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

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Introduction

The ongoing public health crisis from COVID-19 has significantly impacted business activities, government stimulus aid, financial market volatility, and the household daily life in many ways. The stock 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 any proactive or reactive measures registered investment advisors (RIAs) implemented and if that provided added-value to their clients. This examination of RIAs includes their communication with clients and 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 manually downloaded data that combines 13F filing with ADV forms together with RIA tweets. 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 self-discretionary clients. 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

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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 get the maximum overall satisfaction (Ando and Modigliani.1963). For decades, many American households have relied on pensions provided by employers to fund retirement financial needs. However, the provision of pension plans have declined over time and many employers currently rely on and offer defined-contribution plans to help with employee retirement savings.

The Demand for Registered Investment Advisors

With the increased usage of defined-contribution plans, many 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 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 households 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 complex nature of the decumulation of assets. The authors argued that the majority of the population may be better off by putting most of their wealth in annuity products.

The value of RIAs is well documented. Chen and Severn (2016) documented that more than 70% of undergraduate students considered the financial planning profession to some extent. Moreland (2018) used the National Financial Capability Study data and showed that obtaining financial advice is positively associated with many financial behaviors. Guillemette and

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Jurgenson (2017) and Lei and Yao (2016) found values of RIAs regarding investment choices and portfolio performance. Bearden (2015) used cross-sectional data of pending engagements and provided insights in handling conflicts of interests.

Bae and Sandager (1997) highlighted that clients hire RIAs for help with retirement, tax, and investment planning. Block and Sweeney (2004) found that people on average are not confident in their ability to manage their investments and plan for retirement, but found that more than 90% are satisfied in 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 which showed that financial advice can improve investment behavior. Since many consumers rely on RIAs for investment guidance, understanding how down markets affect the client-advisor relationship is useful in managing these relationships. The market downturn in 2020, during the COVID-19 pandemic, presents an ideal environment to examine the 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 amount of losses than to take an equal chance of acquiring the same amount of gains. Significant total net wealth lost during a market downturn negatively impacts the satisfaction of financial clients. Overreaction to chance events, as indicated by Kahneman and Riepe (1998), is another factor to consider during a market downturn. Investors make emotional decisions in response to a loss of wealth.

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Shiller (1987) was among the first to identify how investors behave during a stock market crash. Previous research finds that a common investment mistake is the behavioral tendency to shift wealth from risky to safe assets in volatile and declining markets (Ben-Rephael, Kandel, and Wohl, 2012; Friesen and Sapp, 2007). For example, Bucher-Koenen and Ziegelmeyer (2014) documented that German households with lower levels of financial literacy 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 19 and March 23, 2020 is the most dramatic opportunity yet for researchers to study investor behavior, following a spike in volatility, and a sharp decline in asset markets. Giglio et al. (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 due to COVID-19. The authors cited that investors who were most optimistic in February had the largest decline in expectations and sold the most equity. Glossner et al. (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 Robindhood data and found that retail investors acted as a market-stabilizing

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force during the COVID-19 market crash. Blanchett, Finke, and Reuter (2020) examined the likelihood of investment allocation changes by 401(k) plan participants and Glossner et al. (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. Amore, Pelucco, and Quarato (2020) found that firms with controlling family shareholders fared better during the crisis. Anginer et al. (2020) cited that insiders bought shares of high-leverage and value firms during the same time period.

Data and Methods

There are multiple steps we undertake 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 manually downloaded all data using index from https://www.sec.gov/Archives/edgar/full-index/.

2. After downloading the 13F forms in text format, we manually parsed the CUSIP, classification of "Investment Advice [6282]", "share amount", "company name" with each stock. Another variable we parse from the 13F form was investment discretion. Given that in 13F, some companies have multiple rows of share amounts due to different share classes, we combine the share amounts by CIK and CUSIP for the analysis. After that, we combine the data with Morningstar and Bloomberg data to identify tickers using CUSIP. With the ticker available, equity styles were identified using Morningstar Direct database.

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3. The 13F reports all institutional investors holdings, and we merge it with ADV forms to limit our sample to only wealth management firms. The ADV form was directly downloaded from the SEC website using the link below: https://www.sec.gov/foia/docs/form-adv-archive-data.htm The authors use the "*Form ADV Part 1 data updates RIA July 1, 2020 to September 30, 2020"*. Since the ADV form does not include company ID, we match it by the name of the company. We converted the name to all upper cases, substituted "&" to "AND", removed "LLC", "CO", "LTD", "LP", "INC", "Corporation", /ADV",./CT", "Group" in both the ADV data and 13F data since those names were not exactly the same. For the remaining unmatched ones, we used the business phone numbers to match, converting either 7 or 10 digits format into the same format.

4. With the database above, we were able to identify: company name, CIK and CUSIP, investment discretion, name of issuer; change of shares for each ticker; whether the position is a new position or a closed position, underweighted position, or overweighted position. We were also able to identify the equity style box. The variables we pulled from ADV form are under X5. Those variables identify the portion of assets under management by different group of clients. They include individuals, high net worth individuals, investment companies, Business Development, Pooled investments, pension and profit sharing, and charitable organizations.

The second part of this study analyzes tweets from advisors.

1. We downloaded the ADV form in xml format (https://adviserinfo.sec.gov/compilation using SEC Investment Advisers) and manually parse "BusNm", "LegalNm", and "WebAddrs", renaming them to Business Name, Legal

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Name, and Web Addresses. Under Web Addresses, some companies report their twitter account. We parse those out and match into previous data (step 4 above) using Business Name.

2. The next step is to download tweets from twitter.com based on the twitter accounts provided in the ADV form. We limit the time period from Feb-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) https://arxiv.org/pdf/1908.10063.pdf. We tried other sentiment analysis 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 personal 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 conducted an analysis around the #cashtags reported. Many advisors like to #cashtag specific tickers within their tweets. We manually extracted those tickers and pulled their recent returns (both daily and weekly) using Yahoo Finance API.

The tables below showcase our analyses.

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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 - individual	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

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Table 2

Panel A - % of style by investment action - mean – equal weight by companies										
action	**Large Blend**	**Large Growth**	**Large Value**	**Mid Blend**	**Mid Growth**	**Mid Value**	**NA**	**Small Blend**	**Small Growth**	**Small Value**
closeposition	13.09	7.47	20.55	9.3	7.13	11.25	38.37	8.14	6.77	10.66
newposition	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										
closeposition	11.11	5.56	17.65	7.69	5.56	9.23	34.29	5.56	4.76	7.69
newposition	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

We find that many firms had large positions in stocks. The median was 65 percent. The authors previously assumed that most RIAs use only ETFs and mutual funds. (Mutual funds were not required to be reported in 13F. Pan et al. (2018) states clearly 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."*)

The table below shows the percentage of positions in each company, regressed against the asset under management types (%) of those companies

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Table 3

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

	New position-1	New position-2	New position-3	Closed position-1	Closed position-2	Closed position-3	Overweight-1	Overweight-2	Overweight-3	Underweight-1	Underweight-2	Underweight-3
(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)
individualpct	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)
highnetworthpct		-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)
pensionandprofitsharingpct			-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

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Table 3 above demonstrates that advisors add value by encouraging buying and not selling. As shown in the first row and first three columns of new positions, it is evident that as the percentage wealth of individual clients increase 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 of closing positions (0.089 vs. 0.093) also indicates individual clients are more likely to sell out (close) positions. Individual clients might be noise traders as documented by previous literature.

Another row of interest is that when it comes to high net-worth clients (or accounts with a higher portion of high net-worth clients), they were significantly—both statistically and economically—less likely to underweight positions during the COVID-19 financial market crash. Also, compared to accounts with a higher portion of individual clients, accounts with a greater portion of high net-worth clients seemed to be more passive. The coefficients of opening new positions or closing positions are not significant, leaning toward a passive strategy. The authors argue that there could be two reasons for this: 1.) First, it indicates that high net-worth clients had most of their money in the financial markets before the COVID-19 financial crash. 2.) Secondly, during the COVID-19 financial market crash, these high net-worth clients kept their funds in the market without making withdrawals and waiting for a recovery. Supporting previous studies such as that of Barber et al. (2000), both these reasons are consistent with a passive investment philosophy, and can benefit clients in the long-run.

Advisor sentiment

Data Downloaded and Cleaned

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This section focuses on analyzing company tweets during the COVID-19 pandemic and financial crisis. The Twitter account is not available in the excel data file released in the SEC website. 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 tweets, since they are in a relatively standard format. We used TWINT package in python and downloaded (webscrapped) data from February 25th to April 29th of 2020. We chose the time periods according to how S&P 500 (and other markets) were performing. The authors consider this the time frame that investors panicked the most. Markets after May 2020 experienced positive and relatively smooth returns.

The authors downloaded the firm names from previously matched samples used in the analysis above 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. Our original matched sample has 2,420 firms, and 291 firms actively use twitter as their communication platform.

For firms with twitter accounts, some reported many daily tweets while others rarely used the social media platform.

World embedding and transfer learning of the tweets sentiment

After cleaning the data, we imposed a deep neuro networking model library called finBERT to analyze the sentiment level of each tweet. There are multiple points to clarify in this section of analysis:

1. RIAs are different from individuals who use tweets as a part of personal social media accounts. For RIAs, the platforms mimics a news source and tend to report only positive news to

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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 is also the current state of art training algorithm in the field of natural language processing[1].

Tweet Frequency

Tweet Summary						
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 marketing strategy use numerous tweets. In this study, since we are collecting data during for a two month period (roughly 60 days), our median number of tweets is 14, which means advisors usually tweet once every two days (--excluding weekends and non-trading days). Certainly, this is less than ideal for a 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 introducing a machine learning library and be the first to analyze ADV form together with downloaded tweets using SEC filings from RIAs.

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

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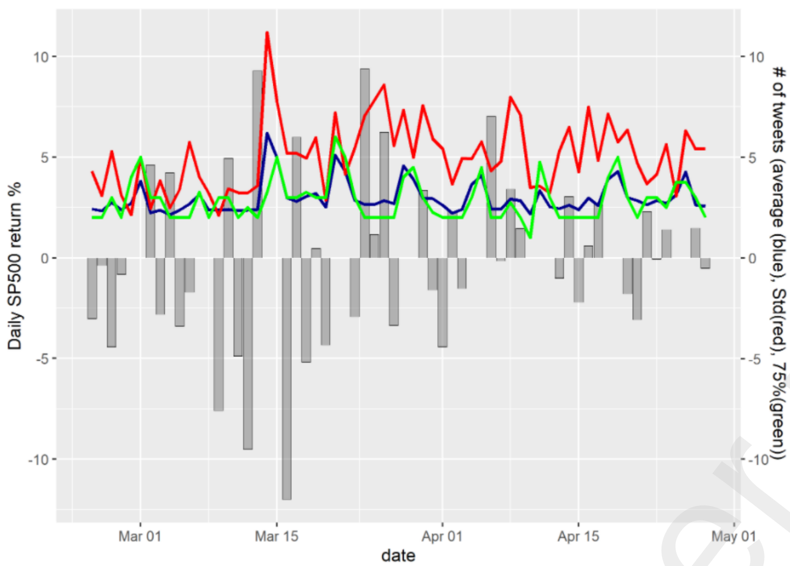
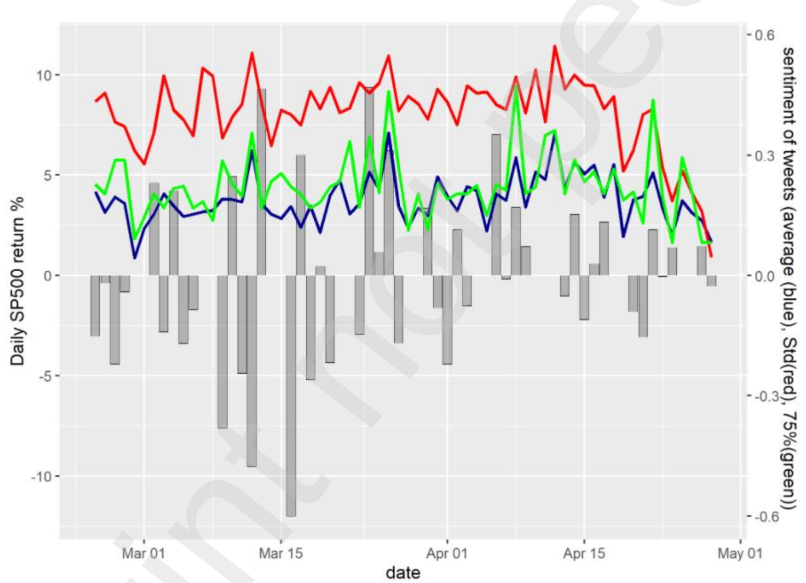
Tweets over time





The two charts above show that advisors send out a greater amount of tweets during days when there are extreme market downturns; during which they seek out positive news in order to comfort clients.

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Cashtag and hashtag analysis

The tweets data also includes cashtag and hastags. We downloaded this data alongside tweets. While manually examining the data, the authors of this paper saw that many cashtags were actual tickers of securities. The authors subsequently analyzed recent performance of these securities with S&P 500 returns on a daily and weekly basis in order to show how advisors use market performance to communicate with or comfort clients. The readers of this paper should note that relatively few financial advisors use twitter, and even fewer use cashtags.

There are 29 accounts of twitter that have active cashtags, some more active than others in usage. The authors extracted these cashtags, and pulled the recent daily and weekly returns associated with each cashtag. We then identified the within of those cashtaged stocks/funds from one twitter account over the study time, which percentage of them had positive returns (as a portion of total cashtags within that tweet). 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 advisors 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 broadcast winners.

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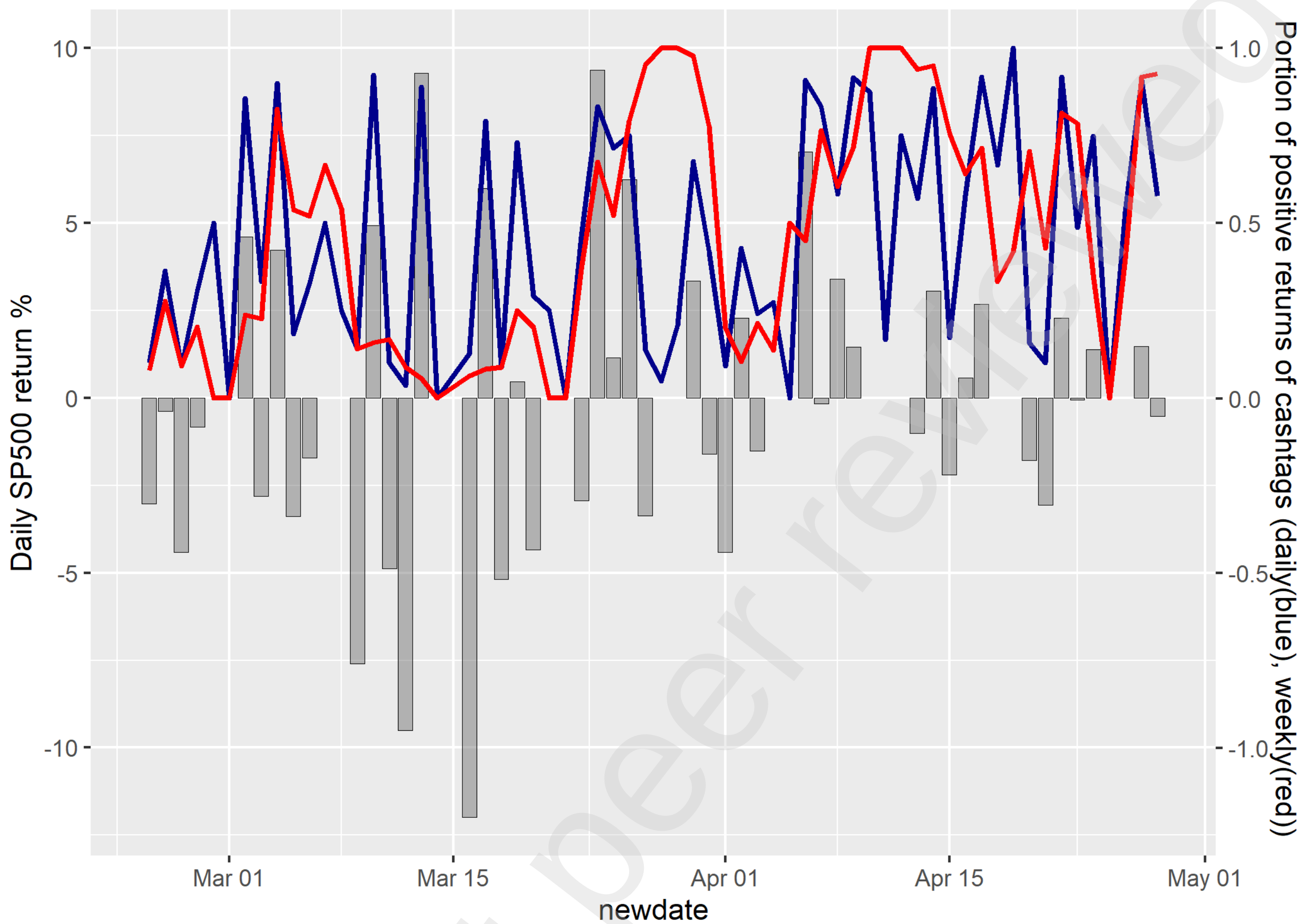

Figure 3

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Are frequency of tweets associated with active trading?

	New position	New position	Closed position	Closed position	Overweight	Overweight	Underweight	Underweight
(Intercept)	0.731	2.802	26.506***	25.676***	31.240***	29.179***	61.158***	68.379***
	(1.079)	(1.936)	(2.633)	(3.996)	(2.413)	(3.943)	(2.864)	(4.444)
numtweets	0.002	0.002	-0.004	-0.002	0.002	0.004	0.002	-0.003
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
sentscore	-0.610	-0.863	-29.514**	-19.439	0.997	-2.367	-30.009**	-14.962
	(5.364)	(6.594)	(13.092)	(13.610)	(12.000)	(13.430)	(14.241)	(15.135)
individualpct		-0.012		0.034		0.026		-0.110*
		(0.027)		(0.056)		(0.055)		(0.062)
highnetworthpct		-0.027		-0.037		0.053		-0.132***
		(0.020)		(0.042)		(0.041)		(0.046)
pensionandprofitsharingpct		-0.067		-0.151		0.078		-0.228
		(0.070)		(0.144)		(0.142)		(0.160)
R-squared	0.004	0.017	0.024	0.027	0.000	0.011	0.021	0.058
N	217	178	217	178	217	178	217	178

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

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Conclusion

This study provides unique insight as to how RIAs added value during the most recent stock market crash associated with the COVID-19 pandemic. We found that RIAs communicated frequently with their clients during this period, reporting positive financial news even during extremely volatile trading days. Additionally, our findings show that clients working with RIAs tend to sell less and buy more during a market downturn, as compared to accounts with a higher portion of client-discretionary options. Supporting prior literature, our study demonstrates that using RIAs as part of the financial planning process is highly valuable during periods of high financial market uncertainty.

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