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ETF flows on the volatility of NAV returns: Evidence from Chinese markets

Jiayuan Tian
Henry Bernstein College of Business Administration, University of New Orleans, LA, USA

Seungho Shin[1]
Lutgert College of Business, Florida Gulf Coast University, Fort Myers, FL, USA

Atsuyuki Naka
Henry Bernstein College of Business Administration, University of New Orleans, LA, USA

The main purpose of this study is to empirically investigate the relationship between ETF flows and the volatility of NAV returns in Chinese ETF markets. Our empirical findings show that there is a positive relationship between ETF flows and the volatility of NAV returns. Additional analysis using flows-interaction terms shows that ETF demand and arbitrage flows are the main drivers of the volatility of NAV returns, compared to unexpected flows. From the analysis of IRFs, demand flow shock emerges as the most influential factor in long-term volatility compared to the other two shocks. Understanding the dynamics of ETF flows and volatility of underlying assets can aid in designing regulatory frameworks that ensure market stability while promoting the advantages of ETF investments to market participants in order to reduce information asymmetry and maintain market efficiency.

Keywords: Exchange-traded funds (ETFs), Fund flows, Volatility of NAV, Chinese equity markets

1. Introduction

Since the first exchange-traded fund (ETF hereafter) was introduced in the United States in 1993, ETFs have gained significant attention across financial markets due to their ease of trading, transparency, and ability to implement various investment strategies (Gastineau, 2010). As ETFs become more popular, many academics have conducted research on their structures, flows, performance, and volatility (Agapova, 2011; Shum et al., 2016; Ben-David et al., 2018). Extending existing literature, Chen et al. (2020) and Xu et al. (2022) decompose ETF flows into three components – investor demand, arbitrage opportunities, and unexpected factor – and these components provide trading motivations. That is, investors demand ETFs to reduce idiosyncratic risk, create arbitrage opportunities from price discrepancy, and trade ETFs to avoid unexpected economic and

[1] Corresponding author, sshin@fgcu.edu.

political events.

This paper contends that the demand flow for ETFs plays a pivotal role in their trading. Unlike developed markets, where institutional investors tend to dominate, China's ETF market is primarily comprised of highly active retail investors, which potentially contributes to greater market volatility and information asymmetry. Additionally, although China's ETFs have experienced rapid growth in recent years, significant shortcomings remain in product innovation and risk management frameworks. For instance, inadequate market supervision and imperfect information disclosure mechanisms exacerbate the challenges faced by a retail-dominated market in accessing and interpreting trading information. Moreover, T + 1 trading system makes investors difficult to respond to information variations timely. For example, Ruan and Zhang (2016) find that retail investors contribute higher volatility to the equity market because of higher attention intensity. Sankaraguruswamy et al. (2013) imply that information asymmetry also increases demand flow and thus exacerbates volatility in the equity market.

From an informational standpoint, ETFs serve as critical vehicles for factor investing, necessitating active decisions regarding which factors to target as well as the optimal timing and allocation of investments (Xu et al., 2022; Cong & Xu, 2016). In China’s ETF market, the formal market maker system is pivotal in mitigating the adverse effects of information asymmetry. Information asymmetry—where certain market participants possess superior or more timely information—can lead to inefficient pricing, widened bid-ask spreads, and overall market instability. By mandating continuous two-way quotations and proactive liquidity management, market makers help align ETF trading prices closely with their underlying net asset values, thereby enhancing price discovery. This transparency reduces the informational advantage held by better-informed investors and contributes to a more equitable trading environment. Furthermore, by buffering against market volatility and ensuring consistent liquidity, the ETF market maker framework plays an essential role in sustaining market efficiency and fairness, which are crucial for the maturation and stability of China’s rapidly evolving ETF market.

In this study, our focus is on the impact of ETF flows on the volatility of net asset value (NAV hereafter) returns in Chinese markets. China has been the world’s largest and fastest-growing emerging economy since the free-market reform starting in the 1980s and has adopted new regulations and rules for its steady financial liberalisation. (Li and Si, 2024; Chen et al., 2011; Liao et al., 2014; Deng et al., 2020). The introduction of cross-border ETFs in 2012 became an opportunity to attract the attention of foreign institutional and individual investors, and despite their short history, Chinese ETFs are currently drawing attention as an alternative investment vehicle by reducing investment uncertainty and increasing efficiency (Fu and Jiang, 2023). There are related studies regarding ETF flows (Chen et al., 2020; Xu et al., 2022; Xu et al., 2019; Wang and Xu, 2019), but no other studies investigate how they impact the volatility of NAV returns. For example, Wang and Xu (2019) show the impact of ETFs flows on the volatility of the underlying index, which covers a broad range of ETFs flows transmitted over the Chinese markets. Laborda et al (2024) state that deviations from the NAV, fund flows, and market capitalisation of the ETF generate significant volatility spillovers from sector ETFs to their constituents, indicating that the NAV deviations and ETF flows create significant volatility spillovers to underlying securities. This can be stronger than those captured by index volatility. To fill the gap, we first decompose Chinese ETF flows into three factors – investor demand, arbitrage opportunities, and unexpected factor – and then analyse how they impact the volatility of NAV returns.

Our empirical results indicate that ETF flows have a positive impact on the volatility of NAV returns, which is consistent with the study by Ben-David et al. (2018). Our additional analysis, motivated by Chen et al. (2020), considers the case where one of the ETF flows dominates the others in trading activities and how such a condition impacts the volatility of NAV returns. We observe an inverse relation between ETF flows and the volatility of NAV returns if one of the ETF flows constitutes a large proportion of the overall ETF flows. Our findings have the potential to help market participants who use ETFs for portfolio diversification and liquidity management. By understanding the dynamics of flows and volatility, regulatory frameworks can be designed to promote the benefits of ETF investments while ensuring market stability.

2. Data and methodology

Daily based Chinese ETFs listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) are obtained from Datastream. We initially observe over 1,039 equity-type ETFs, but only collect those that have been listed and survived at least 625 business days (Xu et al, 2022) to secure uninterrupted long time series data for our analyses.[2] We construct flows and control variables known to influence the volatility of NAV returns (Bae and Kim, 2020; Ben-David et al., 2018), and winsorize them at 1% and 99% levels. We finalise sample data with 429 Chinese ETFs focusing on the period between January 1, 2014, and August 1, 2023. To avoid survivorship bias, delisted ETFs are included from the sample data.

To analyse the role of different market participants' impacts on volatility of NAV returns, we decompose the overall ETF flows into three components (Chen et al., 2020 and Xu et al., 2022) and then estimate each one using the following regression:

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[2] According to the study of Chen et al. (2020) and Broman and Shum (2018), newly launched ETFs experience dramatic creation and redemption activities and therefore do not provide reliable information.

$$ETF\ Flow_{i,t} = \mu + \rho_i ETF\ Turnover_{i,t} + \pi_i ETF\ Discrepancy_{i,t} + \varepsilon_{i,t} \quad (1)$$

where, $\rho_i ETF\ Turnover_{i,t}$ and $\pi_i ETF\ Discrepancy_{i,t}$ are the estimated ETF demand and arbitrage flows, respectively. $ETF\ Turnover_{i,t}$ is the trading volume divided by the share outstanding, $ETF\ Discrepancy_{i,t}$ is the absolute value of ETF price minus NAV divided by ETF price. The estimated residual, $\varepsilon_{i,t}$, represents unexpected ETF flow.

Figure 1. Volatility of NAV returns and ETF components

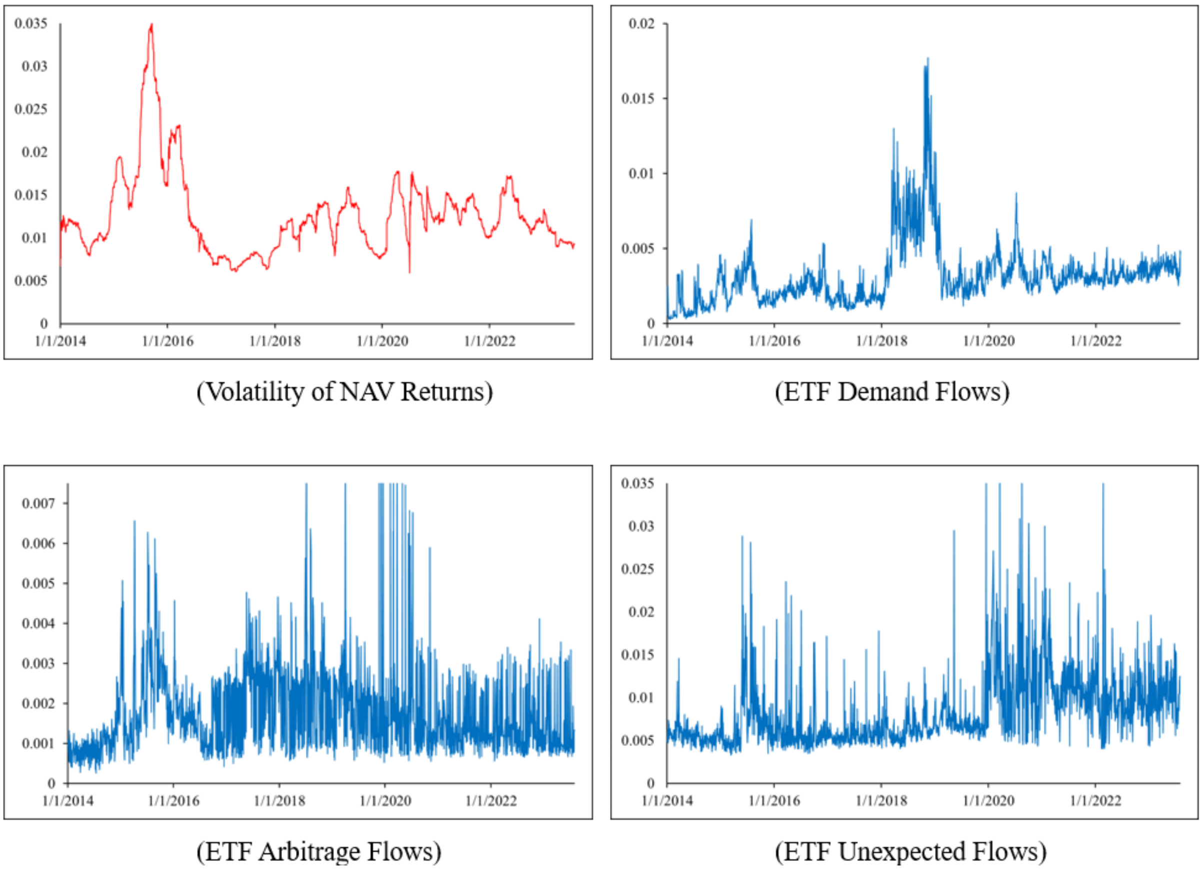

Figure 1 provides patterns of the volatility of NAV returns and three ETF flows. We observe that the volatility increased between 2015 and 2016, but has reduced since then. During the COVID-19 pandemic, there were no significant spikes observed; thus, these patterns can be evidence of diversification benefits from ETF investments.

To examine how ETF flows affect the volatility of NAV returns, we employ the fixed effects panel regression model as follows:

$$Volatility\ NAV_{i,t+1} = \alpha + \beta_1 ETF\ Flow_{i,t}^{Demand} + \beta_2 ETF\ Flow_{i,t}^{Arbitrage} + \beta_3 ETF\ Flow_{i,t}^{Undexpected} + \beta_4 X_{i,t} + \beta_5 Interaction\ Dummies_{i,t+1}^{Type} + Time\ Dummies + Firm\ Fixed\ Effects + \varepsilon_{i,t+1} \quad (3)$$

The $Interaction\ Dummies_{i,t+1}^{Type}$ provides information on which flows dominate the others. For example, for demand flow, $ETF\ Flow_{i,t+1}^{Demand} > ETF\ Flow_{i,t+1}^{Arbitrage} + ETF\ Flow_{i,t+1}^{Undexpected}$, the variable equals to 1, otherwise 0. This indicates that among ETF flow components, demand flows dominate the other two flows, resulting in market participants being more likely to avoid additional risk and information asymmetry. That is, market participants act more rationally, thus alleviating corresponding volatility in Chinese markets. Lastly, to understand how ETF flow shocks impact the volatility of NAV returns, we employ a Panel VAR (2) system with internal GMM (Abrigo and Love, 2016) estimation as follows:

$$Y_{i,t+1} = B_1 Y_{i,t} + B_2 Y_{i,t-1} + U_{i,t+1} \tag{4}$$

where $Y_{i,t}$ is vector of dependent variables for ETF_i. B_1 and B_2 are $(4 * 4)$ coefficient matrix with constant terms that describes the effect of the lagged variables at lags 1 and 2 on the current variables for the company j, respectively. $U_{i,t+1}$ indicates error terms for ETF_i.

3. Empirical findings

The empirical findings of ETF flows – demand, arbitrage, and unexpected – are positively related to the volatility of NAV returns, as reported in Table 1[3] using equation (2).[4] When comparing the coefficient 0.048 with the other two coefficients 0.021 and 0.001, the demand flow dominates the other two flows, and the unexpected ETF flows make the underlying assets more volatile. Decomposing ETF flows into three components shows that ETF demand flows are the main cause of ETF price mispricing, pushing prices further away from NAV returns. Our results reaffirm the study of Ben-David et al. (2018), including control variables.

[3] All tables and figures provide p-values in parentheses, and significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively.
[4] We correct the standard errors by a clustered method. The bootstrapping method provides consistent results.

Table 1. Volatility of NAV returns on ETF flows

	Model 1	Model 2	Model 3	Model 4
ETF demand flow	0.048***	0.047***		
	(0.000)	(0.000)		
ETF arbitrage flow	0.021***		0.021***	
	(0.000)		(0.000)	
ETF unexpected flow	0.001***			0.001***
	(0.004)			(0.001)
ETF log Cap	-0.000**	-0.000**	-0.000***	-0.000**
	(0.019)	(0.027)	(0.01)	(0.022)
Inverse price	-0.023***	-0.023***	-0.023***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Amihud illiquidity	7.769	7.586	7.71	8.695
	(0.159)	0.169	(0.113)	(0.114)
Bid ask spread	0.037***	0.037***	0.034***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)
Log Dollar trading volume	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ETF AUM	-0.022***	-0.022***	-0.022***	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
Shares growth	0.001	0.001	0.001	0.001
	(0.322)	(0.333)	(0.300)	(0.247)
Log shares	0.023***	0.023***	0.022***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Firms Fixed	Yes	Yes	Yes	Yes
Days Fixed	Yes	Yes	Yes	Yes
Observations	238,303	238,476	240,599	238,303
Adjusted R^2	0.039	0.039	0.040	0.039

Table 2 presents results including interaction terms in equation (3). The negative coefficients from two interaction terms, $Interaction\ Term^{Demand}$ and $Interaction\ Term^{Arbitrage}$ indicate that the volatility of underlying assets decreases when demand (or arbitrage) flows are larger than arbitrage (demand) and unexpected flows at following trading day. From the findings in Model 2, high ETF demand flows can be interpreted as a signal of market efficiency, which promotes the price discovery and reduces the volatility of NAV returns. Based on the findings in Model 3, the volatility of underlying assets decreases when arbitrage flows are larger than the other two flows on the next day, indicating that a potentially stronger price recovery will follow the next trading day from the current trading day (Fu and Jiang, 2023). These findings stabilise and mitigate the effects of arbitrage in ETFs in the last period (Madhavan, 2014). To sum up, ETF flows provide a price recovery function to mitigate the effects of arbitrage and minimise any impact from unexpected flows. ETF demand flows are the main driver to reduce noise trading while ETF arbitrage flows provide a price recovery function, and ETF unexpected flows have a minor effect on volatility with limited conditions.

Table 2. The volatility of NAV returns and ETF flows with interaction terms

	Model 1	Model 2	Model 3	Model 4
ETF Demand Flow	0.067***	0.068***		
	(0.000)	(0.000)		
ETF Arbitrage Flow	0.042***		0.042***	
	(0.000)		(0.000)	
ETF Unexpected Flow	0.000			0.000
	(0.938)			(0.310)
ETF Demand Flow*Ind_Demand	-0.026*	-0.028*		
	(0.131)	(0.100)		
ETF Arbitrage Flow*Ind_Arbitrage	-0.023***		-0.024***	
	(0.000)		(0.000)	
ETF Unexpected Flow*Ind_Unexpected	0.001			0.000
	(0.222)			(0.679)
ETF Log Cap	-0.000**	-0.0001**	-0.000**	-0.000**
	(0.021)	(0.027)	(0.011)	(0.022)
Inverse Price	-0.023***	-0.023***	-0.023***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Amihud Illiquidity	7.672	7.537	7.65	8.699
	(0.164)	(0.172)	(0.116)	(0.114)
Bid-Ask Spread	0.036***	0.037***	0.034***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)
Log Dollar Trading Volume	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ETF AUM	-0.022***	-0.022***	-0.022***	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
Shares Growth	0.001	0.001	0.001	0.001
	(0.349)	(0.368)	(0.302)	(0.246)
Log Shares	0.023***	0.023***	0.022***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Firms Fixed	Yes	Yes	Yes	Yes
Days Fixed	Yes	Yes	Yes	Yes
Observations	238,303	238,476	240,599	238,303
Adjusted R^2	0.040	0.039	0.040	0.039

To ensure the validity of our empirical findings, we conduct various robustness checks. First, we use a 30-day rolling window for the volatility of NAV returns and then employ TGARCH(1,1) and EGARCH(1,1) models to estimate the implied volatility. The results are consistent with our prior observations. Second, to mitigate multicollinearity concerns, we generate the correlation analysis and a variance inflation factor (VIF) test on the main variables, confirming that all variables pass the diagnostic and our model is minimally affected by multicollinearity.

Table 3 presents the estimation results of Panel VAR (2), and the decomposition of ETF flows highlights distinct effects on future volatility of NAV returns. The positive coefficient of demand flows, $ETF\ Flow_{i,t}^{Demand}$ and $ETF\ Flow_{i,t-1}^{Demand}$, shown in the table are both statistically significant, suggesting a substantial role of demand–driven flows in influencing the volatility of NAV returns. Arbitrage-driven flows can be attributed to the recovery mechanism following arbitrage activities, based on the negative arbitrage coefficient, $ETF\ Flow_{i,t}^{Arbitrage}$, to the positive arbitrage coefficient, $ETF\ Flow_{i,t-1}^{Arbitrage}$. Unexpected flows appear to have a limited impact on volatility of NAV returns, showing a low level of significance only at $t+1$. This indicates that unexpected flows contribute little to immediate changes in volatility. To further bolster our results, we also re-estimated the model including lags 1, 3, and 4, and obtained qualitatively the same findings.[5]

Table 3. Panel vector autoregression model (PVAR)

	$Volatility\ NAV_{i,t+1}$	$ETF\ Flow_{i,t+1}^{Demand}$	$ETF\ Flow_{i,t+1}^{Arbitrage}$	$ETF\ Flow_{i,t+1}^{Undexpected}$
$Volatility\ NAV_{i,t}$	1.467***	0.018***	2.697*	1.973**
	(0.000)	(0.010)	(0.092)	(0.015)
$Volatility\ NAV_{i,t-1}$	-0.497***	-0.018***	-2.625*	-1.865**
	(0.000)	(0.009)	(0.092)	(0.017)
$ETF\ Flow_{i,t}^{Demand}$	0.006***	0.518***	-0.005	2.807**
	(0.003)	(0.000)	(0.798)	(0.035)
$ETF\ Flow_{i,t-1}^{Demand}$	0.005***	0.294***	-0.008	0.592
	(0.002)	(0.000)	(0.643)	(0.217)
$ETF\ Flow_{i,t}^{Arbitrage}$	-0.004***	0.000	0.022	-0.006
	(0.001)	(0.810)	(0.290)	(0.496)
$ETF\ Flow_{i,t-1}^{Arbitrage}$	0.003***	0.002	0.386***	0.087
	(0.003)	(0.378)	(0.000)	(0.408)
$ETF\ Flow_{i,t}^{Undexpected}$	0.000	0.000**	0.000	0.003
	(0.290)	(0.031)	(0.732)	(0.237)
$ETF\ Flow_{i,t-1}^{Undexpected}$	0.000*	-0.000	0.000	0.004*
	(0.098)	(0.149)	(0.570)	(0.063)
Adjusted R^2	0.919	0.728	0.132	0.002
Observations	254,341	254,341	254,341	254,341

Figure 2 plots impulse response functions (IRFs) with 20-time steps, each figure presents IRFs of the volatility of NAV returns to shocks from demand flow, arbitrage flow, and

[5] Robustness checks for our empirical findings are not reported but are available upon request from the corresponding author.

unexpected flow, respectively. This approach captures the dynamic responses of the volatility of NAV returns to different types of funds flows shocks, providing insights into how each flow shock influences market stability over time. In Figure 2, both the demand and unexpected flow shocks exhibit significant positive shocks to the volatility of NAV returns, while the arbitrage flow shock shows a relatively weak, negative, and short-lived impact. These results suggest the demand and unexpected flow shocks amplify market instability in the short term. Arbitrage flow shock, on the other hand, shows an initial stabilising effect but quickly dissipates, indicating its limited role in influencing the long-term market stability. As a result, demand flow shock emerges as the most influential factor in long-term volatility, making it critical for understanding and managing market risk.

In addition to exhibiting IRFs patterns in Figure 2, Table 4 presents precise numerical values for size effects. We observe that a one-unit demand flow shock has a significant effect on the volatility of NAV returns, as measured by 0.0062 and 0.0174 at horizons 1 and 2, respectively. After reaching a peak of 0.0678 at 11, it then decreases to 0.0541 at horizon 20. From the one-unit change in arbitrage flow shock, we observe that the volatility of NAV returns reaches to –0.0036 and –0.0007 at horizons 1 and 20, respectively. From the one-unit change in unexpected flow shock, we observe similar patterns to those found in the demand flow shock, but it is economically negligible due to its small magnitude. From the findings in Table 4, we conclude that demand flows have a significant and persistent impact on the volatility of NAV returns compared to arbitrage and unexpected flows.

Table 4. Impulse response function (REF)

	Impulse variables		
Forecast Horizon	ETF demand flow	ETF arbitrage flow	ETF unexpected flow
0	0.000000	0.000000	0.000000
1	0.006234	-0.003643	0.000014
2	0.017351	-0.002551	0.000099
3	0.028413	-0.003243	0.000139
4	0.038594	-0.002478	0.000154
5	0.047143	-0.002493	0.000158
6	0.054015	-0.002058	0.000154
7	0.059272	-0.001947	0.000148
8	0.063093	-0.001700	0.000141
9	0.065670	-0.001586	0.000133
10	0.067196	-0.001434	0.000125
11	0.067848	-0.001336	0.000117
12	0.067782	-0.001230	0.000110
13	0.067134	-0.001148	0.000103
14	0.066020	-0.001067	0.000097
15	0.064541	-0.000998	0.000091
16	0.062779	-0.000932	0.000085
17	0.060805	-0.000872	0.000080
18	0.058677	-0.000816	0.000075
19	0.056443	-0.000764	0.000070
20	0.054145	-0.000715	0.000066

4. Conclusion remarks

In this study, our focus is on the relationship between ETF flows and the volatility of NAV returns in Chinese ETF markets. We conclude that Chinese ETFs increase volatility in Chinese equity markets, and our results are consistent with the existing literature. From additional investigations along with interaction terms, we find that the ETF demand and arbitrage flows are the main drivers affecting the volatility of NAV returns compared to unexpected flows. From the analysis of IRFs, demand flow shock emerges as the most influential factor in long-term volatility compared to the other two shocks, making it critical for understanding and managing market risk. Based on our findings, it would be interesting to further investigate how changes in other variables, such as transaction costs, information asymmetry, and market behaviour, affect the volatility of NAV returns.

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