What Drives Closed-End Fund Discounts? Evidence from COVID-19

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ABSTRACT

The literature often uses closed-end fund (CEF) discounts as an inverse measure of investor sentiment, while the source of CEF discounts remains under debate. Exploiting the COVID-19 outbreak as a negative exogenous shock to individual investor sentiment, I examine the causal effect of sentiment on CEF discounts. I find that CEF discounts increased after COVID-19. Using the difference-in-differences (DiD) approach, I find that CEFs with higher sentiment beta or higher retail ownership experienced a larger increase in discounts after COVID-19. The DiD results are unlikely to be driven by alternative channels such as the liquidity, expense, payout, and leverage channels.

Keywords: Closed-End Funds, Discounts, COVID-19, Mispricing, Investor Sentiment

JEL classification: G12, G14, G40

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1 Introduction

One long-standing anomaly in finance is the closed-end fund discount puzzle. Closed-end funds (hereafter CEFs) invest in publicly traded securities, and meanwhile, their shares are also traded on exchanges. The CEF discount puzzle refers to the empirical fact that CEFs usually trade at lower prices (discounts) than their net asset values (hereafter NAVs). This pattern seems to violate the law of one price and challenge neoclassical theory (Ross (2002)).

Over the last several decades, researchers have proposed and examined different explanations of the CEF discount puzzle, and there has been no consensus regarding what drives CEF discounts (Cherkes (2012)). In particular, it remains under debate whether and to what extent CEF discounts arise from investor sentiment (irrationality). On the one hand, proposed by De Long et al. (1990) and Lee, Shleifer, and Thaler (1991), the sentiment-based explanation of CEF discounts has gained popularity. For example, Pontiff (1996) states that "Pricing theories that are based on fundamentals have had very little, if any, ability to explain discounts." On the other hand, several rational theories of CEF discounts without invoking investor irrationality have also been put forward. For example, Cherkes, Sagi, and Stanton (2009) recently propose a liquidity-based model of CEF discounts as an alternative to the sentiment-based explanation.[1]

The question of whether investor sentiment plays a role in driving CEF discounts is important not only for understanding CEF discounts per se but also for sentiment-related financial research in general, given that a growing strand of literature (e.g., Lee, Shleifer, and Thaler (1991), Chopra et al. (1993), and Baker and Wurgler (2006, 2007)) has already moved forward and uses CEF discounts as an empirical (inverse) measure of investor sentiment.[2]

[1] Empirical evidence for the liquidity-based explanation of CEF discounts is mixed. Cherkes, Sagi, and Stanton (2009) find results that support the liquidity-based explanation, while Elton et al. (2013) and Shao and Ritter (2018) do not.

[2] The CEF discount is one main component in the widely-used Baker-Wurgler investor sentiment index proposed by Baker and Wurgler (2006), which has been cited by more than 5,300 times as of October 2021 according to Google Scholar.

In this paper, I attempt to address this question using the novel setting of the COVID-19 outbreak. As discussed in Fahlenbrach, Rageth, and Stulz (2020) and Ramelli and Wagner (2020), the COVID-19 outbreak emerged as a public health crisis and has the advantage of being a truly exogenous and fully unanticipated shock. In particular, as indicated below, the COVID-19 outbreak reduced individual investor sentiment exogenously, which enables identifying the causal effect of sentiment on CEF discounts using the difference-in-differences approach.

I first show that the COVID-19 outbreak caused a negative shock to individual investor sentiment. Figure 1 plots the weekly individual investor sentiment measure from the American Association of Individual Investors (hereafter AAII), from December 2019 to May 2020 and centering around the date of the COVID-19 outbreak, February 24, 2020.[3] There is a large decline in individual investor sentiment around the COVID-19 outbreak. The average sentiment decreased from 11.0% in the pre-COVID period to −15.6% in the post-COVID period, resulting in a sizable decline of 26.6%. Using the index of consumer sentiment from the University of Michigan Surveys of Consumers as an alternative measure of individual investor sentiment, I find a similar decline in sentiment after the COVID-19 outbreak.

Based on the evidence in Figure 1, I derive testable hypotheses from the sentiment-based model of CEF discounts proposed by De Long et al. (1990) and Lee, Shleifer, and Thaler (1991). As discussed in detail in Section 2, this theory builds on a well-known empirical fact about CEFs: different from the underlying assets, CEF shares are held primarily by individual investors. An important implication is that CEF discounts increase when individual investor sentiment decreases. Based on this implication and given that the COVID-19

[3]The AAII individual investor sentiment measure is based on surveys oriented to individual investors and is calculated as the fraction of individual investors who hold a bullish view on the stock market performance in the next six months minus the fraction of individual investors who hold a bearish view. It has been commonly used in previous literature (e.g., Greenwood and Shleifer (2014) and DeVault, Sias, and Starks (2019)) to gauge the sentiment of individual investors. One advantage of this measure is that it is available in weekly frequency, which enables tracing how individual investor sentiment changed around the outbreak of COVID-19. As in Albuquerque et al. (2020) and Ramelli and Wagner (2020), I use February 24, 2020, as the date of the COVID-19 outbreak and hence the beginning of the post-COVID period.

outbreak caused a negative shock to individual investor sentiment (Figure 1), I obtain the first hypothesis: CEF discounts increase on average after the outbreak of COVID-19. More important, if the sentiment channel is at play, the effect of the COVID-19 shock on discounts should be stronger for CEFs more exposed to individual investor sentiment. This leads to the second hypothesis: CEFs more subject to individual investor sentiment experience a larger increase in discounts after the outbreak of COVID-19.

To test the first hypothesis, I plot the time series of the average discounts across all 485 CEFs in the sample, in daily frequency, over the sample period of December 2019 to May 2020. As shown in Figure 2, there is a dramatic increase in CEF discounts after the outbreak of COVID-19 on February 24, 2020. The average discount increases from 3.55% in the pre-COVID period to 7.68% in the post-COVID period. I further test the first hypothesis more formally using regression analyses. I regress discounts onto a dummy variable $POST$ that equals one in the post-COVID period and control for fund fixed effects. Across specifications with and without different control variables, the coefficient on the $POST$ dummy is positive and both statistically significant and economically sizable, consistent with the first hypothesis.

The second hypothesis is the main hypothesis of this paper. It enables the difference-in-differences test that compares the discount change after the COVID-19 shock across CEFs with different exposures to individual investor sentiment, which identifies the causal effect of sentiment on discounts. I use a CEF's sentiment beta, which captures the sensitivity of changes in its premiums to changes in individual investor sentiment, as a measure of its exposure to individual investor sentiment.[4] I calculate sentiment beta using weekly data of CEF premiums and AAII sentiment over the three-year window of February 2017 to January 2020 (prior to the COVID-19 shock) and scale it by the mean value for the corresponding

[4]It is possible that the outbreak of COVID-19 gave rise to shocks to other factors than individual investor sentiment. The premise of the difference-in-differences test is that the changes in other factors do not impact CEFs with different sentiment beta differently. See discussion on evidence supporting this premise below and in Section 5.4.

category of CEFs, to account for potential differences across different categories.[5]

The sample period for the difference-in-differences analysis is December 2019 to May 2020, which covers roughly three months before and three months after the COVID-19 outbreak. I control for fund and time fixed effects and commonly used determinants of CEF discounts in the literature. I find that CEFs with higher sentiment beta experienced a larger increase in discounts after the COVID-19 outbreak. The economic magnitude is sizable. A one-standard-deviation increase of sentiment beta increases CEF discounts by 0.96 to 1.09 percentage points after the COVID-19 shock. Moving from the bottom decile to the top decile of CEFs sorted on sentiment beta, the discount increase after the COVID-19 shock is higher by 3.24 to 3.69 percentage points. I also verify that the parallel trends assumption for this difference-in-differences analysis holds. These results are consistent with the second hypothesis and provide support for the sentiment-based explanation of CEF discounts.

I conduct a battery of robustness checks for the main difference-in-differences results. I use retail ownership of CEF shares as an alternative measure of the exposure to individual investor sentiment and calculate it at the end of December 2019. In the difference-in-differences setting, I find that CEFs with higher retail ownership experienced a larger increase in discounts after the COVID-19 outbreak, consistent with the second hypothesis. I also show that the main difference-in-differences results are robust to using March 11, 2020, the date on which the World Health Organization (WHO hereafter) announced COVID-19 as a pandemic, as an alternative date of the COVID-19 outbreak.

It is possible that the COVID-19 outbreak generated shocks to factors other than individual investor sentiment that could also affect CEF discounts. In the main tests, I use the difference-in-differences approach to identify the effect of the sentiment channel. A natural question is whether the main difference-in-differences results can be attributed to other alternative channels instead of the sentiment channel. I address the question in the last set of robustness checks. I consider four alternative channels, including the liquidity channel, the

[5] As shown in Section 5.2, results are robust if I do not scale sentiment beta.

expense (managerial fees) channel, the payout channel, and the leverage channel. They have been proposed as potentially important mechanisms that drive CEF discounts by rational models of discounts in the literature.

To examine the role of the liquidity channel, I estimate asset illiquidity and share illiquidity using a first-order moving average model with NAV returns and stock returns, respectively, following Getmansky, Lo, and Makarov (2004) and Wu, Wermers, and Zechner (2016). I then measure liquidity gap as the difference between asset illiquidity and share illiquidity. For the liquidity channel to drive the main difference-in-differences results, we should observe a significant decrease in liquidity gap for CEFs with higher sentiment beta or retail ownership after the COVID-19 outbreak because CEF discounts decrease with liquidity gap according to the liquidity-based explanation of discounts (Cherkes, Sagi, and Stanton (2009)). Using the difference-in-differences approach, I find that CEFs with higher sentiment beta or retail ownership did not experience a significant change in liquidity gap after the COVID-19 outbreak. This suggests that the main difference-in-differences results are unlikely to be driven by the liquidity channel. In similar analyses, I find CEFs with higher sentiment beta or retail ownership did not experience a significant change in expense ratio, payout ratio, or leverage after the COVID-19 outbreak. I also show that the main difference-in-differences results are robust when additional control variables associated with the alternative channels are included. Collectively, the results show that the main difference-in-differences results are unlikely to be driven by these alternative channels and offer support to the sentiment channel.

This paper contributes to the literature on CEFs, especially that on explaining the CEF discounts. Since Pratt (1966) documented the presence of discounts, different explanations have been proposed. As discussed earlier and in Cherkes (2012), these explanations broadly fall into two categories: the behavioral explanation based on investor irrationality (or sentiment) and rational explanations. On the behavioral side, based on the insight of Zweig (1973), De Long et al. (1990) and Lee, Shleifer, and Thaler (1991) propose a model in which noise trading driven by sentiment creates non-diversifiable risk and leads to discounts.[6] On the rational side, managerial fees have been argued as the primary source (e.g., Ingersoll (1976) and Ross (2002)) of CEF discounts. Two recent prominent models extend this logic: The trade-off between investors' perception of managerial ability and fees in Berk and Stanton (2007) and that between liquidity benefits and fees in Cherkes, Sagi, and Stanton (2009) lead to the dynamics of CEF discounts/premiums.[7]

Overall, the empirical evidence for both the sentiment-based and rational explanations has been mixed. Most empirical tests rely on (potentially endogenous) proxies for different factors that might affect discounts, making it difficult to draw causal interpretations. This paper exploits the exogenous shock to sentiment induced by the COVID-19 outbreak and uses the difference-in-differences approach to help ascertain the role of sentiment in driving CEF discounts.

This paper also contributes to the emerging literature on the impact of the COVID-19 outbreak on financial markets. Hansen (2020) summarizes several notable papers along this line. Using survey data, Giglio et al. (2021) show that retail investors became more pessimistic about the short-run performance of both the stock market and the real economy after the COVID-19 outbreak. This evidence corroborates my use of the COVID-19 outbreak as a negative shock to individual investor sentiment in the current paper. To the best of my knowledge, this paper is the first to examine the effect of the COVID-19 outbreak on CEF discounts and use the setting of COVID-19 to shed light on the CEF discount puzzle.

The rest of the paper is organized as follows. Section 2 develops testable hypotheses. Section 3 describes the data and sample. Section 4 presents results from the main empirical analysis. Section 5 provides results from robustness checks. Section 6 concludes.

[6] Starting from Lee, Shleifer, and Thaler (1991), Chopra et al. (1993), and Baker and Wurgler (2006, 2007), a growing literature uses CEF discounts as an empirical measure of investor sentiment.

[7] See Cherkes (2012) and the references therein for more discussion on the behavioral and rational explanations of CEF discounts and the empirical tests of these explanations. More recent empirical work along this line includes Chu and Ma (2016).

2 Hypothesis Development

I develop testable hypotheses for empirical analysis from the sentiment-based model of CEF discounts proposed by De Long et al. (1990) and Lee, Shleifer, and Thaler (1991). Within this framework, there are two types of investors: sophisticated investors and noise traders. Sophisticated investors are rational, while noise traders are subject to the impact of sentiment. In equilibrium, asset prices reflect the beliefs of both the rational investors and the noise traders. Due to the non-diversifiable risk from sentiment (noise trader risk), assets trade below fundamental values on average. Relative to fundamental values, asset prices fluctuate over time and become higher (lower) when noise trader sentiment is higher (lower).

As discussed in Lee, Shleifer, and Thaler (1991) (p. 82), a condition needed for the sentiment-based framework to explain CEF discounts is that compared with the underlying assets, CEF shares are associated with more noise traders and therefore are more subject to the influence of noise trader sentiment. Lee, Shleifer, and Thaler (1991) treat noise traders as individual investors empirically and provide supporting evidence for this condition. They show that different from the underlying assets, CEFs are held primarily by individual investors, which has become a well-known empirical fact (Cherkes (2012)).[8] Therefore, it is expected that CEFs are more exposed to individual investor sentiment than the underlying assets.

Because CEFs are more exposed to individual investor sentiment than the underlying assets, an increase in individual investor sentiment would move up CEF prices more than NAVs, which leads to a decrease in discounts, and vice versa.[9] We then have the following important implication. CEF discounts would decrease (increase) when individual investor

[8]Consistent with this stylized fact, CEFs are also held primarily by individual investors in my sample. As shown in Table 1, the average (median) retail ownership for CEFs in my sample is 78% (82%). See also Shao and Ritter (2018) for evidence on much lower institutional ownership in CEFs than in operating companies.

[9]Empirically, the CEF discount is defined as the ratio of NAV per share minus share price to NAV per share. Therefore, the higher the share price is relative to NAV per share, the lower the discount.

sentiment increases (decreases).[10] This implication regarding the negative effect of individual investor sentiment on CEF discounts has spurred a growing literature that uses CEF discounts as an inverse measure of (individual) investor sentiment empirically (e.g., Lee, Shleifer, and Thaler (1991), Chopra et al. (1993), and Baker and Wurgler (2006, 2007)).

I derive testable hypotheses based on this implication—the negative effect of individual investor sentiment on CEF discounts—in the novel setting of COVID-19. As shown in Figure 1 and discussed in the introduction and Section 4.2, the COVID-19 outbreak induced a negative exogenous shock to individual investor sentiment. This suggests that CEF discounts would increase on average after the COVID-19 shock, which leads to the first hypothesis below.

HYPOTHESIS 1: *CEF discounts increase on average after the outbreak of COVID-19.*

Furthermore, if the sentiment channel is at play, the effect of the COVID-19 shock on CEF discounts should be stronger for CEFs more exposed to individual investor sentiment. To see this, consider two CEFs, one with relatively more exposure to individual investor sentiment and the other with relatively less exposure to individual investor sentiment. As the negative shock to individual investor sentiment (due to the COVID-19 outbreak) occurred, the former CEF's price should decline more (relative to the NAV) than that of the latter CEF. In other words, the former CEF would experience a larger increase in the discount than the latter CEF. I then obtain the second hypothesis as follows.

HYPOTHESIS 2: *CEFs more subject to individual investor sentiment experience a larger increase in discounts after the outbreak of COVID-19.*

Hypothesis 2 is the main hypothesis of this paper. It enables the difference-in-differences test that compares the discount change after the COVID-19 shock across CEFs with different exposures to individual investor sentiment, which identifies the causal effect of sentiment on

[10] See p. 81 of Lee, Shleifer, and Thaler (1991) for a similar discussion on the negative effect of individual investor sentiment on CEF discounts.

discounts.

3 Data and Sample

As in Albuquerque et al. (2020) and Ramelli and Wagner (2020), I use February 24, 2020, as the date of the COVID-19 outbreak and hence the beginning of the post-COVID period.[11] The main sample period is December 2019 to May 2020, which covers roughly three months before and three months after the COVID-19 shock, to empirically identify its effect on CEF discounts.

To construct the sample, I start with the list of CEFs incorporated in the U.S. that exist as of the end of 2019. From the Center for Research in Security Prices (CRSP) database, I obtain this list of CEFs as all stocks for which the second digit of the share code (shrcd) is 4. I then retrieve data on daily prices and NAVs for these CEFs from Bloomberg and exclude those without valid prices or NAVs as of the end of 2019. I also exclude CEFs that became delisted prior to February 24, 2020, the date of the COVID-19 outbreak. To be included in the final sample, I require a CEF to have valid prices and NAVs for at least 52 weeks during the three-year window of February 2017 to January 2020, which is needed to calculate the main independent variable sentiment beta. The final sample contains 485 CEFs. Based on the asset class information from Bloomberg, there are 138 equity CEFs, 146 municipal fixed income CEFs, and 134 taxable fixed income CEFs. I classify the remaining 67 CEFs as "other," and most of them invest in the mixed allocation of equity and fixed income, convertible bonds, preferred stocks, or commodities. This classification scheme is consistent with Cherkes, Sagi, and Stanton (2009).

To supplement the main data on daily prices and NAVs, I obtain data on other variables used in empirical analysis from numerous sources. I get data on market capitalization,

[11] Several municipalities of Italy began lockdown on February 21, 2020. February 24, 2020, is the first trading day after that. Ramelli and Wagner (2020) use this date as the beginning of the "fever" period of stock price reactions to COVID-19.

dividends, trading volume, and the first listing date from CRSP, data on institutional ownership from Thomson Reuters 13f holdings, and data on insider ownership from S&P Capital IQ. Data on fund (SG&A) expenses and leverage are also from S&P Capital IQ. When expense and leverage data are unavailable from S&P Capital IQ, I extract them from CEFs' N-CSRS and N-CSR filings on the Electronic Data Gathering, Analysis, and Retrieval (hereafter EDGAR) website of the Securities and Exchange Commission (hereafter SEC). I get data on individual investor sentiment from the website of AAII. I obtain data on the index of consumer sentiment from the website of Surveys of Consumers at the University of Michigan.

4 Empirical Analysis

4.1 Main Variables

This subsection introduces the main variables used in empirical analysis. Section 3 details the data sources for these variables. The main dependent variable is the CEF discount *Discount*. I calculate *Discount* as:

$$Discount_{it} = \frac{NAV_{it} - P_{it}}{NAV_{it}}, \tag{1}$$

where NAV_{it} and P_{it} are the NAV per share and share price of CEF i on day t, respectively. With this definition, the CEF discount is negative (positive) if the share price is higher (lower) than the NAV per share.

A set of variables have been commonly used in the literature as determinants for CEF discounts. I include them in the empirical analysis as control variables, and I follow Pontiff (1996) and Bradley et al. (2010) for the choice of these control variables. The first set of control variables is employed in both Pontiff (1996) and Bradley et al. (2010). Two of them, the inverse of the CEF share price ($1/P$) and the log market capitalization (MV), proxy for transaction costs associated with CEF shares. I measure both $1/P$ and MV at the end of the prior month. The third control variable is the residual standard deviation of a CEF's NAV return ($STDNAV$), which proxies for the difficulty of replicating the CEF's underlying portfolio. I calculate $STDNAV$ as the standard deviation of residuals from regressing a CEF's monthly NAV returns in excess of the risk-free rate onto Fama-French three factors plus the momentum factor over the prior 12 months. The fourth control variable is dividend yield (DIV). It is calculated as total cash dividends paid by a CEF in the prior 12-month period divided by its NAV at the end of the prior month. Following Cherkes, Sagi, and Stanton (2009), a dividend is classified as a cash dividend if the first digit in its CRSP distribution code (distcd) is one and the second digit in its distcd is less than five.

The second set of control variables is employed in Bradley et al. (2010). They include annual share turnover (TO), fund age (AGE), and expense ratio ($FEES$). I calculate TO as total shares traded over the prior 12 months divided by the number of shares outstanding at the end of the prior month. Fund age AGE is the number of years since a CEF's first listing date on CRSP, as of the prior month. As in Cherkes, Sagi, and Stanton (2009), I calculate $FEES$ as quarterly (SG&A) expenses from S&P Capital IQ divided by total NAV, which in turn is the NAV per share multiplied by the number of shares outstanding. When expense data are not available from S&P Capital IQ, I extract them from CEFs' N-CSRS and N-CSR filings on the website of SEC EDGAR.

In the difference-in-differences analyses, I use two independent variables as measures of a CEF's exposure to individual investor sentiment and interact them with the time dummy variable associated with the COVID-19 outbreak. As discussed in Section 2, when individual investor sentiment increases, the CEF price would increase relative to the NAV, which leads to a decrease in the discount, or equivalently, an increase in the premium (negative discount). This effect should be stronger for CEFs more exposed to individual investor sentiment. Therefore, the main measure of a CEF's exposure to individual investor sentiment is its sentiment beta, $Beta^S$, which captures the sensitivity of changes in CEF premiums (negative discounts) to changes in individual investor sentiment.[12] To calculate $Beta^S$, I first regress weekly changes in CEF premiums onto weekly changes in individual investor sentiment obtained from AAII:

$$Premium_{i\tau} - Premium_{i,\tau-1} = \alpha_i + \widetilde{Beta}_i^S (Sentiment_\tau - Sentiment_{\tau-1}) + \epsilon_{i\tau}, \qquad (2)$$

where $Premium_{i\tau} = -Discount_{i\tau}$ is the premium of CEF i in week τ, $Sentiment_\tau$ is AAII sentiment in week τ, and the other variables are self-explanatory.[13] I estimate $\widetilde{Beta}^S$ over the three-year window of February 2017 to January 2020, right before the COVID-19 shock. I require at least one year (52 weeks) of non-missing price/NAV data for a CEF to have a valid value of $\widetilde{Beta}^S$. To account for potential differences in $\widetilde{Beta}^S$ across different CEF categories, I normalize $\widetilde{Beta}^S$ and scale it by the mean value for the corresponding CEF category (i.e., equity, municipal fixed income, taxable fixed income, or other). I denote the scaled version as $Beta^S$ and use it as the main independent variable.

I use retail (investor) ownership (RO) as another measure of a CEF's exposure to individual investor sentiment. Since data on institutional ownership are available quarterly, RO is measured at the end of 2019 as one minus the fraction of CEF shares held by institutional investors and insiders.

The summary statistics of these main variables are presented in Table 1. Their magnitudes are largely in line with those reported in the previous literature. The average discount in my sample is 5.30%, with a standard deviation of 9.33%. In all analyses, I winsorize continuous variables at the 1% and 99% levels to mitigate the effect of outliers.

[12] Following the convention in the literature, I use the term "discounts" instead of "premiums" to characterize the discrepancy between CEF prices and NAVs throughout the paper, except for when sentiment beta is defined. This exception is for ease of exposition because discounts depend on sentiment negatively, as discussed in Section 2.

[13] I run weekly regressions to estimate $\widetilde{Beta}^S$ because AAII individual investor sentiment is in weekly frequency. Although data on CEF premiums are available in daily frequency, I only use weekly data on premiums for the estimation of $\widetilde{Beta}^S$ since I need to match premium and sentiment data by date.

4.2 Effect of COVID-19 on Individual Investor Sentiment

The premise of Hypotheses 1 and 2 is that individual investor sentiment decreased after the outbreak of COVID-19. To verify this premise, I obtain data on individual investor sentiment from AAII. This measure has been commonly used in previous literature (e.g., Greenwood and Shleifer (2014) and DeVault, Sias, and Starks (2019)) to gauge the sentiment of individual investors. Based on surveys oriented to individual investors, this measure is calculated as the fraction of individual investors who hold a bullish view on the stock market performance in the next six months minus the fraction of individual investors who hold a bearish view.[14] One advantage of this measure is that it is available in weekly frequency, which enables tracing how individual investor sentiment changed in my sample period centering around the outbreak of COVID-19.

Figure 1 plots this sentiment measure in weekly frequency, from December 2019 to May 2020. In the pre-COVID period, the sentiment is mostly positive, and the average sentiment is 11.0%, which means the percentage of individual investors holding a bullish view is higher than that of individual investors holding a bearish view by 11. In the post-COVID period, the sentiment is consistently negative, and the average sentiment is -15.6%, which means the percentage of individual investors holding a bullish view is lower than that of individual investors holding a bearish view by 15.6. The decrease in sentiment occurred around the COVID-19 outbreak, and the magnitude of the decrease is 26.6%, which is sizable. In summary, the evidence in Figure 1 supports the premise of Hypotheses 1 and 2 that the COVID-19 outbreak led to a decrease in individual investor sentiment.

To complement the evidence in Figure 1, I also consider the index of consumer sentiment from the University of Michigan Surveys of Consumers as an alternative measure of individual investor sentiment. In Figure A1 in the Appendix, I show that that the index of consumer

[14]The fraction of individual investors holding a bullish view and that of individual investors holding a bearish view do not sum up to one. Some investors hold a neutral view.

sentiment also had a large decline after the COVID-19 outbreak.[15]

4.3 Effect of COVID-19 on CEF discounts

In this section, I test Hypothesis 1 and examine the effect of the COVID-19 outbreak on average CEF discounts. Figure 2 plots the time series of the average discounts across all 485 CEFs in the sample, in daily frequency, over the sample period of December 2019 to May 2020. It is clear that there is a dramatic increase in CEF discounts after the COVID-19 outbreak on February 24, 2020. The average CEF discount in the pre-COVID period (December 1, 2019, to February 23, 2020) is 3.55%, and that in the post-COVID period (February 24, 2020, to May 31, 2020) is 7.68%, more than double the pre-COVID average.

I further conduct the following regression analysis to examine the effect of COVID-19 on average discounts more formally:

$$Discount_{it} = b_0 POST_t + b_1 X_{it} + \gamma_i + \epsilon_{it}, \tag{3}$$

where $Discount_{it}$ is the discount of CEF i on day t, $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, X_{it} denotes the control variables discussed in Section 4.1, and γ_i denotes fund fixed effects. I double-cluster standard errors by fund and day to account for both cross-sectional correlations and auto-correlations of residuals in discounts.

The coefficient b_0 is the main coefficient of interest in this analysis. Table 2 presents the results. In Column (1), I do not include any control variables, and the b_0 estimate is 4.33% ($t = 13.25$). In other words, on average, CEF discounts increase by 4.33%, in line with the evidence in Figure 2. In Columns (2) to (4), I add different sets of control variables and find that the estimates of b_0 are similar across different columns and similar to that in Column (1).

[15]Corroborating the results in Figures 1 and A1, Giglio et al. (2021) surveyed retail investors who are Vanguard clients in February, March, and April 2020. They also find that these retail investors became more pessimistic about the short-run performance of both the stock market and the real economy after the COVID-19 outbreak.

They range from 3.63% to 4.03%, all statistically significant. Overall, the results in Table 2 complement the graphical evidence in Figure 2 and show that the average CEF discounts increased substantially after the outbreak of COVID-19, which supports Hypothesis 1.

4.4 Main Difference-in-Differences Analysis

The results above from testing Hypothesis 1 are suggestive (but not causal) evidence of the effect of sentiment on CEF discounts. Hypothesis 2 is the main hypothesis of this paper. One can test it using the difference-in-differences approach, which identifies the causal effect of sentiment on discounts.

To test Hypothesis 2, I examine whether CEFs more subject to individual investor sentiment had a larger increase in discounts after the COVID-19 outbreak. The main measure of the exposure to individual investor sentiment I use is sentiment beta $Beta^S$. As defined and discussed in Section 4.1, it captures the sensitivity of changes in CEF premiums to changes in individual investor sentiment. CEFs with higher $Beta^S$ are more exposed to individual investor sentiment.

The main difference-in-differences test employs the specification

$$Discount_{it} = b_0 Beta_i^S \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}, \tag{4}$$

where $Discount_{it}$ is the discount of CEF i on day t, $Beta_i^S$ is sentiment beta of CEF i, $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, X_{it} denotes the control variables discussed in Section 4.1, γ_i denotes fund fixed effects, and γ_t denotes time (day) fixed effects. As $Beta_i^S$ and $POST_t$ are subsumed by fund and time fixed effects, respectively, they are dropped from the regression. Fund fixed effects γ_i capture fund-level time-invariant characteristics that might affect discounts, while time fixed effects γ_t capture common factors that drive all CEF discounts together. In these regressions, the unit of analysis is a fund-day observation. Again, I double-cluster standard errors by fund and day to account for both cross-sectional correlations and auto-correlations of residuals in discounts.

Hypothesis 2 predicts that b_0 in equation (4) is positive. Table 3 presents the estimation results. In Column (1), I do not include any control variables to avoid the possibility that the control variables can be endogenous and also affected by the COVID-19 shock. In Column (1), the b_0 estimate, 0.82% ($t = 4.15$), is positive and statistically significant. This suggests that CEFs with higher $Beta^S$ experienced a larger increase in discounts, after the outbreak of COVID-19, in support of Hypothesis 2. In Column (2), I add the first set of control variables: inverse price ($1/P$), log market capitalization (MV), the residual standard deviation of NAV return ($STDNAV$), and dividend yield (DIV). The b_0 estimate, 0.77% ($t = 3.98$), remains positive and statistically significant and is similar to that in Column (1) in magnitude. In Columns (3) and (4), I add the second set of control variables: annual turnover (TO), fund age (AGE), and expense ratio ($FEES$). Since adding $FEES$ as a control variable leads to a slightly lower number of observations, I present results both without (Column (3)) and with (Column (4)) $FEES$ included. The b_0 estimates again are positive and statistically significant and similar in magnitude to that in Column (1). The control variables carry expected signs. The two significant control variables are MV and DIV, both of which affect discounts negatively, consistent with the evidence in Bradley et al. (2010).

In terms of economic magnitude, the standard deviation of $Beta^S$ is 1.33 from Table 1. Across Columns (1) to (4) in Table 3, a one-standard-deviation increase of $Beta^S$ increases CEF discounts by 0.96 ($= 0.72 \times 1.33$) to 1.09 ($= 0.82 \times 1.33$) percentage points after the outbreak of COVID-19. The top-bottom decile spread of $Beta^S$ is 4.50, which corresponds to an increase of discounts by 3.24 ($= 0.72 \times 4.50$) to 3.69 ($= 0.82 \times 4.50$) percentage points. Hence, moving from the bottom decile to the top decile of CEFs sorted on $Beta^S$, the discount increase after the COVID-19 shock is higher by 3.24 to 3.69 percentage points. For reference, the average CEF discount in the pre-COVID period is 3.55 percentage points.

The standard identifying assumption for difference-in-differences analysis is the parallel trends assumption. In the analysis here, the assumption is that the trends in discounts for CEFs with higher and lower values of $Beta^S$ are parallel prior to the COVID-19 shock. To check this assumption, I sort all CEFs into high and low $Beta^S$ groups by the sample median. I then estimate the regression:

$$Discount_{it} = \gamma_i + b_t^l Day_t + b_t^h High_i \times Day_t + \epsilon_{it}, \tag{5}$$

where γ_i denotes fund fixed effects, Day_t equals one for a particular day t and zero for other days, and $High_i$ equals one if CEF i is in the high $Beta^S$ group and zero otherwise.[16] I omit Day_t and $High_i \times Day_t$ for $t =$ February 21, 2020, which is the trading day right before the COVID-19 shock on February 24, 2020. In other words, February 21, 2020, serves as the reference day in this analysis. The time series of b_t^l captures the evolution of the average discount for the low $Beta^S$ group, and that of $b_t^l + b_t^h$ captures the evolution of the average discount for the high $Beta^S$ group. I plot these two time series in Figure 3. It shows that the trends in discounts for the high and low $Beta^S$ groups are parallel prior to the COVID-19 shock on February 24, 2020. This suggests that the parallel trends assumption is likely to be satisfied and therefore provides evidence on the validity of the difference-in-differences analysis.

5 Robustness Checks

The main difference-in-differences results presented in Table 3 suggest that there is a sentiment channel through which the outbreak of COVID-19 affected CEF discounts. These results, therefore, provide support for the sentiment-based explanation of CEF discounts. In this section, I present several robustness checks for the main results.

[16] See Restrepo, Cardona-Sosa, and Strahan (2019) for a similar analysis of examining parallel trends.

5.1 Difference-in-Differences Analysis: Retail Ownership

It is likely that CEFs with higher retail ownership are more exposed to individual investor sentiment. As a robustness check, in this subsection, I use retail ownership of CEF shares as an alternative measure of a CEF's exposure to individual investor sentiment and provide another difference-in-differences test of Hypothesis 2.

As described in Section 4.1, for each CEF i, I measure its retail ownership RO_i at the end of 2019 as one minus the fraction of its shares held by institutional investors and insiders.

I revise equation (4) by replacing $Beta_i^S$ with RO_i:

$$Discount_{it} = b_0 RO_i \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}, \tag{6}$$

where other variables than RO_i are defined as in equation (4).

Hypothesis 2 predicts that b_0 in equation (6) is positive. Table 4 presents the estimation results. The b_0 estimates are similar across the four columns. They range from 2.95% to 3.50% and are all statistically significant. These results suggest that CEFs with higher retail ownership experienced a larger increase in discounts, after the outbreak of COVID-19, in support of Hypothesis 2.

In terms of economic magnitude, the standard deviation of RO is 0.15 from Table 1. Across Columns (1) to (4) in Table 4, a one-standard-deviation increase of RO increases CEF discounts by 0.44 ($= 2.95 \times 0.15$) to 0.53 ($= 3.50 \times 0.15$) percentage points after the COVID-19 shock. The top-bottom decile spread of RO is 0.50, which corresponds to an increase of discounts by 1.48 ($= 2.95 \times 0.50$) to 1.75 ($= 3.50 \times 0.50$) percentage points. Hence, moving from the bottom decile to the top decile of CEFs sorted on RO, the discount increase after the COVID-19 shock is higher by 1.48 to 1.75 percentage points.

5.2 Difference-in-Differences Analysis: Alternative Measure of Sentiment Beta

In the difference-in-differences analysis presented in Table 3, I use the scaled version of sentiment beta $Beta^S$ as the treatment variable. In this subsection, I conduct a robustness test using the unscaled version of sentiment beta, $\widetilde{Beta}^S$, estimated from equation (2).

Specifically, I revise equation (4) by replacing $Beta_i^S$ with $\widetilde{Beta}_i^S$:

$$Discount_{it} = b_0 \widetilde{Beta}_i^S \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}, \tag{7}$$

where other variables than $\widetilde{Beta}_i^S$ are defined as in equation (4).

Table 5 presents the estimation results. The b_0 estimates are similar across the four columns. They range from 1.16% to 1.25% and are all statistically significant. These results suggest that the main difference-in-differences results in Table 3 are not sensitive to the use of the scaled or unscaled version of sentiment beta.

In terms of economic magnitude, untabulated results show that the standard deviation of $\widetilde{Beta}^S$ is 0.92. Across Columns (1) to (4) in Table 5, a one-standard-deviation increase of $\widetilde{Beta}^S$ increases CEF discounts by 1.07 (= 1.16 × 0.92) to 1.15 (= 1.25 × 0.92) percentage points after the COVID-19 shock. The top-bottom decile spread of $\widetilde{Beta}^S$ is 3.14, which corresponds to an increase of discounts by 3.64 (= 1.16 × 3.14) to 3.93 (= 1.25 × 3.14) percentage points. Hence, moving from the bottom decile to the top decile of CEFs sorted on $\widetilde{Beta}^S$, the discount increase after the COVID-19 shock is higher by 3.64 to 3.93 percentage points.

5.3 Difference-in-Differences Analysis: Alternative Date of the COVID-19 Outbreak

In the main difference-in-differences analysis, I use February 24, 2020, the first trading day after several municipalities of Italy began lockdown, as the date of the COVID-19 outbreak, following Albuquerque et al. (2020) and Ramelli and Wagner (2020). In this subsection, I provide a robustness check using an alternative date of the COVID-19 outbreak. Specifically, the WHO announced COVID-19 as a pandemic on March 11, 2020.[17] I therefore use March 11, 2020, as the date of the COVID-19 outbreak here.

I re-estimate equations (4) and (6) with $POST_t$ re-defined as equaling one if day t is on or after March 11, 2020, and zero otherwise. The results are presented in Table 6. For brevity, I only present results without control variables and with full control variables, corresponding to the two specifications in Columns (1) and (4) of Tables 3 and 4, respectively. Unreported results show that results for the other two specifications are similar. Table 6 shows that the coefficients associated with $Beta^S \times POST$ and $RO \times POST$ are qualitatively unchanged relative to their counterparts in Tables 3 and 4. This indicates that the main difference-in-differences results are robust to using the alternative date of the COVID-19 outbreak.

5.4 Alternative Channels

As discussed in the introduction, the COVID-19 outbreak might generate shocks to factors other than individual investor sentiment that could also affect CEF discounts. In this subsection, I explore the possibility that the difference-in-differences results in Tables 3 and 4 can be attributed to other alternative channels than the sentiment channel. I consider the following four channels proposed by rational theories of discounts: the liquidity channel, the expense channel, the payout channel, and the leverage channel.

[17] See https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020.

In the liquidity-based model by Cherkes, Sagi, and Stanton (2009), investing in CEFs provides investors an opportunity for investing in illiquid assets without incurring the illiquidity costs. Due to this liquidity benefit, CEFs trade at premiums relative to their NAVs, absent managerial fees. On the other hand, managerial fees lower CEF prices relative to their NAVs and create discounts. Therefore, we can observe either CEF premiums or discounts, depending on the relative magnitude of liquidity benefits and managerial fees. An increase in the liquidity gap (the difference between the illiquidity of underlying assets and the illiquidity of CEF shares) would lead to a decrease in CEF discounts, while an increase in managerial fees would lead to an increase in discounts.[18] In this model, managerial fees (characterized as the manager's share of dividends) increase with the expense ratio and decrease with the payout ratio, which implies that discounts increase (decrease) with the expense (payout) ratio. Although Cherkes, Sagi, and Stanton (2009) do not consider leverage explicitly, they conjecture that leverage would affect the discount (premium) negatively (positively).

Similar roles of these alternative channels have also been proposed by other rational theories of discounts. In terms of expense ratio, it is also the primary source of CEF discounts in Berk and Stanton (2007). Gemmill and Thomas (2002) and Ross (2002) show that if managers provide nothing of value in return, the discount is simply the ratio between the expense ratio and the sum of the expense ratio and payout ratio and therefore increases (decreases) with the expense (payout) ratio. Based on the tax liability hypothesis, Day, Li, and Xu (2011) argue that CEF dividend distributions reduce tax liability and thereby discounts, which also suggests that discounts decrease with the payout ratio. In terms of leverage, Elton et al. (2013) propose that one reason for the existence of closed-end bond funds is that they allow investors to leverage fixed income investment at low borrowing rates. Accordingly, higher leverage would result in lower discounts (higher premiums).

In summary, a decrease in liquidity gap, an increase in expense ratio, a decrease in payout

[18] As in Wu, Wermers, and Zechner (2016), I use liquidity gap, defined as the difference between underlying asset illiquidity and CEF share illiquidity, to empirically capture the liquidity benefits in the model of Cherkes, Sagi, and Stanton (2009).

ratio, or a decrease in leverage would lead to an increase in discounts, according to rational theories of CEF discounts.

Next, I examine whether these alternative channels play a role in driving the difference-in-differences results in Tables 3 and 4. If CEFs with higher sentiment beta or higher retail ownership experienced a decrease in liquidity gap, an increase in expense ratio, a decrease in payout ratio, or a decrease in leverage after the COVID-19 shock, then the main difference-in-differences results may not be attributed to the sentiment channel. Therefore, I examine the effect of the COVID-19 shock on liquidity gap, expense ratio, payout ratio, and leverage for CEFs with different sentiment beta (retail ownership), using the difference-in-differences approach. Naturally, the sample periods for the analysis below largely coincide with that for the difference-in-differences analysis in Tables 3 and 4.

5.4.1 The Liquidity Channel

The liquidity gap *LiquidityGap* captures the difference between the illiquidity of underlying assets and the illiquidity of CEF shares. Following Getmansky, Lo, and Makarov (2004) and Wu, Wermers, and Zechner (2016), I estimate asset illiquidity and share illiquidity using a first-order moving average model with NAV returns and stock returns, respectively. Specifically, it is measured for the pre-COVID (December 1, 2019, to February 23, 2020) and post-COVID (February 24, 2020, to May 31, 2020) periods separately. For each period, I run the following regression:

$$R_{i\tau} = \alpha_i + \epsilon_{i\tau} + \theta_{it}\epsilon_{i,\tau-1}, \tag{8}$$

where $R_{i\tau}$ denotes daily NAV or stock return of CEF i on day $\tau \in t = [12/1/2019, 2/23/2020], [2/24/2020, 5/31/2020]$. The estimated coefficient $\hat{\theta}_{it}$ is the corresponding asset (share) illiquidity of CEF i in the pre- or post-COVID period t, and $LiquidityGap_{it}$ is taken as their difference.

I calculate *LiquidityGap* for each CEF in the sample. I obtain two observations of *LiquidityGap* for each CEF, one from the pre-COVID period and the other from the post-COVID period. *LiquidityGap* is available for all 485 CEFs in the sample, leading to 970 observations for this analysis. Untabulated results show that the average *LiquidityGap* for CEFs in the sample is 0.23, in line with the mean value (0.237) in Wu, Wermers, and Zechner (2016). The fact that the average *LiquidityGap* is positive suggests that underlying assets are on average less liquid than CEF shares, consistent with the argument in Cherkes, Sagi, and Stanton (2009).

To examine the effect of the COVID-19 shock on liquidity gap for CEFs with different sentiment beta or different retail ownership, I estimate the following two difference-in-differences regressions:

$$LiquidityGap_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{9}$$

and

$$LiquidityGap_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{10}$$

where $LiquidityGap_{it}$ is the liquidity gap of CEF i in period t, $POST_t$ equals one if period t is the post-COVID period and zero otherwise, and other variables are defined as in equations (4) and (6).

The coefficient of interest for this analysis is b_0 in equations (9) and (10). For the liquidity channel to potentially contribute to the difference-in-differences results using discounts as the outcome variable in Tables 3 and 4, b_0 needs to be significantly negative.

The results are presented in Table 7. Column (1) shows the estimation results for equation (9). The b_0 estimate, 0.01, is small and statistically insignificant. Column (2) shows the estimation results for equation (10). The b_0 estimate, 0.28, is also small and statistically insignificant. In terms of economic magnitude, a one-standard-deviation (1.33) increase of

$Beta^S$ increases $LiquidityGap$ by 0.01 ($= 0.01 \times 1.33$), and a one-standard-deviation (0.15) increase of RO increases $LiquidityGap$ by 0.04 ($= 0.28 \times 0.15$), after the COVID-19 outbreak. They are both small compared with the mean value of $LiquidityGap$, 0.23.

Overall, these results suggest that it is not the case that CEFs with higher sentiment beta or higher retail ownership had a significant decrease in liquidity gap after the COVID-19 outbreak. Therefore, the evidence here suggests that the results in Tables 3 and 4 are unlikely to be driven by the liquidity channel.

5.4.2 The Expense Channel

As described in Section 4.1, I calculate the expense ratio $FEES$ as quarterly expenses divided by total NAV. It is annualized and in percentage terms. For the analysis here, the sample period contains two quarters, 2019:Q4 and 2020:Q2, which are the last quarter before the COVID-19 shock and the first quarter after the COVID-19 shock, respectively. This sample period is chosen to be consistent with that for the difference-in-differences analysis in Tables 3 and 4. I do not include 2020:Q1 in the sample because the COVID-19 outbreak took place during this quarter. For this analysis, I require data for $FEES$ to be available in both 2019:Q4 and 2020:Q2, which limits the sample to 457 CEFs and 914 observations.

To examine the effect of the COVID-19 shock on $FEES$ for CEFs with different sentiment beta or different retail ownership, I estimate the following two difference-in-differences regressions:

$$FEES_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{11}$$

and

$$FEES_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{12}$$

where $FEES_{it}$ is the expense ratio of CEF i in quarter t, $POST_t$ equals one if quarter t is 2020:Q2 and zero otherwise, and other variables are defined as in equations (4) and (6).

The coefficient of interest for this analysis is b_0 in equations (11) and (12). For the expense channel to potentially contribute to the difference-in-differences results using discounts as the outcome variable in Tables 3 and 4, b_0 needs to be significantly positive.

The results are presented in Table 8. Column (1) shows the estimation results for equation (11). The b_0 estimate is 0.01% (t = 0.50), which is small and statistically insignificant. Column (2) shows the estimation results for equation (12). The b_0 estimate is 0.08% (t = 0.35), which is also small and statistically insignificant. In terms of economic magnitude, a one-standard-deviation (1.33) increase of $Beta^S$ increases expense ratio by 0.01% (= 0.01% $\times$ 1.33), and a one-standard-deviation (0.15) increase of RO increases expense ratio by 0.01% (= 0.08% $\times$ 0.15), after the COVID-19 outbreak. They are both small compared with the mean value of $FEES$, 1.40% (See Table 1).

Overall, these results suggest that it is not the case that CEFs with higher sentiment beta or higher retail ownership had a significant increase in expense ratio after the COVID-19 outbreak. Therefore, the evidence here suggests that the results in Tables 3 and 4 are unlikely to be driven by the expense channel.

5.4.3 The Payout Channel

The majority of CEFs in the sample pay dividends either quarterly or monthly. Therefore, I choose the sample period for this analysis to be November 2019 to May 2020, which covers one quarter before and one quarter after the COVID-19 shock, so that there are observations of cash dividends in both pre- and post-COVID periods for most of the CEFs. I drop February 2020, during which the outbreak of COVID-19 took place.

I obtain monthly data on cash dividends from CRSP. As stated in Section 4.1, I determine a dividend as a cash dividend if the first digit in its CRSP distribution code (distcd) is one and the second digit in its distcd is less than five. For each CEF, I calculate total cash dividends for the pre-COVID period (November 2019 to January 2020) and the post-COVID period (March 2020 to May 2020), respectively. The corresponding payout ratio $PAYOUT$ for the pre- and post-COVID periods is calculated as total cash dividends divided by total cash dividends plus NAV and is in percentage terms. I assign a value of zero to $PAYOUT$ when there is no cash dividend in the pre- or post-COVID period, and there are 970 observations for this analysis. Untabulated results show that the mean value of $PAYOUT$ is 1.49%.

To examine the effect of the COVID-19 shock on $PAYOUT$ for CEFs with different sentiment beta or different retail ownership, I estimate the following two difference-in-differences regressions:

$$PAYOUT_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{13}$$

and

$$PAYOUT_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{14}$$

where $PAYOUT_{it}$ is the payout ratio of CEF i in period t, $POST_t$ equals one if period t is the post-COVID period and zero otherwise, and other variables are defined as in equations (4) and (6).

The coefficient of interest for this analysis is b_0 in equations (13) and (14). For the payout channel to potentially contribute to the difference-in-differences results using discounts as the outcome variable in Tables 3 and 4, b_0 needs to be significantly negative.

The results are presented in Table 9. Column (1) shows the estimation results for equation (13). The b_0 estimate is -0.01% ($t = -0.17$), which is small and statistically insignificant. Column (2) shows the estimation results for equation (14). The b_0 estimate is 0.60% ($t = 1.19$), which is also small and statistically insignificant. In terms of economic magnitude, a one-standard-deviation (1.33) increase of $Beta^S$ decreases payout ratio by 0.01% ($= 0.01\% \times 1.33$), and a one-standard-deviation (0.15) increase of RO increases payout ratio by 0.09% ($= 0.60\% \times 0.15$), after the COVID-19 outbreak. They are both small compared with the mean value of $PAYOUT$, 1.49%.

Overall, these results suggest that it is not the case that CEFs with higher sentiment beta or higher retail ownership had a significant decrease in payout ratio after the COVID-

19 outbreak. Therefore, the evidence here suggests that the results in Tables 3 and 4 are unlikely to be driven by the payout channel.

5.4.4 The Leverage Channel

I calculate leverage LEV as total liabilities divided by total assets and it is in percentage terms. I obtain quarterly data on total assets and total liabilities from S&P Capital IQ. When total assets and total liabilities are unavailable from S&P Capital IQ, I extract them from the N-CSRS and N-CSR filings on the website of SEC EDGAR. Similar to the analysis in Section 5.4.2, the sample period for this analysis contains two quarters, 2019:Q4 and 2020:Q2, which are the last quarter before the COVID-19 outbreak and the first quarter after the COVID-19 outbreak, respectively. Again, I do not include 2020:Q1 in the sample because the COVID-19 outbreak took place during this quarter. For this analysis, I require data for LEV to be available in both 2019:Q4 and 2020:Q2, which limits the sample to 463 CEFs and 926 observations. Untabulated results show that the mean value of LEV is 22.9%.

To examine the effect of the COVID-19 shock on LEV for CEFs with different sentiment beta or different retail ownership, I estimate the following two difference-in-differences regressions:

$$LEV_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{15}$$

and

$$LEV_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}, \tag{16}$$

where LEV_{it} is the leverage of CEF i in quarter t, $POST_t$ equals one if quarter t is 2020:Q2 and zero otherwise, and other variables are defined as in equations (4) and (6).

The coefficient of interest for this analysis is b_0 in equations (15) and (16). For the leverage channel to potentially contribute to the difference-in-differences results using discounts as the outcome variable in Tables 3 and 4, b_0 needs to be significantly negative.

The results are presented in Table 10. Column (1) shows the estimation results for equation (15). The b_0 estimate is 0.39% ($t = 1.11$), which is small and statistically insignificant. Column (2) shows the estimation results for equation (16). The b_0 estimate is 2.53% ($t = 0.69$), which is also small and statistically insignificant. In terms of economic magnitude, a one-standard-deviation (1.33) increase of $Beta^S$ increases leverage by 0.52% ($= 0.39\% \times 1.33$), and a one-standard-deviation (0.15) increase of RO increases leverage by 0.38% ($= 2.53\% \times 0.15$), after the COVID-19 outbreak. They are both small compared with the mean value of LEV, 22.9%.

Overall, these results suggest that it is not the case that CEFs with higher sentiment beta or higher retail ownership had a significant decrease in leverage after the COVID-19 outbreak. Therefore, the evidence here suggests that the results in Tables 3 and 4 are unlikely to be driven by the leverage channel.

5.4.5 Difference-in-Differences Results with More Controls

As another robustness check, I add variables associated with the four alternative channels as additional control variables into the difference-in-differences analysis in Tables 3 and 4. Since the variables associated with the expense channel ($FEES$) and the payout channel (DIV) are already controlled for in Tables 3 and 4, the two additional control variables I add are liquidity gap ($LiquidityGap$) and leverage (LEV). As shown in Table A1 in the Appendix, the coefficients associated with $Beta^S \times POST$ and $RO \times POST$ remain largely unchanged after these two additional variables are controlled for. This also suggests that the main difference-in-differences results are unlikely to be driven by the alternative channels considered above.

6 Conclusion

By exploiting the exogenous COVID-19 shock, this paper attempts to shed light on the CEF discount puzzle and offer insights into the debate between the sentiment-based and rational explanations of CEF discounts. I show that the COVID-19 outbreak caused a negative exogenous shock to individual investor sentiment. This enables identifying the causal effect of sentiment on CEF discounts using the difference-in-differences approach.

I derive two testable hypotheses from the sentiment-based model of CEF discounts proposed by De Long et al. (1990) and Lee, Shleifer, and Thaler (1991). First, CEF discounts increase on average after the outbreak of COVID-19. Second, CEFs more subject to individual investor sentiment experience a larger increase in discounts after the outbreak of COVID-19. Consistent with the first hypothesis, I find that the average discount had a sizable increase after the COVID-19 outbreak, from 3.55% in the pre-COVID period to 7.68% in the post-COVID period.

To test the second hypothesis, I use a CEF's sentiment beta as a measure of its exposure to individual investor sentiment. Using the difference-in-differences approach, I find that CEFs with higher sentiment beta experienced a larger increase in discounts after the COVID-19 outbreak, consistent with the second hypothesis. I also use retail ownership of CEF shares as an alternative measure of the exposure to individual investor sentiment and show that CEFs with higher retail ownership experienced a larger increase in discounts after the COVID-19 outbreak. I further show that the difference-in-differences results are unlikely to be driven by several alternative channels proposed by rational models of CEF discounts in the literature, such as the liquidity, expense, payout, and leverage channels.

Overall, the results suggest that individual investor sentiment plays an important and causal role in driving CEF discounts. They offer support for the sentiment-based explanation of CEF discounts and the use of CEF discounts as an empirical measure of individual investor sentiment.

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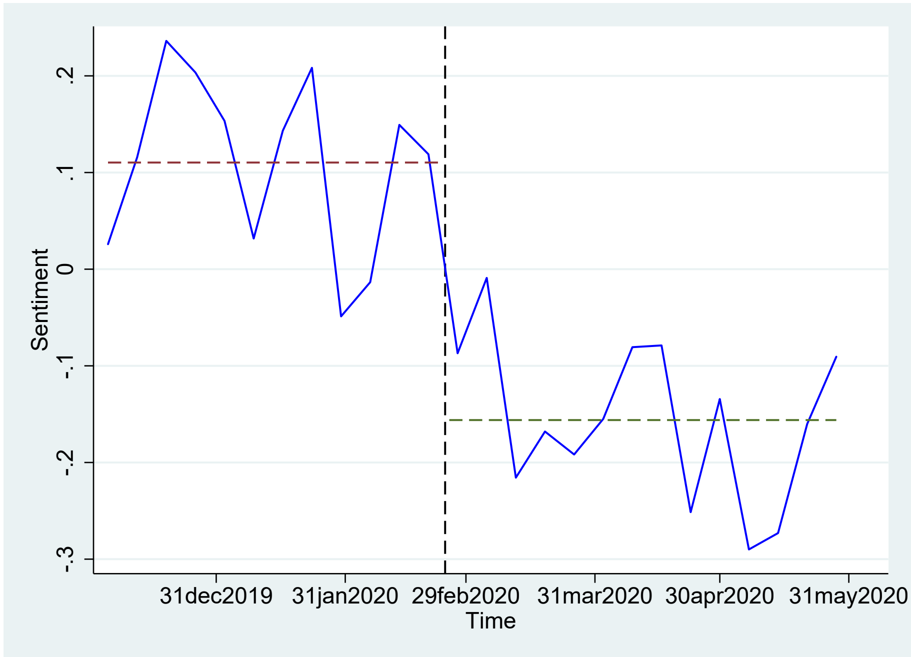

Figure 1. Individual investor sentiment over time. This figure plots weekly individual investor sentiment obtained from the American Association of Individual Investors over the sample period of December 2019 to May 2020. The dashed vertical line denotes February 24, 2020, the date of the COVID-19 shock. The two dashed horizontal lines denote the average sentiment in the pre-COVID and post-COVID periods, respectively.

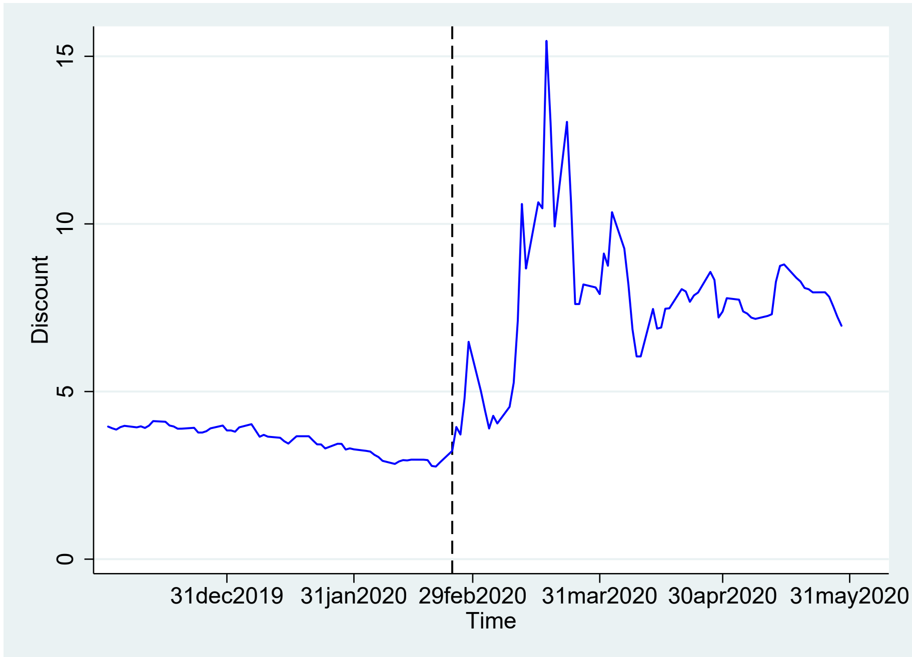

Figure 2. Effect of COVID-19 on CEF discounts. This figure plots the average discounts across all 485 CEFs in the sample, in daily frequency, over the sample period of December 2019 to May 2020. The dashed vertical line denotes February 24, 2020, the date of the COVID-19 shock.

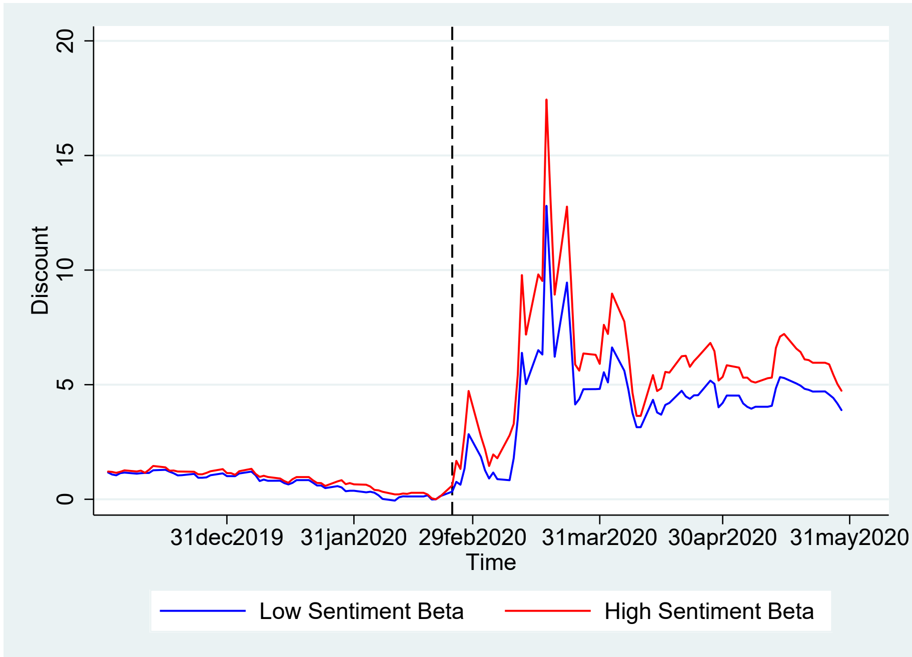

Figure 3. Trends in discounts around the COVID-19 shock for high sentiment beta and low sentiment beta CEFs. The CEFs are sorted into high and low sentiment beta groups by the sample median. I estimate the regression $Discount_{it} = \gamma_i + b_t^l Day_t + b_t^h High_i \times Day_t + \epsilon_{it}$, where γ_i denotes fund fixed effects, Day_t equals one for a particular day t and zero on other days, and $High_i$ equals one if CEF i is in the high sentiment beta group and zero otherwise. I omit Day_t and $High_i \times Day_t$ for t = February 21, 2020 (the reference day), which is the trading day right before the COVID-19 shock on February 24, 2020 (denoted by the dashed vertical line). This figure plots the time series of b_t^l (in blue), which captures the evolution of the average discount for the low sentiment beta group, and that of $b_t^l + b_t^h$ (in red), which captures the evolution of the average discount for the high sentiment beta group.

Table 1
Summary Statistics

This table reports summary statistics of the main variables employed in empirical analysis for all 485 CEFs in the sample. The mean, median, standard deviation (S.D.), 25^{th} percentile (P25), and 75^{th} percentile (P75) are reported. The sample period is December 2019 to May 2020. *Discount* is defined as the ratio of NAV per share minus share price to NAV per share and is in daily frequency. *1/P* is the inverse of CEF share price (in dollars) at the end of the prior month. MV is the log market capitalization (in millions) at the end of the prior month. $STDNAV$ is the residual standard deviation of a CEF's NAV return with respect to the Fama-French three factors plus the momentum factor in the prior 12 months. Dividend yield DIV is the ratio of dividends paid by a CEF in the prior 12 months to its NAV at the end of the prior month. Annual share turnover TO is the ratio of CEF shares traded in the prior 12 months to shares outstanding at the end of the prior month. $FEES$ is the annualized expense ratio, defined as expenses scaled by total NAV, in the prior quarter. Fund age AGE is the number of years since a CEF's first listing date on CRSP, as of the prior month. To obtain sentiment beta $Beta^S$, I regress weekly changes in CEF premiums onto weekly changes in individual investor sentiment from the American Association of Individual Investors over the three-year window of February 2017 to January 2020 and then scale estimated loadings by the mean value for the corresponding CEF category. Retail ownership RO is defined as one minus the fraction of CEF shares owned by institutional investors and insiders as of the end of 2019. *Discount*, $STDNAV$, DIV, and $FEES$ are in percentage terms.

	Mean	Median	S.D.	P25	P75
Discount	5.30	6.59	9.33	0.85	10.52
1/P	0.10	0.08	0.10	0.07	0.11
MV	5.55	5.60	1.12	4.90	6.28
$STDNAV$	3.72	3.36	1.27	3.01	3.95
DIV	7.10	6.19	7.49	3.94	8.61
TO	1.24	0.67	4.90	0.49	0.92
AGE	18.47	16.33	11.77	9.67	26.67
$FEES$	1.40	1.17	1.63	0.97	1.46
$Beta^S$	1.00	1.04	1.33	0.29	1.62
RO	0.78	0.82	0.15	0.71	0.89

Table 2
Effect of COVID-19 on CEF Discounts

This table presents the effect of COVID-19 on CEF discounts. The coefficients from the regression $Discount_{it} = b_0 POST_t + b_1 X_{it} + \gamma_i + \epsilon_{it}$ are reported. The variable $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, and γ_i denotes fund fixed effects. See the legend of Table 1 for the definitions of other variables. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
POST	4.33***	3.63***	3.99***	4.03***
	(13.25)	(7.58)	(4.82)	(4.73)
1/P		9.68	9.95	7.08
		(1.09)	(1.04)	(0.69)
MV		-4.91***	-5.09***	-6.53***
		(-3.97)	(-3.08)	(-3.04)
STDNAV		-0.09	0.00	-0.10
		(-0.44)	(0.02)	(-0.47)
DIV		-0.27*	-0.28*	-0.33*
		(-1.69)	(-1.69)	(-1.78)
TO			-0.01	-0.03
			(-0.03)	(-0.09)
AGE			-1.79	-1.72
			(-0.84)	(-0.80)
FEES				0.09
				(0.09)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,952	62,952	62,952	60,347
Adjusted R-squared	0.824	0.830	0.830	0.832

Table 3

Difference-in-Differences Results: Sentiment Beta

This table presents the DiD results with respect to sentiment beta. The coefficients from the regression $Discount_{it} = b_0 Beta_i^S \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}$ are reported. The variable $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, γ_i denotes fund fixed effects, and γ_t denotes day fixed effects. See the legend of Table 1 for the definitions of other variables. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$Beta^S \times POST$	0.82***	0.77***	0.77***	0.72***
	(4.15)	(3.98)	(3.96)	(3.50)
1/P		11.02	10.68	6.40
		(1.29)	(1.16)	(0.64)
MV		-4.78***	-4.89***	-6.64***
		(-4.47)	(-3.12)	(-3.14)
STDNAV		0.23	0.23	0.16
		(1.24)	(1.27)	(0.84)
DIV		-0.27*	-0.27*	-0.31*
		(-1.77)	(-1.70)	(-1.75)
TO			-0.05	-0.13
			(-0.17)	(-0.34)
AGE			0.52	1.16
			(0.18)	(0.41)
FEES				0.12
				(0.13)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,952	62,952	62,952	60,347
Adjusted R-squared	0.872	0.878	0.878	0.881

Table 4
Difference-in-Differences Results: Retail Ownership

This table presents the DiD results with respect to retail ownership. The coefficients from the regression $Discount_{it} = b_0 RO_i \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}$ are reported. The variable $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, γ_i denotes fund fixed effects, and γ_t denotes day fixed effects. See the legend of Table 1 for the definitions of other variables. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$RO \times POST$	3.26***	2.96***	2.95***	3.50***
	(3.27)	(3.10)	(3.09)	(3.50)
1/P		9.12	8.63	4.40
		(1.04)	(0.91)	(0.43)
MV		-5.14***	-5.28***	-7.06***
		(-4.81)	(-3.32)	(-3.28)
STDNAV		0.22	0.23	0.15
		(1.20)	(1.22)	(0.74)
DIV		-0.26*	-0.27	-0.32*
		(-1.69)	(-1.62)	(-1.73)
TO			-0.07	-0.17
			(-0.21)	(-0.43)
AGE			1.86	2.42
			(0.68)	(0.86)
FEES				0.17
				(0.18)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,952	62,952	62,952	60,347
Adjusted R-squared	0.869	0.875	0.875	0.879

Table 5

Difference-in-Differences Results: Alternative Measure of Sentiment Beta

This table presents the DiD results with respect to the unscaled version of sentiment beta. The coefficients from the regression $Discount_{it} = b_0 \widetilde{Beta}_i^S \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}$ are reported. The variable $POST_t$ equals one if day t is on or after February 24, 2020, and zero otherwise, γ_i denotes fund fixed effects, and γ_t denotes day fixed effects. $\widetilde{Beta}_i^S$ is the unscaled version of sentiment beta estimated using equation (2). See the legend of Table 1 for the definitions of other variables. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$\widetilde{Beta}^S \times POST$	1.25***	1.22***	1.23***	1.16***
	(4.49)	(4.54)	(4.52)	(4.06)
1/P		10.99	10.80	5.98
		(1.29)	(1.17)	(0.60)
MV		-4.89***	-4.96***	-6.83***
		(-4.48)	(-3.13)	(-3.21)
STDNAV		0.19	0.19	0.12
		(1.03)	(1.06)	(0.64)
DIV		-0.26*	-0.26*	-0.31*
		(-1.74)	(-1.66)	(-1.72)
TO			-0.03	-0.13
			(-0.11)	(-0.33)
AGE			-0.13	0.52
			(-0.05)	(0.19)
FEES				0.14
				(0.16)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,952	62,952	62,952	60,347
Adjusted R-squared	0.873	0.879	0.879	0.882

Table 6

Difference-in-Differences Results: Alternative Date of the COVID-19 Outbreak

This table presents the DiD results using March 11, 2020, as an alternative date of the COVID-19 outbreak. In Columns (1) and (2), the coefficients from the regression $Discount_{it} = b_0 Beta_i^S \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}$ are reported. In Columns (3) and (4), the coefficients from the regression $Discount_{it} = b_0 RO_i \times POST_t + b_1 X_{it} + \gamma_i + \gamma_t + \epsilon_{it}$ are reported. The variable $POST_t$ equals one if day t is on or after March 11, 2020, and zero otherwise, γ_i denotes fund fixed effects, and γ_t denotes day fixed effects. See the legend of Table 1 for the definitions of other variables. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$Beta^S \times POST$	0.82***	0.71***		
	(3.63)	(3.05)		
$RO \times POST$			3.35***	3.59***
			(3.07)	(3.36)
1/P		6.33		4.32
		(0.63)		(0.42)
MV		-6.72***		-7.08***
		(-3.16)		(-3.29)
STDNAV		0.16		0.14
		(0.83)		(0.73)
DIV		-0.32*		-0.32*
		(-1.78)		(-1.73)
TO		-0.15		-0.18
		(-0.39)		(-0.46)
AGE		1.24		2.44
		(0.44)		(0.87)
FEES		0.12		0.17
		(0.13)		(0.18)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,952	60,347	62,952	60,347
Adjusted R-squared	0.872	0.881	0.869	0.879

Table 7
Effect of COVID-19 on Liquidity Gap

This table presents the differential effect of COVID-19 on liquidity gap for CEFs with high versus low sentiment beta (Column (1)) and for CEFs with high versus low retail ownership (Column (2)). In Column (1), the coefficients from the regression $LiquidityGap_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. In Column (2), the coefficients from the regression $LiquidityGap_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. *LiquidityGap* is measured for the pre-COVID (December 1, 2019, to February 23, 2020) and post-COVID (February 24, 2020, to May 31, 2020) periods separately. For each period, asset illiquidity and share illiquidity are estimated using a first-order moving average model with daily NAV returns and stock returns, respectively, and *LiquidityGap* is calculated as asset illiquidity minus share illiquidity. The variable $POST_t$ equals one if period t is the post-COVID period and zero otherwise, and γ_i denotes fund fixed effects. Heteroskedasticity-consistent t-statistics based on standard errors clustered by fund are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Beta^S \times POST$	0.01	
	(0.58)	
$RO \times POST$		0.28
		(1.56)
$POST$	0.24***	0.04
	(6.92)	(0.25)
Fund Fixed Effects	Yes	Yes
Observations	970	970
Adjusted R-squared	0.388	0.392

Table 8
Effect of COVID-19 on Expense Ratio

This table presents the differential effect of COVID-19 on expense ratio for CEFs with high versus low sentiment beta (Column (1)) and CEFs with high versus low retail ownership (Column (2)). In Column (1), the coefficients from the regression $FEES_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. In Column (2), the coefficients from the regression $FEES_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. $FEES$ is measured as quarterly expenses divided by total NAV and is in percentage terms. The sample contains two quarters, 2019:Q4 and 2020:Q2. The variable $POST_t$ equals one if quarter t is 2020:Q2 and zero otherwise, and γ_i denotes fund fixed effects. Heteroskedasticity-consistent t-statistics based on standard errors clustered by fund are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Beta^S \times POST$	0.01	
	(0.50)	
$RO \times POST$		0.08
		(0.35)
$POST$	0.15***	0.11
	(3.71)	(0.58)
Fund Fixed Effects	Yes	Yes
Observations	914	914
Adjusted R-squared	0.806	0.805

Table 9
Effect of COVID-19 on Payout Ratio

This table presents the differential effect of COVID-19 on payout ratio for CEFs with high versus low sentiment beta (Column (1)) and CEFs with high versus low retail ownership (Column (2)). In Column (1), the coefficients from the regression $PAYOUT_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. In Column (2), the coefficients from the regression $PAYOUT_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. Since the majority of CEFs pay dividends either quarterly or monthly, the sample period is November 2019 to May 2020, which covers one quarter before and one quarter after the outbreak of COVID-19. I drop February 2020, during which the COVID-19 outbreak occurred. For each CEF, I calculate total cash dividends for the pre-COVID period (November 2019 to January 2020) and the post-COVID period (March 2020 to May 2020), respectively. The corresponding payout ratio $PAYOUT$ (in percentage terms) for the pre- and post-COVID periods is calculated as total cash dividends divided by total cash dividends plus NAV. The variable $POST_t$ equals one if period t is the post-COVID period and zero otherwise, and γ_i denotes fund fixed effects. Heteroskedasticity-consistent t-statistics based on standard errors clustered by fund are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Beta^S \times POST$	-0.01	
	(-0.17)	
$RO \times POST$		0.60
		(1.19)
$POST$	-0.12*	-0.60
	(-1.76)	(-1.46)
Fund Fixed Effects	Yes	Yes
Observations	970	970
Adjusted R-squared	0.693	0.698

Table 10
Effect of COVID-19 on Leverage

This table presents the differential effect of COVID-19 on leverage for CEFs with high versus low sentiment beta (Column (1)) and CEFs with high versus low retail ownership (Column (2)). In Column (1), the coefficients from the regression $LEV_{it} = b_0 Beta_i^S \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. In Column (2), the coefficients from the regression $LEV_{it} = b_0 RO_i \times POST_t + b_1 POST_t + \gamma_i + \epsilon_{it}$ are reported. LEV is measured as total liabilities scaled by total assets and is in percentage terms. The sample contains two quarters, 2019:Q4 and 2020:Q2. The variable $POST_t$ equals one if quarter t is 2020:Q2 and zero otherwise, and γ_i denotes fund fixed effects. Heteroskedasticity-consistent t-statistics based on standard errors clustered by fund are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Beta^S \times POST$	0.39	
	(1.11)	
$RO \times POST$		2.53
		(0.69)
$POST$	-1.24**	-2.81
	(-2.32)	(-0.97)
Fund Fixed Effects	Yes	Yes
Observations	926	926
Adjusted R-squared	0.919	0.918

A Appendix

A.1 The Index of Consumer Sentiment

To complement the evidence in Figure 1, I consider the index of consumer sentiment from the University of Michigan Surveys of Consumers as an alternative measure of individual investor sentiment and examine how it changed around the COVID-19 outbreak. I obtain data on the index of consumer sentiment, available monthly, from the website of Surveys of Consumers at the University of Michigan. Each month, a minimum of 500 interviews are conducted by telephone, and the interviewees are designed to be representative of all American households, excluding those in Alaska and Hawaii. The index of consumer sentiment is calculated based on the interviewees' responses to five questions related to personal finances, business conditions, and buying conditions. Figure A1 plots the time series of the consumer sentiment index, from December 2019 to May 2020. It is clear that consumer sentiment also had a large decline after the COVID-19 outbreak. In the pre-COVID period (December 2019 to February 2020), the average value is 100.0, while in the post-COVID period (March 2020 to May 2020), the average value is 77.7. The decrease is 22.3% of the pre-COVID average, which is considerable.

A.2 Difference-in-Differences Analysis with More Controls

In Table A1, I add liquidity gap ($LiquidityGap$) and leverage (LEV) as two additional control variables into the difference-in-differences analysis in Tables 3 and 4. I measure $LiquidityGap$ using daily NAV and stock returns from the prior three months. I first estimate asset (share) illiquidity using the first-order moving average model in equation (8), with daily NAV (stock) returns. $LiquidityGap$ is then calculated as asset illiquidity minus share illiquidity. LEV is total liabilities divided by total assets as of the prior quarter.

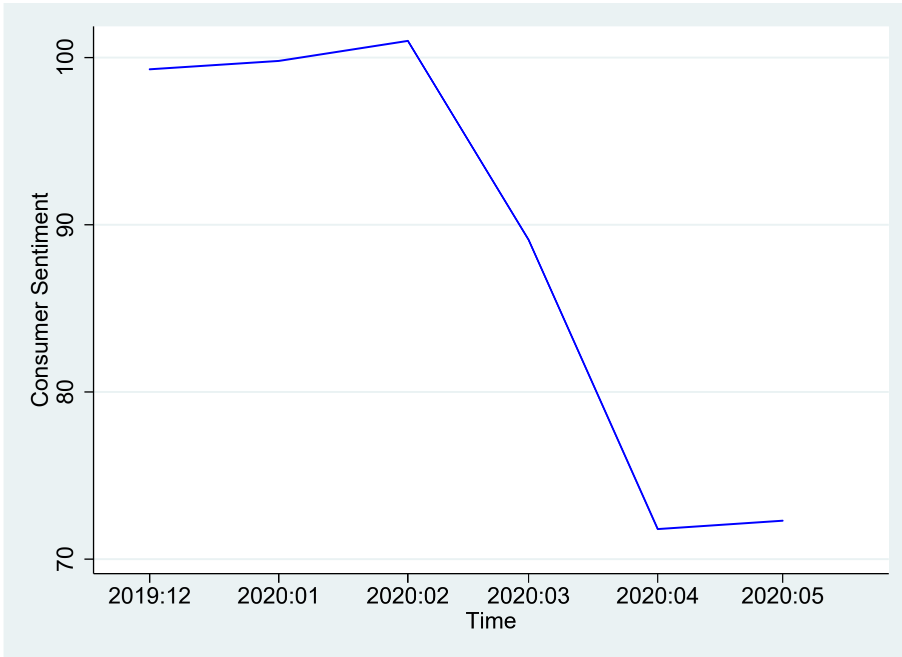

Figure A1. The index of consumer sentiment over time. This figure plots the index of consumer sentiment from the University of Michigan Surveys of Consumers, in monthly frequency, over the sample period of December 2019 to May 2020.

Table A1
Difference-in-Differences Results with More Controls

This table extends the DiD analysis in Tables 3 and 4 by adding two additional control variables, liquidity gap (*LiquidityGap*) and leverage (*LEV*). I estimate asset (share) illiquidity using a first-order moving average model with daily NAV (stock) returns from the prior three months. *LiquidityGap* is then calculated as the difference between asset illiquidity and share illiquidity. *LEV* is total liabilities divided by total assets as of the prior quarter. The sample period is December 2019 to May 2020. Heteroskedasticity-consistent t-statistics based on standard errors two-way clustered by fund and day are presented in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Beta^S \times POST$	0.73***	
	(3.51)	
$RO \times POST$		3.47***
		(3.43)
1/P	5.70	4.23
	(0.58)	(0.42)
MV	-6.58***	-7.08***
	(-2.98)	(-3.14)
STDNAV	0.15	0.14
	(0.76)	(0.67)
DIV	-0.30	-0.31*
	(-1.65)	(-1.67)
TO	-0.16	-0.17
	(-0.45)	(-0.46)
AGE	1.08	2.30
	(0.39)	(0.82)
FEES	0.19	0.19
	(0.20)	(0.19)
LiquidityGap	0.18	0.13
	(0.59)	(0.44)
LEV	-0.02	-0.00
	(-0.48)	(-0.08)
Fund Fixed Effects	Yes	Yes
Day Fixed Effects	Yes	Yes
Observations	60,347	60,347
Adjusted R-squared	0.881	0.879