stock market volatility. We obtain the data from the Economic Policy Uncertainty webpage.[3] We use the natural logarithm of one plus each proxy to normalize the distribution following Drake et al., (2012) and denote them as $NumCases_w$, $Stringency_w$, and $InfectIndex_w$. Our last proxy is a dummy variable, $Covid_w$, that equals one when an observation is recorded after the March 13 of 2020, and zero otherwise. We choose March 13 as the starting date because it is the day the US declared a national emergency. However, our results are robust to choosing as the starting date the week before or the week after March 13.

---

[2] Da et al. (2011) define ASVI as the log of weekly SVI minus the log of the median SVI in the previous 8 weeks. Drake et al. (2012) define ASVI, denoted as AbSearch, as SVI on a given day minus the average SVI on the same day in the previous 10 weeks scaled by the average SVI in the previous 10 weeks and the difference in logs, which is equivalent to our definition.

[3] https://www.policyuncertainty.com/index.html

We obtain the date of earnings announcements for all firms in our sample from Compustat. We define a dummy variable, $EA_{i,w}$, that equals one if stock *i* issues an earnings announcement during week w, and zero, otherwise.

2.3 Control Variables

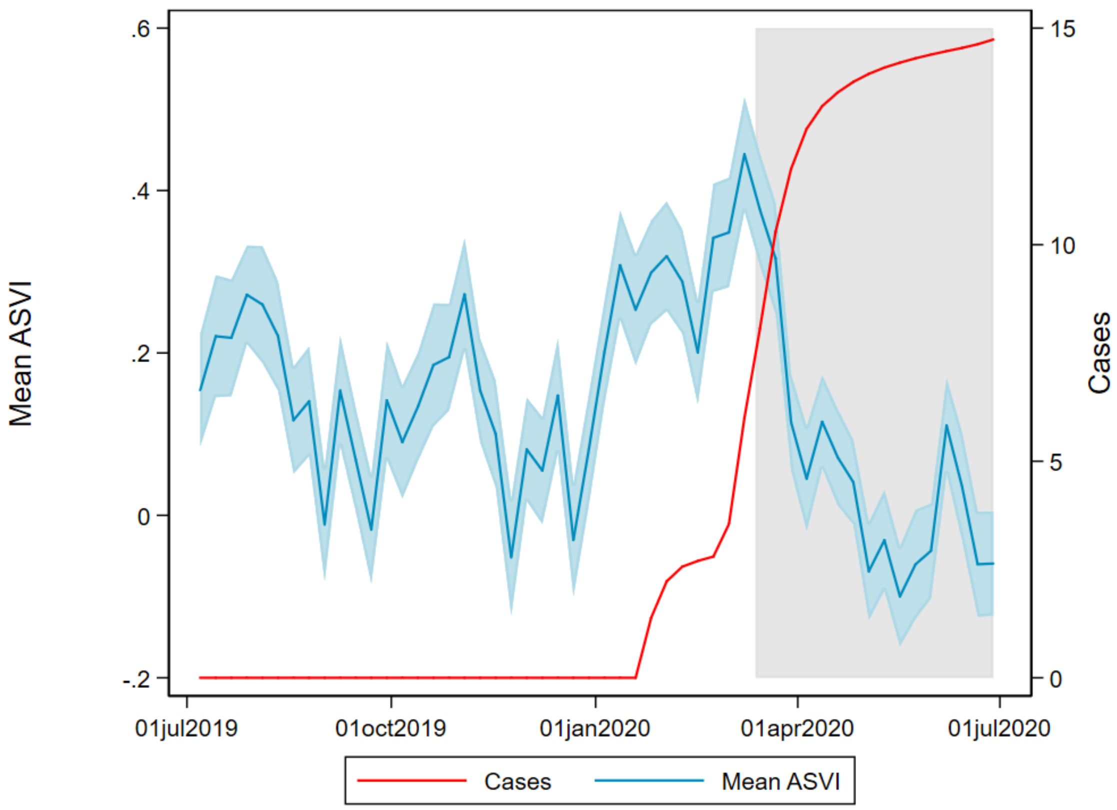
Following Drake et al. (2012), we use several variables as controls. In particular, we include: the number of news on stock *i* during week t ($NumNews_{i,w}$); the number of analysts covering stock *i* during week t ($NumAnalyst_{i,w}$); the absolute value of raw return on stock *i* during week t ($|r_{i,w}|$); the decile of the market capitalization of stock i during week t ($Size_{i,w}$); the decile of Book-to-Market ratio of stock i during week t ($BM_{i,w}$); Turnover ($Turnover_{i,w}$); and the bid-ask spread ($BAS_{i,w}$). We use the natural logarithm of one plus the variable for $NumNews_{i,w}$, $NumAnalyst_{i,w}$ and $Turnover_{i,w}$. These data are obtained from Thomson Reuters' Refinitiv Eikon. Descriptive statistics for the sample are available from the authors.

3. Empirical Method and Results

Before proceeding with the analysis, we explore the evolution of ASVI around the pandemic. Figure 1 displays the average value of ASVI across all stocks in each week of our sample period, as well as 95% confidence bounds. The Figure also reports the time-series of reported COVID-19 infections in the US (in logs), $NumCases_w$. The post-March 13 period is represented by the shaded area. The Figure shows that average ASVI experienced a sharp decline coinciding with the national emergency declaration and a rapid surge in COVID-19 infections. Whereas the value of ASVI centers around 0.2 before the pandemic, it is close to zero in the period from April to June 2020. Therefore, a visual inspection of the data suggests that the demand for financial information, as captured by abnormal searches for stocks, did not increase with the uncertainty surrounding the pandemic and in fact, it decreased fast as the disease spread.

In the following subsections, we formally test for changes in ASVI following the pandemic, while controlling for variation in stock fundamentals that determine the demand for information as well as information supply.

Figure 1: Time-series evolution of ASVI around the Pandemic



3.1 The Baseline Test

To study the link between the pandemic and stock searches, we estimate the following regression equation:

$$ASVI_{i,w} = \gamma_i + \beta_1 Pandemic_w + Controls + \varepsilon_{i,w}, \qquad (1)$$

where $ASVI_{i,w}$ is the Abnormal Google Search Volume for stock i during week w; γ_i denotes stock fixed effects that capture time-invariant determinants of searches for stocks; $Pandemic_w$ is one of four proxies for the severity of the pandemic: $NumCases_w$; $Stringency_w$; $InfectIndex_w$; and $Covid_w$. $\varepsilon_{i,w}$ is a generic error term. Control variables are described in section 2.3.

Table 1 reports the results. The estimated coefficients on all four proxies for the severity of the pandemic are negative and statistically significant. In terms of economic significance, a one standard deviation increase in $NumCases$, $Stringency$, and $InfectIndex$ leads to a decrease in

ASVI of 0.17, 0.14 and 0.11 standard deviations, respectively.[4] The estimated coefficient on $Covid_w$ suggest that ASVI is 0.24 lower in the pandemic months, which implies a decline in ASVI of 0.37 standard deviations. These effects are similar in magnitude to those of other determinants of ASVI. A one standard deviation increase in $NumAnalyst$ increases ASVI between 0.09 and 0.11 standard deviations, depending on the specification, while a one standard deviation increase in $Size$ decreases ASVI between 0.21 and 0.23 standard deviations. The results therefore suggest that search volume declined, relative to the previous months, as the pandemic unfolded in the US, and such decline was both statistically and economically significant.

Table 1: The Relation between ASVI and the Pandemic

	(1)	(2)	(3)	(4)
	$ASVI_{i,w}$			
$NumCases_w$	-0.0180***			
	(-9.94)			
$Stringency_w$		-0.0471***		
		(-5.91)		
$InfectIndex_w$			-0.0486***	
			(-3.39)	
$Covid_w$				-0.2430***
				(-8.39)
$NumNews_{i,w}$	-0.0085	-0.0105	-0.0114	-0.0058
	(-0.31)	(-0.39)	(-0.42)	(-0.21)
$NumAnalyst_{i,w}$	0.1380**	0.1570***	0.1710***	0.1370**
	(2.53)	(2.74)	(2.79)	(2.49)
$\lvert r_{iw} \rvert$	1.0060***	0.9620***	0.8450***	1.1110***
	(4.48)	(3.71)	(2.74)	(4.70)
$Size_{iw}$	-0.0503***	-0.0512***	-0.0521***	-0.0478***
	(-3.10)	(-3.11)	(-3.14)	(-3.05)
BM_{iw}	0.0067	0.0067	0.0067	0.0068
	(0.45)	(0.44)	(0.44)	(0.46)
$Turnover_{iw}$	0.1130	0.1280	0.1450	0.0944
	(1.10)	(1.17)	(1.28)	(0.97)
BAS_{iw}	0.0042	0.0070	0.0124	0.0011
	(0.29)	(0.46)	(0.74)	(0.07)
Stock FE	Yes	Yes	Yes	Yes
Clustered SE-Stock	Yes	Yes	Yes	Yes
Clustered SE-Week	Yes	Yes	Yes	Yes
Observations	16268	16268	16268	16268
Adj. R^2 (%)	27.34	26.72	26.17	27.53

[4] The standard deviations of $NumCases_w$, $Stringency_w$, $InfectIndex_w$, and ASVI are 6.05, 1.92, 1.45, and 0.65, respectively.

3.2 Information Demand around Earnings Announcements during the Pandemic

As argued by Drake et al (2012), Google searches are best identified with demand for financial information when a corporate event takes place. Therefore, we explore how ASVI changes around earnings announcements in the pandemic. For the sake of brevity, we focus on the number of cases as a proxy for the severity of the pandemic. We regress ASVI on the $NumCases_w$, an earnings announcement dummy, and their interaction term:[5]

$$ASVI_{i,w} = \gamma_i + \beta_1 NumCases_w + \beta_2 EA_{i,w+p} + \beta_3 NumCase_w \times EA_{i,w+p} + Controls + \varepsilon_{i,w} \qquad (3)$$

Where γ_i denotes stock fixed effects and $EA_{i,w+p}$ is a dummy variable that equals one if there is an earnings announcement for stock *i* in week w+p. We consider three different values for p: -1, (one week before the announcement), 0 (the week when the announcement is released), and 1 (one week after the announcement). We also define another variable, $EA_{i,w-1/w+1}$, that equals one if there is an earnings announcement for stock *i* from week *w-1* to week w+1, and zero otherwise.

Table 2 reports the estimation results. The coefficients on $EA_{i,w+p}$ and on $EA_{i,w-1/w+1}$ are positive and significant, except that of $EA_{i,w-1}$, consistent with the results in Drake et al. (2012). Our main variables of interest are the interaction terms. The coefficients of the interaction terms are again negative and significant, which suggests that financial information demand around earnings announcements decreases during the pandemic.

[5] Results for the other pandemic proxies are qualitatively similar and available from the authors upon request.

Table 2: The ASVI around Earnings Announcements during the Pandemic

	(1)	(2)	(3)	(4)
	$ASVI_{i,w}$			
$NumCases_w$	-0.0175***	-0.0180***	-0.0178***	-0.0168***
	(-9.28)	(-9.77)	(-14.75)	(-13.52)
$EA_{i, w-1}$	0.0162			
	(0.60)			
$EA_{i, w}$		0.0688*		
		(1.99)		
$EA_{i, w+1}$			0.313***	
			(9.20)	
$EA_{i, w-1/w+1}$				0.160***
				(6.36)
$EA_{i, w-1} * NumCases_w$	-0.0058**			
	(-2.46)			
$EA_{i, w} * NumCases_w$		-0.0026		
		(-0.87)		
$EA_{i, w+1} * NumCases_w$			-0.0146***	
			(-2.94)	
$EA_{i, w-1/w+1} * NumCases_w$				-0.0093***
				(-2.72)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Clustered SE-Stock	Yes	Yes	Yes	Yes
Clustered SE-Week	Yes	Yes	Yes	Yes
Observations	16268	16268	16268	16268
Adj. R^2 (%)	27.35	27.38	28.37	27.95

3.3 Heterogenous Effects

Our results suggest that abnormal searches for stocks declined *on average* with the pandemic. However, one could expect that abnormal searches evolved differently for different firms since the potential impact of the pandemic was also heterogeneous across stocks. In particular, while some firms were more vulnerable to the pandemic, others actually benefitted from it. To explore this possibility, we rank stocks based on their return between March 13 and June 30 and sort them into 5 quintile groups (5 = highest and 1 = lowest). We then estimate again regression equation (1) augmented with interaction variables between the search variable, ASVI, and dummy variables for each group (the bottom decile dummy is omitted). Table 3 reports the results. The estimated coefficients of the interaction terms are all statistically insignificant. Therefore, the decline in overall abnormal searches for stock information appears to have been similar for pandemic winners, losers, as well as stocks less affected by the pandemic.

Table 3: Changes in ASVI and Financial Performance during the Pandemic

	(1)	(2)	(3)	(4)
	Proxy for the severity of the pandemic			
	NumCases$_w$	*Stringency*$_w$	*InfectIndex*$_w$	*Covid*$_w$
Proxy	-0.0162***	-0.0401***	-0.0388**	-0.232***
	(-6.62)	(-4.03)	(-2.23)	(-6.41)
Group 2 * Proxy	-0.00245	-0.00994	-0.0127	-0.0116
	(-0.74)	(-0.99)	(-1.02)	(-0.29)
Group 3 * Proxy	0.000292	-0.0038	-0.00862	0.0237
	-0.1	(-0.39)	(-0.63)	-0.61
Group 4 * Proxy	-0.00277	-0.00805	-0.00949	-0.0211
	(-0.89)	(-0.85)	(-0.79)	(-0.54)
Group 5 * Proxy	-0.00422	-0.0127	-0.0173	-0.0473
	(-1.21)	(-1.20)	(-1.29)	(-1.07)
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Clustered SE-Stock	Yes	Yes	Yes	Yes
Clustered SE-Week	Yes	Yes	Yes	Yes
Observations	16268	16268	16268	16268
Adj. R^2	0.2734	0.2672	0.2617	0.2754

3.4 Robustness Checks

Following Drake et al., (2012), we have chosen a 10-week moving average as a benchmark for search volume. As explained above, by detrending searches, we reduce the risk that our results are driven by a possible pre-trend in Google searches. However, it is a priori unclear what the optimal length of the rolling window should be. As a robustness test, we repeat the analysis for various additional lengths ranging from 15 to 25 weeks. The results (available upon request) are qualitatively similar, although weaker for the longest horizons.

Another potential concern is whether our results are explained by an overall decrease in Google searches. Indeed, there is evidence that individuals in the US and elsewhere in the world changed their technology-related habits because of the pandemic and its associated lockdowns. For instance, average time spent watching Netflix (worldwide) increased from 2 hours per day on average in

2019 to 3.2 hours in 2020 (data up to April).[6] Usage of social media platforms also increased during the pandemic.[7] To verify if this extra time spent watching streaming videos or using social media came at the expense of time spent searching on the Internet, we have obtained data on online queries in the US powered through the top four search engines (Google sites, Microsoft sites, Verizon media, and Ask network).[8] The data, which are reported quarterly, show that total searches not only did not decrease during the pandemic, but actually increased. More specifically, there were 20.4 billion core searches in April 2020 and 19.06 billion searches in January 2020, as opposed to an average of 16.05 billion searches in 2019. We reach an identical conclusion if we focus on Google searches exclusively. Therefore, although the technological habits of the population changed during the period, our results are not explained by a decline in overall searches. Consequently, individuals must have substituted searches for financial information with searches for other types of information.

4. Discussion

In this section, we discuss different explanations for our results. As argued in the introduction, the pandemic and its associated lockdowns may have changed individuals' ability and willingness to engage in the process of collecting and processing financial information. Indeed, the pandemic imposed new demands on individuals' time and attention. Also, lockdowns and social distancing may have had important negative effects on individuals' well-being. However, we also consider two alternative hypotheses. First, it could be that investors consciously chose to avoid risky, potentially negative information about the stock market. This is the "ostrich effect," which has been shown to affect investor behavior and price formation (Galai & Sade, 2006; Karlsson et al., 2009). Second, it is possible that financial information became less relevant about stock values in the new reality.

Although we do not formally test these hypotheses, we discuss some recent academic and anecdotal evidence that may shed light on the reasons behind our findings. Consistent with the

[6] Dean (2021), "Netflix Subscriber and Growth Statistics: How Many People Watch Netflix in 2021?," Backlinko.com (https://backlinko.com/netflix-users).
[7] Nix (2021), "Facebook's Sales, Users Jump as Pandemic Habits Persist," Bloomberg.com (https://www.bloomberg.com/news/articles/2021-04-28/facebook-s-sales-users-jump-as-gains-during-pandemic-persist).
[8] Data from Comscore via Statista (https://www.statista.com/statistics/265796/us-search-engines-ranked-by-number-of-core-searches/).

view that the pandemic lockdown imposed a large burden on many individuals time and energy, Deryugina et al., (2021) survey almost 20,000 academics and document a substantial increase in the amount of time devoted to childcare and housework at the expense of time spent doing research during the pandemic. The effects concentrate in parents of young children and are larger for women. Barber et al., (2021) find similar results for Finance academics. Also, Brodeur et al., (2021) document a large increase in the intensity of Google searches for terms associated with loneliness, worry and sadness. Interestingly, even software engineers, who are used to working with digital tools and often remotely, suffered from distractions, stress, and anxiety (Russo et al., 2021). However, individuals did not respond to the challenges of the new situation by avoiding negative information. To the contrary, the evidence suggests that people actively sought information on the new disease, its evolution, and its consequences, as evidenced by the fact that the number of visitors to the website of the Center for Disease Control and Prevention jumped to over 49 million in March 2020 from only 5 million in December 2019.[9] Moreover, an inspection of top Google searches during 2020 reveals that the terms "Coronavirus," "Coronavirus updates," and "Coronavirus symptoms" were among the five most searched terms during 2020.[10] Other popular searches suggest that people learned new skills that helped them stay safe (e.g., "How to make hand sanitizer," "How to make a mask with fabric"). Taken together, the evidence seems to support the hypothesis that the pandemic challenged individuals' lives in fundamental ways, changing their priorities and concerns. The evidence, however, does not seem consistent with the ostrich effect.

As for the hypothesis that historical financial information became less relevant during the pandemic, Ding et al., (2021) document that firm characteristics before 2020 strongly explain differences in stock returns during the January-May 2020 period. More specifically, the authors find that firms with better financial conditions and more CSR activities experienced better stock returns while those more exposed to COVID-19 through supply chains and customers underperformed. This evidence does not appear to support the hypothesis that financial information became disconnected from financial performance during the COVID-19 crisis.

In sum, searches for stocks declined during the pandemic despite an increase in overall searches. The evidence is not consistent with the ostrich effect (investors avoiding negative information) or with a decrease in the predictive ability of account information. Instead, we believe that many

[9] https://www.websiteiq.com/domain/cdc.gov/
[10] https://trends.google.com/trends/yis/2020/US/

investors have spent more (non-leisure) time and effort in other activities such as childcare, housework, keeping themselves and their families healthy, staying informed, or learning new skills, at the expense of non-essential activities.

Interestingly, the number of retail investors, particularly those trading through zero-commission apps, increased sharply during the pandemic. While one could speculate that newly arrived retail investors would contribute to increasing the demand for information, our results do not support that claim. In fact, several recent studies have used data on Robinhood app users to show that these investors trade on the information provided by the app itself or by the media (Barber et al., 2020; Ozik et al., 2021).

5. References

Baker, S., Bloom, N., Davis, S., Kost, K., Sammon, M., & Viratyosin, T. (2020). *The Unprecedented Stock Market Impact of COVID-19*. Working paper.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2020). Attention Induced Trading and Returns: Evidence from Robinhood Users. Working paper.

Barber, B. M., Jiang, W., Morse, A., Puri, M., Tooks, H., & Werner, I. M. (2021). What Explains Differences in Finance Research Productivity During the Pandemic? *The Journal of Finance*, 76(4), 1655-1697.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, *193*, 104346.

Da, Z., Engelberg, J., & Gao, P. (2011). In Search of Attention. *Journal of Finance*, *66*(5), 1461–1499.

Deryugina, T., Shurchkov, O., & Stearns, J. E. (2021). COVID-19 Disruptions Disproportionately Affect Female Academics. Working paper.

Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate Immunity to the COVID-19 pandemic. *Journal of Financial Economics*, 141(2), 802-830.

Drake, M. S., Jennings, J., Roulstone, D. T., & Thornock, J. R. (2017). The Comovement of Investor Attention. *Management Science*, *63*(9), 2847–2867.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor Information Demand: Evidence from Google Searches around Earnings Announcements. *Journal of Accounting Research*, *50*(4), 1001–1040.

Galai, D., & Sade, O. (2006). The "Ostrich Effect" and the Relationship Between the Liquidity and the Yields of Financial Assets. *Journal of Business*, *79*(5), 2741–2759.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538.

Karlsson, N., Loewenstein, G., & Seppi, D. (2009). The Ostrich Effect: Selective Attention to Information. *Journal of Risk and Uncertainty*, *38*(2), 95–115.

Ozik, G., Sadka, R., & Shen, S. (2021). Flattening the Illiquidity Curve: Retail Trading During the COVID-19 Lockdown. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Russo, D., Hanel, P. H. P., Altnickel, S., & van Berkel, N. (2021). Predictors of Well-being and Productivity Among Software Professionals during the COVID-19 Pandemic – A longitudinal Study. *Empirical Software Engineering*, *26*(62), 1–63.