The Value of Registered Investment Advisors during the COVID-19 Financial Market Crash - Evidence from 13F and Twitter

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Executive Summary

- Prior research shows that during periods of high market volatility, investors tend to shift wealth from risky to safe assets.
- This piece of research is to examine the behavior of Registered Investment Advisors (RIAs) and their clients during the market downturn associated with the COVID-19 pandemic, specifically exploring any value-added provided to clients during this period.
- The authors of this study find that RIAs provided great value to their clients during the COVID-19 market crash, using frequent communication and effective buy or sell strategies.
- Based on the success experienced by many RIAs who aided their clients most notably, using social media strategies, financial advisors can further benefit from continuing education resources around managing investor behavior in the online space.

Introduction

The ongoing public health crisis from COVID-19 has significantly impacted business activities, household finances, created financial market volatility that leading to government intervention in the Form of lockdowns and innovative financial relief programs. The U.S. financial market went through a fifty percent decline in March of 2020 but rebounded quickly within the next two months. Since many investors experience loss aversion when participating in the stock market (Benartzi and Thaler 1995), recent market events associated with the COVID-19 pandemic provides a unique opportunity to examine the proactive and/or reactive measures registered investment advisors (RIAs) implemented and explore whether any value was provided to clients. The examination of RIAs includes their communication with clients, as well as the impact of market volatility this past year on client investment portfolios. This study is the first to our knowledge to address this topic using data that combines 13F filing, ADV forms, and tweets originating from Investment Advisor Representatives (IARs) at RIA firms. When communicating with clients, we find that RIAs communicate frequently and positively, even during extremely negative return days. Clients working with financial advisors tend to sell less and buy more during market downturn as compared with clients with non-discretionary accounts. Therefore, our research indicates that RIAs provided great value to their clients during the COVID-19 market crash, consistent with prior literature in this area of investment performance on subsequent client wealth.

Literature Review

At present, individuals must take more responsibility for their financial health and well-being. Life Cycle Theory posits that individuals ought to smooth their marginal utility of

consumption throughout their lifetime to achieve the maximum overall satisfaction (Ando and Modigliani 1963). For decades, many American households have relied on employers' defined benefit plans to fund retirement needs. However, the number of employers offering defined benefits plans has declined over time (Broadbent, Palumbo, and Woodman 2006; Butrica, Iams, Smith, and Toder 2009; Cobb 2015; Zelinsky 2004), and most employers now provide defined-contribution plans to help with employee retirement savings.

The Demand for Registered Investment Advisors

With the increased usage of defined-contribution plans, various studies have explored how well households manage their finances. Campbell, Jackson, Madrian, and Tufano (2011) argued that the financial system is difficult to understand and navigate. Thus, it is not efficient nor effective in the long run for consumers to learn personal finance through trial and error. Elmerick, Multanto, and Fox (2002) also found that households struggle to make sound financial decisions. Therefore, many families rely on financial planners for advice. Benartzi, Previtero, and Thaler (2011) demonstrated that individuals have difficulty determining how much money to spend each year in retirement due to the complexity around decumulation decisions.

The value of RIAs is well documented. Marsden, Zick, and Mayer (2011) showed that individuals who worked with financial advisors were more likely to make important financial decisions such as setting goals, establishing emergency funds, calculating retirement needs and having retirement confidence, diversifying retirement accounts, using supplemental retirement accounts, and having positive behavioral responses to economic crises. Likewise, Moreland (2018) used the National Financial Capability Study data and provided evidence that obtaining financial advice is positively associated with many financial behaviors. Bae and Sandager

(1997) highlighted that clients hire RIAs for help with retirement, tax, and investment planning. Block and Sweeney (2004) found that, on average, individuals are not confident in their ability to manage their investments and plan for retirement, but found that more than 90% are satisfied with the assistance they receive from RIAs. Xiao and Porto (2016) identified financial advice topics related to satisfaction using the National Financial Capability Study. Hung, Clancy, Dominitz, and Berrebi (2008) reported that over 70% of investors consult RIAs before making investment decisions. Hung and Yoong (2010) provided supporting evidence that showed that financial advice could improve investment behavior. Blanchett (2019) showed that households using a financial planner make better financial decisions than those who rely on the internet or work with a transactional advisor. Financial advisors can help clients in retirement identify reasonable withdrawal rates (Bengen 1994; Finke, Pfau, and Blanchett 2013) with dynamic analysis (Guyton and Klinger 2006) to help with portfolio sustainability. Since many consumers rely on RIAs for investment guidance, a thorough understanding of how market downturns affect the advisor-client relationship is important as the financial planning profession grows and becomes more defined. The market downturn in 2020, during the COVID-19 pandemic, presents a unique environment to examine and extend beyond previous literature.

Influence of Market Downturns

Loss aversion theory (Benartzi and Thaler 1995; Tversky and Kahneman 1991) states that people are much more willing to avoid a given number of losses than take an equal chance of acquiring the same number of gains. A significant total decline in wealth during a market downturn negatively impacts the satisfaction of financial clients. As Kahneman and Riepe (1998) and Borgards and Czudaj (2020) more recently, within the cryptocurrency market, indicated

overreaction to chance events is another factor to consider during a market downturn, as investors are likely to react in response to a loss of wealth.

Shiller (1987) was among the first researchers to identify how investors behave during a stock market crash. He noted numerous ways individuals responded to a market crash, and that many investors believed they could predict the market. Additionally, empirical evidence shows that a typical investment mistake is a behavioral tendency to shift wealth from risky to safe assets in volatile and declining markets (Ben-Rephael, Kandel, Friesen and Sapp 2007; Wohl 2012). Bucher-Koenen and Ziegelmeyer (2014) documented that German households with lower financial literacy levels were the most likely to sell equity at a loss during the global financial crisis of 2008 and 2009.

The COVID-19 Pandemic and Financial Markets

While the COVID-19 pandemic is still ongoing in the U.S., some recent investment studies are worthy of highlighting around this crisis. The COVID-19 pandemic produced more extreme changes in U.S. stock prices over 22 trading days in late February and March 2020 than any other historical period (Baker et al. 2020). The 34 percent drop in the S&P 500 index between February 19th and March 23rd of 2020, following a spike in volatility and a sharp decline in asset markets, is the most dramatic opportunity yet for researchers to study investor behavior. Giglio, Maggiori, Stroebel, and Utkus (2020) used a customized survey from Vanguard to analyze investors' expectations about economic growth and stock returns during the February to March 2020 stock market crash associated with COVID-19. The authors cited that most optimistic investors in February had the largest decline in expectations and sold the most equity. Glossner, Matos, Ramelli, and Wagner (2020) focused on institutional investors and found that

stocks with higher institutional ownership, especially those with active and short-term positions, performed poorly during the market crash. However, they also found that retail investors acted as liquidity providers by using Robinhood data. Barrot, Kaniel, and Sraer (2016) demonstrated that individual investors provided liquidity to the stock market in case of fire sales by institutional investors. Ozik, Sadka, and Shen (2020) and Welch (2020) also used Robinhood data and found that retail investors acted as a market-stabilizing force during the COVID-19 market crash. Blanchett, Finke, and Reuter (2020) examined the likelihood of investment allocation changes by 401(k) plan participants, while Glossner, Matos, Ramelli, and Wagner (2020) studied the sentiment of Vanguard clients. Ortmann, Pelster, and Wengerek (2020) showed that U.K. retail investors significantly increased their trading activities as the COVID-19 pandemic unfolded, but they did not investigate which stocks investors flocked to.

Data and Methods

The data for this study comes from 13F filings, the Form ADV, and Twitter. There are multiple steps we undertook to process the data used in this study:

1. Data was downloaded from SEC EDGAR database on the 13F holdings for the first and second quarter of 2020. The authors batch downloaded all data using index from https://www.sec.gov/Archives/edgar/full-index/.

2. After downloading the 13F forms in text format, we parsed the CUSIP, classification of "Investment Advice [6282]", "share amount", "company name" with each stock, and "investment discretion". Given that in 13F, some companies have multiple rows of share amounts due to different share classes, we combined the share amounts by CIK and CUSIP for the analysis. We then matched the investment holding data with Morningstar

and Bloomberg data to identify ticker names through CUSIP. With the ticker name available, equity styles were identified from the Morningstar Direct database.

3. Investment managers' institutional holdings with over one hundred million assets are required to report their quarterly holdings to the Securities and Exchange Commission (SEC). We matched the 13f filing with Form ADV, limiting our sample to only wealth management firms. The Form ADV was directly downloaded from the SEC website using the link below: https://www.sec.gov/foia/docs/form-adv-archive-data.htm. We use the "*Form ADV Part 1 data updates RIA July 1, 2020 to September 30, 2020".* Since Form ADV does not include company ID, we matched the two datasets by firm name. For firms that not matched by name, we alternatively used the business phone numbers as the identifier.

With the database above, we identified the company name, CIK and CUSIP, investment discretion, the issuer's name, change of shares for each ticker, whether the position is a new position or closed position, and whether a position was underweight or overweighted. We were also able to identify types of client the wealth management firms serve, such as high net worth individuals, investment companies, business development, pooled investments, pension and profit-sharing plans, and charitable organizations, etc.

The second part of this study analyzes tweets from advisors.

1. We downloaded the Form ADV form (https://adviserinfo.sec.gov/compilation using SEC Investment Advisers) and parsed "BusNm", "LegalNm", and "WebAddrs", renaming them to Business Name, Legal Name, and Web Addresses. Under Web Addresses, some

companies reported their Twitter account. We parsed the Twitter names and match them with previous dataset using firm name.

2. The next step is to download tweets from Twitter.com based on the Form ADV twitter accounts. We limit the period from February 25, 2020, to April 29, 2020, since that covers the whole cycle of the financial market crash.

3. The pulled tweets were analyzed using a Machine Learning algorithm trained by Dogu (2020). We tried other sentiment analyses and argue that tweets from advisors are very similar to financial news. In other words, no advisor will use their company tweets the same way they use their Twitter accounts. With professional language used, an appropriate algorithm specifically regarding financial statement analysis by Dogu (2020) was more appropriate. The authors also confirmed some results manually. Additionally, we chose the Machine Learning method as compared with traditional "word counting", as summarized by previous literature: *"Using carefully crafted financial sentiment lexicons such as Loughran and McDonald (2011) [11] may seem a solution because they incorporate existing financial knowledge into textual analysis. However, they are based on "word counting" methods, which come short in analyzing deeper semantic meaning of a given text."*

4. In our study, we also analyzed the “#cashtag” reported. Many advisors frequently use “#cashtag” to reference specific tickers within their tweets. We extracted the tickers from those “#cashtag” and matched them with their recent daily and weekly returns.

Table 1 provides the descriptive statistics of the variables used in our analysis. Table 2 summarizes the equity style of positions that were opened and closed, or underweighted or

overweighted. Interestingly, while we assumed that most firms only held exchange traded funds (ETFs) and mutual funds, we find that many firms had large positions in stocks. The median was 65 percent. It is important to note that mutual funds holdings are not required to be reported in 13F filings. Pan et al. (2018) states that *"Securities required to be reported in Form 13(f) include exchange-traded stocks, equity options and warrants, convertible bonds, and shares of closed-end investment companies."*)

[Table 1 here]

[Table 2 here]

Table 1
Variables of Interest - Descriptive Statistics

	Mean	25% quantile	median	75% quantile	Standard deviation	Max
AUM Discretionary (Million)	4200	300	600	1500	30700	1148200
AUM non-Discretionary (million)	500	0	0	0	4500	148900
AUM Total (million)	4700	300	600	1600	32900	1229600
Account # Discretionary	6479	365	852	1837	75738	2954678
Account # non-Discretionary	486	0	3	43	5635	155346
Account # Total	6965	393	889	1978	76630	2954678
Percentage of asset value – Non high net worth individuals	19.14	3.29	11.79	27.2	20.97	100
Percentage of asset value - High net worth individuals	57.88	36.3	65.26	81.54	29.16	100
Percentage of asset value - investments company	10.39	0	0	6.53	21.82	98.92
Percentage of asset value - business development	0	0	0	0	0.03	0.89
Percentage of asset value - pooled investments	6.54	0	0	4.55	15.36	99.98
Percentage of asset value - pension and profit sharing	6.1	0.4	1.77	6.25	11.55	99.4
Percentage of asset value - Charitable organization	3.91	0.3	1.35	4.32	7.64	96.41
Large Blend %	14.1	9.52	13.48	18.08	7.04	100
Large Growth %	8.69	5.34	7.63	10.54	5.57	60.71
Large Value %	20.55	13.77	20.27	26.62	9.51	62.22
Mid Blend %	4.95	2.53	4.35	6.57	3.24	29.23
Mid Growth %	4.32	1.77	3.16	5.49	4.46	100
Mid Value %	6.14	3.12	5.52	8.2	4.08	50
Small Blend %	4.15	1.38	2.49	4.65	5.07	66.67
Small Growth %	3.46	1.05	1.92	3.91	4.51	42.31
Small Value %	5.34	1.71	3.41	6.45	5.88	47.88
ETF %	6.2	2.18	4.46	8.06	6.25	100
Mutual Fund %	1.44	0.29	0.6	1.39	2.78	28.79
Stock %	62.39	50	65.59	78.57	21.06	100

Table 2: The Percent of Style by Investment Action

Panel A - % of style by investment action - mean – equal weight by companies										
	Large Blend	**Large Growth**	**Large Value**	**Mid Blend**	**Mid Growth**	**Mid Value**	**NA**	**Small Blend**	**Small Growth**	**Small Value**
Closed position	13.09	7.47	20.55	9.3	7.13	11.25	38.37	8.14	6.77	10.66
New position	56.77	22.56	36.92	36.21	47.94	37.74	76.71	35.45	35.35	45.78
Overweight	16.35	12.54	23.55	6.08	6.13	7.37	35.6	6.32	5.84	7.55
Underweight	16.31	11.05	23.39	5.91	5.78	6.88	36.52	6.02	5.4	6.84
Panel B - % of style by investment action - median – equal weight by companies										
	Large Blend	**Large Growth**	**Large Value**	**Mid Blend**	**Mid Growth**	**Mid Value**	**NA**	**Small Blend**	**Small Growth**	**Small Value**
Closed position	11.11	5.56	17.65	7.69	5.56	9.23	34.29	5.56	4.76	7.69
New position	50	14.29	13.39	20.37	33.33	25	100	20	25	33.33
Overweight	15.15	10	22.22	4.63	4.3	5.88	29.41	3.57	3.03	4.35
Underweight	15.26	8.7	22.22	5	4.07	5.88	31.6	3.29	3.03	4.05

Table 3 shows the percentage of each company's investment action regressed against their asset under management types (%). We differentiated the RIA firms by the clients they serve. i.e. non-high-net-worth investors, high-net-worth investors, or pension or profit sharing plans. As shown in first three columns where the percentage of new position is the dependent variable, it is evident that as the percentage wealth of non-high-net-worth individual clients increases within the company, there is a higher chance of opening new positions. While it might not seem noteworthy to add new positions in a market downturn, the positive and significant coefficients in the second sets of models (fourth to sixth columns) where the percentage of closed positions is the dependent variable, also indicates RIAs firms that serving more non-high-net-worth investors are more likely to sell out (close) positions. It is likely these RIAs firms are dually registered as broker-and-dealer, and their positions could be more likely influenced by their clients' short-term preference.

When it comes to high net-worth clients (or managers with a higher portion of high net-worth clients), their portfolio were significant—both statistically and economically—less likely

to underweight positions during the COVID-19 financial market crash. Compared to accounts with a higher portion of non-high-net-worth clients, those with a greater portion of high net-worth clients seemed to be more passive. The coefficients of opening new positions and of closing positions are not significant, leaning toward a passive strategy. We argue that there could be two reasons for this: First, it indicates that high net-worth clients' portfolios had most of their money invested in the financial markets before the COVID-19 financial crash. Secondly, during the COVID-19 financial market crash, these high net-worth clients' portfolios tend to keep their fund in the market without making withdrawals and waiting for a recovery.

[Table 3 here]

Table 3

Regression analysis of investor type and actions during the COVID-19 financial market crash.

	New Position	New Position	New Position	Closed Position	Closed Position	Closed Position	Overweighted Position	Overweighted Position	Overweighted Position	Underweighted Position	Underweighted Position	Underweighted Position
(Intercept)	0.675***	0.741	0.890	19.091***	18.299***	18.287***	29.325***	30.691***	29.964***	53.270***	55.948***	56.429***
	(0.231)	(0.471)	(0.581)	(0.499)	(1.021)	(1.195)	(0.439)	(0.896)	(1.129)	(0.524)	(1.070)	(1.317)
% in non-high-net-worth investors	0.019**	0.019**	0.019*	0.093***	0.099***	0.089***	0.055***	0.046***	0.069***	0.028	0.010	-0.002
	(0.008)	(0.009)	(0.010)	(0.018)	(0.019)	(0.020)	(0.015)	(0.016)	(0.019)	(0.018)	(0.020)	(0.023)
% in high-net-worth investors		-0.001	-0.004		0.012	0.008		-0.021*	-0.013		-0.040***	-0.040**
		(0.006)	(0.007)		(0.013)	(0.015)		(0.012)	(0.014)		(0.014)	(0.016)
% in pension and profit-sharing plan			-0.002			-0.060			0.082**			-0.107***
			(0.018)			(0.037)			(0.035)			(0.041)
R-squared	0.002	0.002	0.003	0.011	0.012	0.015	0.005	0.006	0.012	0.001	0.004	0.006
N	2420	2420	1858	2420	2420	1858	2420	2420	1858	2420	2420	1858

Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1

Advisor sentiment

This section focuses on analyzing RIA firm's tweets during the COVID-19 financial recession. The Twitter account is not available in the excel data file released on the SEC's website. Therefore we downloaded the original XML file in their database and parsed out the Twitter accounts in Item 1 Web Addresses. While firms do list multiple web addresses, such as their website, LinkedIn, and Twitter accounts, we focused only on Twitter accounts in this study. We used the TWINT package in python and web-scraped tweet data from February 25th to April 29th of 2020. We chose the period according to how S&P 500 (and other markets) were performing. We consider this to be the time frame when investors panicked the most. Markets after May 2020 experienced positive and relatively smooth returns.

We downloaded the firm names from our previously matched samples and merged the firm name and Twitter account information. For our analyses, we kept only firms with Twitter accounts. For companies with multiple Twitter accounts, we chose to keep only the last used account to avoid overweighting. Out of our full sample of 2,420 firms, 291 firms actively use Twitter as their communication platform.

Word embedding and transferred learning from the sentiment of tweets

After cleaning the data, we relied on a deep neuro-network model called finBERT to analyze the sentiment level of each tweet. There are multiple points to clarify in this section of analysis. RIA firms are different from individuals who use tweets as a part of personal social media accounts. For RIAs, the platform mimics a news source and tend to report only positive news to encourage clients during the COVID-19 financial crisis. The benefit of using finBERT, as illustrated in their original paper, is that the word embedding is trained based on financial

news from Reuters and the model itself is trained using Financial PhraseBank data. The sentiment category was manually annotated by financial professionals. Since the finBERT model uses BRET model from google brain, it is also the current state of art machine learning algorithm in the field of natural language processing[1].

Table 4: Tweet Frequency

Firms using Tweets	**Tweets within the study period**					
	Min	25%	Median	Mean	75%	Max
291	1	5	14	51	40.5	2,374

The summary above shows a big variation of how companies use tweets. Companies that utilize this form of social media communication strategy at different extent. In this study, since we are collecting data for a two-month period, our median number of tweets is 14, which means advisors usually tweet once every two trading days. Certainly, this is less than ideal for higher quality data analysis, but this is how advisors use the platform. Nevertheless, the authors believe that this study contributes significantly to the literature by being the first to introduce a machine learning library, along with SEC filings from RIAs to analyze ADV forms together with downloaded tweets.

Tweets over time

[1] For more information, the readers can find more information from the field of computer science via this link: https://github.com/ProsusAI/finBERT

Figure 1: Tweets Frequency v.s. Daily Market Return

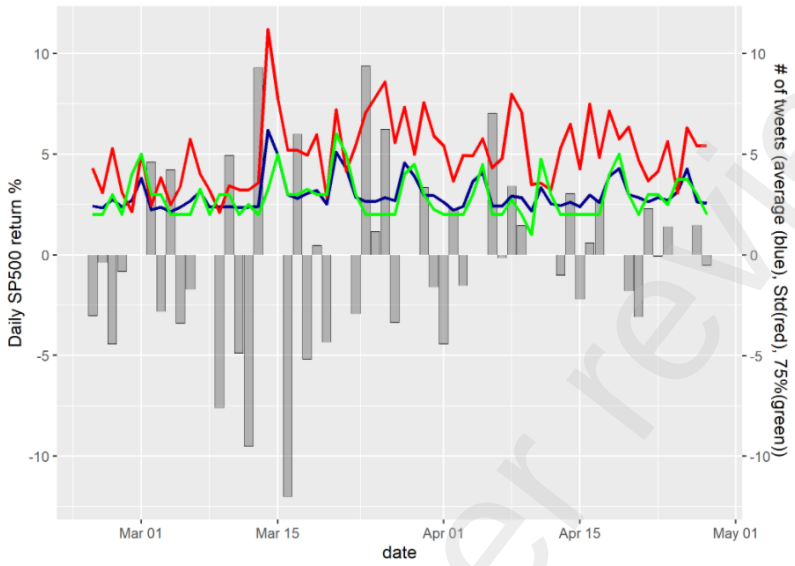
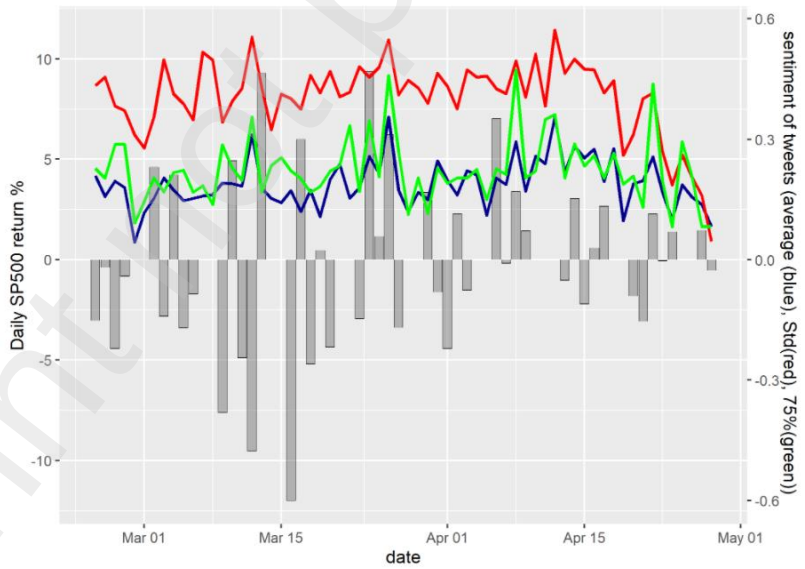


Figure 2: Tweets Sentiments v.s. Daily Market Return



Figures 1 and 2 indicate that RIA firms disseminate a greater number of tweets during days when there are extreme market volatilities. During this period, advisors seek out positive news to comfort clients.

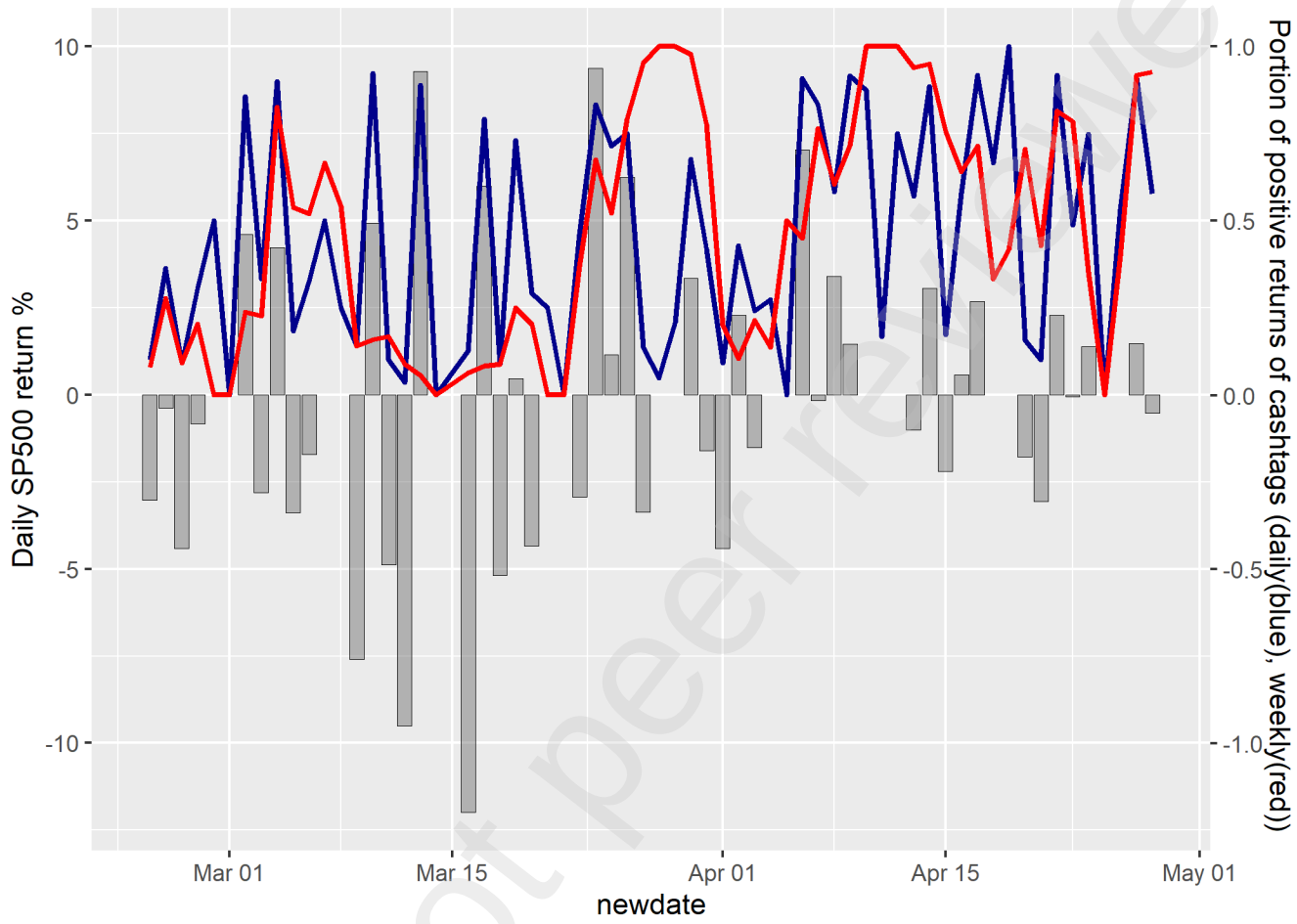
Cashtag analysis

The tweets data also includes cashtag and hastags. We downloaded this data alongside tweets. While examining the data, the authors observed that cashtags were primarily used to reference actual ticker of securities. The authors subsequently analyzed performance of these securities related to the S&P 500 returns on a daily and weekly basis in order to understand what type of securities were highlighted by RIA firms during the time of extreme volatility.

It is important to note that relatively few RIA firms use Twitter accounts, and even fewer firms use cashtags in their tweets. There are 29 accounts in our sample that actively used cashtags, some more active than others. The authors extracted ticker name from these cashtags and pulled the recent daily and weekly returns associated with each security. Then we were able to identify how many securities had positive daily or weekly return out of all securities highlighted through cashtags. The results are shown in Figure 3. While there was a clear challenge in finding stocks with positive daily and weekly returns during the COVID-19 financial market crash, it seems RIA firms were intentionally focusing on winners (--at least among those advisors who tweet frequently). While our findings do not represent the total RIA populace, for RIAs who use cashtags in their tweets, they do tend to highlight winners.

[Figure 3 goes here]

Figure 3: Cashtagged Security Return v.s. Daily Market Return



Conclusion

This study provides a unique insight into how RIAs added value during the most recent stock market crash associated with the COVID-19 pandemic. We found that RIAs frequently communicated with their clients during this period, reporting positive financial news even during extremely volatile trading days. Additionally, RIAs firms that serving more high-net-worth investors are more likely to stick to original portfolio positions comparing to firms that serving more non-high-net-worth investors. Consistent with prior literature, our study demonstrates that working with financial advisors should be an integral part of the financial planning process, which is particularly valuable during periods of high financial market uncertainty.

While we have experienced numerous recessions, this is the first time that financial advisors have navigated through a global pandemic which led to a national shutdown of the U.S. economy. As the financial planning profession continues to evolve, we must understand and underscore the value that financial advisors provide to their clients. During times of economic decline and extreme market volatility, the value added by financial advisors may prove to be extremely important to clients' financial condition in the long run. Our study also demonstrates the necessity of greater continuing education resources around managing investor behavior and the use of social media strategies to influence client behavior.

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