Does the Introduction of Equity ETFs in the Emerging Markets Improve the Liquidity of the Underlying Stocks?

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จุฬาลงกรณ์มหาวิทยาลัย
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น.ส.ลักษมณ ธีระชาญณรงค์

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สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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จุฬาลงกรณ์มหาวิทยาลัย
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TABLE OF CONTENTS

Page

จุฬาลงกรณ์มหาวิทยาลัย
Chulalongkorn University

ABSTRACT

This paper examines whether the introduction of Exchange-Traded Funds (ETFs) has an effect on the liquidity of underlying stocks, specifically its impact on the liquidity of smaller-weight stocks. The sample consists of equity ETFs that were introduced between January 1, 2002 to December 31, 2018 from various emerging markets, including Brazil, China, India, Mexico, South Africa, Turkey, Chile, Colombia, Hungary, and Thailand. From my research, I have found that the liquidity of the underlying stocks tends to decline after the arrival of ETFs, and the reduction is also more pronounced for lower-weighted stocks. The results are robust after controlling for the country fixed effects. The findings support the adverse selection hypothesis that there are lower adverse selection costs in ETF markets than in individual stock markets, however, the adverse selection costs are mitigated by the change of stock-specific informed demand from individual stock market to the ETF market.

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1. INTRODUCTION

Exchange-Traded Fund (ETF) is a listed investment fund traded on stock exchanges. It represents a basket of multiple stocks, which is aimed to replicate the performance of the particular index. Since the first introduction of the ETFs to the world in the 1990s, ETFs have become one of the most well-known investment products, offering the combined benefits of both mutual funds and common stocks. On one hand, ETFs are created and redeemed like a mutual fund, and also provide investors a lower cost to trade compared to other types of mutual funds, such as bond funds, equity funds etc. On the other hand, they can be sold or bought throughout trading hours like common stocks, which provide liquidity advantage to investors. According to their benefits, ETFs are handy to investors, especially for passive investors who seek to replicate and hold a broad market index.

Since the arrival of the first ETFs back in 1993, many academic studies have highlighted its market consequents on the underlying assets and the overall market. In terms of its impact on the market, ETFs have been found to increase access to markets, and also improve liquidity, price discovery, transparency, and tax efficiency **(Hill, Nadig et al. (2015))**. As for its impact on underlying assets, ETFs is known to decrease the informational efficiency **(Israeli, Lee et al. (2017))**, increase the non-fundamental volatility **(Ben-David, Franzoni et al. (2018))**, and increase the co-movement in returns **(Da and Shive (2018))** of underlying assets.

Nevertheless, the existing empirical evidence is inconclusive about the impacts of ETFs on the underlying assets' liquidity. From one point of view, the arrival of ETFs can increase the liquidity of underlying assets. **Hegde and McDermott (2004)** documented that the liquidity of the underlying stocks of Nasdaq 100 index and DJIA 30 index increased following the introduction of ETFs because of a decrease in adverse selection cost. **Richie and Madura (2007)**'s research also concluded consistent results as Hegde and McDermott (2004). They documented that the underlying stocks' liquidity increased after the QQQ trust introduction and the increased liquidity is more intensed for lower-weighted stocks. Moreover, they found that comparing to a control sample, the systematic risk of underlying stocks decreased. The ETFs ownership also can improve the liquidity in underlying assets as well. **Agarwal, Hanouna et al. (2018)** also documented that ETF ownership influences the commonality in stock liquidity. The commonality of stock liquidity could be increased due to arbitrage activities in both the primary and the secondary ETF markets.

On the contrary, some researchers claim that ETFs reduce the liquidity of underlying assets. **Van Ness, Van Ness et al. (2005)** did not conclude a similar result as **Hegde and McDermott (2004)**. Using the matched sample, they found that the bid-ask spreads of the Dow Jones Industrial Average (DJIA 30 index) increased after the introduction of the Diamonds ETF. **Hamm (2014)** examined trading behavior of uninformed investors between the underlying stock and ETFs. He asserted that uninformed investors chose to trade ETFs over underlying stock to avoid trading against informed investors. Hence, there is the negative relationship between the level of liquidity of underlying stock in the market and the percentage of shares being held by ETFs. The negative relation is mitigated for stocks with high-quality earnings. **Petajisto (2017)** found that the non-liquid asset has a significant trading price deviation between ETF and its underlying. **Piccotti (2018)** also suggested that the trading price deviation between underlying asset and ETF in some ETFs is permanent, especially for the stock

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CHULALONGKORN UNIVERSITY

with low liquidity. He concluded that investors may be willing to pay a liquidity premium in order to get an access to ETF. **Dannhauser (2017)** found a reduction in underlying bonds' liquidity after the introduction of corporate bond. He suggested that investors buy the bond ETF while they sell the underlying bond (the crowding-out effect) simultaneously. **Pan and Zeng (2019)** asserted that the authorized participants (APs) with a dual role as market makers and as ETF arbitragers, and the APs in financial markets may sometimes provide less liquidity than they consume. In general, APs are liquidity providers for ETFs, but this could occur during periods of market stress. During such period, investors tend to submit a sell order more than a buy order. With this, the underlying stocks are less liquid, which reduce the APs' willing to engage in arbitrage activities. The authors, Pan and Zeng, documented that when the market volatility is high (captured by the Volatility Index or VIX), APs reduce their trading volume, implying that when volatility is high, APs act as arbitrageurs with limited capital-withdrawing **(Ben-David, Franzoni et al. (2012), Nagel (2012))**.

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In this paper, I examined how equity ETFs affect the liquidity of underlying stocks in the emerging markets. Using equity ETFs and their underlying assets as an observation from the developed market, such as DJIA 30, Nasdaq 100, Diamond, QQQ, and CAC 40, previous research could not explain much about the equity ETFs effect in emerging markets. Even though some papers take data from various countries, more than 70% of ETFs data comes from the United States, which is a developed market. This is because the majority of ETFs appear in the United States. According to the data selection, the liquidity effect can be distorted in the emerging market because if we compare an average ETF transaction costs between a developed market and emerging market, the average costs in the developed market is lower than in the emerging market

(Fong, Holden et al. (2017)). Hence, if the ETF transaction costs are high, there is a possibility that the liquidity of the ETFs and underlying assets will be lowered.

This study contributes to the existing literature in several ways. First, the study directly tests the effect of the arrival of ETFs on the underlying stocks' liquidity in the emerging markets. Studying the arrival of ETFs in the emerging market country may provide a new insight due to the different levels of liquidity. In prior empirical studies, which observes the impact on underlying assets' liquidity following the arrival of ETFs, most focus only on several ETFs that provide similar levels of liquidity. Some studies also looked at international ETFs, but most mainly focused on developed markets. Second, the theories put forward are compared to explain the improvement in liquidity or deterioration in liquidity observed for underlying stocks after the arrival of the ETFs in the emerging markets.

Since ETF is a basket of securities that tracks an underlying index, the price of ETFs should not be diverted from its Net Asset Value (NAV). However, the market price of ETF shares and the NAV of the underlying basket are not always the same because traders do not trade the ETF and the underlying assets at the same time. Therefore, this is an opportunity for traders to make an arbitrage when the discrepancy is greater than the transaction costs.

There are two methods to make the ETF share price align with the NAV of the underlying basket of stocks: the creation and redemption of ETF shares in the primary market, and the arbitraging of ETFs and their underlying portfolios by market participants in secondary market **(Ben-David, Franzoni et al. (2017))**.

1. The creation and redemption of ETF shares in the primary market: Participating Dealers (PD) or Authorized Participants (AP) compare the price between the ETF shares and the NAV. When the discrepancy is high enough to cover the transaction cost, they buy the cheaper assets and convert it to the more expensive assets for selling through the creation and redemption mechanism. By doing this, the PD and AP gain an arbitrage profit.

2. The Arbitraging of ETFs and their underlying portfolios by market participants in secondary market: By observing the discrepancy in price between the ETF shares and the same composition of individual stocks and anticipating that the difference will be reduced to zero, the traders or market makers will take either the long or short position in the ETF and then take an opposite position in the main components of the index or a closely related investment instrument, such as another ETF or futures.

These two methods make ETF prices similar to the basket price which the ETF intend to track. However, the greater the arbitrage activities in both the primary and secondary markets of ETFs, the greater the increase in the commonality of stock liquidity **(Agarwal, Hanouna et al. (2018))**.

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In this paper, we address the following questions: Does the introduction of ETFs improve the liquidity of underlying assets in the emerging markets? Do the smaller-weight securities create a higher impact than the larger-weight securities?

The rest of this paper is structured as follows: Section 2 will review the related literature and hypothesis development; Section 3 contains a description of the data that was studied. The method is presented in Section 4. Section 5 reports the findings and Section 6 presents my conclusion.

2. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Due to the higher ETF transaction cost in emerging markets compared to the developed market, the liquidity effect on underlying assets may be different for the securities in the emerging markets. This part presents theories related to the hypothesis, which explains how the arrival of ETFs affect the underlying assets' liquidity. The theories include: the adverse selection hypothesis, the arbitrage and risk shift hypothesis, and the recognition hypothesis.

2.1 The Adverse Selection hypothesis

Given a choice to trade between baskets of securities and the same composition of individual securities, informed traders with systematic information and uninformed liquidity traders who wish to trade portfolios will prefer the baskets of securities while informed traders with specific information will tend to trade individual securities **(Subrahmanyam (1991))**. Systematic-information traders and uninformed trader prefer to trade in the market for the baskets of securities because there are lower adverse selection costs in such markets than level of adverse selection in markets for individual securities.

Supported by **Gorton and Pennaccchi (1993)**, the existence of composite securities affects the real investment decision. Many studies show that uninformed traders tend to lose to or underperform to the informed traders in the markets **(Odean (1998), Barber and Odean (2000), Barber, Odean et al. (2008))**. To reduce their expected losses to the informed trader, Gorton and Pennacchi suggest the uninformed traders hold composite securities. Therefore, a basket of securities or composite securities can attract uninformed traders to trade in the ETFs market instead of trading in the individual stock market. This means that ETFs could reduce underlying stocks' liquidity, which leads to my first hypothesis:

H1(a): *After the introduction of ETFs in emerging markets, the liquidity of the underlying stocks decreases.*

Though, in **Subrahmanyam (1991)**'s finding, investors who hold a private information prefer to trade in the markets for individual securities since they are able to make a profit by submitting orders in the market for the baskets of securities according to the private information they have. Having security information is equivalent to having noisy information about the basket. Therefore, the more weighted the stocks in the market for the baskets of securities are, the more profit the informed traders can make on the stocks' specific private information. The adverse selection costs hence may be mitigated by the change of some stock-specific informed demand to the market for the baskets of securities. Accordingly, adverse selection costs in the smaller-weight stocks are predicted to be more significant than larger-weight stocks, which leads to my second hypothesis:

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H2: *Provided H1(a) holds, after the introduction of ETFs, a decrease in liquidity would be more pronounced in the smaller-weight stocks rather than in the larger-weight stocks.*

2.2 The Arbitrage and Risk Shift hypothesis

The arrival of new financial instruments that tracks existing stocks, for instance, ETFs, futures, or options, may expand investment opportunities and arbitrage opportunities for investors **(Ross (1976), Hakansson (1982))**. When there are high arbitrage opportunities, traders exploit these opportunities by submitting trading orders into the market. Higher trading activities lead to an improved liquidity and price efficiency of the underlying assets. **Kumar, Sarin et al. (1998)** found that the market efficiency of the underlying stocks is improved by option listings where market efficiency refers to reduction in the adverse selection component of the bid-ask spread, a reduction in the variance of the pricing error, a decrease in the bid-ask spread, and an increase in quoted depth, trading volume, trading frequency, and transaction size. **Deville, Gresse et al. (2014)** and **Kurov and Lasser (2002)** also illustrate that after the arrival of ETFs, index cash-futures arbitrage profits were reduced in both magnitude and frequency.

The arrival of ETFs could bring several arbitrage benefits for investors. First, the cost of informed trading could decline **(Hegde and McDermott (2004))**. Second, Participating Dealers (PDs) or Authorized Participants (APs) can make an arbitrage profit through the creation and redemption mechanism in the primary market **(Richie and Madura (2007))**. Another possible way to make an arbitrage profit comes from the secondary market. Investors can generate profit by taking long and short positions to take advantage of price differences between ETFs and the underlying assets. Therefore, an introduction of ETFs allows market participants to perform an arbitrage between the stock market and the ETF market.

By performing an arbitrage between two markets, investors can transfer information from one market to another. This allows for the reallocation of risk from hedgers on one market to speculators on another and reduces informational asymmetries **(Fremault (1991))**. As suggested by **Richie and Madura (2007)**, after the introduction

จุฬาลงกรณ์มหาวิทยาลัย
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of ETFs, an increase in liquidity will reduce the dispersed beliefs that shareholders hold and, consequently, reduce the risk of the component stocks.

Due to an increase in trading, the reduced risk of the stocks and the allowance of risks to be reallocated between the markets, the ETF market should improve stock liquidity. Therefore, I propose the hypothesis that:

H1(b): *After the introduction of ETFs in emerging markets, the liquidity of the underlying stocks increases.*

2.3 The Investor Recognition hypothesis

The investor recognition hypothesis, proposed by **Merton (1987)**, suggests that when a new event occurs, for instance, the arrival of an investment tool, securities that have little trade will receive more attention from investors. This idea is supported by **Barber and Odean (2008)** who demonstrated that unusual events like the arrival of ETFs may induce both existing investors and new investors to trade in the ETFs. Since introducing new instruments can be considered as promoting the new instrument, **Grullon, Kanatas et al. (2004)** documented that the higher the advertising, the better the liquidity of their common stock due to the increase in the number of new investors.

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Aiming to track a particular index, passive investors tend to select large-weight securities to invest. As a result, they ignore the small-weight securities to avoid disadvantages that may occur, such as illiquidity and higher transaction costs. However, with the introduction of ETFs, investors have a new and attractive opportunity to invest because ETFs provide benefits such as low transaction costs, intraday liquidity, easy way to trade, and arbitrage opportunities. These benefits could induce new-found investors to participate in the market. Trading ETFs would mean buying or selling all the stock components that they initially aim to replicate, via the ETF creation and redemption mechanism. With this, the small-weight securities' liquidity would eventually increase. All in all, the Investor Recognition hypothesis suggests that the liquidity of the underlying stocks would increase after the introduction of ETFs, and that the effect would be more intense for small-weight securities. This leads to my third hypothesis that:

H3: *Provided H1(b) holds, after the introduction of ETFs, an increase in liquidity would be more pronounced in the smaller-weight stocks rather than in the larger-weight stocks.*

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3. DATA

For my studies, countries that are commonly classified as "Emerging economies[1]" were identified. I then listed equity ETFs that were introduced between January 1, 2002 to December 31, 2018 from selected countries. The equity ETFs list was extracted from the Bloomberg database, which includes information on market, style, and sector equity ETFs. Starting with a list of 403 equity ETFs, I began by excluding international equity ETFs from my sample. With this, I focused on the equity ETFs that track stocks in their home country. Using the equity ETF from different countries enable us to see whether the results hold across different ETF market liquidity. Table 1 reports average daily number of shares traded on exchange-traded funds across country from 2002 to 2018. While China has high liquidity trading on the ETF market, other countries tend to have much lower liquidity trading compared to China.

My sample consists of 10 countries, where underlying stocks are tracked by equity ETFs. These countries are Brazil, China, India, Mexico, South Africa, Turkey, Chile, Columbia, Hungary, and Thailand. I then identified the underlying stocks from the Morningstar database and Datastream database.

In the Morningstar database, I identified a list of underlying stocks that were tracked by the ETFs, including the weight of investment and the ETF inception date. I then filtered out the duplicated underlying stocks that have a later ETF inception date. With this, the underlying stocks in my sample are those from the first occurrence of each stock being tracked by an ETF. This ensures that no underlying stocks would have an

[1]. I selected a common list of emerging markets that have been classified by major groups of analysts, i.e. IMF, MSCI, FTSE Russell, S&P and Dow Jones. The selected emerging markets are Brazil, China, India, Mexico, South Africa, Turkey, Chile, Columbia, Hungary, and Thailand.

ETF effect before the new ETF introduction. Afterwards, I extracted the daily data for the period between the date 12 weeks before the ETF introduction until the date 12 weeks after the introduction from the Datastream database, which consists of the trading volume in both currency unit and USD, ask price, bid price, high transaction price, low transaction price, and closing price.

Table 1

Average daily number of shares traded on an equity ETF security across country

The average daily number of shares traded on the ETF stock during 2002-2018 is from Bloomberg database.

Year	Brazil	Chile	China	Colombia	India	Indo nesia	Mexico	South Africa	Thailand	Turkey
2002					171,805					
2003					39,321					
2004					18,205					
2005			241,508,645		23,408					1,192,244
2006			44,282,948		21,217			180,037		1,233,789
2007			45,502,540		25,706		34,184,637	793,424	13,046,763	1,233,512
2008	115,955		136,787,367		140,755		3,752,784	335,953	4,654,785	1,173,255
2009	147,781		204,579,694		175,269		4,689,791	282,305	2,704,581	593,219
2010	118,982		69,937,121		136,299		1,810,737	8,214,886	1,303,256	547,757
2011	155,377		21,012,816	205,457	135,273		898,041	276,653	561,750	235,873
2012	239,745		25,730,539	319,877	79,256	16,378	620,443	144,559	851,291	193,414
2013	226,114	113,363	25,803,391	472,405	41,567	12,326	612,349	97,161	247,062	152,249
2014	235,952	52,479	30,525,535	215,797	142,429	32,063	1,002,177	75,829	137,990	78,716
2015	342,735	106,693	55,350,569	200,336	51,923	5,387	621,612	102,551	61,127	28,838
2016	400,406	130,963	16,968,854	382,860	37,435	8,788	872,263	86,089	114,547	16,274
2017	328,662	231,436	16,396,628	358,951	804,486	17,529	344,910	69,578	111,222	4,382
2018	434,561	316,835	37,677,585	320,047	212,684	10,005	422,807	72,606	123,994	14,567

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From the initial sample, 3,980 underlying stocks have been tracked by the ETFs. Out of these 3,980 stocks, 375 stocks lacked the information that was needed for the study. Therefore, they were excluded from the sample size. After removing the uncompleted stocks, the sample size is reduced to 3,605 stocks. Table 2 reports the distributions of final sample by country across sample periods. The majority of the underlying stocks are from China. The number of underlying stocks tend to increase from 2003 to 2018 due to a growth in popularity of ETFs across the globe. On average, there were 240 underlying stocks annually that were tracked by ETFs for the first time.

Table 2

Distribution of sample of underlying stocks tracked by ETFs across sample periods

The sample consists of 3,605 underlying stocks that were the first occurrence on the market.

Year	Country										Total	%
	Brazil	Chile	China	Colombia	India	Indonesia	Mexico	South Africa	Thailand	Turkey		
2003					38						38	1.1%
2005			47							15	62	1.7%
2006			103					35			138	3.8%
2007							16	10	40		66	1.8%
2008	98							8	3		109	3.0%
2009			57				5	4			66	1.8%
2010	17		149		10			3			179	5.0%
2011	8		935		58				2		1,003	27.8%
2012	10		222					24	4		260	7.2%
2013		36	70		3	36			70		215	6.0%
2014			133	8	14		19	3	2		179	5.0%
2015			258		6						264	7.3%
2016			264		8				2		274	7.6%
2017			244		5			7	26		282	7.8%
2018		4	147		293		6	2	18		470	13.0%
Total	**133**	**40**	**2,629**	**8**	**435**	**36**	**46**	**96**	**167**	**15**	**3,605**	100.0%
%	3.7%	1.1%	72.9%	0.2%	12.1%	1.0%	1.3%	2.7%	4.6%	0.4%	100.0%	

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4. METHODOLOGY

To testing the hypotheses, I measure the liquidity of the underlying stocks on two 3-month periods around the date of the arrival of each ETF. I choose two 12-week trading windows in accordance with **Richie and Madura (2007)**, because the period is long enough to capture the liquidity effect, but not long enough for other factors to intervene in the impact of the introduction of ETFs.

4.1 Univariate analysis

In order to test hypothesis H1(a) and H1(b), I tested the difference of several liquidity measures. Using a one-tailed test, I examined the following measures of the underlying stocks upon the first occurrence of each stock being tracked by an ETF. The tested measures consist of daily trading volume in currency unit, total trading volume in shares, market depth in currency unit, and the daily version of closing percent quoted spread.

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I used the *T*-Statistic to test whether the post-ETF mean subtracted by the pre-ETF mean is more than zero.

According to **Amihud, Mendelson et al. (1997)**, I examined market depth measured as

$$MD_i = \frac{\sum_t Volu_{i,t}}{\sum_t |R_{i,t}|} \qquad (1)$$

where MD_i is market depth of stock *i*, $Volu_{i,t}$ is volume of stock *i* in day *t*, and $R_{i,t}$ is return of stock *i* in day *t*. The daily version of closing percent quoted spread, proposed by **Chung and Zhang (2014),** is a daily liquidity proxy for percent quoted spread, percent price impact, percent effective spread, and percent realized spread. These four liquidity measurements are the standard measures of liquidity adopted from existing microstructure literature. For this study, I used the liquidity proxy as a liquidity measure due to limited sources of data available. However, it is documented by **Fong, Holden et al. (2017)** that its correlations with all four-daily percent-cost benchmarks[2] are surprisingly high, with a predictive power that has a significance level at the 1 percent level. It, therefore, became the best daily liquidity proxy for global research.

The closing percent quoted spread of stock i in week t is calculated as follow

$$Closing\ Percent\ Quoted\ Spread_{i,t} = Average[(Ask_{i,n} - Bid_{i,n})/M_{i,n}] \quad (2)$$

where $Ask_{i,n}$ is the ask price of stock i on day n from the Datastream daily data, $Bid_{i,n}$ is the bid price of stock i on day n from the Datastream daily data, and $M_{i,n}$ is the mean of $Ask_{i,n}$ and $Bid_{i,n}$.

To test hypothesis H1(a) and H1(b), I considered the variables related to trading size and depth. According to H1(a), measures of volume and depth for the underlying stocks are expected to decrease significantly; in contrast, H1(b) expects a significant increase in the liquidity measures for the underlying stocks.

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Chulalongkorn University

4.2 Multivariate analysis

As suggested by **Jegadeesh and Subrahmanyam (1993)**, within the liquidity measure, I decomposed the liquidity measure into three components: volatility, price,

[2] Percent quoted spread, percent price impact, percent effective spread, and percent realized spread

and volume. To examine whether the arrival of ETFs improves the liquidity of the underlying stocks, I established the following fixed-effects panel regression equation according to **Richie and Madura (2007)** and tested it with a fixed effect estimator:

$$LV_{i,t} = \quad \beta_1\, ETF_t + \beta_2\, W_{i,t} + \beta_3\, (ETF_t \times W_{i,t}) + \beta\, X_{i,t} + \beta_5\, \theta_i + u_{i,t} \qquad (3)$$

$LV_{i,t}$ represents two liquidity variables: lnDepth, which is the natural logarithm of market depth of stock *i* in week *t*, and lnSpread, which is the natural logarithm of closing percent quoted spread of stock *i* in week *t*; both use equation (1) and (2) respectively. ETF_t indicates the presence of ETF tracking the stocks through a dummy that takes the value of one if it is after the introduction of ETFs, $W_{i,t}$ characterizes the weight of stock *i* in the stock index during week *t*, which is expressed as percentage of the average market capitalization of the stock's home country for week *t* , $(ETF_t \times W_{i,t})$ denotes the interaction term between the ETF dummy and the stock weight, $X_{i,t}$ represents a set of control variables including $lnVar_{i,t}$, $lnVol_{i,t}$ $lnP_{i,t}$, $MktUp_{i,t}$ and $MktDown_{i,t}$, θ_i is a country fixed effect, and $u_{i,t}$ denotes the error term.

$lnVar_{i,t}$ is an average of the volatility using **Parkinson (1980)**'s extreme value method, $lnVol_{i,t}$ is the natural logarithm of total trading volume, and $lnP_{i,t}$ is the natural logarithm of the closing price. $MktUp_{i,t}$ equals a benchmark return for stock *i* during week *t* when positive and zero otherwise. $MktDown_{i,t}$ equals the benchmark return for stock *i* during week *t* when negative and zero otherwise. The benchmark return is calculated from the market index, where the underlying stocks are traded in. This is similar to the benchmark of ADVANC (Advanced Info Service) stock and AMX L (America Movil S.A.B. de C.V.) stock being calculated from the SET index and MEXBOL index respectively.

Volatility using **Parkinson (1980)**'s extreme value method is estimated as

$$Var^2 = \frac{(lnHIGH - lnLOW)^2}{4ln(2)} \tag{4}$$

$$lnVar_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} lnVar_{i,n} \tag{5}$$

where *HIGH* and *LOW* are respectively the daily high and low transaction prices. $N_{i,t}$ designates the number of days for stock *i* during week *t*.

$lnVol_{i,t}$ is the average of the natural logarithm of the currency volume traded;

$$lnVol_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} lnVol_{i,n} \tag{6}$$

where $Vol_{i,n}$ represents the volume traded in currency unit on stock *i* at date *n*.

$lnP_{i,t}$ is the average of the natural logarithm of the closing price on stock *i* at week *t*,

$$lnP_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} lnP_{i,n} \tag{7}$$

where $P_{i,n}$ is closing price on stock *i* at date *n*.

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Volatility, volume, and price levels are commonly admitted determinants of liquidity. In caution of macroeconomic factors that might have an impact on the liquidity of the market, $MktUp_{i,t}$ and $MktDown_{i,t}$ are proxies to control.

Referring to H1(a), the value of β_1 should be significantly positive, whereas H1(b) should be significantly negative. A positive value for β_2 and β_3 in the regressions would provide evidence for H2 and H3.

5. FINDINGS

To test whether the underlying stocks of ETFs in emerging markets have an increase or decrease in liquidity after the arrival of the ETFs, I used both the T-statistic test and panel data analysis to examine the effects of ETFs towards the underlying stocks' liquidity.

Table 3 presents a summary of the liquidity measures, where the trading volume, market depth, and closing percent quoted spread are shown for the underlying stocks before and after the introduction of ETFs. Using the one-tailed test of significance, *, **, ***, the symbols indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. In order to reduce the influence of extreme outliers, I first took the natural logarithm for each liquidity measure. The results of the paired t-test from this set of data are illustrated in panel A. I also dropped the extreme outlier by removing the observations that are at least five standard deviation away from the mean. The results of the paired t-test from this set of data are shown in panel B.

The results in Table 3 indicates that ETFs in emerging markets reduce the liquidity of the underlying stocks. In panel A, the natural logarithm of trading volume in both local currency unit and share unit and the natural logarithm of market depth significantly decreased after the introduction of ETFs. The natural logarithm of the closing percent quoted spread also rose with the differences significant at the 1 percent level.

Panel B showed similar results when the extreme outliers were removed instead of the logarithm transformation. The decrease in trading volume in currency is not as sharp as in panel A, yet still is significant at the 10 percent level. With significance at the 1 percent level, the trading volume reduced from 11,257.08 to 10,711.85 shares and the closing percent quoted spread also widened from 0.17 to 0.18%. As shown in Table 3, the results above show that Panel A and Panel B both have similar results, however the only difference between the two was the market depth, which shows that it rose from 5,790.20 to 6,008.11 million local currency on average, with significance at the 5 percent level. The performance was slightly disappointing. This was probably a result of using a different currency in the observations. To sum up, Table 3 shows

Table 3

Average market characteristics pre- and post-ETF

The sample used in this regression has a currency unit in local currency. Using one-tail test of significance, *, **, and *** indicate significance at the 10, 5, and 1% levels, repectively. Average liquidity measures are presented before and after the ETF introduction. Using T-test, I examine the null hypothesis that the post-ETF mean subtracted by the pre-ETF mean is more than zero. Market depth is the summation of volume divided by the summation of absolute return. Closing percent quoted spread is Average[(*Ask* – *Bid*)/*M*] where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. Panel A uses the sample set that all liquidity measures have taken natural logarithm. Panel B uses the sample set that has drop some extreme outliers that are at least five S.D. away from the mean.

Panel A: take a natural logarithm for each liquidity measure

Variable	Pre-ETF (N = 3,605)	Post-ETF (N = 3,605)	T-statistic	Pr(T < t)		Pr(T > t)	
Natural logarithm of Trading Volume (Million currency)	18.21	18.12	9.37	1.000		0.000	***
Natural logarithm of Trading Volume (shares)	8.44	8.36	8.97	1.000		0.000	***
Natural logarithm of Market Depth (Million currency)	22.28	22.20	7.77	1.000		0.000	***
Natural logarithm of Closing Percent Quoted Spread (%)	-6.47	-6.45	-4.40	0.000	***	1.000	

Panel B: drop the extreme outlier by removing the observations that are at least five S.D. away from the mean

Variable	Pre-ETF (N = 2,762)	Post-ETF (N = 2,762)	T-statistic	Pr(T < t)		Pr(T > t)	
Trading Volume (Million currency)	109.80	107.57	1.30	0.902		0.098	*
Trading Volume (shares)	11,257.08	10,711.85	3.83	1.000		0.000	***
Market Depth (Million currency)	5,790.20	6,008.11	-2.02	0.022	**	0.978	
Closing Percent Quoted Spread (%)	0.17	0.18	-4.60	0.000	***	1.000	

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that liquidity for the underlying stocks decreased after the introduction of ETFs. The following analysis in Table 4 to Table 7 will focus on the sample used in panel A.

The univariate test for depth, spreads, and volume was complemented by panel regressions following the method of **Richie and Madura (2007)** that incorporated price level, trading volume, volatility , and macroeconomic factors. Within the liquidity variable, I considered the market depth and the average daily closing percent quoted spread and computed the variable on a weekly basis. I thus have 3,605 stocks with 24 weekly observations per cross-section. The regression model is as stated in the equation (3);

$$LV_{i,t} = \beta_1 ETF_t + \beta_2 W_{i,t} + \beta_3 (ETF_t \times W_{i,t}) + \beta X_{i,t} + \beta_5 \theta_i + u_{i,t} \qquad (3)$$

Table 4

Descriptive statistics for Sample Observations

* indicates the variable before taking logarithm. The descriptive statistics of the variables used in the regressions are shown from the period from 2-week before to 2-week after the ETF introduction. Spread is closing percent quoted spread calculated by Average[(*Ask* – *Bid*)/*M*] where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. Depth is market depth calculated by the summation of volume divided by the summation of absolute return. Var is volatility using Parkinson's (1980) extreme value method. Vol is volume traded in currency unit. P is closing price. Other variables are defined as in Section 4 Methodology.

Variable	N	Mean	S.D.	Min	Max
lnSpread	85,035	-1.90	1.03	-5.90	5.30
Spread*	87,385	0.29	1.27	-0.04	199.93
lnDepth	88,353	8.38	1.67	-4.53	18.77
Depth*	88,386	82,944.39	1,127,755.00	0.00	141,000,000.00
lnVar	88,322	-3.91	0.46	-8.96	-1.59
Var*	70,192	0.00	0.00	0.00	0.05
lnVol	88,605	8.14	1.94	-2.30	14.59
Vol*	88,614	12,499.57	29,718.08	0.00	2,417,518.00
lnP	92,048	2.87	1.66	-2.75	11.18
P*	92,048	313.46	2,440.18	0.06	71,604.84
MktUp	95,324	0.01	0.02	0.00	0.11
MktDown	95,324	-0.01	0.02	-0.22	0.00
ETF	95,520	0.50	0.50	0.00	1.00
W	92,362	0.46	1.41	0.00	38.02
ETFxW	92,362	0.23	1.02	0.00	37.48

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Table 4 presents summary statistics for the variables used in the multivariate regression analysis. I also present the correlation between variables in Table 5 and Table 6 to avoid the problem of multicollinearity, where independent variables employed in the regression analysis are correlated. Table 7 summarizes the estimated coefficients of the variables employed in the multivariate regression models. I also incorporated country fixed effect in the regression.

Table 4 demonstrates the summary statistics, which includes the number of observations, mean, the standard deviation, the minimum value and maximum value for the dependent variable, and the explanatory variables used in the multivariate regression analysis.

Table 5 and Table 6 represent the correlation between the variables used in the multivariate regression analysis. The correlation coefficient examines the strength and direction of the relationship between variables. In Table 5 and 6, the maximum correlation coefficient is the coefficient between lnVol and lnP[3], which has a value of -0.4502. According to **Andreassen (1988)**, though, there is no relationship between the price and volume, but only when the price changes (where prices increase and decrease), does the volume increase. The negative correlation indicates that there are aggressive sellers and weak buyers in the stock market, which suggests that investors should have a negative view of the stock's development. This is in line with **Pan and Zeng (2019)**'s findings, where ETFs have been progressively invested in illiquid assets. The correlation between lnVar[4] and lnVol is worth mentioning because the coefficient is much higher than the others. Nevertheless, volatility was caused by an imbalance in

[3] The definition of lnVol and lnP is shown in Chapter 4 Methodology
[4] The definition of lnVar is shown in Chapter 4 Methodology

trade order, and not the volume of the order. Furthermore, as suggested by **Tull and Hawkins (1990)**, multicollinearity is not a problem if no correlation exceeds some predefined cutoff value, which is typically at around 0.5. Since the table shows the correlation between variables are less than 0.5, the results have no multicollinearity problem among the variables.

Table 5

Correlation between variables

The dependent variable is the natural logarithm of market depth. The sample used has a currency unit in local currency. All variables are defined as in Section 4 Methodology.

	lnDepth	lnVar	lnVol	lnP	MktUp	MktDown	ETF	W
lnDepth	1.0000							
lnVar	-0.1394	1.0000						
lnVol	0.4497	-0.3295	1.0000					
lnP	0.3871	-0.1107	-0.4502	1.0000				
MktUp	0.0457	0.1010	0.0663	-0.0575	1.0000			
MktDown	0.1824	-0.1505	-0.0166	0.1062	0.3409	1.0000		
ETF	-0.0219	-0.0183	-0.0182	-0.0042	-0.0391	-0.0209	1.0000	
W	0.2447	-0.0563	0.0680	0.1491	0.0134	-0.0216	-0.0013	1.0000

Table 6

Correlation between variables

The dependent variable is the natural logarithm of closing percent quoted spread. The sample used has a currency unit in local currency. All variables are defined as in Section 4 Methodology.

	lnSpread	lnVar	lnVol	lnP	MktUp	MktDown	ETF	W
lnSpread	1.0000							
lnVar	-0.0621	1.0000						
lnVol	-0.3942	-0.3295	1.0000					
lnP	0.1328	-0.1107	-0.4502	1.0000				
MktUp	-0.0463	0.1010	0.0663	-0.0575	1.0000			
MktDown	-0.0766	-0.1505	-0.0166	0.1062	0.3409	1.0000		
ETF	0.0114	-0.0183	-0.0182	-0.0042	-0.0391	-0.0209	1.0000	
W	0.1524	-0.0563	0.0680	0.1491	0.0134	-0.0216	-0.0013	1.0000

The fixed effect model examines whether the arrival of ETFs increases the liquidity of the underlying stocks and also answers whether the liquidity impact is more pronounced in smaller-weight stocks than in larger-weight stocks after the arrival of the

ETFs. Table 7 shows the regression analysis, which examines whether the arrival of ETFs affects the liquidity of the underlying stocks. Column (1) through (3) show the results when the natural logarithm of market depth is used as the dependent variable, while column (4) through (6) represent the results when the natural logarithm of closing percent quoted spread is used as the dependent variable.

Table 7

Regression analysis

The sample used in this regression has a currency unit in local currency. In model (1)-(3), the dependent variable is a natural logarithm of market depth which calculated by the summation of volume divided by the summation of absolute return, while in model (4)-(6), the dependent variable is a natural logarithm of closing percent quoted spread which calculated by Average[(*Ask* – *Bid*)/*M*] where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. All explanatory variables are defined as in Section 4 Methodology. In parenthesis is robust standard errors. The robust standard errors are clustered by country. Coefficients of country dummy are not reported. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, repectively.

Dependent Variable	**lnDepth**			**lnSpread**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
lnVar	-1.007***	-1.008***	-1.008***	0.135	0.15	0.15
	(-0.0321)	(-0.0329)	(-0.0329)	(-0.102)	(-0.0963)	(-0.0963)
lnVol	0.945***	0.946***	0.946***	-0.219***	-0.229***	-0.229***
	(-0.00505)	(-0.00489)	(-0.00489)	(-0.0535)	(-0.0508)	(-0.0508)
lnP	0.962***	0.962***	0.962***	-0.359***	-0.366***	-0.366***
	(-0.00635)	(-0.00557)	(-0.00557)	(-0.0679)	(-0.0701)	(-0.0701)
MktUp	-0.468**	-0.460**	-0.460**	-0.605	-0.677	-0.678
	(-0.159)	(-0.161)	(-0.161)	(-0.718)	(-0.707)	(-0.706)
MktDown	2.281***	2.269***	2.269***	-1.899***	-1.727***	-1.725***
	(-0.484)	(-0.492)	(-0.492)	(-0.15)	(-0.225)	(-0.225)
ETF	-0.0055	-0.0054	-0.00568	-0.00572	-0.00606	-0.00411
	(-0.0115)	(-0.0115)	(-0.0113)	(-0.0176)	(-0.0176)	(-0.0174)
W		-0.00231	-0.00263		0.0332*	0.0354*
		(-0.00466)	(-0.00478)		(-0.0164)	(-0.0179)
ETFxW			0.000619			-0.00444
			(-0.00227)			(-0.0046)
Observations	88,093	88,045	88,045	84,925	84,901	84,901
R-squared	0.88	0.879	0.879	0.258	0.261	0.261
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors		Clustered robust			Clustered robust	

Clustering standard errors by country are used in the panel regressions, with country fixed effect included. Definitions of each variable is shown in Section 4 Methodology.

Similar to the previous literatures, a significant negative relationship between the market depth and volatility was found, with an inverse relationship between the market depth and trading volume, and also between the market depth and prices. Conversely, though it was not significant, there is a positive relationship between the spread and volatility, while a significant negative relationship was shown in trading volume and prices. This demonstrates that the higher the stock price, the higher the market depth and also the narrower the spread, which lead to higher liquidity. For dealers, in order to protect themselves from high volatile stocks, they have to set the spread wider. However, when the stock enjoys greater trading volume, the dealers need to set the spread narrower.

The coefficient of the ETF dummy variable is statistically insignificant in all six models, which is inconsistent with **Van Ness, Van Ness et al. (2005)** and **Richie and Madura (2007)** 's findings. When the determinants of liquidity and macroeconomic factors were controlled, the results from using local currency data did not show the liquidity of the underlying stocks improving after the arrival of ETFs in emerging markets. Moreover, unlike the results in **Richie and Madura (2007)**'s findings, the W variable shows a positive and significant sign in model (5) and (6), which means the greater the weight of the underlying stock, the wider the spread.

Since there is no sign that the liquidity would increase or decrease after the introduction of ETF, we can neither support nor reject hypothesis 1. However, to reduce

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the bias from the different currency unit, I converted the observations' unit of currency to be USD and conducted the tests observed in Table 3 through Table 7 again.

Table 8 illustrates the results of the same testing methods done as Table 3, with changes in unit of currency to USD. Both Panel A and B presents a summary of the liquidity measures, with the influence of extreme outliers being reduced in two different ways.

Table 8

Average market characteristics pre- and post-ETF

The sample used in this regression has a currency unit in USD. Using one-tail test of significance, *, **, and *** indicate significance at the 10, 5, and 1% levels, repectively. Average liquidity measures are presented before and after the ETF introduction. Using T-test, I examine the null hypothesis that the post-ETF mean subtracted by the pre-ETF mean is more than zero. Market depth is the summation of volume divided by the summation of absolute return. Closing percent quoted spread is Average[(*Ask* – *Bid*)/*M*] where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. Panel A uses the sample set that all liquidity measures have taken natural logarithm. Panel B uses the sample set that has drop some extreme outliers that are at least five S.D. away from the mean.

Panel A: take a natural logarithm for each liquidity measure

Variable	Pre-ETF (N = 3,605)	Post-ETF (N = 3,605)	T-statistic	Pr(T < t)		Pr(T > t)	
Natural logarithm of Trading Volume (Million dollar)	16.02	15.92	9.68	1.000		0.000	***
Natural logarithm of Trading Volume (shares)	8.44	8.36	8.97	1.000		0.000	***
Natural logarithm of Market Depth (Million dollar)	20.05	19.96	8.34	1.000		0.000	***
Natural logarithm of Closing Percent Quoted Spread (%)	-6.47	-6.45	-4.40	0.000	***	1.000	

Panel B: drop the extreme outlier by removing the observations that are at least five S.D. away from the mean

Variable	Pre-ETF (N = 3,033)	Post-ETF (N = 3,033)	T-statistic	Pr(T < t)		Pr(T > t)	
Trading Volume (Million dollar)	14.74	14.41	1.43	0.923		0.077	*
Trading Volume (shares)	10,375.10	9,873.59	3.88	1.000		0.000	***
Market Depth (Million dollar)	757.14	771.14	-1.20	0.115		0.885	
Closing Percent Quoted Spread (%)	0.18	0.19	-6.37	0.000	***	1.000	

As seen in Panel A of the local currency data, the results in Table 8 also indicate that ETFs in emerging markets reduce the liquidity of the underlying stocks. In Panel A, the natural logarithm of trading volume in both US dollar and share unit and the natural logarithm of market depth significantly decreased after the introduction of ETFs. The natural logarithm of the closing percent quoted spread also rose with significance at the 1 percent level.

Panel B shows similar results as Panel A. The decrease in trading volume in million dollars is not as sharp as in Panel A, yet the significance is at the 10 percent level. The trading volume reduced from 10, 375.10 to 9,873.59 shares and the closing percent quoted spread also widen from 0.18 percent to 0.19 percent with both differences significant at the 1% level. Unlike the results of Panel A, Panel B's results show that the market depth rose on average from 757.14 to 771.14 million dollars, but it is not statistically significant. This suggests that the significant increase in market depth in Table 3 could have occurred because of the different currency. To sum up, Table 8 shows that liquidity for the underlying stocks decreases after the introduction of ETFs. The following analysis in Table 9 to Table 12 will focus on the sample used in panel A.

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The multivariate test was conducted next. In this data set, there are 3,605 stocks with 24 weekly observations per cross-section. The regression model is the same as the one shown in model (3). Table 9 presents the summary statistics for the variables used in the multivariate regression analysis, which consists of the number of observations, mean, standard deviation, the minimum value, and the maximum value for the dependent variable and explanatory variables. The correlation between variables is presented in Table 10 and 11 to ensure that all independent variables employed in the regression analysis are not correlated to cause multicollinearity. Table 12 summarizes the estimated coefficients of the variables used in the multivariate regression models. Country fixed effect is included in the regression.

Table 9

Descriptive statistics for Sample Observations

* indicates the variable before taking logarithm. The descriptive statistics of the variables used in the regressions are shown from the period from 2-week before to 2-week after the ETF introduction. Spread is closing percent quoted spread calculated by Average[(*Ask* – *Bid*)/*M*] where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. Depth is market depth calculated by the summation of volume divided by the summation of absolute return. Var is volatility using Parkinson's (1980) extreme value method. Vol is volume traded in currency unit. P is closing price. Other variables are defined as in Section 4 Methodology.

Variable	N	Mean	S.D.	Min	Max
lnSpread	81,822	-1.89	1.03	-5.86	5.30
Spread*	86,520	0.29	1.24	-0.04	199.93
lnDepth	84,345	6.11	1.73	-4.39	17.34
Depth*	86,520	8,603.78	168,016.80	0.00	33,900,000.00
lnVar	86,520	-3.81	0.78	-8.96	0.00
Var*	86,520	0.00	0.00	0.00	0.05
lnVol	86,520	7.43	2.97	-2.30	14.59
Vol*	86,520	12,054.57	29,274.84	0.00	2,417,518.00
lnP	86,520	0.64	1.36	-4.58	8.64
P*	86,520	23.04	212.61	0.01	5,650.08
MktUp	86,520	0.01	0.02	0.00	0.11
MktDown	86,520	-0.01	0.02	-0.22	0.00
ETF	86,520	0.50	0.50	0.00	1.00
W	86,520	0.40	1.20	0.00	38.02
ETFxW	86,520	0.20	0.87	0.00	37.48

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Table 10 and 11 represents the correlation between the variables used in the multivariate regression analysis. Interestingly, the correlations that are higher than the others in Table 5 and 6 (the correlation between lnVar and lnVol, and lnVol and lnP) decrease after changing the currency unit to USD. Therefore, it is possible that the results shown in Table 5 and 6 are biased due to the various currency units involved in their calculations. As suggested by **Tull and Hawkins (1990)**, multicollinearity is not a problem if no correlation exceeds some predefined cutoff value, which is typically around 0.5. Since the correlation between variables has a value of less than 0.5, there is no multicollinearity among the variables in the results.

Table 10

Correlation between variables

The dependent variable is the natural logarithm of market depth. The sample used has a currency unit in USD. All variables are defined as in Section 4 Methodology.

	lnDepth	lnVar	lnVol	lnP	MktUp	MktDown	ETF	W
lnDepth	1.0000							
lnVar	-0.0539	1.0000						
lnVol	0.3948	-0.2228	1.0000					
lnP	0.3044	-0.0509	-0.2643	1.0000				
MktUp	0.0882	0.1010	0.0560	-0.0133	1.0000			
MktDown	0.0964	-0.1505	-0.0291	0.0317	0.3409	1.0000		
ETF	-0.0232	-0.0183	-0.0106	-0.0061	-0.0391	-0.0209	1.0000	
W	0.2507	-0.0563	0.0164	0.2142	0.0134	-0.0216	-0.0013	1.0000

Table 11

Correlation between variables

The dependent variable is the natural logarithm of closing percent quoted spread. The sample used has a currency unit in USD. All variables are defined as in Section 4 Methodology.

	lnSpread	lnVar	lnVol	lnP	MktUp	MktDown	ETF	W
lnSpread	1.0000							
lnVar	-0.0621	1.0000						
lnVol	-0.3745	-0.2228	1.0000					
lnP	0.0750	-0.0509	-0.2643	1.0000				
MktUp	-0.0463	0.1010	0.0560	-0.0133	1.0000			
MktDown	-0.0766	-0.1505	-0.0291	0.0317	0.3409	1.0000		
ETF	0.0114	-0.0183	-0.0106	-0.0061	-0.0391	-0.0209	1.0000	
W	0.1524	-0.0563	0.0164	0.2142	0.0134	-0.0216	-0.0013	1.0000

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Table 12 shows the regression analysis examining whether the arrival of ETFs affects the underlying stocks' liquidity. Similar to the previous results seen in Table 7, a positive relationship was found between the market depth and trading volume, the market depth and prices, and the spreads and volatility, while there was an inverse relationship between the market depth and volatility, the spreads and trading volume, and the spreads and prices.

Table 12

Regression analysis

The sample used in this regression has a currency unit in USD. In model (1)-(3), the dependent variable is a natural logarithm of market depth, which is calculated by the summation of volume divided by the summation of absolute return, while in model (4)-(6), the dependent variable is a natural logarithm of closing percent quoted spread which calculated by Average[(*Ask* – *Bid*)/*M*], where *Ask* is the ask price, *Bid* is the bid price, and *M* is the mean of *Ask* and *Bid*. All explanatory variables are defined as in Section 4 Methodology. In parenthesis is the robust standard errors. The robust standard errors are clustered by country. Coefficients of country dummy are not reported. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, repectively.

Dependent Variable	**lnDepth**			**lnSpread**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
lnVar	-0.202**	-0.172**	-0.172**	0.0215	0.0211	0.0211
	(-0.0688)	(-0.0684)	(-0.0684)	(-0.0976)	(-0.0938)	(-0.0937)
lnVol	0.207***	0.193***	0.193***	-0.0667**	-0.0665**	-0.0666**
	(-0.049)	(-0.0485)	(-0.0486)	(-0.025)	(-0.024)	(-0.024)
lnP	0.533***	0.501***	0.501***	-0.272**	-0.272**	-0.272**
	(-0.0516)	(-0.0559)	(-0.0559)	(-0.105)	(-0.108)	(-0.108)
MktUp	3.796***	3.378**	3.376**	-1.414**	-1.409**	-1.409**
	(-1.163)	(-1.144)	(-1.145)	(-0.539)	(-0.57)	(-0.57)
MktDown	7.536***	8.144***	8.135***	-2.907***	-2.915***	-2.913***
	(-1.449)	(-1.517)	(-1.52)	(-0.553)	(-0.527)	(-0.529)
ETF	-0.0519*	-0.0518	-0.0613*	0.0108	0.0108	0.0141
	(-0.028)	(-0.0283)	(-0.031)	(-0.0181)	(-0.018)	(-0.0166)
W		0.220***	0.208***		-0.00268	0.00145
		(-0.0517)	(-0.0538)		(-0.028)	(-0.0275)
ETFxW			0.0238*			-0.00815
			(-0.0116)			(-0.0056)
Observations	84,345	84,345	84,345	81,822	81,822	81,822
R-squared	0.267	0.301	0.302	0.162	0.162	0.162
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	Clustered robust			Clustered robust		

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After converting the currency unit to USD, Table 12 shows a slightly different result compared to the results shown in Table 7. The coefficient of the ETF dummy variable in model (1) and (3) presents a negative relationship and significance at the 10 percent level, while in model (4) through (6), there is a positive relationship, but it is insignificant. This shows that the underlying stock's liquidity's relationship after the introduction of ETFs in emerging markets is weak. The positive and significant interaction terms between the ETF and W variable in model (3) and a negative interaction terms between the ETF and W variable in model (6) suggests that a decrease in market depth for the less heavily weighted stocks is more affected compared to the more heavily weighted stocks after the arrival of the ETFs.

In all, these results support and are consistent with **Subrahmanyam (1991)**'s findings that the creation of the basket of securities will stimulate investors to trade in the markets for baskets of securities. However, one concern which showed up through the findings was that each ETF may affect the underlying stocks' liquidity differently due to the various levels of liquidity of ETFs.

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6. CONCLUSIONS

Using sample from emerging markets, this study provides evidence on whether the liquidity of underlying stocks improves after the introduction of ETFs. The countries that were assessed consisted of Brazil, Chile, China, Columbia, Hungary, India, Mexico, South Africa, Thailand, and Turkey.

There were two key empirical findings within my study. First, a univariate analysis shows that the liquidity of underlying stock, represented by the closing percent quoted spreads, increases after the introduction of ETFs. On the other hand, the trading volume and market depth decreased following the introduction of the ETFs. Secondly, I have demonstrated that the regression of the market depth and the closing percent quoted spreads shows a weak relationship in the liquidity, as the liquidity decreases after the introduction of the ETFs, and that the decrease is more pronounced in the smaller-weight stocks.

My empirical results support the adverse selection hypothesis that lesser informed traders trade in markets for baskets of securities (i.e. ETF) rather than in the individual securities to reduce their trading losses, while our findings reject the investor recognition hypothesis and the arbitrage and risk shift hypothesis.

APPENDIX

Table 13

Emerging markets classified by each group of analysts[5]

No.	Country	IMF	BRICS+ Next Eleven	FTSE	MSCI	S&P	EM bond index	Dow Jones	Russell	Columbia University EMGP
1	Brazil	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	Chile	✓		✓	✓	✓	✓	✓	✓	✓
3	China	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	Colombia	✓		✓	✓	✓	✓	✓	✓	✓
5	Hungary	✓		✓	✓	✓	✓	✓	✓	✓
6	India	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	Mexico	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	South Africa	✓	✓	✓	✓	✓	✓	✓	✓	✓
9	Thailand	✓		✓	✓	✓	✓	✓	✓	✓
10	Turkey	✓	✓	✓	✓	✓	✓	✓	✓	✓

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[5] Latest update in October 2019

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REFERENCES

Agarwal, V., et al. (2018). Do ETFs increase the commonality in liquidity of underlying stocks? 28th Annual Conference on Financial Economics and Accounting.

Amihud, Y., et al. (1997). "Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange." Journal of Financial Economics **45**(3): 365-390.

Andreassen, P. B. (1988). "Explaining the price-volume relationship: The difference between price changes and changing prices." Organizational Behavior and Human Decision Processes **41**(3): 371-389.

Barber, B. M. and T. Odean (2000). "Trading is hazardous to your wealth: The common stock investment performance of individual investors." The Journal of Finance **55**(2): 773-806.

Barber, B. M. and T. Odean (2008). "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors." The Review of Financial Studies **21**(2): 785-818.

Barber, B. M., et al. (2008). "Do retail trades move markets?" The Review of Financial Studies **22**(1): 151-186.

Ben-David, I., et al. (2012). "Hedge fund stock trading in the financial crisis of 2007–2009." The Review of Financial Studies **25**(1): 1-54.

Ben-David, I., et al. (2017). "Exchange-traded funds." Annual Review of Financial Economics **9**: 169-189.

Ben-David, I., et al. (2018). "Do ETFs increase volatility?" The Journal of Finance **73**(6): 2471-2535.

Chung, K. H. and H. Zhang (2014). "A simple approximation of intraday spreads using daily data." Journal of Financial Markets **17**: 94-120.

Da, Z. and S. Shive (2018). "Exchange traded funds and asset return correlations." European Financial Management **24**(1): 136-168.

Dannhauser, C. D. (2017). "The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs)." Journal of Financial Economics **125**(3): 537-560.

Deville, L., et al. (2014). "Direct and indirect effects of index ETFs on spot-futures pricing and liquidity: Evidence from the CAC 40 index." European Financial Management **20**(2): 352-373.

Fong, K. Y., et al. (2017). "What are the best liquidity proxies for global research?" Review of Finance **21**(4): 1355-1401.

CHULALONGKORN UNIVERSITY

Fremault, A. (1991). "Stock index futures and index arbitrage in a rational expectations model." Journal of Business: 523-547.

Gorton, G. and G. Pennaccchi (1993). "G.(1993)” Security Baskets and Index-linked Securities,”." Journal of business: 1-27.

Grullon, G., et al. (2004). "Advertising, breadth of ownership, and liquidity." The Review of Financial Studies **17**(2): 439-461.

Hakansson, N. H. (1982). "Changes in the financial market: Welfare and price effects and the basic theorems of value conservation." The Journal of Finance **37**(4): 977-1004.

Hamm, S. (2014). "The effect of ETFs on stock liquidity." Available at SSRN 1687914.

Hegde, S. P. and J. B. McDermott (2004). "The market liquidity of DIAMONDS, Q's, and their underlying stocks." Journal of Banking & Finance **28**(5): 1043-1067.

Hill, J. M., et al. (2015). A comprehensive guide to exchange-traded funds (ETFs), CFA Institute Research Foundation.

Israeli, D., et al. (2017). "Is there a dark side to exchange traded funds? An information perspective." Review of Accounting Studies **22**(3): 1048-1083.

Jegadeesh, N. and A. Subrahmanyam (1993). "Liquidity effects of the introduction of the S&P 500 index futures contract on the underlying stocks." Journal of Business: 171-187.

Kumar, R., et al. (1998). "The impact of options trading on the market quality of the underlying security: An empirical analysis." The Journal of Finance **53**(2): 717-732.

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Kurov, A. A. and D. J. Lasser (2002). "The effect of the introduction of Cubes on the Nasdaq-100 index spot-futures pricing relationship." Journal of Futures Markets: Futures, Options, and Other Derivative Products **22**(3): 197-218.

Merton, R. C. (1987). "A simple model of capital market equilibrium with incomplete information." The journal of Finance **42**(3): 483-510.

Nagel, S. (2012). "Evaporating liquidity." The Review of Financial Studies **25**(7): 2005-2039.

Odean, T. (1998). "Volume, volatility, price, and profit when all traders are above average." The Journal of Finance **53**(6): 1887-1934.

Pan, K. and Y. Zeng (2019). "ETF arbitrage under liquidity mismatch." Available at SSRN 2895478.

Parkinson, M. (1980). "The extreme value method for estimating the variance of the rate of return." Journal of Business: 61-65.

Petajisto, A. (2017). "Inefficiencies in the pricing of exchange-traded funds." Financial Analysts Journal **73**(1): 24-54.

Piccotti, L. R. (2018). "ETF premiums and liquidity segmentation." Financial Review **53**(1): 117-152.

Richie, N. and J. Madura (2007). "Impact of the QQQ on liquidity and risk of the underlying stocks." The Quarterly Review of Economics and Finance **47**(3): 411-421.

Ross, S. A. (1976). "Options and efficiency." The Quarterly Journal of Economics **90**(1): 75-89.

Subrahmanyam, A. (1991). "A theory of trading in stock index futures." The Review of Financial Studies **4**(1): 17-51.

Tull, D. S. and D. I. Hawkins (1990). Sampling and Research: The Sampling Process. Marketing Research, Macmillan Publishers New York**:** 58-64.

Van Ness, B. F., et al. (2005). The impact of the introduction of index securities on the underlying stocks: The case of the Diamonds and the Dow 30. Advances In Quantitative Analysis Of Finance And Accounting: New Series, World Scientific**:** 105-128.

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