A Study on Pricing Efficiency of

Exchange-Traded Funds:

Empirical Evidences from China

by

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**Abstract**

Probing into the pricing efficiency of China’s exchange-traded fund (ETF) market, this study explores four popular ETFs on both Shanghai Stock Exchange and Shenzhen Stock Exchange and examines their price premium/discount dynamics with up-to-date data. SSE 50 ETF, Huatai-PineBridge CSI 300 ETF, Harvest CSI 300 ETF, and E Fund ChiNext Price Index ETF are investigated over the period from October 22, 2013 to October 22, 2019 with the augmented Dickey-Fuller (ADF) test and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. The empirical results find that the cointegrated relationship between the market price and the NAV exists in all sample ETFs. Also, these ETFs tend to trade at a discount over the investigated period. Further, the GARCH modelling reveals that all four ETFs exhibit significantly poorer pricing efficiency when the Chinese stock market suffers from surging risks.

Key words: pricing efficiency, ETF, China’s ETF market, GARCH

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**1 Introduction**

The emergence of exchange traded funds (ETFs) offers a new investment alternative for both institutional investors and retail investors to manage their portfolios. Over the past years, the ETF market has grown drastically and expanded across the globe. As more investors come to recognize the benefits of using ETFs to gain diverse market exposures, the total market capitalization of global ETF is expected to continue the strong growth and double the market size to 12 trillion in 2023 (BlackRock, 2018). The continuing growth of the ETF market is driven by many factors, among which one important reason is the low-cost market access (BlackRock, 2018). ETF, as a highly-liquid instrument, can trade on secondary market like stocks, which significantly reduces the cost of transactions that used to involve expensive individual brokers to deal trades.

 While the US market has pioneered in introducing ETFs to the market, the ETF market in Asia holds different potentials in its future development based on distinctive legal and financial environments (PwC, 2020). China, in particular, has witnessed waves of new ETF issuances in the market over the past years. Currently, the overall ETF market in China is still soaring and has reached a record level volume, featuring a variety of tracked indexes. Institutional investors are the main players in market and engage actively in trading ETFs and a continuously growing number of domestic funds are fighting to grip a piece of this promising market. Meanwhile, more overseas funds rise in action and are including A share stocks into their indices. The landscape of China’s ETF market is constantly changing and urges more researches to shed light upon this field. The significant presence of ETFs in Chinses market urges in-depth study on this particular field. Among different aspects of China’s ETF market, its pricing efficiency is an important dynamic to examine.

Focusing on China’s booming ETF market, this research aims to analyze up-to-date daily transaction data using statistical modeling and infers mechanisms that can influence the pricing efficiency of ETFs. The study endeavors to answer the following question: what is the degree of pricing efficiency of China’s ETF market? How does the market price of ETFs deviate from the net asset value (NAV) of underlying securities over the course of a volatile market? Taking the period from October 2013 to October 2019 as the interested time frame, this paper will closely examine the past 6 years of a turbulent yet dynamic market in China.

**2 Literature Review**

 ETFs are innovative financial products that allow investors to access a variety of assets in the market at a low trading cost. During the trading day, the underlying securities of ETFs can go in and out of the asset pool based on investors’ demands. Consequently, this demand and supply relationship creates the arbitrage channel in ETFs. The embedded pricing mechanism of ETF makes it possible for the same underlying securities to have different prices: one is the market price of ETF (which is basically a bundle of different marketable securities) traded on exchanges; another is the NAV of underlying assets. In theory, these two prices should trade at the same level given the same fundamentals. However, abrupt volatility shock in the market can affect the demand and supply relationship of ETF or its the underlying securities, leading to temporary price differences and arbitrage opportunities. This gives rise to in-depth researches on how the market price of ETFs and the NAV react to different dynamics in the financial market.

At large, existing researches concerning China’s ETF market still remain limited. The first paper ever to examine the pricing efficiency of China’s ETF market was published in 2010 by Jiang, Guo and Lan on *The Chinese Economy*. This study provides important guidance in statistical modelling of ETFs. In this paper, they took Shanghai Stock Exchange 50 ETF (SSE 50 ETF) as an example and worked with Generated Autoregressive Conditional Heteroskedasticity framework to investigate its pricing efficiency. This study used high-frequency data from February 24, 2005 to September 26, 2008 and found supporting evidences to show that the market price of ETFs in Chinese market can unidirectionally influence the underlying NAV. Further, the researchers noticed that the differences between the market price and the NAV widened when the overall stock market in China underwent strong fluctuations in prices during the second half of 2007. Also, Hung, Wang & Chiu (2014) have examined Yuanta SSE 50 ETF and Fuh Hwa CSI 300 ETF in a paper and the empirical results suggested that the market price of ETFs is more robust to changes in the market than the NAV and therefore is a more suitable vehicle for price discovery.

Apart from research endeavors on evaluating the pricing efficiency of China’s ETF market, increasing academic interests have been drawn to studying the volatility spillover effect of ETFs onto the tracking indexes. Studies in this area, while not directly correlated to this paper, enrich the scope of study on ETFs across the world and provide meaningful insights in interpreting the empirical results of this study. Ben-David, Franzoni & Moussawi (2011) argued that “ETFs may increase the non-fundamental volatility of the securities in their baskets” and found supporting evidences with equity ETFs in the US market. Meanwhile, a recently published article emphasized on the effect of ETFs on the total and fundamental volatility of the underlying indexes based on empirical evidences from China’s equity ETFs (Wang & Xu, 2019). These two studies both highlights the decomposition of the volatility effect of ETF flows on the underlying index. They acknowledge that the underlying index fluctuations are differently motivated by either fundamental demands or non-fundamental dynamics, which provides opportunities of in-depth investigations for meaningful results. While they collect data from equity ETFs on different markets (the US and China), their studies shed light on practical approaches and feasible frameworks for future researches on the topic of volatility spillover effect in emerging ETF markets.

**3 Data and Methodology**

**3.1 Data**

The raw data of daily closing price and the NAV extracted from ETF’s trading history is the primary subject for this research. Wind databases, namely the “Chinese Bloomberg”, is the top domestic data vendor and provides raw data to this study. The scope of data covers the period from October 22, 2013 to October 22, 2019. This time window is chosen based on the historical data of new ETF issues in China. In 2012, only 5 new ETFs were launched. After that, China ETF market maintains a relatively strong and consistent performance in terms of new ETF issues[[1]](#footnote-1). Also, the established time window covers multiple periods during which the stock market witnessed loads of surprise events, both economically and politically speaking: i.e. the market crash in 2015, the trade frictions between China and US dating from 2018. Hence, the behavior of price movement between ETFs and underlying NAV is worth investigating with fresh data points from the exchanges to account for the latest years’ market efficiency.

 Four ETFs are used in this study: 1) China Asset Management Co. Shanghai Stock Exchange 50 ETF (SSE 50 ETF), 2) Huatai-PineBridge China Securities Index 300 ETF (300.SH ETF), 3) Harvest China Securities Index 300 ETF (300.SZ ETF), 4) E Fund ChiNext Price Index ETF (GEM ETF, ticket: 159915.SZ).

**Table 1. List of ETFs**

|  |  |  |  |
| --- | --- | --- | --- |
| Abbreviation | English name | Chinese name | Ticker |
| SSE 50 ETF | China AMC SSE 50 ETF | 华夏上证50ETF | 510050.SH |
| 300.SH ETF | Huatai-PineBridge CSI 300 ETF | 华泰柏瑞沪深300ETF | 510300.SH |
| 300.SZ ETF | Harvest CSI 300 Index ETF | 嘉实沪深300ETF | 159919.SZ |
| GEM ETF | E Fund ChiNext Price Index ETF | 易方达创业板ETF | 159915.SZ |

The chosen ETFs are representative of the Chinese ETF market and have different values added to this study. To begin with, SSE 50 ETF is the first ETF issued in China and is still one of the most popular ETFs among the Chinese market. It replicates the component stocks of Shanghai Stock Exchange 50 Index (SSE 50 Index), which consist of 50 stocks with top market capitalizations and active trading activities on the Shanghai Stock Exchange. Although SSE 50 ETF has been treated as a subject in the previous research on China’s ETF market (Jiang, Guo & Lan, 2010), it is still well worth the efforts today to inquire into its pricing efficiency over the recent years.

Both Huatai-PineBridge CSI 300 ETF and Harvest CSI 300 ETF track the performance of the CSI 300 index and hence are trading at similar levels. However, they employ different trading mechanisms: Huatai-PineBridge CSI 300 ETF allows intraday subscription and redemption while requests for subscription and redemption of Harvest CSI 300 ETF shares can only be confirmed after 2 days[[2]](#footnote-2). Therefore, juxtaposing these two ETFs in analysis will promote a deeper understanding in the impact of trading rules on pricing efficiency of ETFs. In addition, Huatai-PineBridge CSI 300 ETF is listed on Shanghai Stock Exchange while Harvest CSI 300 ETF is listed on Shenzhen Stock Exchange. The former one also has a greater volume than the latter one, which could have an impact on the pricing efficiency. Investigating whether ETFs tracking the same index will have divergent trading patterns due to different marketplaces is also interesting to consider. For the purpose of simplicity and easy understanding, the ensuing parts will refer to these two ETFs as 300.SH ETF and 300.SZ ETF respectively.

The forth E Fund ChiNext Price Index ETF listed on Shenzhen Stock Exchange tracks the Growth Enterprise Market (GEM) index, which represents a group of innovative, high-technology companies in the Chinese market. These companies usually feature intensive investments in product/service innovation and therefore bear higher uncertainty in the capital market. Analyzing the pricing efficiency of this GEM-focused ETF alongside the above ETFs which include more mature companies and more comprehensive industry coverage will provide valuable insights into the overall China’s ETF market. For the rest of the paper, the E Fund ChiNext Price Index ETF will be referred to as GEM ETF to highlight the nature of its underlying assets.

**3.2 Methodology**

This research first conjectures on the hypothesis that the market price of ETFs is closely correlated with the NAV of the underlying securities. In a perfectly efficient market, the market price of ETFs should always trade at the same level as the underlying NAV. However, when the overall market undergoes a highly volatile period, the market price of ETFs is anticipated to incorporate the volatility shock and therefore deviates from the underlying NAV, creating an instantaneous arbitrage window. Hypothetically, such temporary impact on ETF pricing will transmit through the arbitrage channel between ETFs and the underlying securities[[3]](#footnote-3).

The study also assumes the role that investors with short investment horizon play in shaping the dynamic between demand and supply of ETFs. When the uncertainties arise and the market expectation plummets, the burdened short-term investors tend to look for more liquid investment classes like ETFs to hedge their risks. Non-fundamental price movement of ETFs driven by surging market demands should be reversed later while fundamental-related value changes persist.

To further analyze the pricing efficiency of China’s ETF market, it’s also important to look at whether ETFs are trading at a premium or discount over a long period and during certain market events. In this study, the price premium/discount series is calculated by subtracting daily NAV from the market closing price of ETFs:

$$gap\_{t}= price\_{t}- NAV\_{t}$$

 The variable *gapt* taking value greater than 0 indicates that the ETF was traded at a premium at day *t* and a negative *gapt* indicates a discount in ETF pricing at day *t*.

In analysis of the data collected, the research wants to explore quantitative information on the pricing efficiency of these ETFs. Two main statistical methods are used to estimate the data: 1) augmented Dickey-Fuller (ADF) test and 2) generalized autoregressive conditional heteroskedasticity (GARCH) framework.

ADF test is also known as the unit root test. It is tested against the null hypothesis that there exists a unit root in the given time series. In addition, ADF test allows lags in model construction so that the autoregressive process can be estimated with higher orders. In this study, ADF test is conducted after the differencing of time series. A new differenced series of a variable $α\_{t}$ is defined as:

$$diff\left(α\_{t}\right)=α\_{t+1}-α\_{t}$$

The differenced series formulation is used on all market closing price series, NAV series and the price premium/discount series denoted by *gapt* of all ETFs. After the transformation, ADF test will determine whether the examined time series is stationary or not. For the differenced price premium/discount series, the property of stationarity is especially important because it indicates the cointegrated relationship between the market price of ETFs and the underlying NAV, supporting the assumption that the ETF price closely follows the NAV in the long term and the temporary price differences between them can be eliminated by the ETF creation/redemption mechanism.

Moreover, the conditional variance of the price discount/premium series is examined under the generalized autoregressive conditional heteroskedasticity (GARCH) framework with autoregressive (AR) process. The equations used for estimating the price premium/discount series *gapt* under the AR (h) - GARCH (p, q) framework are given as follows:

$$gap\_{t}=α\_{0}+\sum\_{i=1}^{h}α\_{i}gap\_{t-i}+ϵ\_{t}$$

$$ϵ\_{t}\~N(0,σ\_{t}^{2})$$

$$σ\_{t}^{2}=β\_{0}+\sum\_{i=1}^{q}β\_{1,i}ϵ\_{t-i}^{2}+\sum\_{j=1}^{p}β\_{2,j}σ\_{t-j}^{2}$$

In this study, all ETFs follow the GARCH (1, 1) model and takes different value of *h* in the AR process. The ensuing part will explain how different lags are chosen for different ETFs.

**4 Empirical Results**

**4.1 Summary Statistics of Chosen ETFs and Initial Observations**

**Table 2. Descriptive Statistics of ETFs**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SSE 50 ETF | 300.SH ETF | 300.SZ ETF | GEM ETF |
|  | Price | NAV | Price | NAV | Price | NAV | Price | NAV |
| Mean | 2.367 | 2.368 | 3.398 | 3.400 | 3.559 | 3.571 | 1.752 | 1.756 |
| Standard deviation | 0.470 | 0.470 | 0.639 | 0.640 | 0.697 | 0.701 | 0.438 | 0.437 |
| Kurtosis | -0.606 | -0.607 | 0.006 | 0.004 | -0.071 | -0.068 | 3.220 | 3.104 |
| Skewness | -0.437 | -0.439 | -0.270 | -0.275 | -0.350 | -0.363 | 1.489 | 1.455 |
| Minimum | 1.408 | 1.406 | 2.082 | 2.082 | 2.135 | 2.131 | 1.153 | 1.141 |
| Maximum | 3.427 | 3.41 | 5.306 | 5.322 | 5.532 | 5.572 | 3.790 | 3.796 |
| Corr. coefficient | 0.999968 | 0.999842 | 0.999549 | 0.999423 |

Table 2 presents the descriptive statistics of these four ETFs and hints a discount in their pricing on average. According to Table 2, the average market closing prices of all ETFs are smaller than the average NAV of ETFs given very close standard deviation in the series. For all ETFs, the market closing prices are highly correlated with the NAV as expected. Notably, while the 300.SH ETF and the 300.SZ ETF are tracking the same index performance, their pricing dynamics are different due to differences in fund sizes, turnover rates and etc. In addition, the table results suggest significant kurtosis and skewness in all the time series data distributions, indicating the complexity of working with financial data.

**4.2 Augmented Dickey Fuller Test**

Now that the highly correlated relationship between the market price of ETFs and the NAV is established for all sample ETFs, this study moves on to ADF test to check for the cointegrated relationship between the ETF price and the NAV. Table 3 exhibits the results from running ADF test on the preprocessed difference series for all ETFs. The ADF test is performed by utilizing a method adfuller() in the python package statsmodels and the lag term for each test is chosen based on Akaike information criterion (AIC) by default setting. As Table 3 reveals, all differenced series demonstrate stationarity. More importantly, the cointegrated relationship between the market closing price of ETFs and the NAV are confirmed by ADF test.

**Table 3. ADF Test Results of ETFs**

|  |  |  |
| --- | --- | --- |
|  | t-stats | lags |
| SSE 50 ETF |
| diff(price) | -7.356067\* | 22 |
| diff(NAV) | -7.044384\* | 20 |
| diff(price-NAV) | -11.553219\* | 24 |
| 300.SH ETF |
| diff(price) | -7.122712\* | 20 |
| diff(NAV) | -7.311074\* | 22 |
| diff(price-NAV) | -14.369108\* | 19 |
| 300.SZ ETF |
| diff(price) | -10.137323\* | 13 |
| diff(NAV) | -7.370165\* | 22 |
| diff(price-NAV) | -11.893103\* | 22 |
| GEM ETF |
| diff(price) | -8.058951\* | 23 |
| diff(NAV) | -7.982102\* | 23 |
| diff(price-NAV) | -16.733563\* | 14 |

Notes: \* indicates that the null hypothesis is rejected at 1% significant level.

**4.3 Price Premium/Discount under GARCH framework**

 The most important part of the analysis on ETF pricing efficiency is to examine the price premium/discount dynamic in the market. Table 4 presents summary statistics for these four ETFs. On average, all ETFs are trading at a discount in the market over the investigated period from October 22, 2013 to October 22, 2019. Figure 1 visualizes the movements of the price premium/discount variable *gapt* and offers a more straightforward view of how ETFs tend to trade at a discount in the Chinese market.

**Table 4. Summary Statistics of Price Premium/Discount Series of ETFs**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SSE 50 ETF | 300.SH ETF | 300.SZ ETF | GEM ETF |
| Mean | -0.001074 | -0.002621 | -0.012113 | -0.003663 |
| Standard Deviation | 0.003777 | 0.011404 | 0.021331 | 0.014879 |
| Kurtosis | 24.254136 | 132.308725 | 38.032132 | 126.767580 |
| Skewness | 0.789906 | -5.582858 | -1.014837 | -7.180494 |
| Minimum | -0.035 | -0.2248 | -0.2407 | -0.3006 |
| Maximum | 0.039 | 0.1415 | 0.2561 | 0.0843 |

**Figure 1. Price Premium/Discount Series Visualization**

*SSE 50 ETF* *300.SH ETF*



*300.SZ ETF* *GEM ETF*



The observation of a potential discount in China’s ETF market is further explored by decomposing the trading days into premium and discount. Table 5 summarizes the total days of ETFs trading at a premium or discount and shows a clear, persistent discount on pricing in China’s ETF market since all of ETFs trade at a discount more often than at a premium. As the data suggest, all ETFs were traded at a discount on more than half of the days over the last 6 years. Among these four ETFs, the 300.SZ ETF has the highest percentage of discounted trading days, which is in line with its lowest average of the price premium/discount series (*gapt*). Notice that the sum of two percentages of an ETF does not equal to 100% because there are days when the market closing price of ETFs matches the NAV[[4]](#footnote-4).

**Table 5. Days of ETFs Trading at Premium/Discount**

|  |  |  |
| --- | --- | --- |
|  | Days | Percentage (%) |
| SSE 50 ETF |
| Premium | 402 | 27.44 |
| Discount | 871 | 59.45 |
| 300.SH ETF |
| Premium | 500 | 34.13 |
| Discount | 955 | 65.19 |
| 300.SZ ETF |
| Premium | 198 | 13.52 |
| Discount | 1264 | 86.28 |
| GEM ETF |
| Premium | 501 | 34.20 |
| Discount | 945 | 64.51 |

To further the understanding in the price premium/discount dynamics, AR (h) - GARCH (p, q) model is used to estimate the conditional variance of the ETF price premium/discount series. In this study, the parameters in GARCH(p, q) model are set to be (1, 1). After experimenting with the data, different lags for the autoregression model are chosen to improve the explanatory power while avoiding redundant regressors with low statistical significance. As a result, SSE 50 ETF takes an AR(3) process while other ETFs use AR(2) for the mean function. The statistical modelling results are reported as follows:

**Table 6. Model Results for AR (3) - GARCH (1,1) on SSE 50 ETF**

|  |  |
| --- | --- |
| Mean Model | Volatility Model |
| Constant | -7.9344e-04\*(-17.671) |  Constant | 2.6365e-07\*(3.644e+04) |
| $α$1 | 0.2264\*(5.398) |  $β$1 | 0.1000\*(2.001) |
| $α$2 | 0.0877\*(2.285) |  $β$2 | 0.8800\*(24.771) |
| $α$3 | 0.0474\*(1.532) |  |  |
|  |  |  R2 | 0.076 |

**Table 7. Model Results for AR (2) - GARCH (1,1) on 300.SH ETF**

|  |  |
| --- | --- |
| Mean Model | Volatility Model |
| Constant | -1.3044e-03\*(-4.716) |  Constant | 2.3299e-06\*(2.716e+05) |
| $α$1 | 0.3459\*(3.465) |  $β$1 | 0.2000\*(3.110) |
| $α$2 | -0.0827\*(-4.097) |  $β$2 | 0.7800\*(19.118) |
|  |  |  R2 | 0.105 |

**Table 8. Model Results for AR (2) - GARCH (1,1) on 300.SZ ETF**

|  |  |
| --- | --- |
| Mean Model | Volatility Model |
| Constant | -3.1208e-03\*(-5.398) |  Constant | 6.0562e-06\*(6.236e+06) |
| $α$1 | 0.5709\*(10.999) |  $β$1 | 0.2000\*(12.279) |
| $α$2 | 0.0164(0.264) |  $β$2 | 0.7800\*(30.460) |
|  |  |  R2 | 0.328 |

**Table 9. Model Results for AR (2) - GARCH (1,1) on GEM ETF**

|  |  |
| --- | --- |
| Mean Model | Volatility Model |
| Constant | -7.5443e-04\*(-3.837) |  Constant | 2.6768e-06\*(4.886e+05) |
| $α$1 | 0.6347\*(9.138) |  $β$1 | 0.2000\*(5.141) |
| $α$2 | 0.0116(0.138) |  $β$2 | 0.7800\*(46.039) |
|  |  |  R2 |  0.395 |

Notes: \* indicates that the coefficient is statistically significant at 1% level. The t-stats for all coefficients are reported in parenthesis.

The tested variable *gapt* measures the degree of premium or discount in ETF pricing. In the mean model of SSE 50 ETF, all three coefficients for the lag terms are statistically significant, indicating that a premium or discount in ETF pricing three days ago will have an impact on today’s pricing. Other ETFs employ two lags in their mean models and find similar evidences supporting the influences that previous ETF pricing has on today’s prices. Another interesting point to notice here is that the two ETFs on Shenzhen Stock Exchange-300.SZ ETF and GEM ETF-report significantly higher R-squared values than the other two ETFs traded on Shanghai Stock Exchange. I expect further researches to probe into the differences between ETFs traded on Shanghai Stock Exchange and Shenzhen Stock Exchange.

In Figure 2, each GARCH conditional volatility of the price premium/discount measure *gapt* is visualized so that easier observations can be made from these plots. First, there exist similar patterns in the conditional volatility of each ETF. From the graph, intense volatility fluctuations happen around the 400th data points, which corresponds to the period of June 2015 when the Chinese stock market crashed and the risks suddenly spiked in the market. This conforms to the assumption that when the market undergoes a turbulent period, the pricing efficiency of ETFs also suffers from the sudden increase in the market uncertainty. Second, compared to other ETFs, the SSE 50 ETF demonstrates more substantial fluctuations in its GARCH conditional volatility in response to the volatility rise in the stock market. This phenomenon may be a result of its small number of component stocks in the asset pool compared to other ETFs.

**Figure 2. GARCH Conditional Volatility of Price Premium/Discount Series**

*SSE 50 ETF* *300.SH ETF*



*300.SZ ETF GEM ETF*



**5 Conclusions**

 In a nutshell, this paper contributes to the discourse on the pricing efficiency of China’s ETF market. SSE 50 ETF, Huatai-PineBridge CSI 300 ETF, Harvest CSI 300 ETF, and E Fund ChiNext Price Index ETF are investigated over the period from October 22, 2013 to October 22, 2019 for empirical study.

Overall, the Chinese ETF market tends to trade at a discount. While statistical tests support that the market price of ETFs closely follows NAV and there exists cointegrated relationship between the market price and NAV in the long term, the pricing efficiency of China’s ETF possesses more complex traits. By constructing the price premium/discount series and modeling its conditional variance under the GARCH framework, the study finds empirical evidences that the ETF exhibits significantly poorer pricing efficiency when the overall market undergoes a turbulent period. Events such as financial crisis, unexpected trade frictions will have a salient influence on the pricing efficiency of ETFs in the market. In this study, all four ETFs demonstrate unusually high volatility in the price premium/discount series when the Chinese stock market suffers from surging risks.

A less efficient pricing of ETFs can be leveraged to make profits. The deviation between the market price of ETFs and NAV presents an arbitrage opportunity. This price gap can be captured by authorized participants by creating new ETF shares at a high market price or redeeming ETF shares at a relative low level. Such ETF creation/redemption mechanism will also narrow down the gap between the market price and NAV until equilibrium. I expect more researches in the future to explore the price discovery mechanism of ETFs.

This study can be improved in several aspects. First, in further research, a wider scope of ETFs can be chosen to better reflect the overall Chinese ETF market. While the four ETFs in this paper are selected after careful consideration, better empirical results can be reached with larger sample to account for the diverse kinds of ETFs in the Chinese market. Second, this paper mainly focuses on investigating the movements of premium and discount in the ETF pricing. However, there are other important dynamics in ETFs that can be exploited in future study, such as the predictability of price differences in China’s ETF market. Up till now, the researches in the area of China’s ETF market are still limited. In the future, I hope to see more academic efforts in this field as the Chinese ETF market continues to grow.

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1. 40 new issues in 2018, 25 in 2017, 17 in 2016, 18 in 2015, 18 in 2014, 29 in 2013. Data obtained from Wind. [↑](#footnote-ref-1)
2. Public information from these funds’ official websites is used as references here. For more details please see: <https://www.huatai-pb.com/service/faq/chanpin/zhishu/510300/index.html> and <https://pic.bankofchina.com/bocappd/agreement/201205/P020120510492463118389.pdf> [↑](#footnote-ref-2)
3. Creation unit, referring to a bundle of shares of ETF, is a crucial concept in the mechanism of ETF. When the market of ETF deviates from the underlying NAV, authorized participants can create and redeem creation units to capture the price difference. [↑](#footnote-ref-3)
4. The data downloaded from Wind database are accurate to 3 decimal places. This means that the market closing price of ETFs may not be exactly the same as the NAV but is equivalent at the 3 decimal precision level. [↑](#footnote-ref-4)