LIBERA UNIVERSITÀ INTERNAZIONALE DEGLI STUDI SOCIALI
"LUISS - GUIDO CARLI"

LUISS

Department of Economics and Finance

Chair of Asset Pricing

THE EFFECTS OF ETFs ON MARKET LIQUIDITY

Supervisor:
Prof. Emilio Barone

Co-Supervisor:
Prof. Nicola Borri

Candidate:
Elena Perugini

Academic Year 2019-2020

Contents

Introduction

In 1976, Jack Bogle pioneered the idea of the Index Fund. When Vanguard 500 Index Fund was launched, it was greeted with scorn by the investment professionals. No one would have predicted that it would become one of the largest mutual funds in the world and completely revolutionized asset management forever. A new way of allocating capital was born, and the distinction between *active investing* and *passive investing* started taking shape. Then, many basket alternatives were introduced. Despite few subtle differences, all of them were aimed at easing the exchange on markets of a large diversified portfolio of stocks. Rubinstein (1989) outlined the characteristics of the different alternatives and "prophesied" that "the winners of the competitive experiment in market innovation will have set standards for basket trading".

Now, in the asset management industry, a significant reallocation of capital from active to passive investment strategies is ongoing. In the last years, this trend has been sped up even more by a new investment alternative, the Exchange Traded Fund (ETF). Although the first ETF was launched in 1993, it has been after 2008 they grew exponentially in popularity among retail investors. In 2020, 276 new ETFs were launched and as of 31st December 2020, there exist 2,288 exchange traded funds. Thanks to their mechanics and intrinsic characteristics, these new securities are well suited to reshape, as their ancestors Index Funds before them, the asset management industry and to become the winners of Rubinstein's prophecy.

Since Jack Bogle created Vanguard 500 Index, the financial literature about *market basket vehicles* has proliferated and tried to explain the impacts of these new investment instruments on financial markets and, in particular, on *market liquidity*. This concept represents one of the cornerstones of finance and as such, it appears essential to understand what are its drivers. Despite its critical role in the functioning of financial markets, its definition is slippery and sometimes it suddenly "disappears" to leave market participants unable to react.

Through this thesis, we will try to connect together the creation of asset management, i.e. the exchange traded funds, with the broad concept of market liquidity and understand the effects of the former on the latter.

In the first chapter, we will describe the broad topic of market liquidity seeing how it is measured and what are its main determinants. We will introduce the concept of financial innovation as a driver of changes in financial markets and, sometimes, as potential causes of *crashes*. We will conclude with a historical background of market liquidity.

In the second chapter, we will present the exchange traded funds and describe their characteristics. We will show how, in the last years, these investment vehicles have been reshaping the industry and provide an overview of their growing popularity with a watchful eye to the COVID-19 crisis and the oil crash of April 2020.

In the third chapter, we will review the studies about the effects that the basket of securities may have on market liquidity. In particular, we will focus on ETFs and will present many different views.

Finally, in the fourth chapter, we will empirically verify how ETFs can affect market liquidity considering four exchange traded funds and testing whether after their launch date the market liquidity of their underlying securities has changed.

Chapter 1

Market Liquidity

This chapter is aimed at introducing the concept of market liquidity and providing its general definition, the main determinants as well as the measures which will be applied in the dissertation to evaluate it.

1.1 Definition and Measures of Market Liquidity

Despite an unambiguous definition of market liquidity is not easily achievable in financial literature, generally speaking, it could be addressed as the easiness through which an asset can be converted into cash. It follows that cash is the most liquid asset.

In a liquid market, large orders are quickly filled without significantly affecting the price and at low costs.

The aforementioned definition of market liquidity encompasses 3 dimensions: depth, resilience, and immediacy. The deeper a market is, the smaller the price impact of trades will be; the resilience is the prices' capability of reverting back to their original level after a liquidity shock; finally, the immediacy, which can be traced back to Grossman and Miller (1988), is the possibility of executing a trade at any time without delay or missed trading opportunities. Conversely, in an illiquid market, buy orders tend to push transaction prices up, while sell orders do the opposite. In extreme cases, the deviation from the consensus price value is so large that it is not worthwhile to trade, and the market freezes. Intuitively, different securities are characterized by a different degree of liquidity which changes over time. For instance, while stocks like Amazon and Apple are extremely liquid, smaller and less well-known ones have much lower liquidity and potential investors will have to face substantial illiquidity costs. Market liquidity and its measures are of paramount importance to market participants as well as policymakers. On the one hand, investment managers and ordinary investors will gain lower returns from the exchange of illiquid assets which are more expensive to buy and cheaper to sell; at the same time institutional investors and stockbrokers care about minimizing trading costs and provide good-quality service; on the other hand, market liquidity is a key issue to policymakers since, as the 2008 financial crisis underlined, the illiquidity of securities markets can alter their fundamentals. Then, since a unique definition of this concept does not exist, different measures must be considered in order to take into account its multiple dimensions.

1.1.1 Transaction Cost Measures

Estimating the trading costs and the market frictions of a given transaction can provide an initial evaluation of the liquidity of certain security. If we supposed to buy a small amount of the stock and sell it immediately after, the cost associated with the orders would be the quoted bid-ask spread:

$$S = a - b \tag{1.1}$$

Where a is the best ask price available at the moment of the transaction and b the best bid (i.e. the lowest ask and the highest bid). We could normalize it by the midprice (the average of the ask and the bid price) and get the relative quoted spread:

$$s = \frac{S}{m} \tag{1.2}$$

In the case of orders so large that they can not be completely filled at the best bid/ask, we should compute the weighted-average bid-ask spread for an order of size q:

$$S(q) = a(q) - b(q) \tag{1.3}$$

and the relative weighted-average bid-ask spread:

$$s(q) = \frac{S(q)}{m(q)} \tag{1.4}$$

However, the quoted spread does not always reflect the real cost for market participants. Indeed, dealers may offer better prices, lower (higher) than the quoted ask (bid), in a kind of *trading inside the spread*. Thus, the quoted spread may be an upwardly biased estimate of the true transaction costs incurred. In response to this drawback, the effective spread and the relative effective spread are computed:

$$S_e = d \times (p - m) \tag{1.5}$$

$$s_e = \frac{S_e}{m} \tag{1.6}$$

where d is the order direction indicator ($+1$ for buyer-initiated and -1 for seller-initiated trades) and m is the previous mid quote prevailing on the market before the transaction is executed at price p. This measure seems more efficient since it takes into account both the final transaction price effectively paid by the market participants and the previous mid-price, so representing the impact, i.e. the *slippage*, of the transaction on the price as well. The effect will be always positive since the market liquidity is limited and the initiation of an order will inevitably alter the price.

We could assume the implicit trading costs of the investors represent the gains of the liquidity providers, but this is not the case because of lasting pressures on prices which are of detriment to their returns. One way to estimate the real implicit costs is to find the realized half-spread. It represents the difference between the transaction price and the mid quote at a certain point in time after the transaction execution:

$$S_r = d_t \times (p_t - m_{t+\Delta}) \tag{1.7}$$

and it can be rewritten as:

$$S_r = d_t \times (p_t - m_t) - d_t \times (m_{t+\Delta} - m_t) \tag{1.8}$$

So, the average realized bid-ask spread becomes:

$$\mathbb{E}(S_r) = \mathbb{E}(S_e) - \mathbb{E}(d_t \times (m_{t+\Delta} - m_t)) \tag{1.9}$$

Δ represents market participants' quickness to adjust their quotes after a transactions. It is possible to observe the lower the effective spread is, the higher the cost for the liquidity providers will be. Evidently, the aforementioned measures of market liquidity are static and do not consider the time dimension of execution quality.

When a portfolio manager makes his investment decision, there can be a delay between the elaboration of the strategy and the beginning of its implementation. This delay can turn into a cost. So, Perold (1988) proposed a more exhaustive measure of market liquidity which encompasses both the price impact of trades and the opportunity cost of delayed or unexecuted orders, the *implementation shortfall*, i.e. the difference between a paper portfolio return and the actual one:

$$IS = \underbrace{q(m_t - m_0)}_{R_p} - \underbrace{\kappa q(m_t - \bar{p})}_{R_a} \tag{1.10}$$

While it is supposed in the paper portfolio no transaction costs arise and the acquisition price corresponds to m_0, in the actual portfolio, only the fraction κ of the order is executed at the average execution price $\bar{p}$. So, the implementation shortfall can be split into two components and Equation 1.10 can be rewritten as:

$$IS = \underbrace{\kappa q(\bar{p} - m_0)}_{\text{execution cost}} - \underbrace{(1-\kappa) q(m_t - m_0)}_{\text{opportunity cost}} \tag{1.11}$$

1.1.2 Volume Based Measures

The market's depth can be estimated through volume based measures. The main ones are the turnover rate and the Amihud illiquidity ratio. The turnover rate basically is a measure of comparison between the traded volume of a stock and its outstanding shares:

$$Tn = \frac{Vol_t}{S \times \bar{P}} \tag{1.12}$$

Where Vol_t is the total dollar volume traded over a given period, S is the number of instruments outstanding, and $\bar{P}$ is the average closing price of the instrument over the same period. A high turnover rate should indicate high liquidity for given security. However, this is not always the case. Indeed, for instance, volume usually increases around the announcement of new information and in periods of market turmoils, which are also a time of high volatility and wide bid-ask spreads.

Finally, a further volume-based measure of market liquidity is the Amihud illiquidity ratio which gives a high value for the less liquid stocks.

$$I_t = \frac{|r_t|}{Vol_t} \tag{1.13}$$

Intuitively, investors require a premium for trading illiquid securities. Their absolute return is high when compared with the trading volume over the same period of time.

1.1.3 Market Impact Measures

Additional measures of liquidity are based on the impact of orders on the security's price. If the midprice change is proportional to the buying or selling pressure, the relationship can be expressed by running a regression of the change in the mid quote, Δm_t, over a fixed time interval on the order imbalance q_t, i.e. the total value of the buy orders net of the sell ones:

$$\Delta m_t = \lambda q_t + \epsilon_t \tag{1.14}$$

λ is the coefficient capturing the pressure net demand put on the price and $1/\lambda$ represents the depth of a market. The higher $1/\lambda$ is, the less sensitive prices are to order imbalance.

1.1.4 The Roll Measure

Roll (1984b) proposed an alternative measure of market liquidity. Provided that assets are traded in an informationally efficient market and the probability distribution of observed price changes is stationary (at least for short intervals of, say, two months), the effective bid-ask spread is based on the first-order serial covariance of returns. According to Roll, orders hit the ask and the bid price randomly and transaction prices bounce between them, straddling the mid quote m_t (the fundamental value) which in Figure 1.1 is represented by the dashed line.

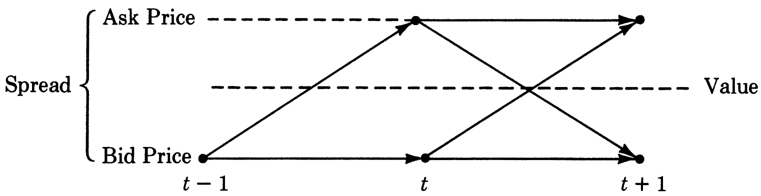


Figure 1.1: Bid-Ask spread bounces (Source: Roll (1984b))

The security fundamental value and the p^{th} transaction price are:

$$m_t = m_{t-1} + \epsilon_t \tag{1.15}$$

$$p_t = m_t + \frac{S}{2}d_t \tag{1.16}$$

Where ϵ_t mean-zero white noise, implying m_t follows a random walk d_t is $+1$ or -1 for buyer initiated or seller initiated orders, respectively. Then, the price change becomes:

$$\Delta p_t = \frac{S}{2}d_t - \frac{S}{2}d_{t-1} + \epsilon_t \tag{1.17}$$

Assumption	
Balanced order flow	$\mathbb{P}(d_t = +1) = \mathbb{P}(d_t = -1) = \frac{1}{2}$ and $\mathbb{E}(d_t) = 0\,\forall t$
No autocorrelation in orders	$\mathbb{E}(d_t d_s) = 0$ for $t \neq d$
No effect on the midquote	$\mathbb{E}(\epsilon_t d_t) = \mathbb{E}(\epsilon_{t+1} d_t) = 0$ for $\forall t$
Constant (zero) expected return	$\mathbb{E} = (m_t - m_{t-1}) = \mathbb{E}(\epsilon_t) = 0$

Table 1.1: Roll's Measure Assumptions

Given the set of assumptions in Table 1.1, we have:

$$\mathbb{E}(p_t - p_{t-1}) = 0$$

and we derive:

$$\begin{aligned} cov(\Delta p_{t+1}, \Delta p_t) &= \frac{S^2}{4}\mathbb{E}\left[(d_{t+1} - d_t + \epsilon_{t+1})(d_t - d_{t-1} + \epsilon_t)\right] \\ &= \frac{S^2}{4}\mathbb{E}[d_{t+1}d_t - d_t^2 - d_{t+1}d_{t-1} - d_t d_{t-1}] \\ &= -\frac{S^2}{4} \end{aligned} \tag{1.18}$$

Finally, it follows from Equation (1.18) that the Roll's measure for the effective bid-ask spread is:

$$S_R = 2\sqrt{-cov(\Delta p_{t+1}, p_t)} \tag{1.19}$$

1.1.5 The Corwin-Schultz (CS) Bid-Ask Spread Estimator

Corwin and Schultz (2012), exploiting the widely accepted hypothesis that daily high (low) prices are almost always buy (sell) trades and then that the ratio of high-to-low prices for a day reflects both the stock's variance and the bid-ask spread, proposed the High-Low estimator.

The main steps to arrive at the final CS spread are:

$$\begin{aligned} \beta &= \mathbb{E}\Big\{\sum_{j=0}^{1}\Big[ln\Big(\frac{H^0_{t+j}}{L^0_{t+j}}\Big)\Big]^2\Big\} \\ \gamma &= \Big[ln\Big(\frac{H^0_{t,t+1}}{L^0_{t,t+1}}\Big)\Big]^2 \\ \alpha &= \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \\ S &= \frac{2\Big(e^\alpha - 1\Big)}{1 + e^\alpha} \end{aligned} \tag{1.20}$$

Here, H and L represent the daily high and low prices, respectively. β is the expectation of the sum of the daily price ranges between 2 consecutive trading days; γ represents the maximum range of the high-to-low price ratio for a two-day period.

One of the issues when applying Equation (1.20) might be that, when $\alpha < 0$, i.e. $\frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} < \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, we will get a negative value for the CS estimator. For instance, that may occur in volatile periods in which the 2-day variance may be more than twice as large as the single-day variance[1]. Roughly speaking, if the realized 2-day variance is large enough, the high-low spread will be negative. Corwin and Schultz (2012) dealt with this by substituting 0 to all negative 2-day spreads before calculating monthly averages. Following this procedure, they managed to get better monthly estimates than either including or deleting negative values.

Since its introduction, the Corwin-Schultz spread has been highly employed by researchers and practitioners because of its practicality as well as outperformance with respect to other low-frequency estimators. Lin (2014), studying the accuracy of the estimator, found that the performance of the spread is positively impacted by the trade frequency and spread size, but negatively affected by price volatility. Finally, its validity stays strong even when acknowledging that two of the assumptions the model relies on, i.e. that the stocks trade continuously during market opening hours and that the value does not change when the market is closed, are wrong.

1.2 Determinants of Market Liquidity

Market Liquidity is determined by several factors. Transaction costs are among its major drivers and they can be split into three components: the adverse selection, the inventory risk, and the order processing costs (see Figure 1.2).

In a classic asset pricing model, the fundamental value of a security ν_t, represents the expected present value of future cash flows. $\mu_t = \mathbb{E}[\nu_t|\mathbf{H_t}]$ is the conditional expectation of ν_t given the set of public information at time t, $\mathbb{H}_t$, and p_t is the log price of the risky asset in t.

[1] One of the model's underlying assumptions is that the expectation of a stock's true variance over a 2-day period is twice as large as the expectation of the variance over a single day, this may not be the case for the observed 2-day variance.

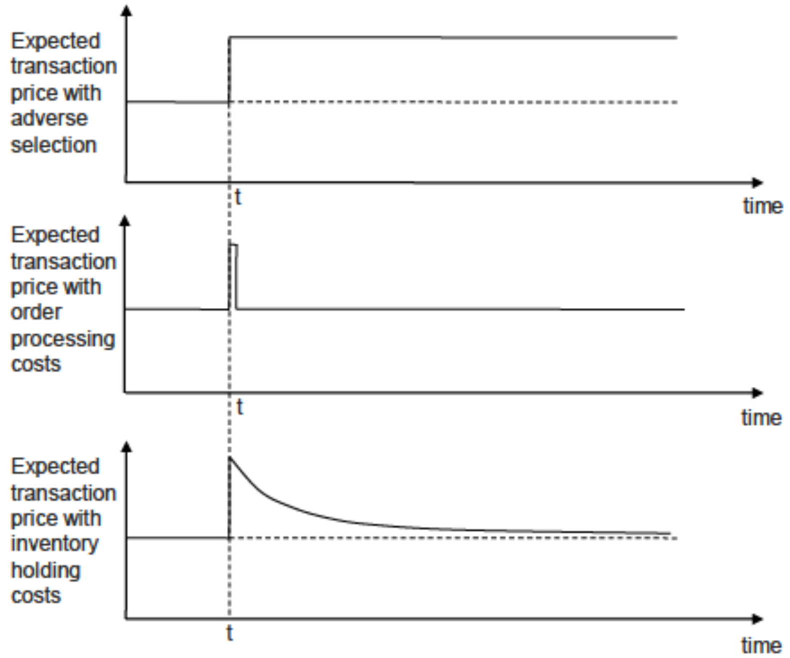


Figure 1.2: The Components of the Transaction Costs (source: Foucault et al. (2013))

So, according to the weakly form of the EMH, in the absence of asymmetric information and with negligible frictions, $p_t = \mu_t$. Then:

$$r_t = p_t - p_{t-1} = \epsilon_t \tag{1.21}$$

$$\epsilon_t = \mu_t - \mu_{t-1} = \mathbb{E}[\nu_t|\mathbf{H_t}] - \mathbb{E}[\nu_{t-1}|\mathbf{H_{t-1}}] \tag{1.22}$$

where ϵ_t represents the innovation in beliefs. Allowing for market frictions, p_t would become:

$$p_t = \mu_t + s_t$$

where s_t is an error term having 0 mean and variance $\sigma(s_t)$. However, it is evident that variations in the bid-ask spread must depend on something more. In Smidt (1971) and Garman (1976), market-makers adjust their quotes in response to inventory level fluctuations, so that not accumulate relevant exposure just on one side of the market. Garman's model explains the relationship between dealer quotes and inventory levels. We define:

$$I_t = I_0 - \sum_{k=1}^{t-1} d_k \tag{1.23}$$

Where $d_k \in \{-1, 0, +1\}$ represents the order direction; I_0 is the dealer's opening inventory level, I_t is the inventory level at time t with $I_t > 0$ in the case of a long position and $I_t < 0$ in the case of a short one. Since dealers have finite capital K, it must be $|I_t| < K$. In the absence of asymmetric information and assuming market makers set bid and ask prices to equate expected demand and expected supply, i.e. they set p_t to equate $\mathbb{E}[d_{t+1}|p_t] = 0$, from Equation (1.23) we find inventory follows a random walk with zero drift: $\mathbb{E}[I_{t+1} - I_t|I_t] = 0$. It follows that, for some T, if dealer capital is finite, market failure is certain, since $\mathbb{P}[|I_t| > K] = 1$. This is the Gambler's Ruin. So, market makers must adjust prices to meet their inventory's needs. In its simplest form the inventory model could be written as:

$$p_t = \mu_t - \phi(I_t - I^*) + sd_t \tag{1.24}$$

Equation (1.24) still ignores the adverse selection component. However, when trading with better-informed investors, liquidity suppliers inevitably lose money and so, they will try to offset the loss by profiting from uninformed investors. The asymmetric information, which is negatively related to market liquidity, represents a paramount risk "hedged" through the setting of an appropriate bid-ask spread. This concept was introduced and developed by Glosten and Milgrom (1985).

1.2.1 Glosten and Milgrom Model

Given that traders can be informed or uninformed, Θ will be the random variable denoting their types, $\Theta = i \,\mathrm{or}\, u$ and ω will be the fraction of those with superior information. The asset can equivalently take on two possible values, high and low, ν^H and ν^L, respectively. The expected value is denoted by $\bar{\nu}_t$ and $\sigma = \nu^H - \nu^L$ is the range of uncertainty. Hence, the market makers will quote prices conditional on the direction of the trade. The ask (bid) price is the expected value of the security given that the order is buyer (seller) initiated ($d_t = +1 \,\mathrm{or}\, -1$):

$$p_t^{ask} = \mathbb{E}[\nu_t|d_t = +1] = \nu^H \mathbb{P}[\Theta = i|d_t = +1] + \bar{\nu}_t \mathbb{P}[\Theta = u|d_t = +1]$$

And the bid-ask spread becomes:

$$p_t^{ask} - p_t^{bid} = \omega\sigma$$

According to Glosten and Milgrom model, transaction costs may exist even in the absence of market frictions and inventory costs.

1.2.2 Kyle Model

Similar to Glosten and Milgrom, even in Kyle's model there exist traders with superior information who place orders to maximize their profit through the informational advantage. The underlying assumptions are that all the orders are at the market and submitted simultaneously and traders' identity is unknown. Market makers observe aggregate order flow and then set prices according to a 0 expected-profit rule:

$$p_t = \mathbb{E}[\nu_t | q_t] = \mu_{t-1} + \lambda q_t$$

Here the price is the expected value of the security and the model can be viewed as a linear regression where μ_{t-1} and q_t represent the market makers' prior beliefs and the aggregate order flow, respectively. Thus, λ represents the market makers' sensitivity to the aggregate order flow. It increases with the uncertainty on the security's value and it decreases with the number of uninformed traders.

1.2.3 Glosten and Harris Model

This asymmetric information model has the merit to combine together the costs components seen so far. The bid-ask spread is broken into a transitory component (the order processing and the inventory costs) and a permanent one (adverse selection):

$$S_t = 2(C_t + Z_t) \tag{1.25}$$

While the adverse selection (Z_t) leads to a permanent revision of a security's value estimate, the order processing fees and the inventory costs (C_t) are not related to the underlying value and their price impact should dissipate over time inducing reversals in returns. The Glosten and Harris model is represented as follows:

$$p_t = \mu_t + d_t C_t \tag{1.26}$$

$$\mu_t = \mu_{t-1} + d_t Z_t + \epsilon_t \tag{1.27}$$

$$C_t = c_0 + c_1 Vol_t \tag{1.28}$$

$$Z_t = z_0 + z_1 Vol_t \tag{1.29}$$

Where p_t is the observed price process at time t; while μ_t is the true price process over the same period; d_t represents the order direction and corresponds to $+1$ if the order is a buy one and to -1 if it is a sell one; C_t and Z_t are the transitory spread component and the permanent one, respectively. It follows from Equations (1.26) to (1.29) that:

$$\Delta P_t = c_0(d_t - d_{t-1}) + c_1(d_t Vol_t - d_{t-1} Vol_{t-1}) + z_0 d_t + z_1 x_t Vol_t + \epsilon_t \tag{1.30}$$

Then, if we evaluate this expression for $d_t = 1$ and $d_{t-1} = -1$, i.e. the round-trip price change for a sale which immediately follows a purchase of equal size, Equation (1.30) becomes:

$$\Delta P_t = 2C_t + Z_t + \epsilon_t \tag{1.31}$$

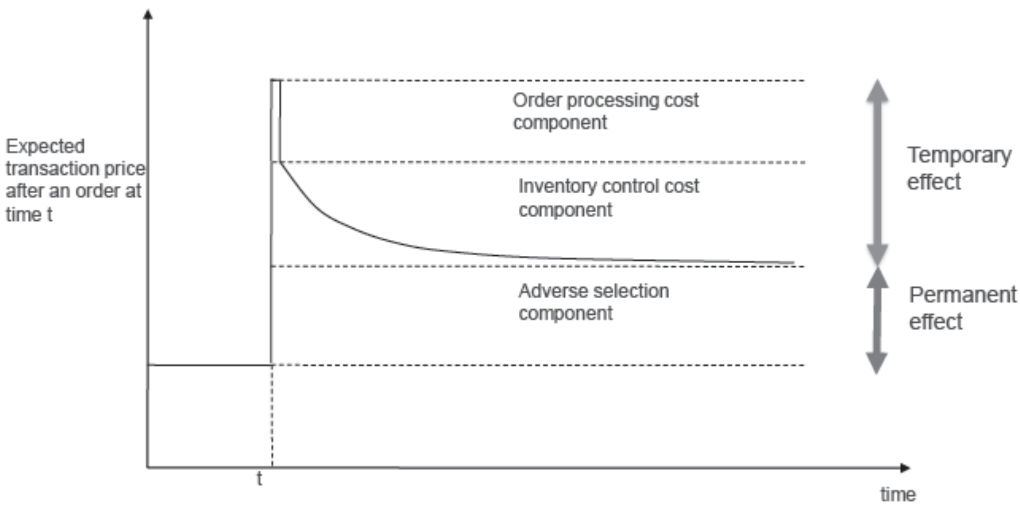


Figure 1.3: The Permanent and the Transitory components of the Transaction Costs (source: Foucault et al. (2013))

1.2.4 Market Fragmentation and Transparency

Among the other relevant factors influencing market liquidity, fragmentation and transparency are of paramount importance. In the last decade, the number of trading venues has dramatically increased and securities are usually traded in multiple venues. So, despite we could expect an improvement in market liquidity, through rising competition among exchanges, this is not always the case and the effects are heterogeneous on large and small stocks. Haslag and Ringgenberg (2016) have analyzed the causal impact of market fragmentation on liquidity using a sample of approximately 8,000 unique assets for 16.5 million daily observations covering the period from 2006 and 2013. They found that, on the one hand, for large stocks, there is a decrease in transaction costs which arise from the increased competition; on the other hand, in small stocks, the increase in negative externalities, which arise from thin markets, dominates.

Together with fragmentation, market transparency represents another important element of liquidity. Broadly speaking, it is the ability of market participants to observe information about prices, quotes, or volumes, the sources of order flow, and the identities of market participants. We can have pre-trade and post-trade transparency. While the first one refers to the wide dissemination of current bids and asks quotations and depths; the latter one consists of the public and timely transmission of information on past trades, such as execution time, volume, price, as well as buyer and seller's identity. The effects of market transparency differ between markets. Madhavan (1996) has shown that while it reduces price volatility and increases market liquidity if the market is large enough; where trading activity is thin, the quality decreases with lower liquidity and higher transaction costs.

1.3 Liquidity Crunches

Market crashes and liquidity crunches move often in tandem. During these episodes, there is a drop in asset prices which is not motivated by big news on the fundamentals. Large selling pressure, quick drops, and slow recovery characterize crashes.

The first documented phenomenon of a market crash dates back to 1987. Amihud et al. (1990) presented an early explanation for it. They suggested the price decline reflected, at least in part, a revision of investors' expectations about the liquidity of the equity markets. They compared the returns and the bid-ask spreads of 451 stocks included in the S&P500 for three periods: October 5-9, 1987; October 19, 1987, and October 30, 1987. The estimation model that they proposed was represented by the following regressions:

$$R^i_{2,1} - \beta^i R^m_{2,1} = \alpha_0 + \alpha_1 DSP^i_{2,1} + \alpha_2 PERSP^1_i + \epsilon^i \tag{1.32}$$

$$R^i_{3,2} - \beta^i R^m_{3,23,2} = \alpha_0 + \alpha_1 DSP^i_{3,2} + \alpha_2 PERSP^2_i + \epsilon^i \tag{1.33}$$

Where $DSP^i = \frac{SP^i}{SP^i} - 1$ is the percentage change in the dollar spread for a given stock and $PERSP_i$ is the relative (percent) spread. $R^i - \beta^i R^m$ represents the "abnormal" price change.

Their findings confirmed the hypothesis of the relationship between liquidity and price differentials during the crash. Stocks whose bid-ask spread increased more on October 19, had a greater price decline, after controlling for the market effect. Similarly, between the second and the third periods stocks whose bid-ask spreads shrunk relative to their crash levels knew a greater recovery than stocks that remained illiquid. While the variable $PERSP$ is insignificant in the crash, it has a negative and significant coefficient in the following period. We assist to a "flight to liquidity" phenomenon. Investors, to protect themselves against another liquidity shock, reallocated assets toward the most liquid stocks.

A further explanation of market crashes and liquidity shocks has been provided by Huang and Wang (2009). They proposed a model in which trading costs drive liquidity shortages. Indeed, since participation in the market is costly, traders will take part in the market only when potential gains outweigh the costs. Besides, as traders are hit by idiosyncratic shocks (negative or positive), they will become more risk-averse and less willing to hold the asset. So, the buy demand triggered by positive shocks will not be able to offset the selling one triggered by negative shocks and the price will decrease.

Spillover effects exacerbate liquidity shocks. Cespa and Foucault (2014) showed that price informativeness can both be a source of reinforcing liquidity and fragility. Even a small drop in the liquidity of security can turn into a liquidity shock through a sort of domino effect. One of the most representative examples of how always more interconnected markets and the continuous progress in information technology may facilitate illiquidity spillovers and thus the shocks in liquidity is the Flash Crash of 2010. In that circumstance, a drop in the liquidity of the E-mini S&P500 futures instantaneously propagated to other asset classes. Indeed, the pressure from a sell algorithm combined with HFTs and other traders drove the price of the E-Mini down approximately 3% in just four minutes. Contemporaneously, cross-market arbitrageurs who did buy the E-Mini, sold equivalent amounts in the equities markets, driving the price of SPY also down approximately 3%.

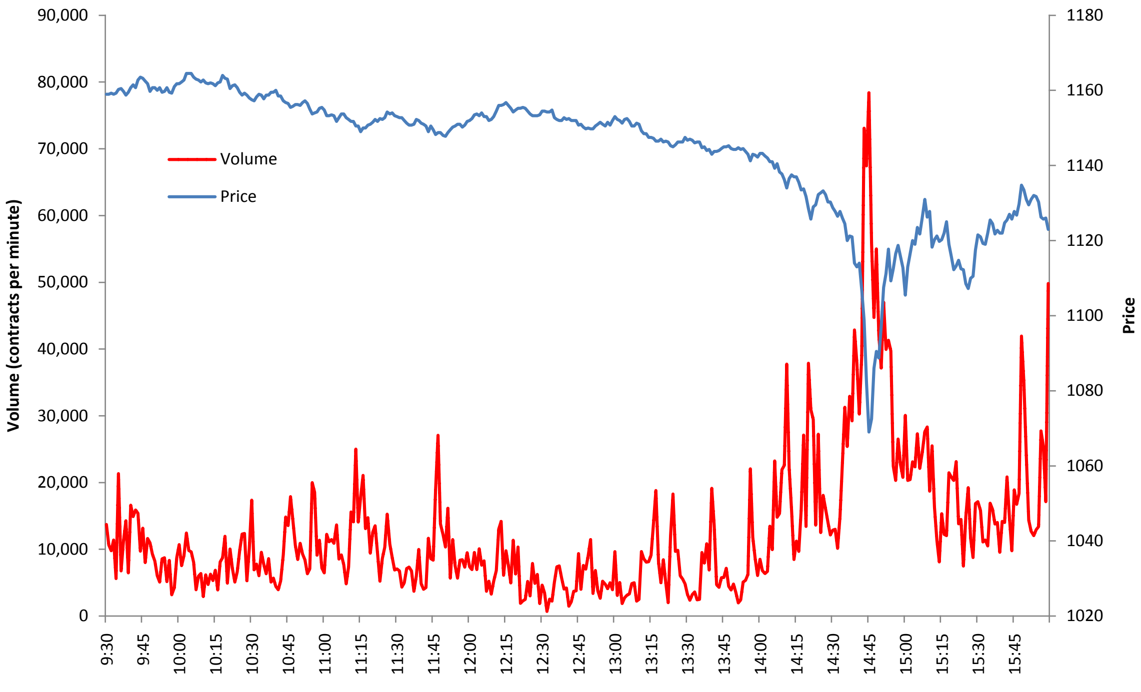


Figure 1.4: E-Mini Volume and Price (Source: Securities et al. (2010))

Actually, the episode of 2010 has not been a one-off and on February 5, 2018, markets suffered a liquidity drop triggered by equity sell-off.

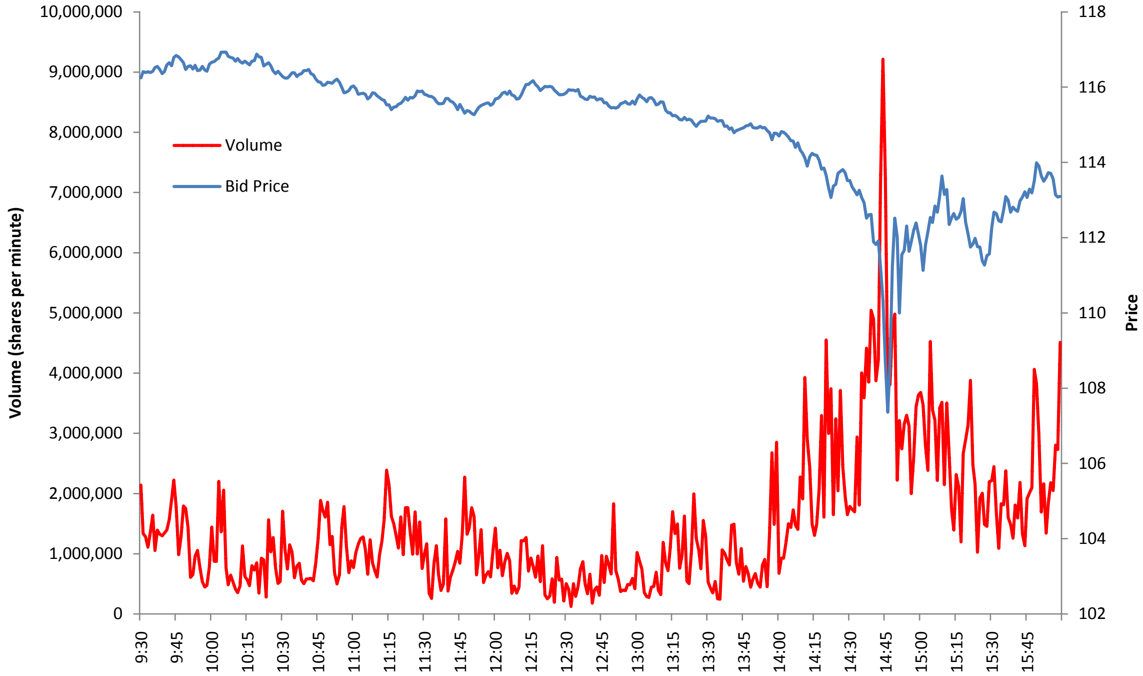


Figure 1.5: SPY volume and price (Source: Securities et al. (2010))

Figure 1.6 shows the dramatic increase in the VIX bid-ask spread.

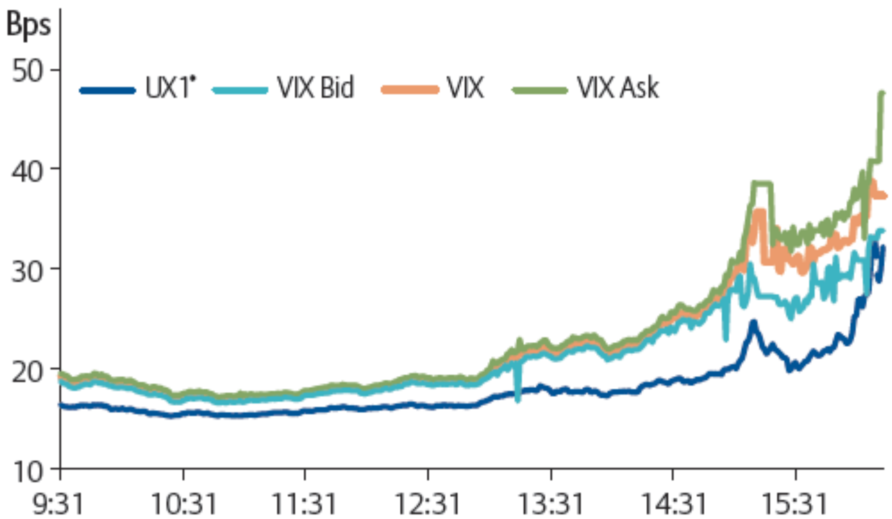


Figure 1.6: Feb 5, 2018 bid-ask spreads on VIX (Source: AllianzGI)

Besides, we can assist to the liquidity shortage of S&P500 which is testified by a sharp widening in the S&P500 bid-ask spread (see Figure 1.7). The episode of February 5 was essentially the result of a tightening in the funding liquidity and a preeminent example of how the latter one can severely affect market liquidity. Indeed, traders could not afford the cost of entering the market because of the increase in the borrowing costs in the short-term funding market. The higher rates worsened the volatility. In a similar scenario, where the liquidity dries up, the trades of individual market participants may have a big impact on markets and even a small event can generate a collapse.

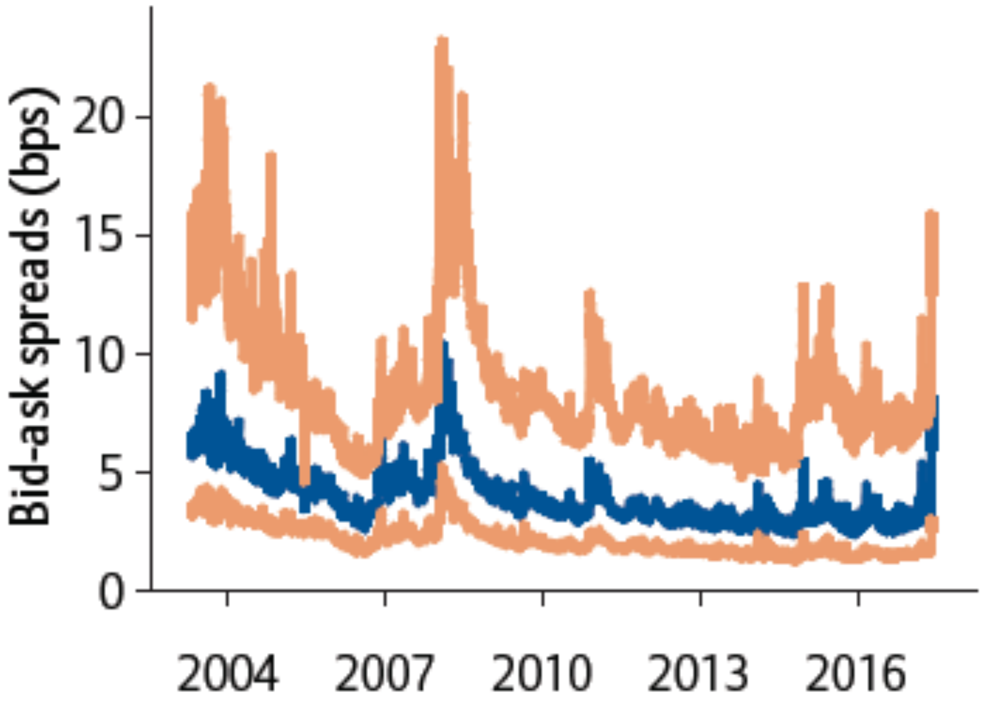


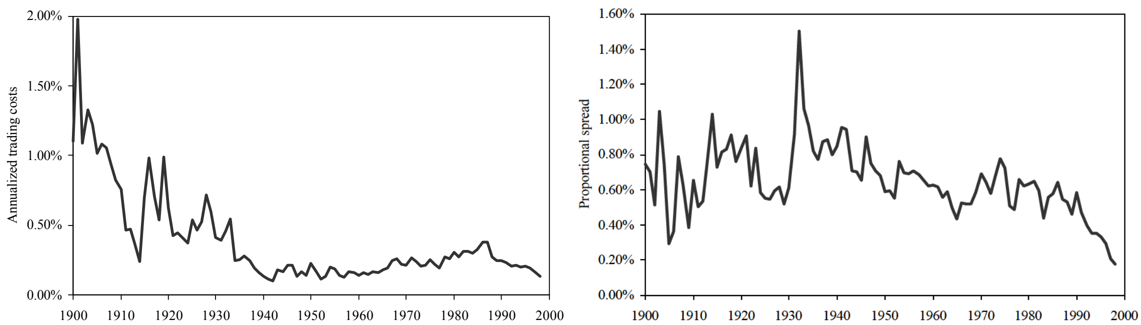
Figure 1.7: Bid-ask spread for S&P 500 stocks (High-Median-Low) (Source: AllianzGI)

The aforementioned episodes depict how fast-paced financial innovations, like algorithmic trading and high-frequency trading practices, the regulatory adjustments put in place after the 2008 crisis, the diminished bank bond inventories, as well as the proliferation of ETFs and rules-based trading strategies are a major source of volatility spikes and liquidity shock risks.

1.4 Evidences from the Market

Looking back in time, we can observe market liquidity has dramatically increased since 1930. Jones (2002) reports the bid-ask spreads on Dow Jones tightened and transaction costs decreased. However, during periods of market stress, we can assist to sharp increases in both. For instance, between the end of the '60s and the early '70s, fees tapped a peak of 1%, declining from 1975 when the brokerage industry deregulated commissions. For the first time in history trading fees would have become negotiable and been set by market competition, instead of being at a fixed price. This marked a turning point as households could benefit from the reform. Before 1975, trading fees were too high for retail investors and just institutional ones could afford the cost of entering the market, taking advantage of economies of scale.

Figure 1.8 shows the aforementioned trend: both the annual trading costs and the average commissions on the NYSE have improved over the last century. The estimated annualized trading cost on NYSE in Figure 1.8a is computed as the product between the turnover (i.e. the ratio of the annual shares volume and the market capitalization) and the sum of the half bid-ask spread and the commission costs.



(a) Estimated annualized trading costs on NYSE stocks 1900-1998

(b) Average commissions on round-lot transactions in NYSE stocks

Figure 1.8: Annualized bid-ask spreads and average commissions on NYSE (Source:Jones (2002))

Despite the general improvement in the overall market liquidity, in the late 90s,' there were some events that led to its gradual deterioration both in emerging markets and developed ones. Among others, the South Korean "devaluation" in November 1997 and the Russian crisis in 1998 contributed to worsening the situation. Despite the US Federal Reserve Bank's interest rate cuts at the end of 1998, exacerbated by the collapse of the hedge fund Long-Term Capital Management, market liquidity stagnated at low levels (Figure 1.9).

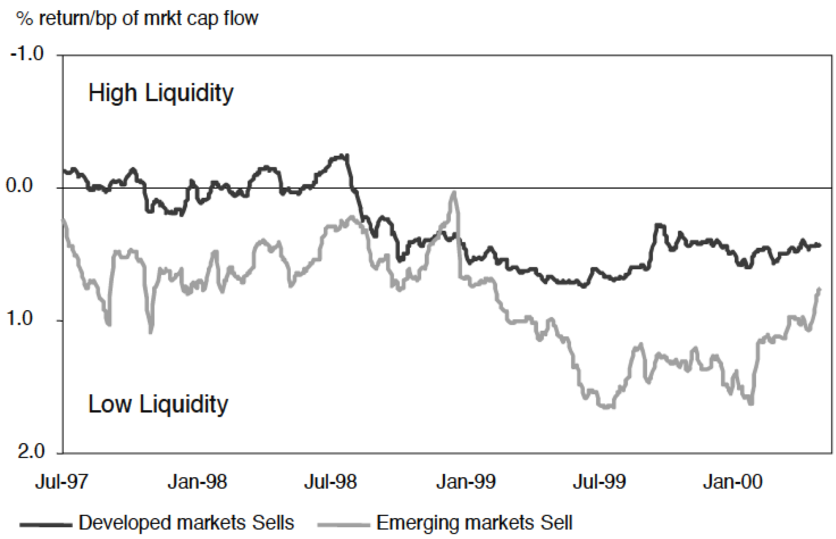
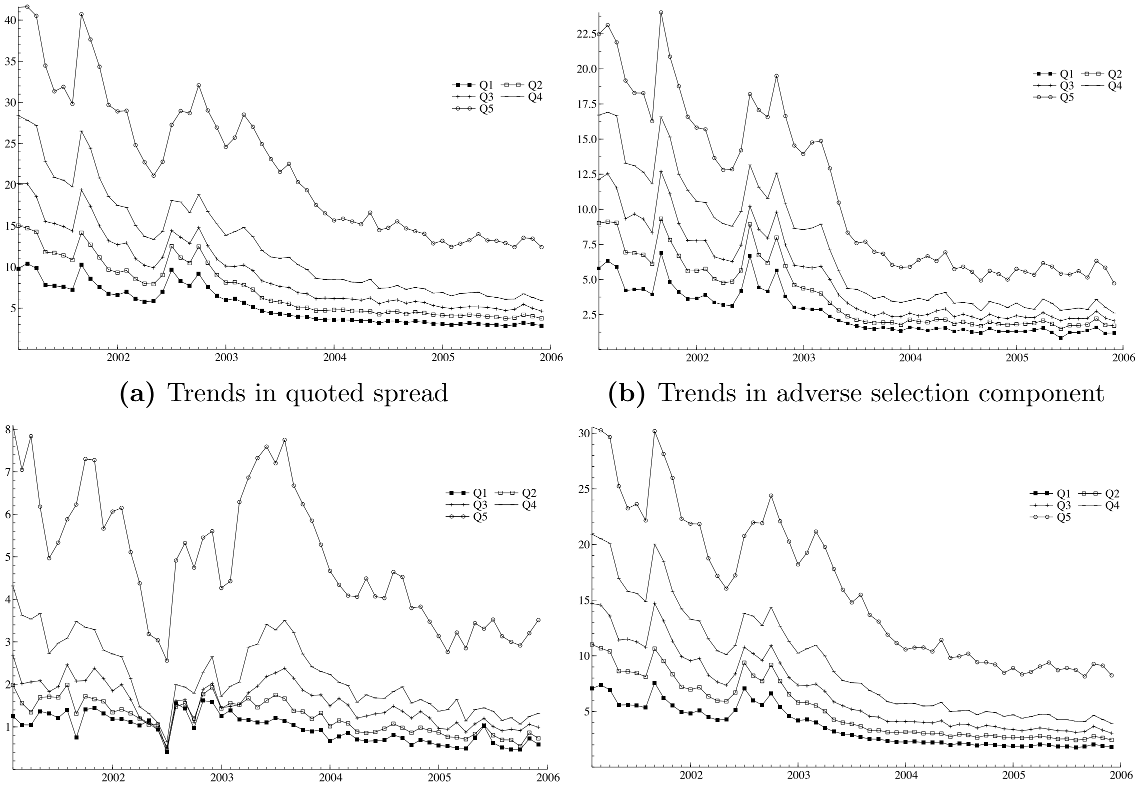


Figure 1.9: Liquidity index for emerging and developed markets - a measure of the price-impact of trading source: Persaud (2001)

However, the beginning of the new millennium brought with it numerous innovations that drove market liquidity up to new highs. The technological change would have revolutionized the way in which securities were traded on financial markets, with Algorithmic Trading (AT) the protagonist of such a "revolution". Hendershott et al. (2011) were among the first ones to analyze its impact on market liquidity and they found an impressive improvement in the latter one since the introduction and widespread of automated quote. From the inception of the automated quote on the NYSE in 2003 to 2009, the AT arrived to be responsible for as much as 73% of the trading volume in the United States. So, as it is possible to observe in Figure 1.10, the beginning of the XXI century was characterized by a sharp decrease in bid-ask spreads and in the adverse selection component. The large cap stocks (Q_1) were the ones with the lowest spreads. This path of enhancement of market liquidity went on up till the global financial crisis (GFC). Indeed, after 2008 the market liquidity abruptly decreased. The reduction was due to a sharp deleverage of market makers and dealer's balance sheets. The new regulatory framework, sanctioned by the Dodd-Frank Act and the Basel III, as well as voluntary changes in risk-management practices, following the housing market burst, were the main drivers of the shrinkage in market dealers' assets.

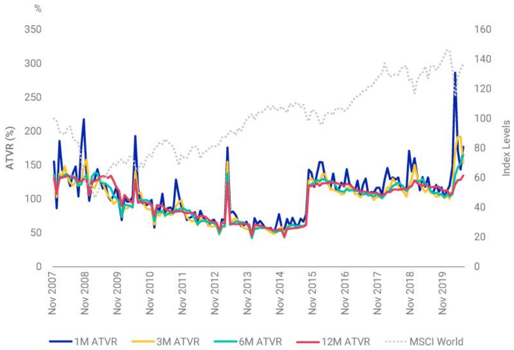


(a) Trends in quoted spread **(b)** Trends in adverse selection component

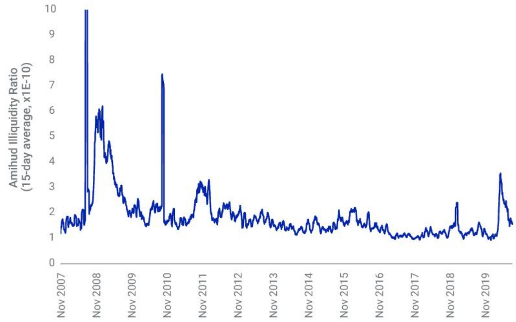
(c) Trends in realized spread **(d)** Trends in effective spreads

Figure 1.10: Trends in market liquidity measures (Source: Hendershott et al. (2011))

Figure 1.11 provide us with a clear representation of the last decade equity market liquidity. The ATVR is the ratio between traded value and then floated one (i.e. the market capitalization) and while it depicts a good picture of the liquidity during normal periods, it is less reliable during market turmoils. As it is possible to observe, in periods of stress, like the bankruptcy of Lehman Brothers on September 15, 2008, and during the turmoil related to the coronavirus crisis, we assist to peaks of ATVR since the trading activity is higher, but the transaction costs, bid-ask spreads and Amihud illiquidity ratio indicate worsening liquidity. The Amihud Ratio reflects the magnitude of price sensitivity to trading volumes and in Figure 1.11b it is computed for a hypothetical world common securities portfolio, that is global equity universe based on the MSCI World Index. The exhibit shows significant spikes during the 2008 GFC, in 2010, and during the recent market correction last March. These peaks in the ratio move in tandem with the most relevant spikes in the bid-ask spread depicted in Figure 1.11d. Now we are assisting to a recovery in the level of market liquidity, but we are still far apart from the pre-COVID 19 crisis levels.

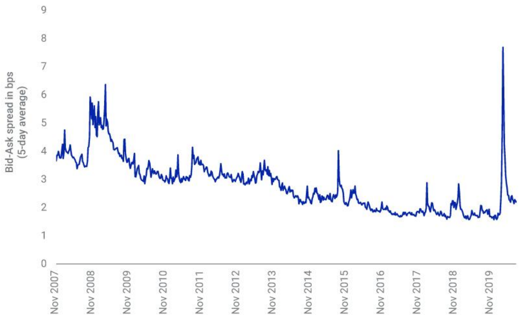


(a) ATVR - annual traded value ratio



(b) Amihud Illiquidity ratio

(c) Transaction costs



(d) Bid-Ask Spreads

Figure 1.11: Trends in market liquidity measures after the GFC (Source: MSCI)

Chapter 2

Exchange Traded Funds

In this chapter, we will introduce and describe the Exchange Traded Funds. Their characteristics will be examined in connection with the growing popularity surrounding them and with the effect they may have on financial markets and market liquidity.

2.1 History, Structure, and Dynamics

The Exchange Traded Funds are investment vehicles whose aim is to track an underlying index as closely as possible, either holding a basket of securities passively or through active investment strategies (for instance by entering into derivative contracts). ETFs can be structured as open-end index funds or unit investment trusts (UIT). The former is a diversified portfolio of pooled investor money with the faculty to issue an unlimited number of shares. The fund sponsor can both sell shares directly to investors and redeem them as well. These shares are priced daily, on the base their most recent Net Asset Value (NAV). Dividends in these types of funds are immediately reinvested and paid to shareholders each month or quarter. UITs are the oldest and best-known ETFs. Among these, we have the BLDRs, Diamonds, SPDRs, and PowerShares QQQ Trust. This kind of fund does not reinvest dividends in the fund but instead holds dividends until they are paid to shareholders quarterly or annually. UITs must fully replicate the indexes they track they are not allowed to receive income from loaned securities. Unlike open-end funds, UITs have expiration dates that can range from a period of years to decades and are continuously rolled or extended. Both open-end index funds and UITs are registered under the Investment

Company Act of 1940.

To sum up, ETFs can be associated with index mutual funds and mutual funds, but differently from them, they trade intra-daily on exchanges; while, mutual funds and index mutual funds' shares can be exchanged only at the market closure. Besides, the former are characterized by lower management fees and expense ratios than the latter as well as by some tax advantages. However, when buying and selling ETFs, investors incur transaction costs, while to trade the no-load mutual funds, they do not.

ETFs' origins date back to 1989, when the Index Participation Shares (IPS), i.e. synthetic instruments tracking the S&P 500 index, started to be traded on the American Stock Exchange and the Philadelphia Stock Exchange. However, they had short life since a lawsuit by the Chicago Mercantile Exchange and the Commodity Futures Trading Commission (CFTC), to stop their trading, was won. Then, in 1990, the Toronto Index Participation Units (TIPs), replicating the Toronto 35, were introduced in the Toronto Stock Exchanges. Three years later, the American Stock Exchange (AMEX), began trading Standard & Poor's 500 Depositary Receipt (SPDR), also known as "Spider" (ticker symbol SPY) and addressed as the first ETF in history. The structure of the Spider was the UIT which was used by ETFs like the MidCap SPDRs and the Diamond (ticker symbol DIA), the one based on the Dow Jones Industrial Average, too. In 1999, the ETF marketplace knew its boom with the QQQ (i.e. the ETF on the Nasdaq 100 Index), then changed to QQQQ.

In 2000, European stock exchanges started listing their first ETFs in the Deutsche Börse and the London Stock Exchange. In a couple of years, they were followed by the Stockholm Stock Exchange, Euronext, and the Swiss Stock Exchange. Then, the ETFs of the Helsinki Stock Exchange, Borsa Italiana, and of the other European markets were added. In the seventeen years since their inception, the ETF marketplace has grown exponentially and as of September 2020, it topped US$7 trillion of AUM.

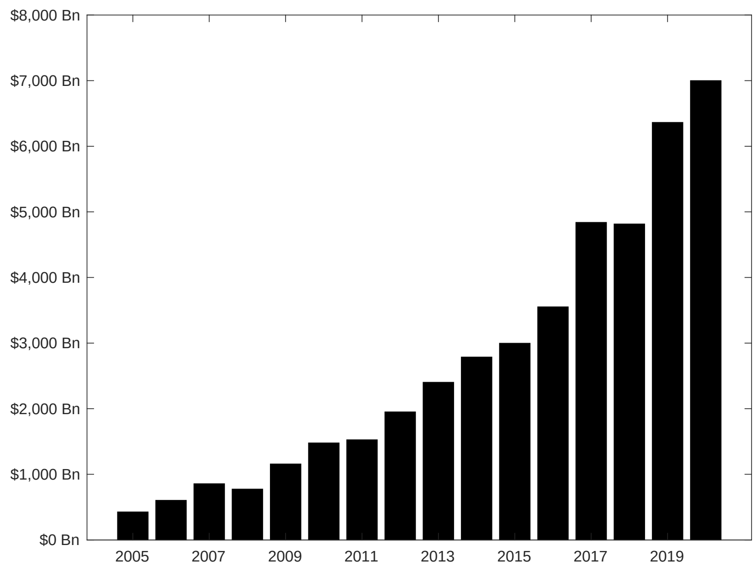


Figure 2.1: Worldwide ETFs AUM over years

2.1.1 The Mechanics of ETFs

ETFs are hybrids between open- and closed-end funds. While they have in common with the former creation and redemption mechanism, they are similar to the latter for trading shares on exchanges. ETF trading process is conducted both on the primary market by the fund itself and the Authorized Participants (AP) and on the secondary one where investors can buy and sell ETFs shares on the Exchange paying the brokerage fees, just like for individual securities.

Once the ETF has been created, after the approval of the competent authority (the SEC in the U.S. and the Consob in Italy), its sponsor agrees with the APs, for instance, market makers or large institutional investors, who borrow stocks and deposit them in a trust (i.e. the fund) to form the ETFs creation units, bundles usually of 50,000 shares. In Figure 2.2 we can observe that first APs engage in the ETFs' shares creation with the fund: the Authorized Participants exchange the basket of underlying stocks and cash in return for ETF shares. Then the latter is placed and traded on the secondary market, in which both institutional and retail investors take part. The redemption works like the creation but in the opposite way: the ETF shares are given back to the fund which swaps them for the basket of stocks and cash.

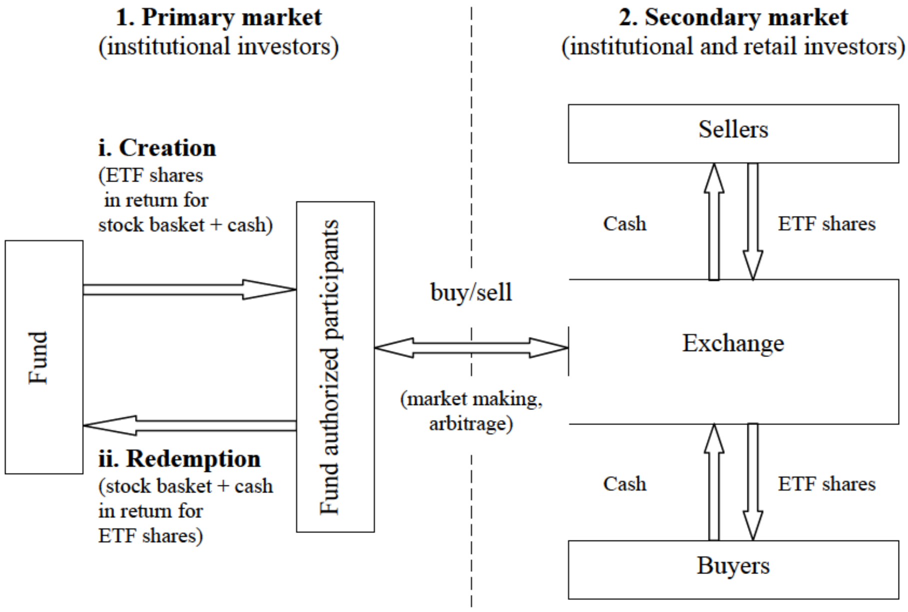


Figure 2.2: The trading process of ETFs (Source: Deville (2008))

Given that ETFs are negotiated on the primary and secondary market, they also have two prices, the NAV[1] and the market price. This duality may give rise to price deviations which in turn create arbitrage opportunities between the ETF shares and the underlying basket of securities when the mispricing exceeds the transaction costs. Usually, APs make to eliminate the deviations by buying the cheaper asset and selling the more expensive. Thus, through upward and downward pressures on the prices, the mispricing is tightened. On the secondary market, arbitrageurs like market makers or traders open a short or long position in the ETF and an opposite one in the main components of the index or a very closely related instrument (like another ETF or futures), hoping the price misalignment will align. We should note this is not a classical arbitrage because of the risk that price discrepancy between the ETF and the underlying securities could widen, while the time of convergence is unknown.

2.1.2 Physical and Synthetic ETFs

The Physical ETFs were the first ones to have been introduced. As their name suggests, they buy and hold the actual securities on which the ETF value is based.

[1] The Net Asset Value is computed at the end of each trading day as: $\frac{\text{Fund Assets - Fund Liabilities}}{\text{ETF shares outstanding}}$

So, they are like a duplicate of their benchmark and just try to get the same return of the index. This is the case, for instance, for the Vanguard S&P500 ETF. By acquiring a share of the latter, an investor can get direct exposure to the S&P500 Index. In Figure 2.3 we can observe the functioning of a physical ETF. Its simplicity makes it an appealing instrument for the majority of investors who regard a direct investment in stocks, bonds, and metals as more secure.

Figure 2.3: The Physical ETF (Source: Vanguard)

On the opposite, synthetic ETFs represent a newer and more exotic alternative to the aforementioned ones. They were first introduced in Europe in 2001 and while they are very popular among European and Asian investors; they are much less widespread in the US market because of restricting SEC regulations. Their peculiarity is in the use of derivatives, like swaps, to track the underlying index. The main two types of synthetic ETFs are the unfunded and funded ones. In the unfunded swap structure, the ETF enters into a swap agreement with a counterparty, usually a bank, paying it a fee and getting the return of the desired underlying index in which the counterparty invests. Then, the issuer creates the new ETF shares which are sold to the APs. The fund acquires a substitute basket of liquid securities, often sourced from the bank's balance sheet, and posted it as collateral in a custody account. Funded synthetic ETFs were born in the aftermath of the GFC. They mainly differ from the previous category in the way in which the basket of securities is bought and hold. Indeed, the cash which the ETF pays to the counterparty bank is used by the latter to buy the basket which is posted as collateral in a separate account pledged to the fund. So, the collateral is legally the property of the fund and therefore investors can recourse should the counterparty fail.

To sum up, on the one hand, physical ETFs represent a valid investment alternative as they combine liquidity, transparency, and diversification all in one; on the other hand, synthetic ETFs allow market participants to get exposure to markets that are less easily accessible, such as those with trade or property restrictions and different time zones, as well as to some asset classes, like commodities and money market, which are possible to invest in only by synthetic replication.

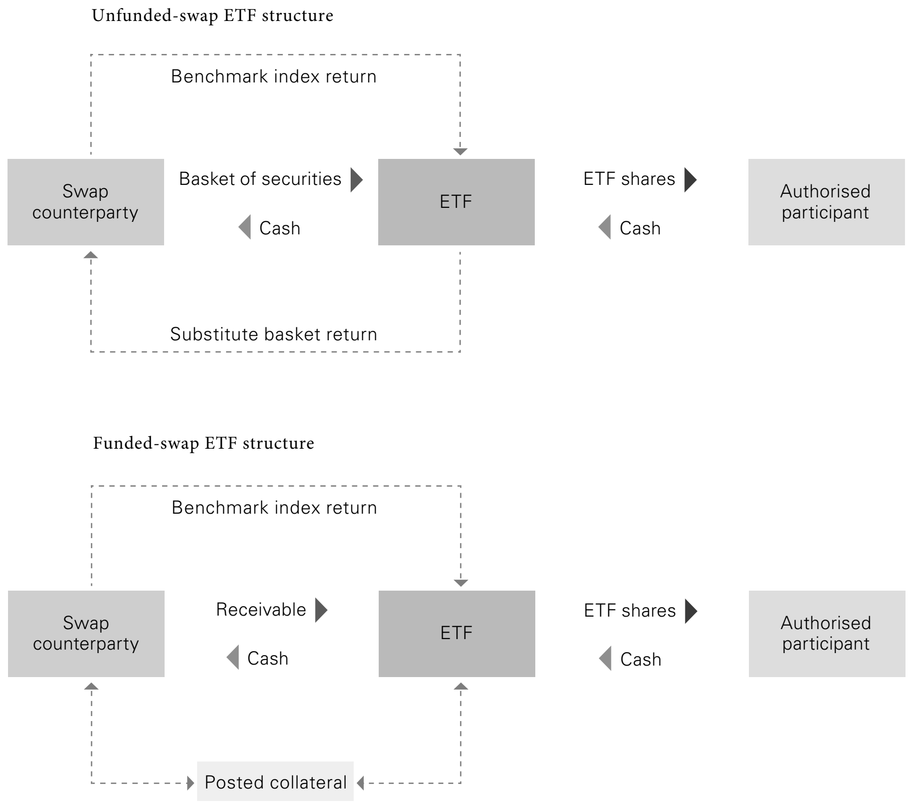


Figure 2.4: The Synthetic ETF (Source: Vanguard)

2.2 The Growing Popularity of ETFs

ETFs have probably been one of the most revolutionary innovations of the last decades. Hull (2007) reports that, of investment professionals surveyed in March 2008, "67% called ETFs the most innovative investment vehicle of the previous two decades and 60% reported that ETFs have fundamentally changed the way they construct investment portfolios". The industry has grown tremendously over the past decades since its inception. Figure 2.1 shows in 2020 global ETF AUM reached US$7 trillion and they are expected to top US$8 trillion by 2021. They can be seen as a "catch-all" investment vehicle. Indeed, for instance, investing in the Spider offers the diversification benefit of exposure to 500 of the largest U.S. companies as well as a high degree of liquidity. The possibility to trade ETFs shares during the entire trading session fulfills the demand for immediacy from market participants. This, combined with the low transaction costs, some tax advantages, low investment threshold, and the potential for short and margin trades, makes them extremely appealing to retail and institutional investors who are showing a preference toward these vehicles, even to the detriment of mutual funds. Besides, among others, an ETF may represent both a good hedging instrument and an efficient way to implement the dollar-cost averaging (DCA) strategy. The latter consists of buying a certain fixed-dollar amount of a certain ETF regularly (for instance the first day of every month), regardless of its changing cost. Through it, the price impact of trade will be much lower than a lump-sum investment and will guarantee more flexibility in the investment planning. Finally, we should also point out that, as reported by Clements (2020), net of fees, passive funds routinely outperform actively managed funds over a ten-year time period.

2.2.1 Market Trends

In the last years, ETF's net inflows have been constantly increasing, setting a record US$509 billion for 2020 (see Figure 2.5). The advances in technology and data analytics, pushed even further by the COVID-19 crisis, have significantly contributed to this result. The AuM of EU domiciled ETFs have grown at a CAGR of 20.5% since 2008. Today, over 250 issuers offer more than 6,700 ETFs.

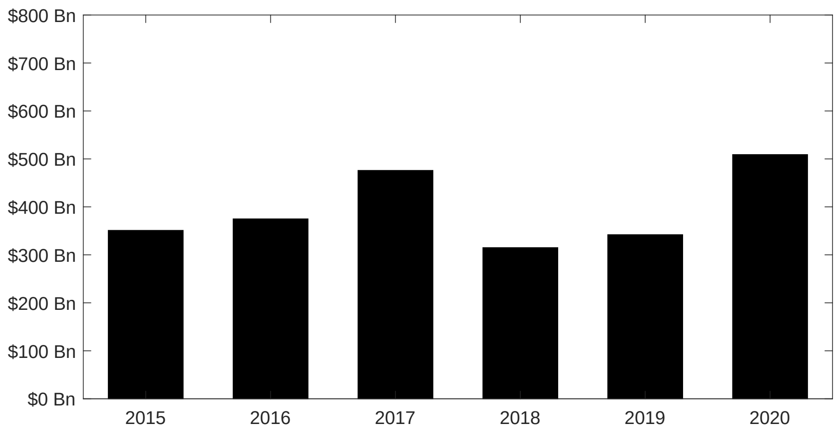


Figure 2.5: Global ETFs Net Inlows

Though, ETFs market is particularly concentrated. Nearly 60% of the market share is held by the three biggest providers: BlackRock, Vanguard, and State Street (see Figure 2.6).

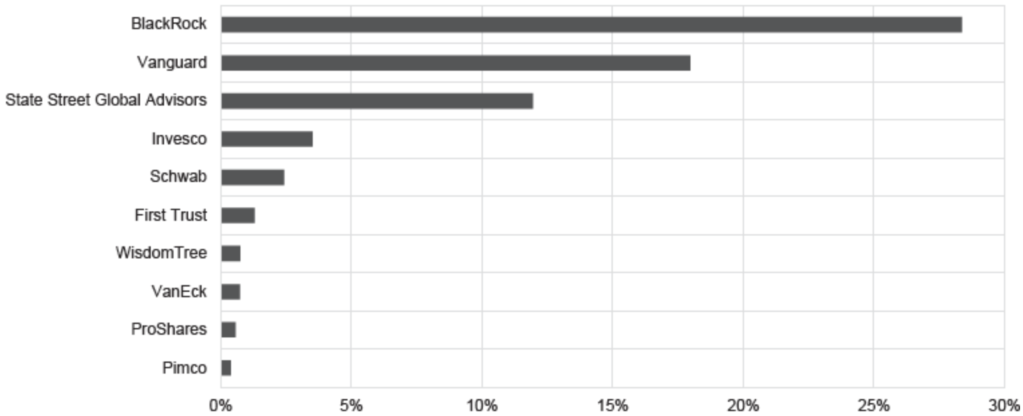
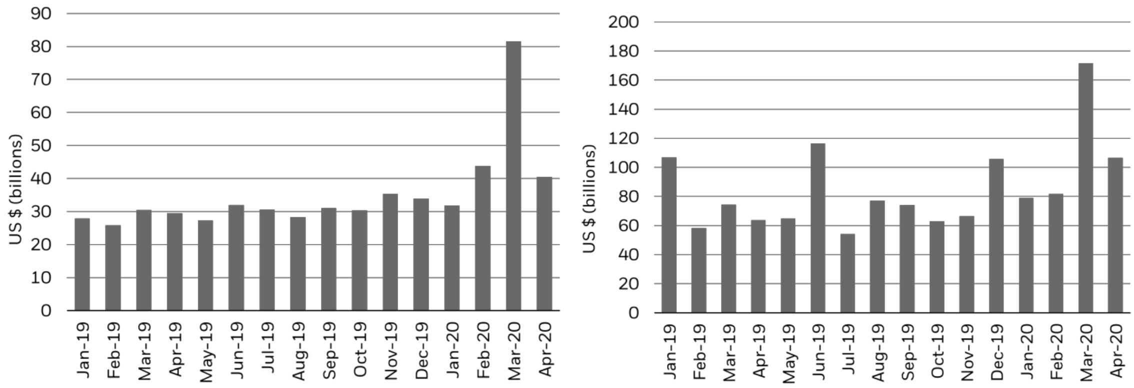


Figure 2.6: Market share of the ten largest providers of ETFs worldwide (Source: Pagano et al. (2019))

In particular, the scenario is largely dominated by ETFs in U.S. equity which has known an unprecedented growth since bottoming out in March, and investors have added \$187.4 billion to U.S. equity ETFs so far this year; while the inflows for the U.S. fixed income ETFs have been of \$177.8 billion. Meanwhile, international equity ETFs and commodities have seen US\$62.1 and US\$39.5 billion of inflows year to date, respectively. Besides, during the COVID-19 crisis, ETFs have behaved stably. Both at the beginning of the pandemic in March and throughout it, investors have been allocating capital in ETFs. Thus, the trading volumes of ETFs have been high and the latter turned out to be more liquid and transparent than their underlying. Fixed income ETFs, allowing for efficient trading of baskets of securities that may otherwise be inaccessible individually, resulted in a clear example of this. As the underlying cash bond market liquidity deteriorated, many investors relied on ETFs for bond market exposure. In the US and Europe, fixed income ETF volumes reached an average of \$33.5 billion per day (over three times the 2019 daily average) and \$18.75 billion in March 2020, respectively. In March 2020, both the primary and secondary market activity knew a peak high (see Figure 2.7 and Figure 2.8).

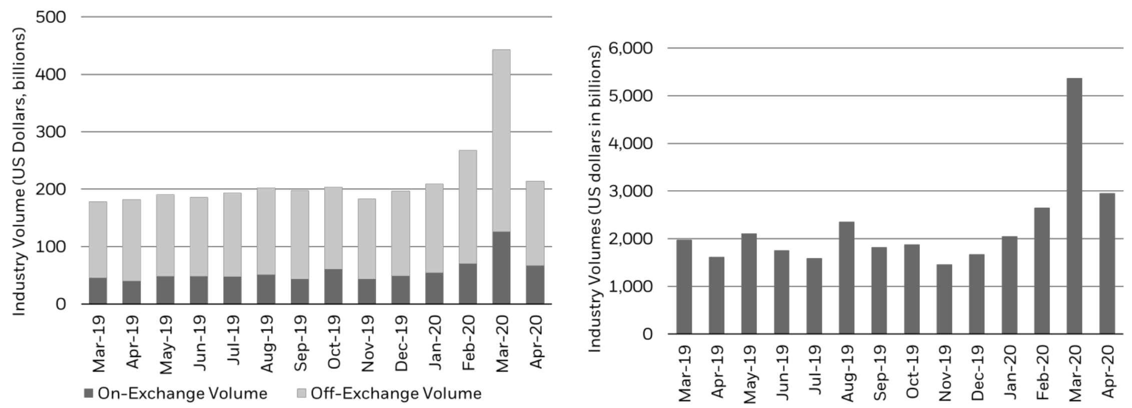
Specifically, European-domiciled ETFs' primary market trading increased by 168% year-over-year, registering a record of \$81.6 billion, which was 155% higher than the trailing 12-month average (see Figure 2.7a). Similarly, US primary market trading volumes, with a peak of $171.6 billion in March 2020, registered a 231% increase YOY and were over 200% higher than the TTM average (see Figure 2.7b).



(a) Primary market activity in Europe **(b)** Primary market activity in the US

Figure 2.7: Trading Volume on Primary Market (Source: BlackRock)

In the same period, the secondary market trading volumes increased significantly as a response to the outbreak of the pandemic as well. As we can observe in Figure 2.8a, the European ETF market traded $443 billion, 231% more than the average monthly volume in 2019. The growth was even wider in the US, where ETFs traded $5.41 trillion in March, almost 300% more than the average month in 2019 (Figure 2.8b). To sum up, we can effectively observe how investors have been shifting their preferences over the last decades and in particular from the GFC. However, we should also investigate what possible downside and risks ETFs can bring.



(a) Primary market activity in Europe **(b)** Primary market activity in the US

Figure 2.8: Trading Volume on Secondary Market (Source: BlackRock)

2.3 Market Herding and Possible Disruptions

The substantial growth of exchange traded funds examined in Section 2.2 has drawn increased attention not only by investors and academics but also by regulators. In particular, after the Flash Crash of May 2010, the latter started to voice concerns about ETFs. The event pointed out that exchange traded funds might exacerbate liquidity shortage. In similar market turmoils, APs, worrying about widening mispricing between the market price and the NAV, may choose to stay on the sideline and stop to provide liquidity to the market. Besides, several studies have found ETFs may present some other risks as well, such as an incremental co-movement and volatility in security prices.

Among others, Da and Shive (2018) attribute the increased co-movement to the fact that investors in posses of index-related news, trade the corresponding ETF more intensely, in a way that the underlying securities are impacted via the arbitrage channel and become more responsive to index-related news than to news related to idiosyncratic factors. Besides, ETFs may attract sentiment-driven noise traders who affect the underlying stock index. Consequently, the increased co-movement among security prices may be due to the widespread of noise trading shocks rather than of faster discovery of information about fundamentals.

Ben-David et al. (2018) have found that, because of their easiness of access, ETFs may attract high-frequency investors whose activity leads to a rise in the volatility of underlying stocks and noise trading. Similarly, Bhattacharya and O'Hara (2018) have shown ETFs can alter the informational efficiency of underlying securities. In particular, speculators, through the herding phenomenon, can trade similarly and thus induce fragility into the market. In the presence of ETFs, market makers learn not only from their own market order flow but also from the ETF price, so prices are doubly influenced. It follows that greater volatility can arise as changes in the ETF price can affect the underlying securities, even when there is no news related to the latter. This kind of untying between asset prices and fundamental values makes markets inefficient in their role of allocating capital, undermining investors' confidence in them.

A further cause of concern can derive from leveraged and inverse ETFs which use structured products to reach their goals. While the former employ total return swaps or futures to multiply the exposure to a benchmark, for example by holding a notional position in futures contracts; the latter use them intending to hedge investors exposure or to speculate in case of a market fall. Some funds can even combine both strategies. So, these Exchange Traded Funds must rebalance their portfolio daily by buying or selling the underlying securities to keep their target leverage. Their trading behavior is procyclical: they buy when the underlying return is positive and sell when it is negative, influencing in this way the price of the assets, increasing their volatility and contributing to price momentum.

Furthermore, we can observe growing interrelations between ETFs and other segments of the financial markets. Indeed, given that Exchange Traded Funds are extremely liquid, investors can be persuaded to open large, short-term and correlated positions, which can trigger a domino's effect with systemic risk implications for the overall financial system. Assuming the aforementioned positions produce large losses to leveraged investors such as banks, the latter may end up defaulting on other investors, initiating a vicious chain reaction mechanism. Then, the interconnection between ETFs and other parts of the financial system may spread the malfunctions in the redemption mechanism of ETFs shares during market turmoils to other segments of the markets and affect the overall financial stability. We treat in the following Section 2.3.1 a recent example of this.

2.3.1 Exchange Traded Funds and the Oil Crash

In April 2020, oil prices went negative for the first time in history. At the end of March 2020, 76% of the oil storage across the globe was already full and it was expected that the global liquidity supply will have exceeded demand by more than 1.8 billion barrels during the first half of 2020. This, together with the reduced demand, due to the outbreak of the coronavirus pandemic, and the "war" between Saudi Arabia and Russia announcing an increase in oil production to secure their respective market share, was at the origin of the crash. So, on April, 20, the West Texas Intermediate (WTI) May Future plunged to -$37.63.

Figure 2.9: WTI May Future Price - Adj Close

The event not only adversely affected tens of millions of jobs worldwide, but it also shed new light on the risks behind Exchange Traded Products (ETP).

The United States Oil Fund (USO) ETF fell 8% to \$20.08 on April, 22 (see Figure 2.10). The objective of USO is to reflect the daily changes, in percentage terms, of the spot price of light sweet crude oil delivered to Cushing, Oklahoma, tracking the Benchmark Oil Futures Contract over the same period. Thus, the fund's rolling out of the position in the May futures at the end of April contributed to the oil crash. Indeed, as the expiration of the front month contract approached, the fund's sponsors had to close the position since ETFs like USO are not created to take physical delivery. However, the lack of storage across the globe have forced investors with long positions in the May contract to pay to close them with huge losses for the fund and its shareholders, of who nearly 70% were retail investors who had allocated their capital in the ETF believing to invest in the spot oil and that the prices would have risen.

Figure 2.10: United States Oil Fund LP - Adj Close

At the end, we can observe how ETFs are not just a benefit for investors. They bring with them some intrinsic risks which may have severe consequences on market stability and can be detrimental to investors' confidence in financial markets. From this, it follows the growing attention to ETFs by regulatory institutions around the world. In particular, ETPs like inverse and leveraged ETFs as well as ETFs investing in futures deserve special consideration since their dynamics are much more complicated than the ones of physical ETFs.

2.4 The COVID-19 crisis and the ETFs

As we have seen in Section 2.2.1, during the COVID-19 crisis, ETFs resulted from a popular choice among investors in the secondary market as well as a safe harbor for APs whose activity in the primary market increased considerably. Indeed, contrary to the theories by Ben-David et al. (2018) and Pan and Zeng (2019) among others, per who APs stay on the sideline when the VIX is high, the latter together with the market makers contributed to increase the ETF trading volumes.

Despite the increase in the bid-ask spreads, as a consequence of deteriorating liquidity and raising volatility, ETFs had lower spreads than their underlying assets. This proved to be particularly evident for fixed income ETFs.

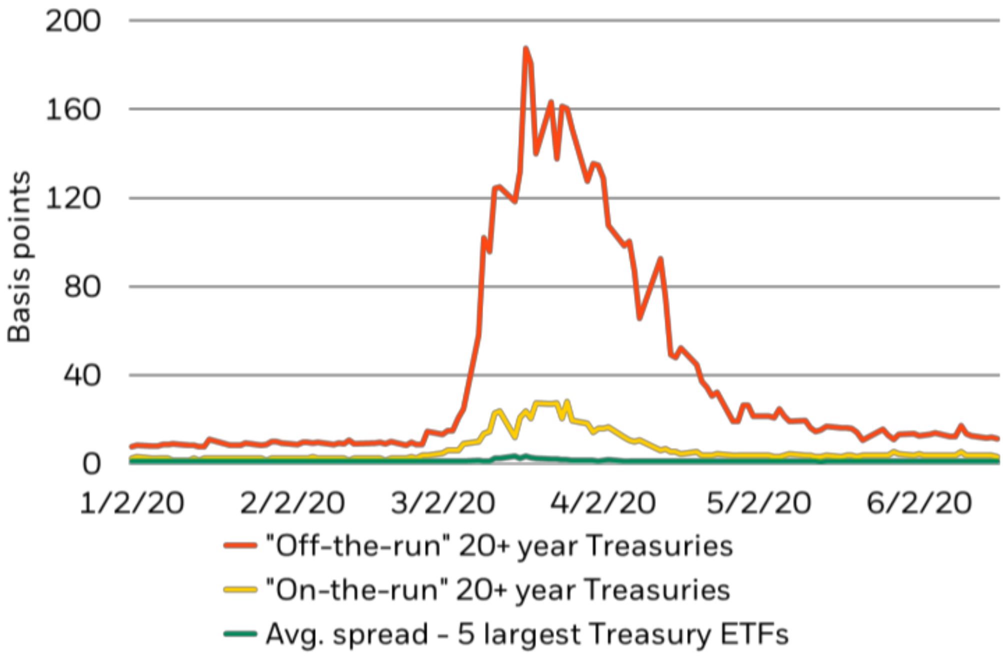


Figure 2.11: Treasury ETFs versus Treasuries (Source: Blackrock)

As we can observe from Figure 2.11, in March 2020, at the outbreak of COVID-19, and in the months immediately after, while average bid-ask spreads on the five largest Treasury bond ETFs oscillated from one to three basis points, the spreads on-off- and on-the-run Treasury bonds were much larger: a peak of nearly 188 basis points and of 27 bps was reached on March 18 and on March 20, respectively.

Additionally, over this period, we could assist to a wide mismatch between the fixed income ETFs price and the corresponding NAV. Since the NAV is calculated once daily by using actual trades for bonds that are traded that day or estimates for bonds that trade infrequently or did not trade on a given day, it is common the ETF market price deviates from the NAV. However, in normal times, these discrepancies are insignificant; while, during periods of stress, they tend to widen. This has effectively been the case in the recent crisis too, where, for example, when market volatility spiked on March 12, shares of the ETF, whose underlying is the US dollar investment grade (IG) credit, closed at nearly 600 bps below its NAV (see Figure 2.12).

Figure 2.12: Divergence between ETF price and NAV - $IG end of day premium / discount to NAV (Source: Blackrock)

Thus, the aforementioned deviations represented a source of transparency during the crisis: where the bond market may have been opaque and discontinuously liquid for those bonds which traded infrequently, ETF's market price drove the price discovery, by reflecting the actual market price. Indeed, for example, the turnover rate of the IG credit ETF was roughly 30 times its underlying holdings.

Chapter 3

Literature Review

In this chapter, we will present previous works about the impact of ETFs as well as security baskets and index-linked securities on market liquidity. There exists contrasting pieces of evidence and alternative hypotheses showing how the aforementioned instruments may both increment the liquidity of underlying securities and, on the opposite, impair it.

3.1 Security Baskets and Index-Linked Securities

Even before the advent of exchange traded funds, financial innovations have led to the birth of composite securities, whose values are represented by the aggregation of cash flows of their underlying assets. Gorton and Pennacchi (1989) showed in their model that the need of uninformed agents to trade even when information about securities has not been revealed yet combined with their wish to minimize the losses to informed traders, push the former to create and trade in these composite securities which, thanks to the diversification, are characterized by a lower level of variance and hence information asymmetries. Following the steps of Gorton and Pennacchi (1989), Subrahmanyam (1991) demonstrated that the markets for security baskets and index-linked products enhance the trading efficiency of uninformed market participants. The improvement could be due to a weaker adverse price impact of trades for securities more heavily weighted in a basket or an index than for less weighted ones. A further reason of the amelioration may lie in greater analysts and media coverage of those assets with a higher weight in the basket; indeed the larger coverage, in turn, favours the informativeness of prices in the security-specific component.

In later studies, Fremault (1991) and Kumar and Seppi (1994) analyzed the role of arbitrage between index-linked securities and the component stocks. They found that the liquidity of the stock can be improved by the activity of arbitrageurs who eliminate the information asymmetry. Kumar and Seppi (1994) went even deeper and noted that the lower the arbitrage entry costs are, the better the market liquidity of the underlying securities will be as not only a larger number of arbitrageurs will be able to enter the market but also the competition among informed traders will increase.

Thus, given this framework, the studies on Exchange Traded Funds, which are the "modern incarnation" of the preexisting security baskets, follow.

3.2 Propagation of Liquidity Shocks into ETFs' underlying securities

Ben-David et al. (2012) showed that, being ETFs prices closely related by arbitrage activity (see Section 2.1.1) to the ones of their underlying securities, that arbitrage activity can lead to the propagation of non-fundamental shocks from the ETFs to the underlying. Roughly speaking, in this view, ETFs add a new layer of liquidity shock to their basket of securities.

As we can observe in Figure 3.1, in the initial equilibrium stage, ETF market price and NAV are on the same level; then, a non-fundamental shock occurs hitting first the ETF price and, through the arbitrage channel, propagating to the NAV which thus is adjusted to the ETF price. In the long-run, both revert to the fundamental value.

Despite their potential to spillover liquidity shocks to the underlying basket, ETFs might enhance price discovery, as it happened during the coronavirus crisis (see Section 2.4). When a shock hits the fundamental value, the ETF price "chases" the latter and the NAV follows it to the new equilibrium level (see Figure 3.2).

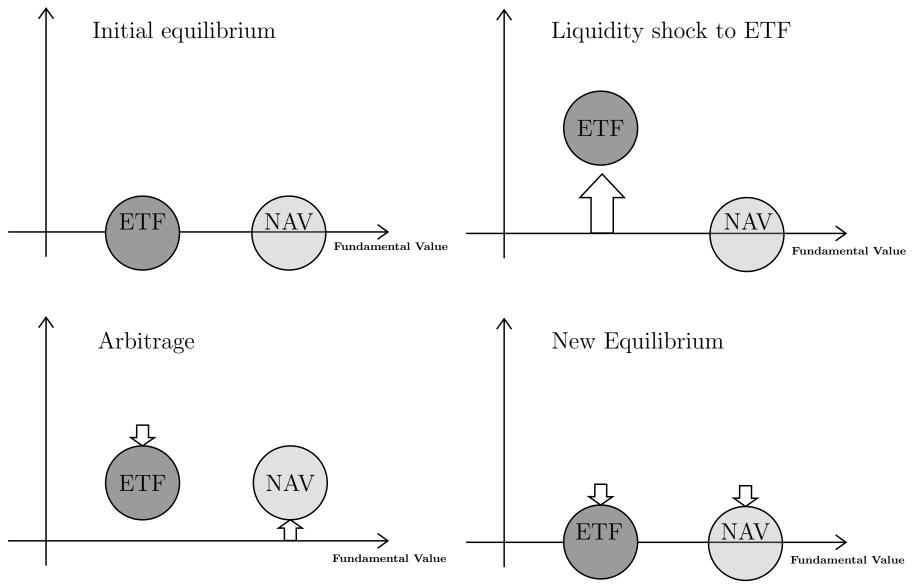


Figure 3.1: Liquidity Trading Hypothesis (Source: Ben-David et al. (2012))

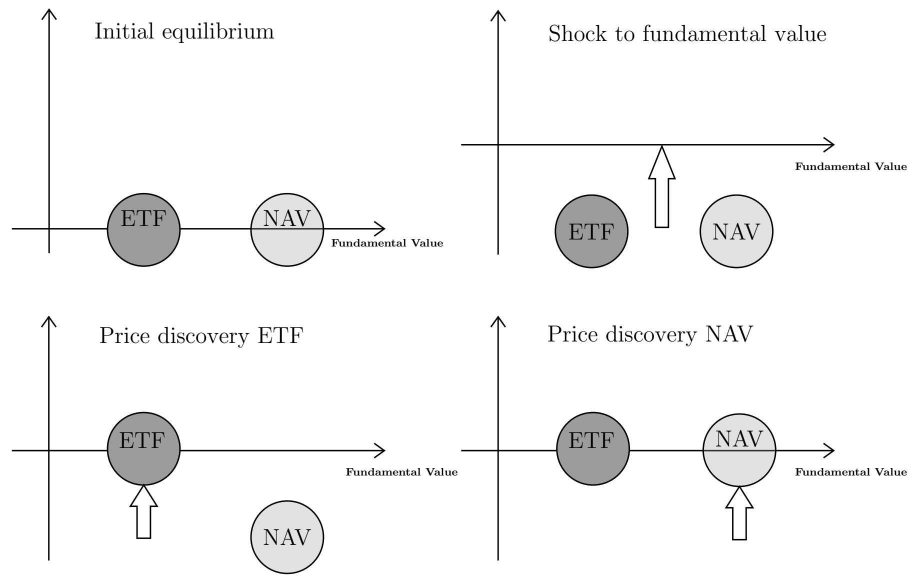


Figure 3.2: Price discovery hypothesis (Source: Ben-David et al. (2012))

In following studies, Ben-David et al. (2018) found that, through the liquidity shock in the arbitrage channel, an increase in the ETF ownership (i.e. what percentage of security is held by ETFs) induces an increment in the non-fundamental volatility of the underlying securities. That, in turn, results in a source of undiversifiable risk in prices.

3.2.1 The Malamud Model

In the footsteps of Ben-David et al. (2012), Malamud (2016) states that aggregate risk in the market changes following the introduction of ETFs and there exists a *shock propagation channel* between ETFs and the respective underlying. However, contrary to the findings of Ben-David et al. (2012), he shows that the ETFs ownership impact on the basket of securities is ambiguous and depends on the level of Authorized Participants' risk aversion. On the one hand, when the latter is high, Malamud's results are coherent with Ben-David et al. (2012) and there are no significant differences between the impact of ETFs in the long and the short run; on the other hand, when the risk aversion is low, APs provide a lot of liquidity in the ETF markets, also because they have fewer constraints due to hedging purposes, and while in the short period volatility is independent of the liquidity of the ETF's primary market, in the long period it has a concave relationship with ETF's primary market liquidity and the Exchange Traded Funds may improve the trading volume and the liquidity of the underlying securities.

Malamud (2016) also shows that the introduction of a new ETF to the existing market may result in draining of the liquidity from the "incumbent" ETFs since, because of the demand substitution effect, APs could step in to provide liquidity to the new market withdrawing it from the existing ones.

3.2.2 The Holden and Nam model

Holden and Nam (2019) analyzed and developed a model for the effects which the introduction of ETFs have on corporate bonds. They found that the impact depends on the market accessibility: the less (more) the last one is, the more the liquidity of the underlying market improves (deteriorates) when basket trading is introduced. Under their hypothesis, they empirically prove that, in the case of corporate bonds, the introduction of ETFs results in a larger liquidity improvement for highly arbitraged, low-volume, high yield (HY), and with long-duration bonds as well as for 144A bonds[1]. In Figure 3.3 we can observe the behaviour of the liquidity in the case

[1] Those bonds which are privately placed and whose access is prohibited to retail investors. They owe their name to Rule 144A which in 2012 shortened their minimum holding period from two

of limited market access: investors shift their capital from risk-free securities to the new ETF whose new layer of liquidity, in turn, through the arbitrage channel, spills over into the underlying, similarly to Ben-David et al. (2012) and Malamud (2016).

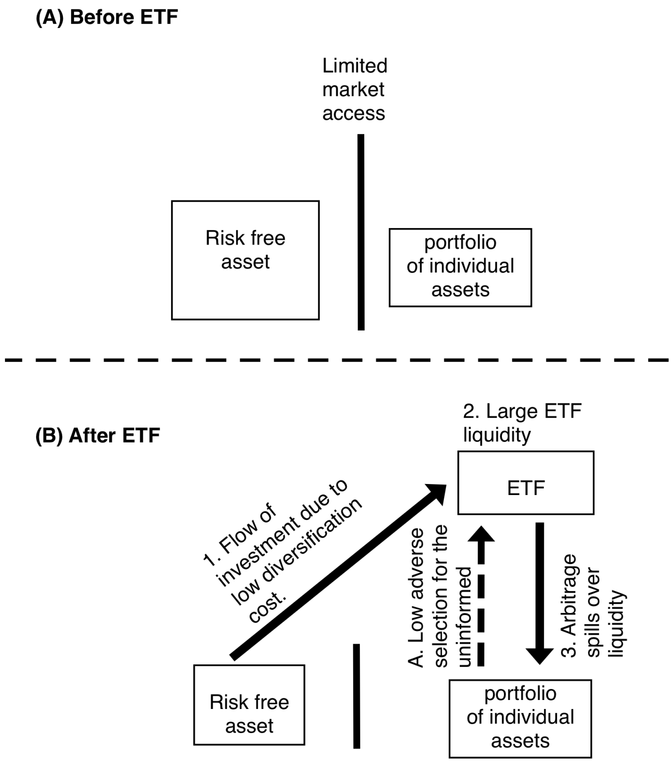


Figure 3.3: The Effect of ETFs introduction on less accessible market (Source: Holden and Nam (2019))

Besides, a further implication of Holden and Nam (2019)'s model is that the larger the difference between the ETF and its underlying is, the wider the increase or decrease of the market liquidity will be. If a market is already highly accessible, the investors will have an incentive to move their capital to the new ETFs draining liquidity from the underlying basket; on the opposite, if a market is poorly accessible, the ETFs will attract a new layer of liquidity, which will flow to the basket of securities (see Figure 3.4).

years to six months.

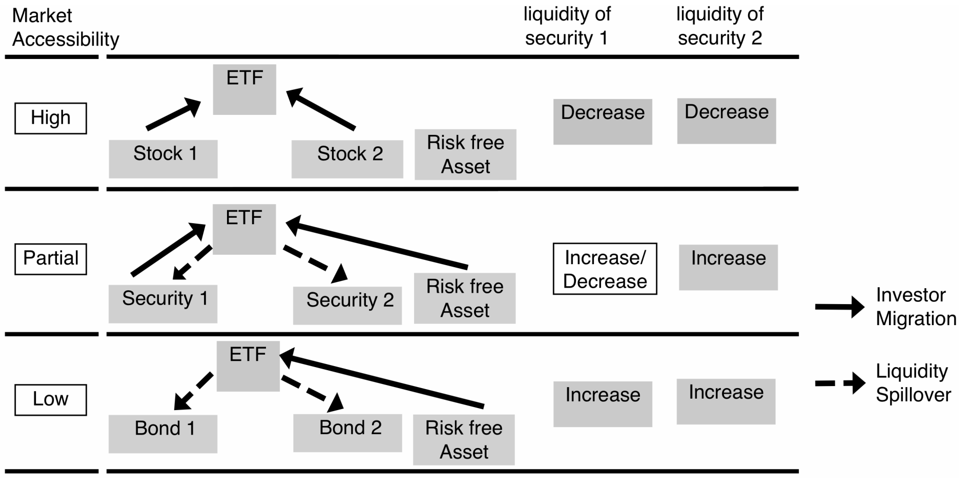


Figure 3.4: Market Accessibility and The Effect of ETFs (Source: Holden and Nam (2019))

3.3 Alternative Views

Further studies and researches have presented different theories showing that market liquidity can effectively dry up following the introduction of ETFs; that may in particular occur during stressed markets. Pan and Zeng (2019) analyzed the case of corporate bonds ETFs and proposed a model explaining how the deterioration of the arbitrage activity of APs in case of highly volatile markets could pose severe risks to the underlying securities liquidity. The liquidity mismatch between liquid corporate bonds ETFs and their OTC basket of securities[2] exacerbates the inventory risk of APs. Given that corporate bonds are traded in the over the counter market with large transaction costs, APs hold bond inventory. A conflict of interest then arises since, in the case of corporate bonds, authorized participants have contemporaneously the role of market makers. Thus, APs could choose not to engage in the creation/redemption mechanism and provide liquidity, instead, they would prefer to act as market makers and seek liquidity. Besides, if transaction costs rise because corporate bonds become more illiquid, the profitability of the arbitrage activity decrease, discouraging APs to pursue it.

While Dannhauser (2016) suggested that the ETF ownership increases the liq-

[2] Corporate bonds are mainly traded on over the counter markets being so less liquid and more opaque than the respective ETFs whose shares, on the opposite, are exchanged on trading venues.

uidity of IG corporate bonds; Sultan (2014) found that ETF ownership effectively improves their market liquidity, even for junk bonds, although during the GFC of 2008 corporate bonds with a greater ETF ownership experienced a lower degree of liquidity. Recent studies, Marta (2019) among others, on the opposite, discovered a positive relationship between ETFs ownership and corporate bonds, persisting even in times of market stress like the taper tantrum of 2013 and the recent COVID-19 crisis.

While the results of the studies about the ETF effects on the liquidity of corporate bonds agree in denoting liquidity improvements; there are conflicting findings about equity. Boehmer and Boehmer (2003), Hegde and McDermott (2004), and Marshall et al. (2015), for instance, found significant positive relationships between the introduction of new ETFs and the liquidity of underlying securities. Other studies take into account how the information efficiency could be influenced by Exchange Traded Funds.

Hamm (2014), retrieving stock market data from 2002 to 2008, focused on the effects of ETFs ownership on adverse selection cost. She found robust pieces of evidence that increasing the percentage of shares hold by ETFs induces an increase in the adverse selection cost component measured by Kyle's λ. Uninformed investors prefer to reallocate their capital from individual securities to the respective ETF because of the diversification benefit. This behaviour drains the liquidity from ETFs underlying securities where there will be a high concentration of informed traders, making the cost of adverse selection extremely high.

Similarly, Israeli et al. (2017) suggested the trading costs of market participants increase together with the ETF ownership and found significant evidence to the support of their hypothesis. According to them, ETF ownership can affect a stock's pricing efficiency. When ETFs increase the percentage of shares that they hold, it follows that a smaller number of the securities will be available for trading individually. Additionally, the migration of noise traders (uninformed traders) to ETFs, in the long run, will turn into a disincentive for informed traders to pay for firm-specific information, increasing, as in Hamm (2014), the adverse selection costs.

Chapter 4

The ETFs and the Liquidity of Underlying Securities

In the footsteps of Boehmer and Boehmer (2003) and Hegde and McDermott (2004), this chapter is aimed at investigating the effects of the introduction of some Exchange Traded Funds on the market liquidity of their underlying securities. We choose the ARK Innovation ETF (ticker symbol ARKK), iShares Automation & Robotics UCITS ETF (ticker symbol RBTX), Vanguard S&P500 Growth Index Fund (VOOG) and iShares Core High Dividend ETF (HDV) which are relatively recently launched equity ETFs traded on the New York Stock Exchange (NYSE) Arca. The primary goal is to verify whether following their inception date, the market liquidity of the underlying securities has changed.

4.1 Empirical Analysis

The transactions volume and price data for the ETFs' underlying securities are taken from the NYSE Transactions and Quotes (TAQ) and from the Center for Research in Securities Prices (CRSP) databases through WRDS [1]. For this research, we use the daily summary of each variable employed, provided by WRDS. We retrieve the information relatively to Exchange Traded Funds holdings from Thomson Reuters as of the period of the ETF launch date and the daily overall market volume of the NYSE and NASDAQ from the Cboe and NASDAQ. We focus on the 50 trading days

[1] Wharton Transaction Data Services: The Monash Business School granted the access, which this research would have not been possible without.

before the ETFs launch date and on the 50 trading days following it, corresponding to the period August 21st, 2014 - January 13rd, 2015 for ARKK; June 28th, 2016 - November 16th, 2016 for RBTX; June 25th, 2010 - November 15th, 2010 for VOOG; January 14th, 2011 - June 8th, 2011 for HDV. The selected time frame of 100 days represents an acceptable compromise between having a relatively ample dataset and minimizing the effects that exogenous liquidity shocks could have on the basket of underlying securities.

4.1.1 Liquidity and Volume

To evaluate the market liquidity of the securities of interest, we used the liquidity measures discussed in Section 1.1. In particular, we consider the percentage and the dollar quoted and effective spreads, we compute the Corwin-Schultz estimator from the daily high and low prices; then, we retrieve the data of depth at the bid and ask quotes in shares as well as dollars and equally average these to get the depth in shares and dollars, respectively. The quoted spread is actually the time-weighted quoted spread, implying the bid and ask prices are weighted for the time their respective quotes are active in proportion to the overall length of the trading day. The percentage spread corresponds to the relative spread that we defined in Section 1.1.1. The final measures of the daily spreads (quoted and effective) for each stock i represent the average of all the N trades over the trading day:

$$S^i_{day} = \frac{1}{N}\sum_{t=1}^{N} s^i_t$$

The effective spread is retrieved from WRDS which employs the Lee and Ready (1991) algorithm to classify the orders direction. In particular an order is a buy one when $P_k > M_{t-1}$ and a sell one when $P_k < M_{t-1}$, with P_k denoting the price of a trade and M_{t-1} the previous mid quote. To compute the CS estimator, we follow the Corwin and Schultz (2012) approach and before averaging the daily spread over the period of interest, i.e. the 50 days after and before the ETF launch date, we set to 0 all the negative 2-day spread estimates (see Section 1.1.5). In this way, we can get better estimates than simply removing the negative values or leaving them unchanged.

For each stock, we consider the daily volume of shares exchanged over the 100 days period of interest. We then compute the relative daily volume as the proportion of each stock's daily trading volume on the daily trading volume of the overall market in which the stock is exchanged. We also analyzed the standard deviation of daily returns and the Amihud ratio (see Section 1.1.2).

4.1.2 Methodology

To assess the change in market liquidity after the ETF introduction, we compute the mean and the median of each variable of interest over the 50 days preceding and following the launch date for every component security. From them, we compute a *post/pre ratio*:

$$Post/Pre\,Ratio^i = \frac{\bar{X}^i_{post}}{\bar{X}^i_{pre}}$$

with X and i representing a certain variable and stock, respectively. Once we have computed the ratio for each stock, we calculated its average as:

$$Average\,Post/Pre\,Ratio^i = \frac{1}{N}\sum_{i=1}^{N}\frac{\bar{X}^i_{post}}{\bar{X}^i_{pre}}$$

where N is the total number of stocks held by a given ETF. Thus, we perform the Student's t-test to verify whether the variable of interest changes significantly. The null and alternative hypotheses, respectively, are:

$$H_0 : Average\,Post/Pre\,Ratio_X = 1$$
$$H_a : Average\,Post/Pre\,Ratio_X \neq 1$$

and the test statistic for the variable X and stock i:

$$t_X = \frac{Average\,Post/Pre\,Ratio_X - 1}{\sigma_X/\sqrt{n}}$$

4.2 Empirical Results

4.2.1 iShares Core High Dividend ETF Results

The iShares Core High Dividend ETF is Blackrock's ETF whose aim is to track an index composed of relatively high dividend-paying U.S. equities.

The results, as we can observe in Tables 4.1 and 4.2, predict a general improvement in the market liquidity of HDV's underlying assets. The fact that the *post/pre ratio* trading volume is significantly different from 1 (0.923 with a t-stat of -2.81) while the *post/pre ratio* of the relative volume is 1.078 with a t-stat of 2.85 may suggest that the 50 days following the HDV's launch date corresponded to a period of lower trading activity in the markets. Thus, it is difficult to attribute the reduction in the trading volume to the introduction of the ETF.

	Quoted Spread		**Effective Spread**		**Depth**		**CS**
	%	**$**	**%**	**$**	#	**$**	**$**
mean pre HDV	0.000452	0.0184	0.00036	0.0141	1,880.5	64,237.5	0.0045
mean post HDV	0.000423	0.0175	0.00034	0.0138	1,842.5	65,598.1	0.0039
median pre HDV	0.000447	0.0181	0.00035	0.0139	1,811.8	61,952.5	0.0042
median post HDV	0.000421	0.0173	0.00034	0.0136	1,776.2	62,719.8	0.0034
Post/Pre Ratio							
Mean	0.93	0.95	0.955	0.97	1.04	1.05	0.88
Median	0.94	0.96	0.96	0.98	1.05	1.046	0.87
Hypothesis Test							
t-stat	-4.68	-2.60	-3.91	-1.85	1.07	1.86	-4.96
p-value	0.00001	0.012	0.0002	0.069	0.287	0.067	0.00001

Table 4.1: HDV - Spreads and Depth

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre HDV	293,178,621.3	0.447%	1.45%	5×10^{-5}
mean post HDV	260,780,067.3	0.452%	1.14%	1.2×10^{-9}
median pre HDV	5,197,522.8	0.398%	1.26%	1.5×10^{-9}
median post HDV	4,760,978.4	0.415%	1.05%	4.95×10^{-10}
Post/Pre Ratio				
Mean	0.923	1.078	0.872	0.710
Median	0.896	1.058	0.850	-0.021
Hypothesis Test				
t-stat	-2.81	2.85	-4.94	-0.28
p-value	0.0065	0.0059	0.00001	0.78

Table 4.2: HDV - Volume Measures and Standard Deviation

4.2.2 Vanguard S&P 500 Growth Index Fund ETF Results

Vanguard S&P 500 Growth ETF invests in the growth companies of the S&P 500, focusing on replicating the index's return.

	Quoted Spread		Effective Spread		Depth		CS
	%	$	%	$	#	$	$
mean pre VOOG	0.00043	0.02949	0.00037	0.02364	2,955.6	92,558.1	0.012
mean post VOOG	0.00038	0.02143	0.00032	0.01744	3,117.3	104,276.8	0.011
median pre VOOG	0.00062	0.02826	0.00050	0.03324	2,830.6	89,367.4	0.001
median post VOOG	0.00032	0.02061	0.00028	0.01783	3,004.6	111,209.0	0.002
Post/Pre Ratio							
Mean	0.93	0.95	0.955	0.97	1.04	1.051	1.3
Median	0.94	0.96	0.96	0.98	1.05	1.046	0.97
Hypothesis Test							
t-stat	0.61	0.20	0.55	-0.45	2.23	6.27	1.85
p-value	0.542	0.842	0.586	0.656	0.029	2.7×10^{-8}	0.068

Table 4.3: VOOG - Spreads and Depth

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre VOOG	523,677,845.5	0.707%	2.62%	-5.6×10^{-11}
mean post VOOG	487,373,677.2	0.666%	1.47%	3.4×10^{-10}
median pre VOOG	9,503,956.8	0.641%	1.81%	2.1×10^{-11}
median post VOOG	8,764,051.8	0.595%	1.31%	3.2×10^{-10}
Post/Pre Ratio				
Mean	0.92	0.93	0.81	-0.71
Median	0.86	0.90	0.77	0.87
Hypothesis Test				
t-stat	-4.88	-3.96	-2.7	-0.029
p-value	6.6×10^{-6}	0.0002	0.009	0.98

Table 4.4: VOOG - Volume Measures and Standard Deviation

The *post/pre ratio* of quoted and effective spreads would suggest an improvement in the market liquidity, however, the results are not significantly different from 1. The average *post/pre ratio* of the dollar (shares) depth is 1.051 (1.04) and significantly different from 1 with a t-stat of 6.27 (2.23) (see Table 4.3). The trading volume of the underlying assets decreases after VOOG has been launched: the *post/pre ratio* is 0.92 (t-stat -4.88) and 0.93 (t-stat -3.96) for the trading volume and the relative volume, respectively. Besides the ETF seems to have improved the average volatility of the underlying securities as the *post/pre ratio* for the standard deviation is 0.81 with a t-stat of -2.7.

4.2.3 iShares Automation & Robotics ETF Results

iShares Automation & Robotics ETF is Blackrock's ETF launched on 8th September 2016 and aimed at replicating the performance of an index composed of companies that invest in the research and development of automatic and robotic technology.

	Quoted Spread		Effective Spread		Depth		CS
	%	$	%	$	#	$	$
mean pre RBTX	0.0017	0.121	0.0009	0.063	59,768.5	31,898	0.006
mean post RBTX	0.0018	0.127	0.0010	0.066	57,059.1	28,841.8	0.007
median pre RBTX	0.0016	0.117	0.0009	0.061	1,134.2	30,865.9	0.004
median post RBTX	0.0017	0.124	0.0009	0.063	1,072.8	27,674.6	0.005
Post/Pre Ratio							
Mean	1.073	1.134	1.049	1.107	0.959	1.007	1.244
Median	1.062	1.111	1.039	1.089	0.934	0.984	1.141
Hypothesis Test							
t-stat	3.34	3.52	2.47	4.66	-1.44	0.24	4.77
p-value	0.0017	0.001	0.0175	0.00003	0.156	0.809	1.92×10^{-5}

Table 4.5: RBTX - Spreads and Depth

After the introduction of RBTX the average spreads of the underlying securities have widened: the *post/pre ratio* for the percentage (dollar) quoted spread is 1.073 (1.134) (the t-stat is 3.34 (3.52)) and the *post/pre ratio* for the percentage (dollar) effective spread is 1.049 (1.107) (the t-stat is 2.47 (4.66)), the CS estimator *post/pre ratio* is 1.244 (t-stat 4.77). At the same time, the *post/pre ratio* for both the trading volume and the standard deviation is significantly larger than 1, with a value of 1.13 and a t-stat of 2.78 for the trading volume and a value of 1.32 and a t-stat of 5.08 for the standard deviation. The *post/pre ratio* for the Amihud measure is 0.27 with a t-stat of -6.23.

We observe a worsening in the market liquidity of the underlying assets after the ETF's introduction. These results are strengthened by the fact that the 50 trading days preceding the launch date were from 28th June to 7th September and that during the summer the market liquidity is usually lower.

	Trading Volume	**Relative Volume**	**St. dev.**	**Amihud Ratio**
mean pre RBTX	2,725,811.8	0.32%	1.67%	1.45×10^{-8}
mean post RBTX	3,412,952.0	0.35%	2.01%	9.84×10^{-9}
median pre RBTX	2,291,498.4	0.27%	1.43%	4.67×10^{-9}
median post RBTX	2,877,293.0	0.29%	1.92%	6.39×10^{-10}
Post/Pre Ratio				
Mean	1.13	0.987	1.32	0.27
Median	1.121	0.99	1.29	0.7
Hypothesis Test				
t-stat	2.781	-0.312	5.08	-6.232
p-value	0.008	0.756	6.72×10^{-6}	1.3×10^{-7}

Table 4.6: RBTX - Volume Measures and Standard Deviation

4.2.4 ARK Innovation Results

ARK Innovation differs from the other exchange traded funds analyzed from Sections 4.2.1 to 4.2.3. Launched on October 31st, 2014, it began trading on NYSE Arca under the ticker symbol of ARKK as an *active* ETF and with the investment objective of investing at least 65% of its assets in shares of companies engaging in *disruptive innovation*[2]. While preserving the core characteristics of their passive counterparts (see Section 2.1), an active ETF is more flexible since it is not limited to the pure replication of its underlying index, but it aims to beat a benchmark. The only constraint for the fund's manager is to keep adhering to the prospectus's statement. They will generally have a higher turnover and thus larger expense ratios[3] as they aim to deliver better performance than the index they follow.

[2] A *disruptive innovation* is a new technology with potential of changing how the world works.
[3] ARKK's expense ratio is of 0.75%, while the ones of RBTX, HDV, and VOOG are of 0.40%, 0.08%, and 0.10%, respectively.

	Quoted Spread		Effective Spread		Depth		CS
	%	$	%	$	#	$	$
mean pre ARKK	0.0027	0.0692	0.0018	0.0455	947.5	23,633.4	0.0105
mean post ARKK	0.0041	0.0921	0.0017	0.0436	863.5	22,283.3	0.0097
median pre ARKK	0.0026	0.0681	0.0018	0.0446	894.8	23,095.9	0.0069
median post ARKK	0.0026	0.0668	0.0017	0.0426	813.8	21,307.5	0.0067
Post/Pre Ratio							
Mean	1.509	1.558	0.970	0.999	0.982	1.005	0.942
Median	1.004	1.024	0.975	0.997	0.987	1.009	1.049
Hypothesis Test							
t-stat	4.080	4.179	-1.046	0.031	-0.717	0.142	-1.657
p-value	0.0005	0.0004	0.307	0.975	0.48	0.89	0.11

Table 4.7: ARKK - Spreads and Depth

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre ARKK	1,623,403.8	0.198%	2.644%	-5.30873×10^{-9}
mean post ARKK	1,507,579.4	0.203%	2.748%	-5.18822×10^{-9}
median pre ARKK	1,395,950.1	0.170%	2.386%	-7.3025×10^{-9}
median post ARKK	1,358,157.7	0.179%	2.789%	-6.1009×10^{-11}
Post/Pre Ratio				
Mean	1.072	1.178	1.25	0.348
Median	0.91	1.001	1.2	-1.48
Hypothesis Test				
t-stat	0.94	2.14	3.26	1.56
p-value	0.36	0.044	0.004	0.13

Table 4.8: ARKK - Volume Measures and Standard Deviation

Table 4.7 shows that the percentage (dollar) quoted spread for the 50 days following the ARKK's launch date is significantly higher, with an average post/pre ratio of 1.509 (1.558) and at-stat of 4.08 (4.179). At the same time, the post/pre ratio for the percentage (dollar) effective spread as well as for the depth and the

Corwin-Schultz estimator is not significantly different from 1. At the same time, the trading activity of the ETF's underlying securities seems to have significantly increased, with a post pre ratio relative volume of 1.178 and at-stat of 2.14 (see Table 4.8). The augmented trading activity is accompanied by a higher standard deviation of the components assets (average post/pre ratio of 1.26 and t-stat of 3.26).

4.3 Observations

Our analysis presents contrasting results. We can observe a significant worsening in the market liquidity of the component securities after the introduction of ARK Innovation and iShares Robotics ETFs (see Sections 4.2.3 and 4.2.4). Instead, in the 50 days following the launch of iShares Core High Dividend and Vanguard S&P 500 Growth Index, we have a general improvement in the spreads of the underlying assets (see Sections 4.2.1 and 4.2.2). Despite the apparently incoherent results, our analysis actually seems to reconcile the two opposite theories about the impact that the trading of a basket of securities may have on its underlying assets. The so-called *adverse selection hypothesis* and *arbitrage hypothesis* coexist in the market for exchange traded funds. On the one hand, in accordance with the former, the launch of a new ETF induces an increase in the adverse selection component of the bid-ask spread of the underlying securities: (uninformed) liquidity traders will prefer the composite security to its underlying stocks because of the lower transactions costs. Thus, with the migration of uninformed market participants, the concentration of informed traders will rise in the market for underlying securities which, in turn, will induce market makers to increase (decrease) the ask (bid) quote. This theory seems to predominate for the underlying securities of ARKK and RBTX which are sector ETFs investing just in technology companies. Here, the benefit derived from the enhanced diversification and lower transaction costs provided by the basket of securities seems to be larger than in the component stocks of HDV and VOOG which are ETF tracking the broad market. For them, on the other hand, the *arbitrage hypothesis* effects prevail and thanks to the activity of cross-market arbitrageurs (see Section 2.1.1), the market liquidity of underlying securities increases.

Conclusion

This thesis wanted to be a liaison between two broad areas of finance: asset management and market microstructure. Thus, through the independent description of the concepts of market liquidity and exchange traded funds, we introduced the reader to their convoluted interconnections.

In financial literature, many doubts have arisen about the effects that the mechanics of modern financial markets may have on market liquidity. While transaction costs still remain important drivers negatively affecting it, market fragmentation and many other financial innovations may have a less unquestionable impact.

Then, in this "opaque" framework, a particular treatise deserves *volatility*. Usually, in periods of market turmoils, the last one spikes, and liquidity collapses. So, it is natural to wonder why we assist to such spikes. Is it the flow of new information to lead to sudden changes in prices or, as Roll (1984a) suggested studying the orange juice futures prices, may the trading itself cause them? Thus, since the launch of the first Index Fund in 1976, the study of market basket alternatives has become an essential element to understand volatility and liquidity because of their close relationships with securities trading. In particular, ETFs, having shares that are continuously exchangeable during market hours, are of critical importance.

In this thesis, we analyzed how the launch of a new ETF may affect the market liquidity of its underlying securities. We found that the effects may both be positive and negative at the same time. In some circumstances, exchange traded funds seem to improve the market liquidity, while in others, they deteriorate it. We saw how these opposite results may be due to differences in the market conditions in which a new ETF is launched or, to the nature itself of the fund.

Finally, this work lies in the middle of a broad financial literature on the studies of the effects of basket securities on market liquidity. We recognize the impossibility to find a unique answer to the issue. There exist many exogenous variables, and ETFs' ownership of the underlying securities or a new ETF launch date are just a few of them. So, although we observed exchange traded funds may be greatly beneficial to investors, they can become detrimental to market liquidity and an enemy to financial markets' stability in general.

Bibliography

Abucay, R., Gosar, C., & Katiyar, S. (2020). Alternative views of equity-market liquidity during covid-19. https://www.msci.com/www/blog-posts/alternative-views-of-equity/02055860458

Agarwal, V., Hanouna, P., Moussawi, R., & Stahel, C. W. (2018). Do etfs increase the commonality in liquidity of underlying stocks? *28th Annual Conference on Financial Economics and Accounting.*

Amihud, Y., Mendelson, H., & Wood, R. (1990). Liquidity and the 1987 stock market crash. *Journal of Portfolio Management*, *16*(3), 65–69.

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). Etfs, arbitrage, and shock propagation. *Working paper.*

Ben-David, I., Franzoni, F., & Moussawi, R. (2016). Exchange traded funds (etfs).

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do etfs increase volatility? *The Journal of Finance*, *73*(6), 2471–2535.

Bhattacharya, A., & O'Hara, M. (2018). Can etfs increase market fragility? effect of information linkages in etf markets. *Effect of Information Linkages in ETF Markets (April 17, 2018).*

Boehmer, B., & Boehmer, E. (2003). Trading your neighbor's etfs: Competition or fragmentation? *Journal of Banking & Finance*, *27*(9), 1667–1703.

Bogle, J. C. (2018). *Stay the course: The story of vanguard and the index revolution.* John Wiley & Sons, Incorporated.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *The Review of Financial Studies*, *27*(6), 1615–1660.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The journal of finance*, *56*(2), 501–530.

Clements, R. (2019). New funds, familiar fears: Are exchange traded funds making markets less stable? part ii–interaction risks. *Houston Business and Tax Law Journal, Forthcoming.*

Clements, R. (2020). New funds, familiar fears: Do exchange traded funds make markets less stable? part i, liquidity illusions. *Hous. Bus. & Tax LJ*, *20*, 14.

Cohen, S., Fisher, S., Merwin, S., Novick, B., Takasaki, M., Tiwari, R., van Nugteren, S., & Warr, J. (2020). Lessons from covid-19: Etfs as a source of stability. https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-lessons-from-covid-19-etfs-as-a-source-of-stability-july-2020.pdf

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719–760.

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

Dannhauser, C. D. (2016). The impact of innovation: Evidence from corporate bond etfs. *Journal of Financial Economics (JFE), Forthcoming.*

Deville, L. (2008). Exchange traded funds: History, trading, and research. *Handbook of financial engineering* (pp. 67–98). Springer.

Foucault, T., Pagano, M., Roell, A., & Röell, A. (2013). *Market liquidity: Theory, evidence, and policy*. Oxford University Press.

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

Garman, M. B. (1976). Market microstructure. *Journal of financial Economics*, *3*(3), 257–275.

Glosten, L. R., & Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of financial Economics*, *21*(1), 123–142.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, *14*(1), 71–100.

Gorton, G. B., & Pennacchi, G. G. (1989). Security baskets and index-linked securities. *Working paper, Wharton School, University of Pennsylvania, Philadelphia.*

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *the Journal of Finance*, *43*(3), 617–633.

Hamm, S. (2014). The effect of etfs on stock liquidity. *Working Paper.*

Haslag, P. H., & Ringgenberg, M. (2016). The causal impact of market fragmentation on liquidity. *Fourth Annual Conference on Financial Market Regulation.*

Hegde, S. P., & McDermott, J. B. (2004). The market liquidity of diamonds, q's, and their underlying stocks. *Journal of Banking & Finance*, *28*(5), 1043–1067.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of finance*, *66*(1), 1–33.

Holden, C., & Nam, J. (2019). Market accessibility, corporate bond etfs, and liquidity. *Kelley School of Business Research Paper*, *3083257.*

Huang, J., & Wang, J. (2009). Liquidity and market crashes. *The Review of Financial Studies*, *22*(7), 2607–2643.

Hull, J. (2007). Risk management and financial institutions.

Israeli, D., Lee, C. M., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? an information perspective. *Review of Accounting Studies*, *22*(3), 1048–1083.

Jones, C. M. (2002). A century of stock market liquidity and trading costs. *Working Paper.*

Kumar, P., & Seppi, D. J. (1994). Information and index arbitrage. *Journal of Business*, 481–509.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746.

Liebi, L. J. (2020). The effect of etfs on financial markets: A literature review. *Financial Markets and Portfolio Management*, 1–14.

Lin, C.-C. (2014). Estimation accuracy of high–low spread estimator. *Finance Research Letters*, *11*(1), 54–62.

Madhavan, A. (1996). Security prices and market transparency. *Journal of Financial Intermediation*, *5*(3), 255–283.

Malamud, S. (2016). A dynamic equilibrium model of etfs.

Malin, S. (2018). Liquidity shock: The hidden risk in modern markets. https://www.allianzgi.com/-/media/allianzgi/globalagi/documents/allianzgi-liquidity-shock-white-paper-march-2018.pdf

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2015). Etf liquidity. *Work. Pap., Massey Univ.*

Marta, T. (2019). Fixed income etfs, bond liquidity, and stressed markets. *Bond Liquidity, and Stressed Markets.*

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

Pagano, M., Sánchez Serrano, A., & Zechner, J. (2019). *Can etfs contribute to systemic risk?* (Tech. rep.). Reports of the Advisory Scientific Committee.

Pan, K., & Zeng, Y. (2019). Etf arbitrage under liquidity mismatch. *Working Paper.*

Perold, A. F. (1988). The implementation shortfall: Paper versus reality. *Journal of Portfolio Management*, *14*(3), 4.

Persaud, A. (2001). The puzzling decline in financial market liquidity.

Rodriguez-Masiu, P., & Karagiannopoulos, L. (2020). Tanker freight rates explode. https://www.rystadenergy.com/newsevents/news/press-releases/historys-largest-oil-glut-months-away-from-topping-world-storage-while-tanker-freight-rates-explode/

Roll, R. (1984a). Orange juice and weather. *The American Economic Review*, *74*(5), 861–880.

Roll, R. (1984b). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance*, *39*(4), 1127–1139.

Roy, S. (2020). 2020 etf inflows. https://www.etf.com/sections/weekly-etf-flows/weekly-etf-flows-2020-12-17-2020-12-11?nopaging=1

Rubinstein, M. (1989). Market basket alternatives. *Financial Analysts Journal*, *45*(5), 20–29.

Sarr, A., & Lybek, T. (2002). Measuring liquidity in financial markets.

Securities, U., Commission, E., Commission, C. F. T., et al. (2010). Findings regarding the market events of may 6, 2010. *Washington DC.*

Smidt, S. (1971). Which road to an efficient stock market: Free competition or regulated monopoly? *Financial Analysts Journal*, *27*(5), 18–20.

Smith, R. (2020). Global liquids surplus will hit hardest in crude sector. https://ihsmarkit.com/research-analysis/global-liquids-surplus-will-hit-hardest-in-crude-sector.html

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

Sultan, S. G. (2014). A study on bond exchange-traded funds (etfs) and corporate bond liquidity.

Turner, G., Sushko, V. et al. (2018). What risks do exchange-traded funds pose? *FSR*, 133.

Summary

Market liquidity represents the easiness through which an asset can be converted into cash. It encompasses three dimensions: depth, resilience, and immediacy. The deeper a market is, the smaller the price impact of trades will be; the resilience is the prices' capability of reverting to their original level after a liquidity shock; finally, the immediacy is the possibility of executing a trade at any time without delay or missed trading opportunities.

The main ways to evaluate a security's liquidity can be split into *transaction cost measures* and *volume based measures*.

Among the main transaction cost measures we have the *quoted bid-ask spread*:

$$S = a - b$$

and the *relative quoted bid-ask spread*:

$$s = \frac{S}{m}$$

Here, a represents the best ask price available at the moment of the transaction and b the best bid (i.e. the lowest ask and the highest bid), while m is midprice.

As the quoted spread may be an upwardly biased estimate of the true transaction costs incurred, the effective spread and the relative effective spread are computed:

$$S_e = d \times (p - m)$$
$$s_e = \frac{S_e}{m}$$

with d the order direction indicator ($+1$ for buyer-initiated and -1 for seller-initiated

trades) and m the previous mid quote prevailing on the market before the transaction is executed at price p.

Corwin and Schultz (2012) built a spread estimator from the daily high and low prices. The CS spread is computed as:

$$S = \frac{2\Big(e^{\alpha} - 1\Big)}{1 + e^{\alpha}}$$

Where:

$$\begin{aligned}
\alpha &= \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \\
\beta &= \mathbb{E}\Big\{\sum_{j=0}^{1}\Big[ln\Big(\frac{H^0_{t+j}}{L^0_{t+j}}\Big)\Big]^2\Big\} \\
\gamma &= \Big[ln\Big(\frac{H^0_{t,t+1}}{L^0_{t,t+1}}\Big)\Big]^2
\end{aligned}$$

Here, H and L represent the daily high and low prices, respectively. β is the expectation of the sum of the daily price ranges between 2 consecutive trading days; γ represents the maximum range of the high-to-low price ratio for a two-day period.

On the other hand, one of the most widely used volume based measure is the *Amihud Ratio*:

$$I_t = \frac{|r_t|}{Vol_t}$$

where r_t and Vol_t represent the daily return and the daily volume, respectively.

The main determinants of the market liquidity are the *transaction costs*, i.e. *the adverse selection, the inventory risk, and the order processing costs.* Other factors influencing it are *fragmentation* and *transparency*, whose effects on market liquidity may differ between large and small stocks. Besides, in the last years, many other financial innovations have deeply altered the trading on Exchanges. Among the main protagonist of such changes, we look at the Exchange Traded Funds (ETFs) and their impact on the market liquidity of the underlying securities.

An ETF is an investment vehicle whose aim is to track an underlying index as closely as possible, either holding a basket of securities passively or through active investment strategies (for instance by entering into derivative contracts). It is similar to an Index Mutual Fund, but, differently from the latter, the former's shares can be traded during the entire market session. Besides, ETFs' shares can be traded both on the primary market between the ETF and the Authorized Participants (APs), under the *creation-redemption mechanism* shown in Figure 1, and on the secondary market.

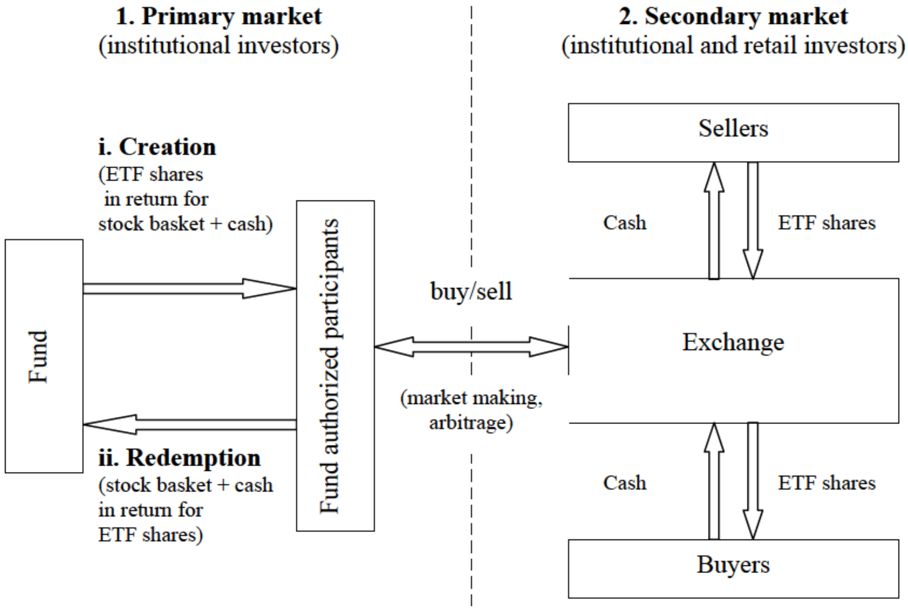


Figure 1: The trading process of ETFs (Source: Deville (2008))

The creation-redemption mechanism is of paramount importance for market liquidity. Indeed, as ETFs are negotiated on the primary and secondary market, they also have two prices, and APs can arbitrage through the potential differences between the Net Asset Value (NAV) and the market price. Usually, APs make to eliminate the deviations by buying the cheaper asset and selling the more expensive. Thus, through upward and downward pressures on the prices, the mispricing is tightened. On the secondary market, arbitrageurs like market makers or traders are providers of liquidity. They open a short or long position in the ETF and an opposite one in the main components of the index or a very closely related instrument (like another ETF or futures).

Exchange traded funds' benefits have been evident in March 2020, at the outbreak of the COVID-19 crisis. Thanks to their better liquidity and higher turnover rate, they favored the *price discovery* of many OTC corporate bonds.

Although, in general, the mechanics of exchange traded funds may be beneficial to the smooth functioning of financial markets, they can trigger disruptive dynamics. In April 2020, oil prices went negative for the first time in history. The United States Oil Fund (USO) ETF [1] fell 8% to $20.08 on April, 22 and USO proved to be one of the crash's trigger.

The contrasting pieces of evidence from financial markets about the effects of ETFs on them are confirmed by a wide literature. In particular, the findings on the influence of exchange traded funds on the market liquidity of their underlying stocks do not agree.

Boehmer and Boehmer (2003), Hegde and McDermott (2004), and Marshall et al. (2015), for example, found significant positive relationships between the introduction of new ETFs and the liquidity of underlying securities.

On the opposite, Hamm (2014) and Israeli et al. (2017), focused on the effects of ETFs ownership on adverse selection cost and found robust pieces of evidence that increasing the percentage of shares hold by ETFs induces an increase in the adverse selection cost component measured by Kyle's λ. Uninformed investors prefer to reallocate their capital from individual securities to the respective ETF because of the diversification benefit. This behavior drains the liquidity from ETFs underlying securities where there will be a high concentration of informed traders, making the cost of adverse selection extremely high.

Thus, in the footsteps of Boehmer and Boehmer (2003) and Hegde and McDermott (2004), we investigate the effects of the introduction of some exchange traded funds on the market liquidity of their underlying securities. We choose the ARK Innovation ETF (ticker symbol ARKK), iShares Automation & Robotics UCITS ETF (ticker symbol RBTX), Vanguard S&P500 Growth Index Fund (VOOG) and iShares Core High Dividend ETF (HDV), that are relatively recently launched equity ETFs traded on the New York Stock Exchange (NYSE) Arca. The primary goal is to verify whether following their inception date, the market liquidity of the

[1] USO is the ETF which reflects the daily changes, in percentage terms, of the spot price of light sweet crude oil delivered to Cushing, Oklahoma, tracking the Benchmark Oil Futures Contract over the same period.

underlying securities changes.

The transactions volume and price data for the ETFs' underlying securities are taken from the NYSE Transactions and Quotes (TAQ) and from the Center for Research in Securities Prices (CRSP) databases through Wharton Transaction Data Services (WRDS). For this research, we use the daily summary of each variable employed, provided by WRDS. We retrieve the information relatively to Exchange Traded Funds holdings from Thomson Reuters as of the period of the ETF launch date and the daily overall market volume of the NYSE and NASDAQ from the Cboe and NASDAQ. We focus on the 50 trading days before the ETFs launch date and on the 50 trading days following it, corresponding to the periods August 21st, 2014 - January 13rd, 2015 for ARKK; June 28th, 2016 - November 16th, 2016 for RBTX; June 25th, 2010 - November 15th, 2010 for VOOG; January 14th, 2011 - June 8th, 2011 for HDV. The selected time frame of 100 days represents an acceptable compromise between having a relatively ample dataset and minimizing the effects that exogenous liquidity shocks could have on the basket of underlying securities.

We evaluate the market liquidity of the securities of interest using the percentage and the dollar quoted and effective spreads, we compute the Corwin-Schultz estimator from the daily high and low prices; then, we retrieve the data of depth at the bid and ask quotes in shares as well as dollars and equally average these to get the depth in shares and dollars, respectively. The quoted spread represents, actually, a time-weighted quoted spread, implying the bid and ask prices are weighted for the time their respective quotes are active in proportion to the overall length of the trading day. Here, the percentage spread is equivalent to the relative spread. The final measures of the daily spreads (quoted and effective) for each stock i represent the average of all the N trades over the trading day:

$$S^i_{day} = \frac{1}{N}\sum_{t=1}^{N} s^i_t$$

The effective spread is retrieved from WRDS which employs the Lee and Ready (1991) algorithm to classify the orders direction. In particular an order is a buy one when $P_k > M_{t-1}$ and a sell one when $P_k < M_{t-1}$, with P_k denoting the price of a trade and M_{t-1} the previous mid quote. To compute the CS estimator, we follow the Corwin and Schultz (2012) approach and before averaging the daily spread over the period of interest, i.e. the 50 days after and before the ETF launch date, we set to 0 all the negative 2-day spread estimates. In this way, we get better estimates than simply removing the negative values or leaving them unchanged.

For each stock, we considered the daily volume of shares exchanged over the 100 days period of interest. We then compute the relative daily volume as the proportion of each stock's daily trading volume on the daily trading volume of the overall market in which the stock is exchanged. We also analyze the standard deviation of daily returns and the Amihud ratio.

To assess the change in market liquidity after the ETF introduction, we compute the mean and the median of each variable of interest over the 50 days preceding and following the launch date for every component security. From them, we compute a *post/pre ratio*:

$$Post/Pre\,Ratio^i = \frac{\bar{X}^i_{post}}{\bar{X}^i_{pre}}$$

with X and i representing a certain variable and stock, respectively. Once we have computed the ratio for each stock, we calculated its average as:

$$Average\,Post/Pre\,Ratio^i = \frac{1}{N}\sum_{i=1}^{N}\frac{\bar{X}^i_{post}}{\bar{X}^i_{pre}}$$

where N is the total number of stocks held by a given ETF. Thus, we perform the Student's t-test to verify whether the variable of interest changes significantly. The null and alternative hypotheses, respectively, are:

$$H_0 : Average\,Post/Pre\,Ratio_X = 1$$
$$H_a : Average\,Post/Pre\,Ratio_X \neq 1$$

and the test statistic for the variable X and stock i:

$$t_X = \frac{Average\,Post/Pre\,Ratio_X - 1}{\sigma_X/\sqrt{n}}$$

iShares Core High Dividend ETF Results

The iShares Core High Dividend ETF is Blackrock's ETF whose aim is to track an index composed of relatively high dividend-paying U.S. equities.

The results predict a general improvement in the market liquidity of HDV's underlying assets. The fact that the *post/pre ratio* trading volume is significantly different from 1 (0.923 with a t-stat of -2.81), while the *post/pre ratio* of the relative volume is 1.078 with a t-stat of 2.85 may suggest that the 50 days following the HDV's launch date correspond to a period of lower trading activity in the markets. Thus, it is difficult to attribute the reduction in the trading volume to the introduction of the ETF.

	Quoted Spread		**Effective Spread**		**Depth**		**CS**
	%	**$**	**%**	**$**	#	**$**	**$**
mean pre HDV	0.000452	0.0184	0.00036	0.0141	1,880.5	64,237.5	0.0045
mean post HDV	0.000423	0.0175	0.00034	0.0138	1,842.5	65,598.1	0.0039
median pre HDV	0.000447	0.0181	0.00035	0.0139	1,811.8	61,952.5	0.0042
median post HDV	0.000421	0.0173	0.00034	0.0136	1,776.2	62,719.8	0.0034
Post/Pre Ratio							
Mean	0.93	0.95	0.955	0.97	1.04	1.05	0.88
Median	0.94	0.96	0.96	0.98	1.05	1.046	0.87
Hypothesis Test							
t-stat	-4.68	-2.60	-3.91	-1.85	1.07	1.86	-4.96
p-value	0.00001	0.012	0.0002	0.069	0.287	0.067	0.00001

Table 1: HDV - Spreads and Depth

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre HDV	293,178,621.3	0.447%	1.45%	5×10^{-5}
mean post HDV	260,780,067.3	0.452%	1.14%	1.2×10^{-9}
median pre HDV	5,197,522.8	0.398%	1.26%	1.5×10^{-9}
median post HDV	4,760,978.4	0.415%	1.05%	4.95×10^{-10}
Post/Pre Ratio				
Mean	0.923	1.078	0.872	0.710
Median	0.896	1.058	0.850	-0.021
Hypothesis Test				
t-stat	-2.81	2.85	-4.94	-0.28
p-value	0.0065	0.0059	0.00001	0.78

Table 2: HDV - Volume Measures and Standard Deviation

Vanguard S&P 500 Growth Index Fund ETF Results

Vanguard S&P 500 Growth ETF invests in the growth companies of the S&P 500, focusing on replicating the index's return.

	Quoted Spread		Effective Spread		Depth		CS
	%	$	%	$	#	$	$
mean pre VOOG	0.00043	0.02949	0.00037	0.02364	2,955.6	92,558.1	0.012
mean post VOOG	0.00038	0.02143	0.00032	0.01744	3,117.3	104,276.8	0.011
median pre VOOG	0.00062	0.02826	0.00050	0.03324	2,830.6	89,367.4	0.001
median post VOOG	0.00032	0.02061	0.00028	0.01783	3,004.6	111,209.0	0.002
Post/Pre Ratio							
Mean	0.93	0.95	0.955	0.97	1.04	1.051	1.3
Median	0.94	0.96	0.96	0.98	1.05	1.046	0.97
Hypothesis Test							
t-stat	0.61	0.20	0.55	-0.45	2.23	6.27	1.85
p-value	0.542	0.842	0.586	0.656	0.029	2.7×10^{-8}	0.068

Table 3: VOOG - Spreads and Depth

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre VOOG	523,677,845.5	0.707%	2.62%	-5.6×10^{-11}
mean post VOOG	487,373,677.2	0.666%	1.47%	3.4×10^{-10}
median pre VOOG	9,503,956.8	0.641%	1.81%	2.1×10^{-11}
median post VOOG	8,764,051.8	0.595%	1.31%	3.2×10^{-10}
Post/Pre Ratio				
Mean	0.92	0.93	0.81	-0.71
Median	0.86	0.90	0.77	0.87
Hypothesis Test				
t-stat	-4.88	-3.96	-2.7	-0.029
p-value	6.6×10^{-6}	0.0002	0.009	0.98

Table 4: VOOG - Volume Measures and Standard Deviation

The *post/pre ratio* of quoted and effective spreads would suggest an improvement in the market liquidity. However, the results are not significantly different from 1. The average *post/pre ratio* of the dollar (shares) depth is 1.051 (1.04) and significantly different from 1 with a t-stat of 6.27 (2.23). The trading volume of the underlying assets decreases after VOOG has been launched: the *post/pre ratio* is 0.92 (t-stat -4.88) and 0.93 (t-stat -3.96) for the trading volume and the relative volume, respectively. Besides, the ETF seems to improve the average volatility of the underlying securities as the *post/pre ratio* for the standard deviation is 0.81 with a t-stat of -2.7.

iShares Automation & Robotics ETF Results

iShares Automation & Robotics ETF is Blackrock's ETF launched on 8th September 2016 and aimed at replicating the performance of an index composed of companies that invest in the research and development of automatic and robotic technology.

After the introduction of RBTX the average spreads of the underlying securities have widened: the *post/pre ratio* for the percentage (dollar) quoted spread is 1.073 (1.134) (the t-stat is 3.34 (3.52)) and the *post/pre ratio* for the percentage (dollar) effective spread is 1.049 (1.107) (the t-stat is 2.47 (4.66)), the CS estimator *post/pre* *ratio* is 1.244 (t-stat 4.77). At the same time, the *post/pre ratio* for both the trading volume and the standard deviation is significantly larger than 1, with a value of 1.13 and a t-stat of 2.78 for the trading volume and a value of 1.32 and a t-stat of 5.08 for the standard deviation. The *post/pre ratio* for the Amihud measure is 0.27 with a t-stat of −6.23.

	Quoted Spread		**Effective Spread**		**Depth**		**CS**
	%	**$**	**%**	**$**	#	**$**	**$**
mean pre RBTX	0.0017	0.121	0.0009	0.063	59,768.5	31,898	0.006
mean post RBTX	0.0018	0.127	0.0010	0.066	57,059.1	28,841.8	0.007
median pre RBTX	0.0016	0.117	0.0009	0.061	1,134.2	30,865.9	0.004
median post RBTX	0.0017	0.124	0.0009	0.063	1,072.8	27,674.6	0.005
Post/Pre Ratio							
Mean	1.073	1.134	1.049	1.107	0.959	1.007	1.244
Median	1.062	1.111	1.039	1.089	0.934	0.984	1.141
Hypothesis Test							
t-stat	3.34	3.52	2.47	4.66	-1.44	0.24	4.77
p-value	0.0017	0.001	0.0175	0.00003	0.156	0.809	1.92×10^{-5}

Table 5: RBTX - Spreads and Depth

We observe a worsening in the market liquidity of the underlying assets after the ETF's introduction. These results are strengthened by the fact that the 50 trading days preceding the launch date were from 28th June to 7th September and that during the summer the market liquidity is usually lower.

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre RBTX	2,725,811.8	0.32%	1.67%	1.45×10^{-8}
mean post RBTX	3,412,952.0	0.35%	2.01%	9.84×10^{-9}
median pre RBTX	2,291,498.4	0.27%	1.43%	4.67×10^{-9}
median post RBTX	2,877,293.0	0.29%	1.92%	6.39×10^{-10}
Post/Pre Ratio				
Mean	1.13	0.987	1.32	0.27
Median	1.121	0.99	1.29	0.7
Hypothesis Test				
t-stat	2.781	-0.312	5.08	-6.232
p-value	0.008	0.756	6.72×10^{-6}	1.3×10^{-7}

Table 6: RBTX - Volume Measures and Standard Deviation

ARK Innovation Results

Launched on 31st, October 2014, ARK Innovation began trading on NYSE Arca

	Quoted Spread		Effective Spread		Depth		CS
	%	$	%	$	#	$	$
mean pre ARKK	0.0027	0.0692	0.0018	0.0455	947.5	23,633.4	0.0105
mean post ARKK	0.0041	0.0921	0.0017	0.0436	863.5	22,283.3	0.0097
median pre ARKK	0.0026	0.0681	0.0018	0.0446	894.8	23,095.9	0.0069
median post ARKK	0.0026	0.0668	0.0017	0.0426	813.8	21,307.5	0.0067
Post/Pre Ratio							
Mean	1.509	1.558	0.970	0.999	0.982	1.005	0.942
Median	1.004	1.024	0.975	0.997	0.987	1.009	1.049
Hypothesis Test							
t-stat	4.080	4.179	-1.046	0.031	-0.717	0.142	-1.657
p-value	0.0005	0.0004	0.307	0.975	0.48	0.89	0.11

Table 7: ARKK - Spreads and Depth

under the ticker symbol of ARKK as an *active* ETF and with the investment objective of investing at least 65% of its assets in shares of companies engaging in highly innovative projects.

	Trading Volume	Relative Volume	St. dev.	Amihud Ratio
mean pre ARKK	1,623,403.8	0.198%	2.644%	-5.30873×10^{-9}
mean post ARKK	1,507,579.4	0.203%	2.748%	-5.18822×10^{-9}
median pre ARKK	1,395,950.1	0.170%	2.386%	-7.3025×10^{-9}
median post ARKK	1,358,157.7	0.179%	2.789%	-6.1009×10^{-11}
Post/Pre Ratio				
Mean	1.072	1.178	1.25	0.348
Median	0.91	1.001	1.2	-1.48
Hypothesis Test				
t-stat	0.94	2.14	3.26	1.56
p-value	0.36	0.044	0.004	0.13

Table 8: ARKK - Volume Measures and Standard Deviation

The percentage (dollar) quoted spread for the 50 days following the ARKK's launch date is significantly higher, with an average post/pre ratio of 1.509 (1.558) and a t-stat of 4.08 (4.179). At the same time, the post/pre ratio for the percentage (dollar) effective spread as well as for the depth and the Corwin-Schultz estimator is not significantly different from 1. At the same time, the trading activity of the ETF's underlying securities seems to have significantly increased, with a post pre ratio relative volume of 1.178 and a t-stat of 2.14 (see Table 8). The augmented trading activity is accompanied by a higher standard deviation of the components assets (average post/pre ratio of 1.26 and t-stat of 3.26).

After the introduction of ARK Innovation and iShares Robotics ETFs, we observe a significant worsening in the market liquidity of the component securities. Instead, in the 50 days following the launch of iShares Core High Dividend and Vanguard S&P 500 Growth Index, we assist to a general improvement in the spreads of the underlying stocks.

Despite the apparently incoherent results, our analysis seems to reconcile the two opposite theories about the impact that the trading of a basket of securities may have on its underlying assets.

The so-called *adverse selection hypothesis* and *arbitrage hypothesis* coexist in the market for exchange traded funds. On the one hand, according to the former, the launch of a new ETF induces an increase in the adverse selection component of the bid-ask spread of the underlying securities: (uninformed) liquidity traders will prefer the composite security to its underlying stocks because of the lower transactions costs. Thus, with the migration of uninformed market participants, the concentration of informed traders will rise in the market for underlying securities which, in turn, will induce market makers to increase (decrease) the ask (bid) quote. This theory seems to predominate for the underlying securities of ARKK and RBTX which are sector ETFs investing only in technology companies. Here, the benefit derived from the enhanced diversification and lower transaction costs provided by the basket of securities seems to be larger than in the component stocks of HDV and VOOG, which are ETF tracking the broad market. For them, on the other hand, the *arbitrage hypothesis* effects prevail, and thanks to the activity of cross-market arbitrageurs, the market liquidity of underlying securities increases.

Bibliography

Agarwal, V., Hanouna, P., Moussawi, R., & Stahel, C. W. (2018). Do etfs increase the commonality in liquidity of underlying stocks? *28th Annual Conference on Financial Economics and Accounting.*

Amihud, Y., Mendelson, H., & Wood, R. (1990). Liquidity and the 1987 stock market crash. *Journal of Portfolio Management*, *16*(3), 65–69.

Ben-David, I., Franzoni, F., & Moussawi, R. (2016). Exchange traded funds (etfs).

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do etfs increase volatility? *The Journal of Finance*, *73*(6), 2471–2535.

Boehmer, B., & Boehmer, E. (2003). Trading your neighbor's etfs: Competition or fragmentation? *Journal of Banking & Finance*, *27*(9), 1667–1703.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *The Review of Financial Studies*, *27*(6), 1615–1660.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The journal of finance*, *56*(2), 501–530.

Clements, R. (2019). New funds, familiar fears: Are exchange traded funds making markets less stable? part ii–interaction risks. *Houston Business and Tax Law Journal, Forthcoming.*

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719–760.

Deville, L. (2008). Exchange traded funds: History, trading, and research. *Handbook of financial engineering* (pp. 67–98). Springer.

Foucault, T., Pagano, M., Roell, A., & Röell, A. (2013). *Market liquidity: Theory, evidence, and policy.* Oxford University Press.

Glosten, L. R., & Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of financial Economics*, *21*(1), 123–142.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, *14*(1), 71–100.

Hamm, S. (2014). The effect of etfs on stock liquidity. *Working Paper*.

Hegde, S. P., & McDermott, J. B. (2004). The market liquidity of diamonds, q's, and their underlying stocks. *Journal of Banking & Finance*, *28*(5), 1043–1067.

Israeli, D., Lee, C. M., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? an information perspective. *Review of Accounting Studies*, *22*(3), 1048–1083.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746.

Lin, C.-C. (2014). Estimation accuracy of high–low spread estimator. *Finance Research Letters*, *11*(1), 54–62.

Madhavan, A. (1996). Security prices and market transparency. *Journal of Financial Intermediation*, *5*(3), 255–283.

Malamud, S. (2016). A dynamic equilibrium model of etfs.

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2015). Etf liquidity. *Work. Pap., Massey Univ.*

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance*, *39*(4), 1127–1139.

Sarr, A., & Lybek, T. (2002). Measuring liquidity in financial markets.