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DISENTANGLING HIGH-FREQUENCY TRADERS' ROLE IN ETF MISPRICING

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ABSTRACT OF THE MASTER'S THESIS

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Abstract

Exchange Traded Funds (ETFs) should trade at a price equal to their fundamental Net Asset Value (NAV). However, ETFs' can occasionally pose economically significant premiums/discounts to their NAV prices, i.e. arbitrage opportunities. The theoretical part focuses on ETF arbitrage and explains why this arbitrage trading is attractive to high-frequency traders (HFTs).

In the empirical part, we introduce HFT activity proxies to a factor model explaining the observed SPDR trust (SPY) premiums during 2.1.2002–15.1.2013. A range of statistical and econometrical tools are then employed to study the detailed relationship between these factors and the SPY premiums. In addition, we replicate a popular method used to study HFTs' effects on stock markets, and apply it to analyze HFTs' effects on ETF pricing process. By utilizing an exogenous technology shock (implementation of Regulation National Market System) which improved U.S. market infrastructure, we should be able to dissect the effects caused by heightened HFT activity.

The absolute size of SPY premium is significantly related to endogenous ETF factors. The exogenous factors serving as proxies for available arbitrage capital improve the explanatory power. The Reg. NMS implementation fails to serve as an exhaustive structural break point in ETF pricing dynamics. Although, the post-Reg. NMS era has very low ETF premiums and higher trading volumes. This can indicate that Reg. NMS made markets more suitable for HFT, and therefore high-frequency ETF arbitrage might have been more efficient during the post-Reg. NMS era.

Simple implications are: ETF premiums can be significant in relation to their annual expense ratios and investors can improve their trade execution by understanding the drivers behind ETF premiums. ETF premium volatility modeling can also be useful in risk management and in investment decision making. Understanding HFTs' role in ETF mispricing adds to our incomplete knowledge on the effects of individual HFT strategies.

Keywords
Volatility modeling, ETF arbitrage, Regulation NMS, Time-varying beta estimation

Additional information

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1 INTRODUCTION

High-frequency trading has recently been in the spotlight. Contemporary economical publications and business media publish articles considering the effects of this new trading norm on a weekly basis[1]. HFT[2] refers to the use of fast computer-driven operations for trading purposes. Several researchers agree that the recent attention towards HFT partly stems from the events of May 6, 2010 (e.g. Brogaard 2010; Easley et al. 2011; Gomber et al. 2011; Kirilenko et al. 2011). On that day, the Dow Jones Industrial Average fell within minutes about 1 000 points (-9.2 %) and then gained most of those losses immediately. The event has been named as the Flash Crash referring to its rapid and irregular structure. Many HFT related incidents has followed since: including single stock Micro Crashes (see Golub et al. 2012; Nanex 2012), the Shanghai Flash Spike (see Bloomberg 2013; Noble 2013), and malfunctioning algorithms (see Philips 2012).

These market problems are connected to HFTs and algorithms behind the trade orders. The latter refers to algorithmic trading (henceforth AT), a trading method where orders are conducted through complex mathematical algorithms without human intervention (see Chaboud et al. 2009; Hendershott & Riordan 2011). The Flash Crash also drew the regulators' interest to investigate the role of HFT during the Flash Crash. However, the following report on the subject does not find HFT as the direct cause of the event (CFTC-SEC 2010). Kirilenko et al. (2011) note that while HFTs cannot be blamed for the Flash Crash their behavior might have built up the volume of the incident. Interestingly, these papers relate exchange-traded funds (ETFs) and their pricing procedure to problems faced during times of market uncertainty. CFTC-SEC (2010) finds that HFT activity increased over 250 % in NYSE Arca, the main exchange for ETFs, during a three minute period of the Flash Crash. This trading activity was higher than the trading in corporate stocks at the same time.

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[1]For concrete examples, see the following international articles (Creswell 2010; Krudy 2010; The Economist 2013a) and the corresponding Finnish one (Saario 2011).
[2]Through the study, the abbreviation HFT is used for both high-frequency trading and high-frequency traders.

As has been stressed in various studies, the whole variety of HFT should not be considered as a single trading strategy, but a tool to implement existing strategies (e.g. AFM 2010; Gomber et al. 2011; Hagströmer & Nordén 2013). Therefore, in order to address HFT activity and its relation to systemic risk, market quality measures, and its future direction we should investigate the individual trading strategies which operate at higher frequency, such as the ETF arbitrage (see Ben-David et al. 2012; Benos & Sagade 2012). This is clearly a sufficient reason to examine HFT in a detailed manner. The overall social value behind increased trading speed and high-frequency data analysis has also been questioned (Sornette & von der Becke 2011; Riordan & Storkenmaier 2012).

This paper examines the relationship between a well-known trading strategy called the ETF arbitrage and HFT. Previous research and their findings are used to form the rationale behind the research design: research methods and chosen factors behind ETF mispricing are partly inspired by prior HFT and ETF studies. We aim to contribute more in connecting HFT activity to ETF pricing process by demonstrating HFTs' role in arbitrage activity. This is done by adding some HFT activity proxies to a simple factor model. The purpose is to address HFTs' role in ETF mispricing in a detailed manner and formally test[3] if the noted change in ETF mispricing trend is connected to the rise of HFT. Additional robustness and accuracy examination includes rolling regression analysis and estimating time-varying factor betas with Kalman filter method. Finally, the proposed time-series model for ETF mispricing volatility aims to update premium volatility modeling to incorporate the modern changes in ETF mispricing trend.

Regression analysis reveals that the absolute size of ETF premium is significantly related to endogenous ETF factors. In addition, the exogenous factors serving as proxies for available arbitrage capital improve the explanatory power. The Chow test proposes that the implementation date of Reg. NMS, which was used as a measurement point for heightened HFT activity, might provide only one possible structural

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[3]This is tested using the Chow Test for structural breaks. The Chow Test is a statistical and econometric test to see if the regression coefficients on different data sets can be considered equal (see Chow 1960).

break for the time-series evolution of the ETF premium. Further analysis shows that the significant regression coefficients and explanatory power behind used factors are mainly due to the observations during the financial crisis. This analysis also reveals that the only factors whose relationship with ETF premiums are somewhat persistent are TED spread and feature scaled ETF trading volume. TED spread shows it significance predicting ETF premiums during times of high market stress while ETF trading volume might serve as a naive factor for heightened HFT activity which is shrinking ETF premiums via arbitrage activity.

The era of heightened HFT activity has characteristically lower ETF premiums and the starting point of such an era coincides with the observed changes in the relationships between the significant factors and ETF premiums. However, the statistical significance cannot be verified using the 95 % confidence intervals in the fluctuation process of recursive residuals. The proposed simple GARCH(1,1) model with exogenous forecasting variables is able to produce satisfactory predictions for the ETF premium volatility time-series.

The rest of the paper is structured as follows: Section 2 introduces the basic terminology and related concepts needed to understand the research topic more broadly. Section 3 introduces previous research while section 4 gives more detailed information about the nature of HFT, including HFT strategies, difficulties in academic research, and possible consequences HFT might impose to modern risk management. Section 5 introduces theoretical aspects of arbitrage activity and connects HFT to ETF arbitrage. In the main body of this paper, covering sections 6 to 8, research design, methods, and research questions are explained (6), followed by data sources, introduction to data sample, and descriptive statistics (7), finally, empirical results are presented (8). The following section (9) briefly summarizes and the last section (10) concludes.

As this thesis is a continuum to author’s earlier seminar work, particular sections are to some extent replicated from the previous work. This mainly concerns terminology and literature reviews.

2 TERMINOLOGY

2.1 Algorithmic trading

Algorithmic trading (AT) is a form of trading where the orders are conducted through complex mathematical algorithms. Computers using algorithms can create orders independently. This has reduced trading costs as trading can go on without human intermediates. Wide range of algorithms are used: some are focusing on finding arbitrage opportunities, some are trying to close large orders at the lowest cost possible, and some are made to trade on longer-term strategies (Chaboud et al. 2009; Gomber et al. 2011). Commonly algorithms decide the timing, price level, quantity and order routing by monitoring markets (Hendershott et al. 2011). AT is often used by large buy-side traders to group large orders into smaller chunks to manage market impacts and risks (Fabozzi et al. 2007; Hendershott & Riordan 2011).

2.2 High-frequency trading

High-frequency trading (HFT) refers to the use of rapid computer-driven operations for trading in financial markets[4]. The aim is to use large trade volumes to accumulate the small profits earned per trade (Zhang 2010). Commodity Futures Trading Commission and Securities and Exchange Commission (CFTC-SEC 2010: 45) jointly define HFT in the following manner: "…*professional traders acting in a proprietary capacity that engages in strategies that generate a large number of trades on a daily basis*." Categorization by SEC (2010) adds that HFTs tend to end the trading day with near zero inventories, often submit and cancel limit orders, take advantage of co-location services and algorithms, and have very short holding periods.

HFT is based on the possibility to remove obstacles from the normal order routing system. By doing this, it is possible to obtain a speed advantage compared to other market participants. The key competencies are abilities to handle data flows and

[4]For this thesis, the HFT is loosely defined: it is measured by using proxies related to high trading volume and available arbitrageurs' capital. By doing this, the HFT category can include various other traders as well, given that their activity is also captured by these measures. The assumption is that ETF arbitrage measured by ETF premiums should be the turf of HFTs, and therefore, the results should mostly reflect HFTs' effects.

submit orders as fast as possible (Gomber et al. 2011). HFTs can include big banks, broker-dealer operated proprietary trading firms, companies specialized to HFT, and hedge funds (Easthope & Lee 2009; The Economist 2013a). Nowadays HFT is controlling the overall trading volumes in equity markets. Gomber et al. (2011) list that HFTs' shares of the total trading volumes in European equities are between 13 % – 40 %. Nasdaq OMX being at the lower end of the range and Chi-X being at the top end. In the U.S. the range is changing from 40 % to 70 % (Narang 2010; Zhang 2010). The dramatic growth of HFT related trading volume is also documented in Easley et al. (2011) who note that since 2009, HFTs accounted for over 73 % trading volume while representing only 2 % of all trading firms in the U.S. markets. The rise of AT and HFT is often used as one explanation for the dramatic growth in overall trading volume and turnover in recent years (Chordia et al. 2011).

HFT is a subset of algorithmic trading as it uses algorithms to produce large number of quotes and then sends those into the markets with high speed via sophisticated computers. The time scale of orders to reach the market can be measured in microseconds. HFT differs from basic AT by having shorter holding periods and different trading purposes as its trading is based on the rapid routing system, while AT usually has longer-term trading needs. (Aldridge 2010; Brogaard 2010; Zhang 2010.) More definitions about AT and HFT can be found from Gomber et al. (2011) where they have gathered all the definitions published by academic and regulatory entities.

2.3 Exchange-traded funds

Exchange-traded funds (ETFs) are important trading and investing tools in modern finance. As an asset class, its popularity has grown lately, having globally $1.76 trillion of assets under management (December 2012). Interestingly, these products have also captured a significant size of trade volumes in financial markets. Blackrock (2011) notes that in August 2010 exchange-traded products (ETPs) caused around 40 % of all U.S. market trading volume.

The history of ETFs goes back to January 1993 with the launch of the first ETF, called the SPDR trust (SPY) from State Street. Since then, the ETF industry gained relatively slow growth if measured by the numbers of ETFs and their assets under management. In October 2005 there were only 200 funds available. Since then industry growth has taken more speed and in December 2010 the number of ETFs had grown to 982 U.S. funds, with more listed elsewhere. The amount of global ETF market products increased to 3 329 as of the end of 2012. (Deutsche Bank 2013; Petäjistö 2013; The Economist 2013b.)

ETFs are listed investment companies which focus on a designated underlying asset basket. Most often this is an index they are following. By doing so, they allow investors to have an exposure to a variety of diversified asset baskets without having to invest individually to all of these securities. Therefore, the pricing of an ETF should be the same as the price of its underlying asset basket. This underlying fundamental value is called the net asset value (NAV). (Engle & Sarkar 2002; Gastineau 2008.) For different reasons the ETF pricing is not always equal to its NAV (see Petäjistö 2011; Davidson 2013; Petäjistö 2013). Significant premiums/discounts[5] can cause a range of unwanted consequences to investors whose aim is to track the underlying portfolio. For example, when considering portfolio performance, buying an ETF at a premium results a lower overall return than buying an ETF at a discount. Similar return impacts occur inversely when selling the ETF.

As most ETFs are designed to track a certain index, the way their assets are invested should achieve the same target return as the underlying index. This is commonly executed by two different ways. First method is physical replication where the ETF holds all or a sample of the securities which it aims to track. The second strategy is to use synthetic replication where the ETF enters to a contract with a counterparty using a swap-contract. These contracts guarantee a certain level of return which is tied to the underlying asset basket, while the ETF does not directly invest its funds to these assets as is done in the physical replication. (Kosev & Williams 2011; Ramaswamy 2011.)

[5]For simplicity, hereafter the ETF mispricing is referred as premium, whether it is positive (ETF price above NAV = premium) or negative (ETF price below NAV = discount).

2.4 ETF arbitrage

Since ETFs are listed in exchanges and their prices are determined by investors in the secondary market, their values and share prices can vary substantially. In order to make the pricing process tied to fundamental NAV authorized participants are assigned. These designated investors are supposed to take part in ETF creation/redemption process by bundling ETF shares to creation units (normally 50,000 shares) and trading these with the issuer of the ETF. By reducing or adding outstanding ETF shares, the authorized participant can affect ETF supply and demand and change the ETF price towards its fundamental value. The arbitrage trading is done in relation to ETFs' premiums and their underlying NAVs: if the ETF sells at a premium (higher than the NAV), the arbitrageur sells the ETF and buys the underlying assets and vice versa if the ETF sells at a discount. (see Brown et al. 2010; Petäjistö 2013.) However, ETF arbitrage activity is not solely done by assigned participants but other arbitrageurs can take part in secondary markets. Various studies emphasize that ETF arbitrage is most tempting for trading at high-frequency (e.g. Ben-david et al. 2012; Chan 2013).

3 PRIOR LITERATURE

There are various definitions of HFT and the public opinion about its effects on markets mostly relies on speculation and anecdotal evidence. Committee of European Securities Regulators (2010, henceforth CESR) states that there is no clear agreement on HFT even among active market participants. In a questionnaire made by CESR, most of the market participants said that HFT contributes to price discovery process, market quality and liquidity, reduces bid-ask spreads and limits volatility. Several empirical research papers have similar findings (e.g. Brogaard 2010; Angel et al. 2011; Gomber et al. 2011; Brogaard et al. 2013a; Hasbrouck & Saar 2013; Hägströmer & Nordén 2013), although, critical views occur as well (e.g. Zhang 2010; Kirilenko et al. 2011). The criticism towards HFT is usually related to malfunctioning algorithms, market abuse, sudden liquidity removal, and problems in price formation process.

Majority of empirical research papers conducted on HFT address its effects on stock market quality, which is usually understood through traditional market quality measures such as liquidity, volatility, bid-ask spreads, and price discovery (e.g. Brogaard 2010; Zhang 2010; Hasbrouck & Saar 2013). In addition to the empirical HFT research, a variety of theoretical frameworks has been introduced[6]: For example Cohen and Szpruch (2012) and Biais et al (2013) consider single asset market with fast and slow traders. Normative theoretical model by Cartea and Penalva (2012) is used to analyze the impact that HFT has on a market with interacting three different types of traders. Wah and Wellman (2013) propose a theoretical model to address the effects of a HFT strategy called the latency arbitrage in cross-markets. Other notable theoretical models for analyzing HFT are derived by Cvitanic and Kirilenko (2010) and Jovanovic and Menkveld (2010).

Examples of papers which formally consider the relationship between arbitrageurs like HFT and ETFs are Ben-David et al. (2012) and Madhavan (2012). At least one

[6]As a broad literature review about HFT and its effects on stock markets is out of the scope of this paper, the interested reader is pointed to Jones (2013) for a more detailed review of recent theoretical and empirical research on HFT.

paper examines the relationship between AT and ETFs by employing volume turnover modeling (Brownlees et al. 2011). A Range of research has also covered the possible market problems caused by ETFs and their pricing process (e.g. Borkovec et al. 2010; Trainor 2010; Bradley & Litan 2011; Ramaswamy 2011). ETF premiums to their net asset values are discussed in Engle and Sarkar (2006), Petäjistö (2011), Davidson (2013) and Petäjistö (2013). Various reasons have been noted to cause this return spread: for example limits of arbitrage[7], illiquidity, stale prices, differences in dividend treatment, and market uncertainty.

The majority of ETF literature focuses on U.S. based funds but international research exist as well: Jares and Lavin (2004) study Japan and Hong-Kong ETFs finding that non-synchronous trading is the main cause for ETF mispricing. Gallagher and Segara (2005) study the trading characteristics and performance of Australian ETFs, while Milonas and Rompotis (2006) examine Swiss ETFs and their tracking errors to underlying indexes.

The most meaningful previous research in relation to this paper considers the factors behind ETF mispricing and its volatility. The following paragraphs clarify the connections between these previous findings and how they are used to base the rationale behind this paper.

Ben-David et al. (2012) study the arbitrage activity between ETFs and their underlying assets, finding that shocks to ETF prices trickle down to underlying asset prices causing more volatility. By using Vector Auto-Regression (VAR) analysis they find that a shock to ETF premium is induced to underlying securities price. Ben-David et al. also argue that HFT arbitrage activity might be one reason for this, because ETF premiums are found to be bigger when arbitrageurs' profits are constrained. One important finding is that ETF mispricing seems to grow bigger during high volatility. The wider mispricing also seems to be affected by market liquidity. Therefore, the ETF mispricing is found to be driven by various different measures such as VIX index, TED spread and past arbitrageurs' profits. Arbitrageurs' ability to fund their ac-

[7]Limits of arbitrage means the restrictions, due to some risk sources, to take part in observed arbitrage opportunity (see Shleifer & Vishny 1997).

tivity is distorted in market stress which forces them to reduce their activity, further widening the ETF mispricing. In relation to HFT activity, Ben-David et al. state that HFT amplifies the non-fundamental market volatility and may cause market disturbance during market stress.

Petäjistö (2011) explore the ETFs bid-ask spreads and premiums to their NAVs. Results indicate that ETF end-of-day premiums are near zero in the cross-sectional ETF universe. Various exceptions exist but usually these are concentrated to bond funds. This is partly explained by the difficult features in their NAV calculations. Similar findings are shown in Engle and Sarkar (2006) as their main findings note that non-synchronous trading is a remarkable driver behind ETF premiums. When this is taken into consideration, the premiums for U.S. based ETFs are small with a standard deviation of 15 basis points. For international ETFs the premiums are much wider and they may last several days. Although, in a fund level analysis the premiums can vary greatly during different periods and even the most traded funds face times of high premiums. Petäjistö (2011) states that even the SPY (the largest ETF) shows few days when the premiums are size of 50 basis points in 2009. This indicates that periods of market stress can have serious implications on ETF pricing procedures.

In relation to these findings, Davidson (2013) proposes a framework to model ETF premiums. The results state that ETF premiums are affected by simultaneous and previous changes in the equity markets, their volatility, and with equity market liquidity. This leads to at least short-term predictability of ETF premiums. Davidson emphasizes that ETF premium changes are highly valuable from investors' viewpoint as being able to predict the ETF mispricing can improve trade execution and be economically reasonable. The cost of acting improperly during high mispricing can be equal or even higher than the entire annual expense ratio of the ETF in question. This is in line with Petäjistö (2013), who argues that the volatility of the ETF premium is definitely economically significant and it should be noted and understood by investors.

It is worth noting that Davidson (2013) also finds a dramatic shift in the observed relationships between ETF mispricing and a range of exogenous factors used as drivers behind the ETF premium. Before 2007, the ETF mispricing had opposite relation to equity market movements and volatility than in post-2007 period. Concerning similar findings, Petäjistö (2013) notes that ETF pricing dynamics may have changed with the industry's recent growth. Davidson (2013) concludes that this shift in ETF mispricing process is due to growth in ETF industry, mainly this means the insufficient amount of ETFs and lower trading volume prior-2007.

In a partially related study, Kim and Murphy (2013) show that the effective spreads of S&P 500 trust (SPY) have also changed after 2007. They document notable changes in trading patterns post-2007: The average trade size dropped from 2,700 (during 1997 to 2006) to 400 (in 2007-2009) while the average number of consecutive trades increased from 4 to 12. For SPY, the average time between trading activity has also decreased dramatically as in 1997 it was 67.5 seconds while in 2009 this figure was only 0.1 seconds. The authors note that these changes suggest the rise of HFT.

4 THE NATURE OF HIGH-FREQUENCY TRADING

4.1 A brief history

HFT activity is usually pinpointed to have started in a big scale around 1999. One reason for its rising popularity is the change in stock prices (in the U.S.). They are now listed in decimalization, not in eights of a dollar. This quote decimalization was executed in April 9th 2001. Short-term trades are now more tempting as price movements are not so radical. Technical changes have thus had a huge role in the formation of a high-frequency trader. (Brogaard 2010.)

The attractiveness of AT and HFT are also related to new market models such as *direct market access* (see LSE 2012a) and *sponsored access* (see LSE 2012b). These are highly useful for anyone using HFT as their main benefit is to reduce the time needed to reach the market by skipping some of the normal infrastructure needed for order routing (Gomber et al 2011). Market operators are also encouraging market participants towards HFT by offering discounted fee structures for aggressive order levels. This is mainly linked to multilateral trading facilities (MTFs), such as Chi-X, BATS and Turquoise, which are challenging the traditional exchange places with their fee schedules. (Menkveld 2013.)

Besides special HFT firms, like some hedge funds and proprietary trading firms, HFT is also used by traditional institutions. The differences between these groups are usually determined by the source of investable capital, holding periods, and trading purposes. The dramatic trading volume growth in recent years is mainly caused by just a few hundred HFT firms. Hence the scope of HFT used by traditional institutions is assumed to be rather low, excluding proprietary trading desks at big investment banks. The few hundred HFT firms are said to be causing around 73 % of the total stock trading volume in the U.S. (Zhang 2010.) Brogaard (2010) adds that HFTs are somewhat profitable as they make around $3 billion each year with the yearly trading volume of $30 trillion. Kearns et al. (2010) propose that the upper bound for HFTs' combined yearly profits can be as much as $21.3 billion[8].

As many firms have been able to reduce their latency by significant amounts, the relative speed advantages among these traders have grown thinner. This relative speed to other traders is a very important tool when dealing with intraday profit opportunities. Many researchers have already pointed that as more HF traders appear, the more we seem to be sliding towards an arms race between traders who are chasing the fraction of a second advantage over their competitors (e.g. Biais et al. 2013; Hasbrouck & Saar 2013).

4.2 HFT strategies

HFT is a technical tool to execute existing investment strategies. Therefore, HFT can be said to be a natural course of development of the market system (Fabozzi et al. 2011; Gomber et al 2011). Aldridge (2010) emphasizes that HFT is not a clear trading strategy but more like a trading methodology which binds sophisticated tools together in order to achieve advantages.

In high speed trading, the key competencies are the abilities to handle data flows and submit orders as fast as possible, in other words to reduce latency (e.g. Cvitanic & Kirilenko 2010; Jarrow & Protter 2012). Low latency means that the order carries less risk being accepted at different price than it was meant to be. This risk is minimized by having priority access to servers constructing the actual market place. Users of HFT are ensuring this by using co-locations and proximity services offered by the market operators. In reality this happens by establishing the computers right next to the market's infrastructure (Garvey & Wu 2010; Gomber et al. 2011).

HFT strategies have a need to update orders rapidly and not to hold their positions overnight. They base their profits from short-term (intra-day) price movements and differences. HFTs need to focus on liquid instruments as they need to execute a huge number of orders (Zhang 2010; Gomber et al. 2011). Table 1 lists common features

[8]For stylized facts about HFT profitability, the reader is pointed to Baron et al. (2012).

that describe HFT, while table 2 divides the most popular HFT strategies to four groups.

Table 1. Characteristics of HFT (Gomber et al. 2011).

1) Very high number of orders
2) Rapid order cancellation
3) Proprietary trading
4) Profit from buying and selling (as middleman)
5) No significant position at end of day (flat position)
6) Very short holding periods
7) Extracting very low margins per trade
8) Low latency requirement
9) Use of co-location/proximity services and individual data feeds
10) Focus on high liquid instruments

Table 2. Classification of high-frequency strategies (Aldridge 2010: 4).

Strategy	Description	Typical holding period
Automated liquidity provision	Quantitative algorithms for optimal pricing and execution of market-making positions	< 1 minute
Market microstructure trading	Identifying market participants order flow through reverse engineering of observed quotes	< 10 minutes
Event trading	Short-term trading on macro events	< 1 hour
Deviations arbitrage	Statistical arbitrage of deviations from equilibrium: e.g. triangle trades, basic trades	< 1 day

HFT strategies are often re-categorized more briefly into two groups, to market making and to more aggressive strategies (Kearns et al. 2010; Smith 2010; Zhang 2010; Hagströmer & Nordén 2013). Market making is a strategy where HFTs act as liquidity providers. This means doing buy and sell limit orders at the same time. The idea is to make the needed quotes for other market participants to have a visible market (enough liquidity) for a certain instrument. The market maker gets profit from the bid-ask spread between its own buy and sell orders. Liquidity provision strategies also relate to the fact that some markets (e.g. MTFs) are offering asymmetric pricing schedules. Traders who increase the liquidity are paying less in trading fees and in some cases they might be offered a compensation for their act. (Gomber et al. 2011.) Avellaneda and Stoikov (2008) also note that modern financial markets allow anyone to act as a market maker, even without formal registration, by just submitting synchronized limit orders. Usually these HFT market making strategies are not seen as the source of controversy because market making is not directional trading and its profits are not related to price trends (see Guilbaud & Pham 2013). In comparison, aggressive strategies include for example directional trading activities and arbitrage strategies such as the ETF arbitrage (Hagströmer & Nordén 2013).

4.3 How to spot a player?

There are still many unanswered questions and problematic issues related to HFT data gathering and reliability for research purposes. We clearly need a broader data and longer time periods as most of the critic given to existing literature relates to these two issues. HFT research has so far been over-representing the short-term effects while the long-term effects might be more economically meaningful. One problem in academic research is the difficulty to determine the unobservable HFT activity. As noted by Cartea and Penalva (2012), the huge task of empirical HFT research is to find a way to study HFT indirectly, using proxies of different trading behavior. Publicly available information about trading does not include identifiers for different traders, which makes it hard to dissolve the high-frequency strategies for research (Cartea & Jaimungal 2013).

One major difficulty is to identify order-by-order from the data which trade has been HFT activity. So far there has been different measures to categorize traders (e.g. Aldridge 2010; Zhang 2010; Kirilenko et al. 2011; Hasbrouck & Saar 2013), but clearly there should be better and more specific ways. Gomber et al. (2011) suggest that in order to find the best method, researchers should do more co-operation with the market participants using HFT strategies. This could be a way to have more reliability as HFT activity is often related to trades in dark pools. These have very limited amount of data available for research purposes.

Hagströmer and Nordén (2013) point out that one caveat in academic research is the difficulty to address different HFT and AT strategies individually. The division is important in order to objectively investigate the real impacts of such activities as it is not reasonable to consider them as a whole. This categorization of traders and strategies is, however, problematical as traders usually do not use only one strategy. They can change their strategies and methods in relation to market situations. This leads to difficulties if the research is done by dividing HFT activity using trader identifiers.

Hasbrouck and Saar (2013) introduce a framework to study HF activity from exchange message data which has the advantage that it can be constructed from publicly-available data. Like other measures, this is a proxy of HFT activity which causes some drawbacks being just a directional estimate. Other researchers have acquired unique data sets in co-operation with exchanges, for example Brogaard (2010) and Brogaard et al. (2013a) used a data set provided by NASDAQ which identified HFT as a specialized proprietary traders leaving out the HFT activity stemming from larger traders like investment banks. Problems with unique data sets are also related to issues in robustness as replicating and verifying the results may be difficult or even impossible.

Researchers have also been using exogenous technology shocks on market infrastructure as a circumstance which assumedly amplifies HFT activity (see Zhang 2010; Hendershott & Moulton 2011; Riordan & Storkenmaier 2012; Brogaard et al. 2013b). Because these technological advantages allow lower latency they are seen as a turning point in high speed trading. By comparing the time period before and after such an improvement we should be able to see some of the HFT effects. Hendershott and Moulton (2011) examine the introduction of NYSE's Hybrid Market in 2006 and find that the following time period was characterized by increased spreads and improved price discovery processes. Similar study conducted by Riordan and Storkenmaier (2012) finds that the improvements in Deutsche Boerse Xetra system also enhanced liquidity measures in the post-shock period.

Smith (2010) gives useful details about the two remarkable market infrastructure changes that occurred in the last decade. First was the decimalization of U.S. price quotes, followed by SEC's revision of Regulation National Market System (Reg. NMS) which started in August 2005. This automated trading system allowed more high speed transactions, and it is generally thought to be the excuse for mushrooming HFT activity. Usually the effects of Reg. NMS are measured from 2005 and after (e.g. Smith 2010), but a closer look to SEC's (2007) report on the implementation of

Reg. NMS reveals that the final phase of renovations started as late as July 9th 2007 and reaching its full completion at October 8th 2007[9].

4.4 A new normal in risk management

A possibility for a rogue algorithm raises discussion about extreme events which could be caused by sudden liquidity removal by HFTs. Liquidity withdrawal has been proved to increase in extreme market movements. In the case of HFT this would happen by suddenly removing the market makers buy and sell orders from the order book. (CFTC-SEC 2010; Easley et al. 2011; Gomber et al. 2011.)

For example in the Flash Crash, HFTs applying market making strategies suddenly stopped providing liquidity as they pulled off their orders. They were not the first cause of the problems but they reacted as the markets were showing unusual movements and high volatility. This reaction caused exacerbating volatility and price movements. As this incident shows, HFT can work in both ways as it can provide liquidity and in extreme cases take liquidity from the markets. More information about HFT activity and its appearance during the Flash Crash can be found from CFTC-SEC (2010), Kirilenko et al. (2011) and Ben-David et al. (2012).

Zhang (2010) notes that HFTs can stop their market making and other trading activities if they spot market conditions that are making it difficult to gain profits or expose them to inventory risks. Bearing inventory that they do not want to hold would lead to abnormal levels of sell orders. When everyone lines up on the same side of a trade, the liquidity shows up as an illusion. This kind of position could appear during high market uncertainty, in a situation where some external cause is amplifying volatility.

Madhavan (2012) notes that employing circuit breakers at a stock specific level can be helpful in times of market stress like in the Flash Crash, but they also can cause some problematic issues. When price movements are stopped at an individual stock

[9]This final phase of Reg NMS is related to Rule 610 and Rule 611, which are the most notable rules related to market system automation, market access, and to quote priorities.

level, these restrictions can complicate the pricing process of ETFs, whose prices are determined by the underlying securities basket. Such a situation can cause unexpected ETF mispricing in times of high volatility. In relation to these ideas, Gomber et al. (2011) note that a significant amount of the problems related to HFT might be caused by U.S. market structures. They compare the situation in U.S. to European markets which have for long used a volatility safeguard regime. So far no market quality related issues with HFT have been noticed in European markets.

HFT activity faces different risks than normal, not latency dependent, trading. Cartea and Jaimungal (2013) argue that commonly used risk metrics (e.g. VaR, ES) are especially invented for trading strategies that are not dependent on trading speed, and therefore these metrics cannot serve for HFT as their risk controls. Of course it is not assumed that HFTs would rely on such measures in their trading, but it clearly shows the need for developing some risk metrics especially for HFT[10].

Various sources consider the introduction of financial transaction tax with the aim to reduce the possible harmful side of high-frequency trading (e.g. Biais & Woolley 2012; Cohen & Szpruch 2012). It is worth noting that the aim of such tax would only be to prevent predatory trading, not the whole range of different HFT strategies. Jarrow and Protter (2012) argue in line that regulators should adjust the policies to exclude the predatory aspect of HFT. Cohen and Szpruch (2012) state that, the transaction tax might even improve the overall market efficiency by making the market more attractive to slower traders.

[10]For comprehensive qualitative discussion on HFT related risks see GOS (2012).

5 THEORETICAL FRAMEWORK

5.1 Arbitrage in financial markets

A typical text book arbitrage is defined as an opportunity to gain profits without neither capital nor risk. The theoretical concept of arbitrage is explained by Sharpe and Alexander (1990) with the definition of: "*…the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices*". These arbitrage opportunities appear to be in some extent different in reality. Shleifer and Vishny (1997) argue that in real financial markets specialized investors take part in arbitrage activity even if it needs capital and exposes them to various risks. In modern markets these specialized investors include hedge funds, proprietary trading desk in big banks, and HFTs[11].

Availability of low risk capital is necessary to take advantage of thin arbitrage opportunities. As the cost of financing rise, say with market stress, arbitrage activities might have to be scaled back. This is due to the fact that market mispricing, like ETF premiums, might stay longer than expected in volatile markets. In some cases the observed mispricing might grow bigger due to similar reasons. A rational arbitrageur has to consider the cost of financing, which also rises in relation to market stress, before partaking into the arbitrage. Davidson (2013) argues that the ability to do arbitrage trading is a function of available financing and of the risks related to the arbitrage. According to Brunnermeir et al. (2009) VIX index can serve as a simplified measure for available arbitrageurs' capital. As volatility begets volatility the capital needs and arbitrage risks can be qualitatively and reasonably related to the VIX index, other proxies for high volatility, and measures of financing costs of short-term trading activities.

[11]It is important to note that HFT is often done by hedge funds, and not solely by proprietary trading firms. The difference between these two definitions is the source of trading capital: Hedge Funds usually use money from their investors while proprietary traders use their own money (or loans). Nevertheless, the effects of these two HFTs are the same and during this study hedge fund based HFT activity is considered in line with other possible sources of HFT.

The unique arbitrage mechanism behind ETF pricing process differs in some manner from the traditional concept of arbitrage. As explained in the terminology, this mechanism is a contract based relationship between the authorized participant and the issuer of the ETF. The creation/redemption process is unlike from other arbitrage situations as in consequence an amount of ETF shares actually is made or redeemed from the markets. This mechanism allows a pure risk-free profit for the AP as long as the prevailing price gap between ETF and NAV is wide enough. It is worth noting that limits of arbitrage are mitigated as the ETF share creation/redemption takes place in primary markets, not in the actual secondary marketplace. More importantly, this exchange takes place on a fair value basis, not with the price the ETF is trading at the secondary markets. What makes the overall concept of ETF arbitrage more complicated is that any other trader is free to arbitrage with ETFs in the secondary market. Therefore, the ETF creation and redemption process is not the only arbitrage force behind ETF pricing process.

5.2 Understanding ETF arbitrage at high-frequency

Simple mean-reverting (pairs trading) strategies work better for ETF pairs and triplets than for stocks. This is due to the fact that ETFs are often highly diversified and hence their fundamental economics do not change as quickly as corporate stocks' (Marshall et al. 2010; Chan 2013). This indicates that ETFs form an attractive range for the algorithmic mean-reverting strategies. ETFs can also be used as a second instrument in a classical index arbitrage where trades are based on the differences in values of a portfolio of stocks (such that form an index, say S&P 500) and their corresponding ETF (in this case SPY). Classical as it is, such a common strategy has been noted and the profits grown thinner since (Reverre 2001). Chan (2013) argues that these thin profits can still be highly attractive, especially if traded intraday at high-frequency. Due to their relative speed advantage high-frequency traders can exploit the intraday index arbitrage by using ETFs and their underlying assets.

Ben-David et al. (2012) argue that ETF arbitrage is mainly done by HFTs. This is also seen as a reason why HFT activity can have impacts on market quality measures as volatility, and in time of market stress HFT activity may cause serious market disruptions. ETF arbitrage can be harder due to the limits of arbitrage which are more relevant when the underlying asset basket is difficult to trade. This might be because of issues related to its liquidity or other complex characteristics. Mainly this is connected to small illiquid funds and to non U.S. based funds whose assets baskets trade at non-synchronized times with the fund itself (Engle & Sarkar 2006). Although larger ETFs face more often creation/redemption processes than smaller and less traded funds, the creation units account only a fraction of the total daily volume because of remarkable higher trading volume (Petäjistö 2011). Therefore, secondary market arbitraging between ETFs and their asset baskets is more suitable in large U.S. based funds as the arbitrageurs' trading cannot be offset by a single creation unit. The attractiveness of these funds for arbitraging is also affected by the fact that their underlying securities are traded simultaneously, making limits of arbitrage less significant.

Remarkably, U.S. market traded ETFs have also been found to trade with different prices than their net asset value would suggest. Even though this difference is partly supposed to be mitigated by authorized participants in ETF creation and redemption process (Petäjistö 2011; Ben-David et al. 2012), it still seems that this activity is inadequate to push the premiums to zero. Still prevailing thin profits might be enough to attract other arbitrageurs to arbitrage between the ETFs and their underlying assets[12]. As noted by Chan (2013), thinner profits require higher trading frequency which makes this arbitrage solely tempting to HFTs.

Petäjistö (2011) finds that the average volatility of the closing price premium in all ETFs is 53 basis points. He also shows that, although, these premiums are more volatile for smaller and illiquid funds, the premium is still significant for the biggest and most liquid funds. Petäjistö (2013) continues with these findings in a detailed manner, showing that in early 2007 the cross-sectional premium volatility was 25 bp, but it increased significantly for the whole 2008, peaking in September 2008. Other times of high premium volatility are noted around the Flash Crash in May 2010, and during November 2010 muni-bond crash.

[12]It is worth noting that ETF arbitrage can also take place between the ETFs and their relevant futures. See Richie et al (2008) and Ben-David et al. (2012) for more information on the usage of futures in these trading activities.

This premium volatility serves as an interesting measure to address the arbitrage activity between ETFs and their underlying assets. The premium volatility can be amplified in times of market stress which motivates us to investigate the matter in more detail. For example, having limit orders in the ETF at the moment of abnormally high premium volatility can lead to unwanted trades as the trade can be executed even though the NAV has not triggered this threshold. This is clearly an important issue for ETF investors as it might reduce the attractiveness to invest in ETFs by having severe economic influences.

6 RESEARCH DESIGN AND RESEARCH QUESTIONS

6.1 Research problems and methodology

This paper aims to contribute in connecting the HFT activity to ETF pricing process by demonstrating HFTs' role in ETF arbitrage activity. This is done by constructing simple factor models to explain the level of ETF mispricing and its volatility. OLS regression analysis is then used to estimate the relationship between ETF mispricing and the chosen features. These multivariate linear regressions take the following linear equation form:

$$mispricing_{\mathrm{t}} = \beta' x_{\mathrm{t}} + \varepsilon_{\mathrm{t}}, \tag{1}$$

where $mispricing_{\mathrm{t}}$ is the observed ETF mispricing at time t (when $t = 1, 2 \ldots T$), β is the vector of regression coefficients including constant, x_{t} contains a dummy for constant term and each relevant predictor variable, including also the lagged variables, and ε_{t} is the error term. After considering possible multicollinearity issues, the linear regression analysis is performed to all predictor variables, and then dropping out one by one the non-significant variables[13] and the independent variables with the smallest absolute t-statistics. Appendix I, shows the full list of independent variables the analysis was started with, while empirical results document only the most statistically, economically, and qualitatively meaningful variables.

Another purpose of this paper is to address HFTs' role in ETF mispricing in a detailed manner and formally test if the noted change in ETF mispricing trend is connected to the rise of HFT. This is conducted by utilizing an exogenous technology shock which improved market infrastructure to make it more suitable for HFT activities. By addressing the time periods before and after such a shock we should see strengthened HFT activity and its effects in a distinguishable manner. Similar methodology is used in Hendershott and Moulton (2011) and Riordan and Storkenmaier (2012) to study HFT effects on stock markets.

[13] Non-significance is measured as $-1.98 < \text{t-stat} < 1.98$.

The technology shock, Reg. NMS, which reduced trading latency, was proposed to have started at 2005, but due to extensions required by market operators it reached its full capacity at the 8th of October 2007 (see SEC 2007; Smith 2010; Madhavan 2012; Pagnotta & Philippon 2012). This renovation of market routing infrastructure also affected NYSE Arca which is the main exchange for ETFs. The methodology for testing the significance of this technology shock is done by applying the Chow test (see Chow 1960). This is used to test if the coefficients in the multivariate and univariate linear regressions have changed prior and after the technology shock, which serves as a structural break in the data set. We divide the original multivariate linear regression into two set of equations. The mathematical expression of this combined model with breaks is as follows:

$$mispricing = (\alpha + \delta d_t) + (X\beta + X\gamma d_t) + \varepsilon\,, \tag{2}$$

where d is a dummy variable getting values 0 and 1 in relation for a given break point t^* such that $d = 1$ if $t > t^*$ and zero otherwise, δ is a vector indicating the change in intercept and γ is a vector containing the changes in slope parameters, while X is the design matrix containing every relevant predictor variable, β is the vector of regression coefficients, and α is a vector for the external expression for the intercept term. This model has constant parameters only if $\delta = \gamma = 0$. Thus the hypotheses for testing are: H_0: $\delta = 0$ and $\gamma = 0$ against H_1: $\delta \neq 0$ and/or $\gamma \neq 0$. This is tested by calculating the Chow test statistic:

$$\frac{(RSS_c - (RSS_1 + RSS_2))/k}{(RSS_1 + RSS_2)/(n_1 + n_2 - 2k)}\,, \tag{3}$$

where RRS_i stands for the sum of squared residuals for the combined data and the two groups with split data when $i = 1,2,c$. The number of observations in each group is given by n_1 and n_2 while k is the total number of parameters. The Chow test statistics then follows the F-distribution with k and $n_1 + n_2 - 2k$ degrees of freedom.

As has been proposed by Davidson (2013) and Petäjistö (2013), ETF pricing structures have changed remarkably after 2007 and the relationship between ETF mispricing and various exogenous factors have twisted. Prior to that time only a limited amount of ETFs were traded and their assets under management have faced similar developments. This arguably affects the cross-section of ETFs but should not concern in such a magnitude the largest ETFs with distant inception dates. Both authors emphasize that the transition in ETF mispricing trend might be due to maturation of ETF markets. One can argue that these explanations are without exhaustive qualitative background. Accordingly, Davidson (2013) notes that the turning point in January 2007 is arbitrary, to result in satisfying connection with the maturation of ETF markets and developments in arbitrage behavior. Appearance of sophisticated arbitrageurs who could be able to engage in arbitrage trading even with thin profits and high-frequency might serve as an explanation for the changes in ETF mispricing trends. This is also in part missed by Davidson (2013) and Petäjistö (2013) as the main renovations to market infrastructure which allowed more HFT activity occurred actually in 2007 (see SEC 2007). Therefore, it is logical to set the structural break point at this Reg. NMS implementation point in order to relate the effects to heightened HFT activity.

In addition to considering the regression results separately for time periods prior and after the Reg. NMS, different statistical tools are employed to analyze the relationships with independent factors and ETF premiums and the possible structural breaks in these time-series in a more detailed manner. Namely these tools include rolling regression analysis, estimating time-varying betas with Kalman filter method, and a test based on the cumulative sum of recursive residuals (Rec-CUSUM).

Finally, we aim to contribute to existing literature by updating ETF premium volatility modeling to incorporate the possible changes in ETF mispricing trend in post-2007 era. The ETF premium volatility process is modeled by employing Generalized AutoRegressive Conditional Heteroskedastic (GARCH) volatility model using HFT related exogenous regressors. Being able to model the premium volatility can be useful for example in risk-management as limit orders in ETFs might be executed unfavorably in times of high premium volatility. Such a situation might occur when ETF return differs from the underlying index triggering the limit order even when the underlying index return does not exceed such a threshold.

Using a GARCH model, we can model the conditional variance of the time-series (see Engle 1982; Bollerslev et al. 1994; Tsay 2005). GARCH models have the benefit of modeling more accurately the volatility clustering phenomena which means that the time-series includes recognizable periods of high and low volatility. The employed volatility model is expressed as follows: For the log ETF mispricing series r_t, let $a_t = r_t - \mu_t$ be the innovation at time t. Then a_t follows a GARCH(p,q) model if

$$a_t = \sqrt{h_t}\varepsilon_t, \qquad h_t = \omega + \sum_{i=1}^{p} \alpha_i a^2_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j}, \tag{4}$$

where $\omega > 0$, $a_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{\max(p,q)}(\alpha_i + \beta_i) < 1$, $\{\varepsilon_t\}$ is a sequence of iid random variables with mean 0 and variance of 1. With the entertained model to match the best the characteristics of log SPY premium time-series we use GARCH(1,1) including exogenous regressors for forecasting purposes. The model selection process is explained in a detailed manner in empirical results, while the equation for the final chosen model is presented here:

$$a_t = \sqrt{h_t}\varepsilon_t, \qquad h_t = \omega + \alpha a^2_{t-1} + \beta h_{t-1} + \gamma z_{t-1}, \tag{5}$$

where z is the vector for exogenous variables and $\{\varepsilon_t\}$ follows Student's t-distribution.

6.2 Research questions and objective

Summarized research questions:

- Can ETF premium and its volatility (end-of-day) be partly explained by factors related to HFT activity?
- Are ETF premium time-series evolution affected by heightened HFT activity as measured by the implementation of Reg. NMS?

Research objective:

- GARCH modeling ETF premium volatility using exogenous regressors related to HFT activity.

7 RESEARCH DATA

7.1 Data description and sources

The empirical part mainly focuses on the SDPR trust (SPY) during a time period from 2nd of January 2002 to 15th of January 2013. The time period relies on several explanations: As SEC ordered all U.S exchanges to convert their quotes to decimals instead of eights of a dollar on April 9th 2001, it is reasonable to consider only the time period after this time point. It is logical to assume that a significant amount of ETF premiums have been due to quotation standards prior the decimalization (see Chen et al. 2008). HFT activity is also assumed to have benefited from this change. Another turning point for HFT is the renovation of U.S. exchanges by implementation of Reg. NMS (July 9th 2007). The examined time period is chosen to reflect equal lengths prior and after this technology shock.

This research concentrates solely on the SPY as it is the largest U.S based ETF. It is worth emphasizing that the aim is not to explain cross-sectional ETF premium differences. We are merely looking for an introductory framework to relate HFT and their effects on exchange-traded products. Another relevant issue in research on ETF premiums is the stale pricing of certain bond funds and non-U.S. based funds. As has been noted in Petäjistö (2011) and Davidson (2013), stale pricing and non-synchronous trading are significant factors behind ETF premiums. These findings serve as a motive to ignore non-U.S based ETFs in this study. Although, different methods has been introduced to address the stale pricing issue (see Engle & Sarkar 2006; Petäjistö 2013), doing so is out of the scope of a Master's Thesis. An additional matter in non-synchronous trading is the fact that many ETFs (including SPY) traded on AMEX, until November 2008, 15 minutes longer than the underlying U.S. equities (Petäjistö 2013). This also concerns the results in this study, but from the accessible data sources it is impossible to correct.

Focusing the research only on SPY serves one more topic: It is reasonable to assume that the cross-sectional ETF market dynamics have evolved around 2007 for the reason stated by Davidson (2013) and Petäjistö (2013), where they namely mean the maturation of ETF markets. As SPY has been around since 1993, and being the biggest, most liquid, and most traded ETF, its micro-market structures must have been developed far earlier. The characteristics of prior-2007 ETF marketplace are mainly due to limited amount of funds in the ETF universe. Thus, addressing the pricing dynamics of only SPY can serve as a reasonable way to dissect the effects of ETF market maturation from the assumed effects caused by heightened HFT activity, which both occurred in a fairly overlapping time point. The change in cross-sectional ETF pricing dynamics is far more difficult to explain following the methodology used in this study as the effects of these two phenomena might merge.

ETF daily price, trading volume, NAV data, number of outstanding shares, and daily high and low prices are obtained from Bloomberg. Thomson Reuters Datastream is used to construct the relevant Fung-Hsieh Mutual Fund factors while multiple other sources are used to construct the other explanatory variables (See Appendix I for complete data sources).

7.2 Descriptive statistics

As the aim is to address HFTs relation to the ETF arbitrage, the main interest is on the absolute size of this premium. The arbitrageur should not care about the sign of this premium, i.e. not to care whether it is a negative one (discount) or a positive one (premium). The only thing that matters profit wise is the absolute size because profits are equal in both situations. This study follows Petäjistö (2011 & 2013) by defining the premium as the percentage difference between the ETF price and its NAV price as a fraction of the NAV price. The descriptive statistics of SPY premium from 2002 to 2013 are presented in table 3. The mean premium is of little interest in our arbitrage setting since having negative and positive premiums cancel each other forcing the mean to be close to zero. By measuring the mean from absolute premiums we note that the average premium is about 10 basis points. This is rather relevant as it is even bigger than the annual expense ratio which is 9 bp. The premium daily volatility is 17 bp and the distribution has extremely fat tails: kurtosis is 18.76 and the highest ETF discount over the time period has been -1.86 % and the highest premium 1.34 %.

Table 3. Descriptive statistics of daily ETF mispricing, mean of the absolute size of ETF mispricing, and annualized premium volatility.

SPY Premium	
Mean	-0.01 %
abs(Mean)	0.10 %
SD (daily)	0.17 %
SD (annual)	2.64 %
Skewness	-1.25
Kurtosis	18.76
Min	-1.86 %
Max	1.34 %
N	2751

Table 4 shows the correlations between the relevant independent variables during the total time period (2002 to 2013). This table includes only the significant factors, leaving the correlations between the full range of variables of which the analysis was started with to Appendix II. It is important to note possible multicollinearity, which is a statistical phenomenon when two or more predictor variables are highly correlated. This might cause problems to regression models robustness and accuracy (e.g. Brooks 2002). The table 4 lists the variables after taking note of possible multicollinearity and statistical significance on predicting the absolute premium size. While CBY and SPY_S still show relatively high correlation with VIX, they were all used in the analysis for their possible economically meaningful role. In addition, the analysis was also conducted by dropping out at least one of these highly correlated factors.

Table 4. Correlations between the statistically significant factors behind the absolute size of ETF premium. Time period 2.1.2002-15.1.2013.

	TED	VIX	CBY	FH2	FH3	MONEY	SP_S	SP_VOL
TED	1.0000							
VIX	0.5651	1.0000						
CBY	0.5905	0.7843	1.0000					
FH2	-0.0658	-0.1508	-0.0151	1.0000				
FH3	-0.0664	-0.1467	-0.0055	0.8080	1.0000			
MONEY	-0.0416	-0.1132	-0.0013	0.4435	0.3705	1.0000		
SPY_S	0.5444	0.7843	0.5727	-0.1929	-0.1916	-0.0809	1.0000	
SPY_VOL	0.5446	0.4791	0.4330	-0.1086	-0.1173	-0.0456	0.4283	1.0000

TED spread and VIX index are serving as proxies for available arbitrageurs' capital while CBY (Corporate Bond Yield) is a bond oriented risk factor. FH2 and FH3 are the only relevant factors from the Fung-Hsieh Mutual Fund risk factor list[14], which was used to serve as a naive proxy for different funds' behavior. The main idea was to estimate hedge fund activity but as Fung-Hsieh Hedge Fund factors[15] are not applicable at a daily level, the mutual fund factors were used instead with relevant bond oriented risk factors. MONEY is Kenneth French's Financial Industry portfolio which is used to serve as a proxy for financial industry's state of nature. While it also correlates highly with wide equity indexes like S&P 500 it also captures U.S. market returns and their effects. SPY_S is a simple estimate of realized daily ETF volatility and SPY_VOL is a feature scaled measure of SPY daily volume. SPY_S and SPY_VOL serve as ETF endogenous factors related to HFT activity on the ETF on a specific day: high daily volatility might cause lower HFT activity as it introduces risks to arbitrage while higher than usual trading volume can indicate high HFT activity as they generate a lion's share of market volumes.

These two endogenous ETF factors are naive measures for HFT activity and its constraints. We recognize that these measures may not be the most relevant proxies for HFT activity and a lot of simplified assumptions had to be done in order to be content in their usage. We also searched for ETF quotation data for a better HFT proxy. By constructing a quote-to-trade ratio we could have build a more satisfactory HFT measure as their behavior has been noted to be highly related to the amount of non-executed trades, i.e. quotes, while using only trading volumes can capture only a messy estimate of HFT activity. The accessible data sources did not provide quotation information, leaving our HFT activity estimation to a fairly unsatisfactory level.

The relationship between the chosen factors and the absolute size of observed ETF premiums is assumed to be linear to justify the use of mostly linear approach for research purposes. Theoretically this assumption is based on the idea of vanishing arbitrage profits: if at some point ETF premiums show arbitrage opportunities (i.e. high

[14]See https://faculty.fuqua.duke.edu/~dah7/8FAC.htm for the full 8-factor list of these factors. Not all are applicable at daily level.
[15]See https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm for the Hedge Fund 7-factor list.

premiums), the arbitrageurs' are assumed to trade on these opportunities forcing the ETF premiums to shrink (i.e. no observable premiums). Therefore, the factors which are related to constrained arbitrage activity should have positive linear relationship between absolute premiums while the factors related to higher arbitrage activity should have negative linear relationship with absolute ETF premiums.

8 EMPIRICAL RESULTS

8.1 The factors behind ETF premiums

Appendix III shows the time-series evolution of SPY premium over the time period. The premium shows some amount of time persistence as high premium volatility occurred in the early part of the time period and during the years of the financial crisis. After the crisis the premiums have shrank and their volatility reduced significantly. SPY realized daily volatility also shows turbulence during 2002 to 2003, in financial crisis, and again during the Flash Crash.

Regression analysis run on ETF premium tries to capture how the actual level and sign of ETF premiums could be predicted similarly to stock returns. Table 5 presents regression results using ETF premium as the dependent variable. The only statistically significant 1-day lagged factors are SPY_S, VIX, and MONEY. R^2 is rather low (3 %) showing that the actual level of ETF premiums is not predicted with accuracy at least on short-term. When considering the arbitrageurs' role in ETF mispricing the exact level of ETF premium is less interesting than the absolute size of the premium. This is because the aim is to explain the factors which are connected to widening or shrinking premiums ignoring whether the premium is negative or positive.

Table 5. Regression results using daily data and actual level of ETF premium as the dependent variable. This is defined as (ETF-NAV)/NAV. Independent variables are lagged one day. Time period is from 02.01.2002–15.01.2013.

	(1)	(2)	(3)
Intercept	0.0247 ***	0.0034	0.0005
	(4.80)	(0.43)	(0.07)
SPY_S_{t-1}	-2.1363 ***	-3.3508 ***	-3.3698 ***
	(-7.84)	(-7.65)	(-7.71)
VIX_{t-1}		0.0018 ***	0.0020 ***
		(3.53)	(3.80)
$MONEY_{t-1}$			0.0055 ***
			(3.40)
N	2750	2750	2750
Adj. R^2	0.02	0.03	0.03

N = number of observations, *t*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

Table 6 presents the regression results using absolute size of the ETF premium as a dependent variable. The time period covered is from start of 2002 to January 2013. In the result interpretation we should note that in a perfect world where no arbitrage opportunities would exist, we would see absolute premium of zero. Therefore, the factors behind constrained arbitrage activity should show have positive coefficients while the factors behind higher HFT activity related to ETF arbitrage should show negative coefficients.

The analysis shows that ETF endogenous factors (SPY_S and SPY_VOL) are major contributors to SPY premiums. The R^2 is 21 % using lagged 1-day values of these two factors. SPY_S, which measures the realized daily SPY volatility, is highly statistically significant and is also qualitatively reasonable as high volatility may lead HFTs and other arbitrageurs to scale back their activities. High value of SPY_VOL is understood to proxy higher than usual trading volume, and as a result also higher HFT activity. Higher arbitrage activity leads to lower premiums as ETF prices revert towards the NAV value. TED spread and VIX also have the expected coefficient sign as constrained arbitrage activity should cause the premiums to grow even wider as arbitrageurs may not be able to participate into trading activities.

Table 7 shows the regression results using 5-day SPY premium volatility as the dependent variable. This tries to reveal if the factors behind the time persistence of premium volatility are the same as the factors explaining the absolute daily premium size. The daily realized SPY premium volatility is calculated by taking the average of daily squared returns over each five day period and taking a square root of this value. This partly follows the methodology recommended by Hasbrouck (2007) where we set the μ in variance calculations equal to zero. For the regression analysis we will use 5-day averages of the independent variables. The results are presented using overlapping and non-overlapping 5-day periods where the non-overlapping lagged $(t-1)$ values represent the last week averages of these factors.

The analysis tells similar story as the regressions run on daily variables. The results are also qualitatively the same using non-overlapping and overlapping observations: SPY_S, SPY_VOL, and TED remain the most powerful explanatory variables with the expected coefficient signs.

Table 6. Regression results using daily data and the absolute daily size of ETF premium as the dependent variable. This is defined as abs((ETF-NAV)/NAV). Independent variables are lagged one day. Time period is from 02.01.2002–15.01.2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0257 ***	0.0087 *	-0.0080 *	0.1420 *	0.0013	0.0017	0.0014	0.0021
	(6.68)	(2.16)	(-2.05)	(2.35)	(0.21)	(0.27)	(0.23)	(0.33)
SPY_S_{t-1}	4.8071 ***	5.9473 ***	4.2533 ***	4.6612 ***	3.4702 ***	3.3665 ***	3.3975 ***	3.4721 ***
	(23.57)	(27.04)	(18.65)	(19.21)	(11.16)	(10.79)	(10.90)	(11.12)
SPY_VOL_{t-1}		-0.0307 ***	-0.0503 ***	-0.0490 ***	-0.0511 ***	-0.0517 ***	-0.0516 ***	-0.0515 ***
		(-12.10)	(-19.11)	(-18.58)	(-19.33)	(-19.54)	(-19.56)	(19.51)
TED_{t-1}			0.0768 ***	0.0841 ***	0.0855 ***	0.0857 ***	0.0856 ***	0.0852 ***
			(18.10)	(18.71)	(19.11)	(19.19)	(19.19)	(19.12)
CBY_{t-1}				-0.0274 ***	-0.0546 ***	-0.0507 ***	-0.0515 ***	-0.0497 ***
				(-4.79)	(-7.55)	(-6.93)	(-7.04)	(-6.78)
VIX_{t-1}					0.0029 ***	0.0027 ***	0.0028 ***	0.0026 ***
					(6.07)	(5.73)	(5.82)	(5.43)
$FH3_{t-1}$						-0.5282 **	-1.1495 ***	-1.1352 ***
						(-3.29)	(-4.35)	(-4.30)
$FH2_{t-1}$							0.8441 **	1.0621 ***
							(2.96)	(3.60)
$MONEY_{t-1}$								-0.0035 **
								(-2.82)
N	2750	2750	2750	2750	2750	2750	2750	2750
Adj. R^2	0.17	0.21	0.29	0.30	0.31	0.31	0.31	0.31

N = number of observations, *t*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

Table 7. Regression results using rolling 5-day averages. Panel A presents the results using 5-day moving averages with overlapping observations. Panel B presents the results using non-overlapping observations. Time period is 2.1.2002 – 15.1.2013.

	(A) Overlapping	(B) Non-overlapping
Intercept	0.0140 ***	0.0209 *
	(3.56)	(2.27)
$avgSPY\_VOL_{t-1}$	-0.0620 ***	-0.0649 ***
	(-34.78)	(-15.56)
$avgSPY\_S_{t-1}$	7.4985 ***	6.1490 ***
	(34.41)	(11.97)
$avgTED_{t-1}$	0.0857 ***	0.0959 ***
	(28.14)	(13.43)
$avgCBY_{t-1}$	-0.0452 ***	-0.0384 ***
	(-11.19)	(-4.04)
$avgFH3_{t-1}$	-1.0306 ***	-1.7134 **
	(-4.80)	(-3.31)
$avgFH4_{t-1}$	-0.0937 *	0.0270
	(-2.02)	(0.25)
N	2747	550
Adj. R^2	0.61	0.57

N = number of observations, *t*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

8.2 ETF premium dynamics prior and after Reg. NMS

Appendix III also presents the plots of the time-series evolution of SPY daily trading volume and closing prices. As can be seen, the turning point in trading volume has been in 2007. At that point the daily trading volume grows dramatically. This happens to be consistent with the implementation date of Reg. NMS, although it needs to be addressed in more detailed manner to draw in-depth qualitative conclusions. The following regression results aim to shed some light on this.

Table 8 shows the regression analysis results using separate time periods prior and after the implementation of Reg. NMS with absolute premium size as the dependent variable (Appendix IV shows the results using actual premium level). Results show significant differences in the explanatory power which rises dramatically after Reg. NMS. When factors' statistical significance is measured from the latter time-series, TED spread alone generates a high R^2 of 47 % while during the previous time period the R^2 is only 3 % using TED as the only independent variable. Interestingly the coefficient sign has also twisted. This is in line with the findings of Davidson (2013) and Petäjistö (2013), but as we are using only SPY it is hard to agree qualitatively that this would be the cause of ETF market maturation. The market for SPY, being the oldest and most traded ETF, should have maturate far earlier than the cross-sectional ETF market. As TED spread is used as a proxy for available arbitrage capital, one conclusion might be that the observed change in regression coefficient and R^2 are at least partly due to heightened HFT activity in the latter time period.

Similar changes in regression coefficients occur in CBY and SPY_VOL. While the observed coefficient signs of CBY are hard to explain quantitatively, the changes in SPY_VOL follow the expectations laid out in research design: negative SPY_VOL regression coefficient should be in line with HFT activity around ETF arbitrage. Indeed, this is the case as the prior-Reg. NMS time period shows positive regression coefficient while the latter period shows negative and statistically significant coefficient.

The Chow test for structural breaks is used to see if regression coefficients have changed in a statistically significant way around the implementation of Reg. NMS. The completion date of Reg. NMS was used as a predefined structural break for the time-series evolution. The Chow test was performed for the full data period separately using the actual level of ETF premium and absolute size of ETF premium as the dependent variables. Table 9 presents the results, where it is clearly seen that using absolute premiums we can reject the null hypothesis in relation to every tested variable. For robustness test the structural break point is changed to $t^* - 250$ and to $t^* + 250$ where t^* is the original break point. The robustness test gives similar results suggesting that the Reg. NMS completion date cannot serve as a single exhaustive break point for regression coefficient dynamics.

Table 8. Regression results prior and after Reg. NMS using the absolute daily size of ETF premium as the dependent variable. Panel A presents the results before the implementation of Reg. NMS. Panel B shows the time period post-Reg. NMS.

Panel A: Time period 2.1.2002 – 6.7.2007

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1521 ***	0.0806 ***	0.0544 **	0.0525 **	0.0379
	(24.20)	(8.01)	(2.75)	(2.65)	(1.89)
TED_t	-0.1402 ***	-0.0666 **	-0.0597 **	-0.0990 ***	-0.0434
	(-7.12)	(-3.20)	(-2.80)	(-3.34)	(-1.33)
SPY_S_t		4.1361 ***	3.7459 ***	2.9981 ***	1.7230 *
		(8.96)	(7.11)	(4.57)	(2.37)
CBY_t			0.0300	0.0525 *	-0.0001
			(1.54)	(2.31)	(-0.00)
SPY_VOL_t				0.0100	0.0063
				(1.91)	(1.19)
VIX_t					0.0038 ***
					(4.00)
N	1376	1376	1376	1376	1376
Adj. R^2	0.03	0.08	0.09	0.09	0.10

Panel B: Time period 9.7.2007 – 15.1.2013

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.0135 ***	-0.0373 ***	-0.0106	-0.0192 *	-0.0307 **
	(-3.46)	(-8.60)	(-1.60)	(-2.45)	(-3.20)
TED_t	0.1149 ***	0.0859 ***	0.0938 ***	0.0934 ***	0.0919 ***
	(34.59)	(20.74)	(21.50)	(21.41)	(20.82)
SPY_S_t		2.7342 ***	3.1446 ***	3.6054 ***	3.3130 ***
		(10.94)	(12.13)	(10.50)	(8.94)
CBY_t			-0.0290 ***	-0.0284 ***	-0.0379 ***
			(-5.32)	(-5.19)	(-5.32)
SPY_VOL_t				-0.0085 *	-0.0112 **
				(-2.04)	(-2.58)
VIX_t					0.0012 *
					(2.08)
N	1376	1376	1376	1376	1376
Adj. R^2	0.47	0.51	0.52	0.52	0.52

N = number of observations, *t*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

Table 9. The Chow test F-statistics using daily data and the most statistically and economically relevant factors. F-statistics are reported using contemporaneous and 1-day lagged independent variables. In panel A the dependent variable is the actual level of daily ETF premium. Panel B presents the results using the absolute size of the ETF premium as the dependent variable. The multivariate row presents the statistics using multivariate linear regressions with all statistically significant factors.

	Time period: 2.1.2002 – 15.1.2013 (Break point 9.7.2007)				
	Panel A: Premium			Panel B: abs(premium)	
	(t)	(t-1)		(t)	(t-1)
Multivariate	5.4433 ***	2.4059 *	Multivariate	15.56 ***	12.69 ***
	(0.000)	(0.025)		(0.000)	(0.000)
MONEY	11.23 ***	1.1973	TED	276.11 ***	267.02 ***
	(0.000)	(0.302)		(0.000)	(0.000)
SPY_S	0.0291	3.4784 *	SPY_S	93.71 ***	85.62 ***
	(0.971)	(0.031)		(0.000)	(0.000)
FH2	0.7491	1.0177	CBY	86.99 ***	83.75 ***
	(0.473)	(0.362)		(0.000)	(0.000)
FH5	1.2253	0.9908	SPY_VOL	174.95 ***	163.26 ***
	(0.294)	(0.371)		(0.000)	(0.000)
CBY	0.1457	0.1580	VIX	144.52 ***	134.16 ***
	(0.864)	(0.854)		(0.000)	(0.000)
SPY_VOL	4.0298 *	8.1340 ***			
	(0.018)	(0.000)			
N	2752	2752	N	2752	2752

N = number of observations, *p*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

Rolling regression coefficients where estimated for more accurate analysis of the relationship between dependent and independent variables. More importantly, this methodology shows the possible change points in regression analysis dynamics. This analysis is conducted to every independent variable revealing that all independent variables and their relationship with absolute ETF premiums have experienced dramatic movements and changes in coefficient signs around the 2008 financial crisis. The analysis shows that these changes occur two days prior the bankruptcy of Lehman Brothers, an investment bank, which triggered the most turbulent period of the 2008 financial crisis. This turbulent time in regression coefficients covers 50 trading days.

In order to see if the implementation of Reg. NMS had potential effect on regression coefficients, this 50-day period is removed from the time-series. Re-plotting the rolling regression coefficients give smoother results showing that the only independent variables with significant and persistent relationship with absolute size of ETF premiums are TED spread and SPY_VOL. Appendix V shows the graphs with and without the 50-day period of the financial crisis for every independent variable while figure 1 presents the graphs for TED and SPY_VOL. The rolling regressions where conducted using a 1376-day rolling window where the starting coefficient values represent the coefficient from regressions run on the pre-Reg. NMS era (2.1.2002 – 6.7.2007). The plots end with the corresponding values from the regressions run on the latter time period (9.7.2007 – 15.1.2013). The changes in coefficient signs happen to occur for both variables around the last phase of Reg. NMS. Similarly the explanatory power measured as R^2 rises steadily post-Reg. NMS. Although, by removing the financial crisis the betas and R^2 values are roughly cut to half.

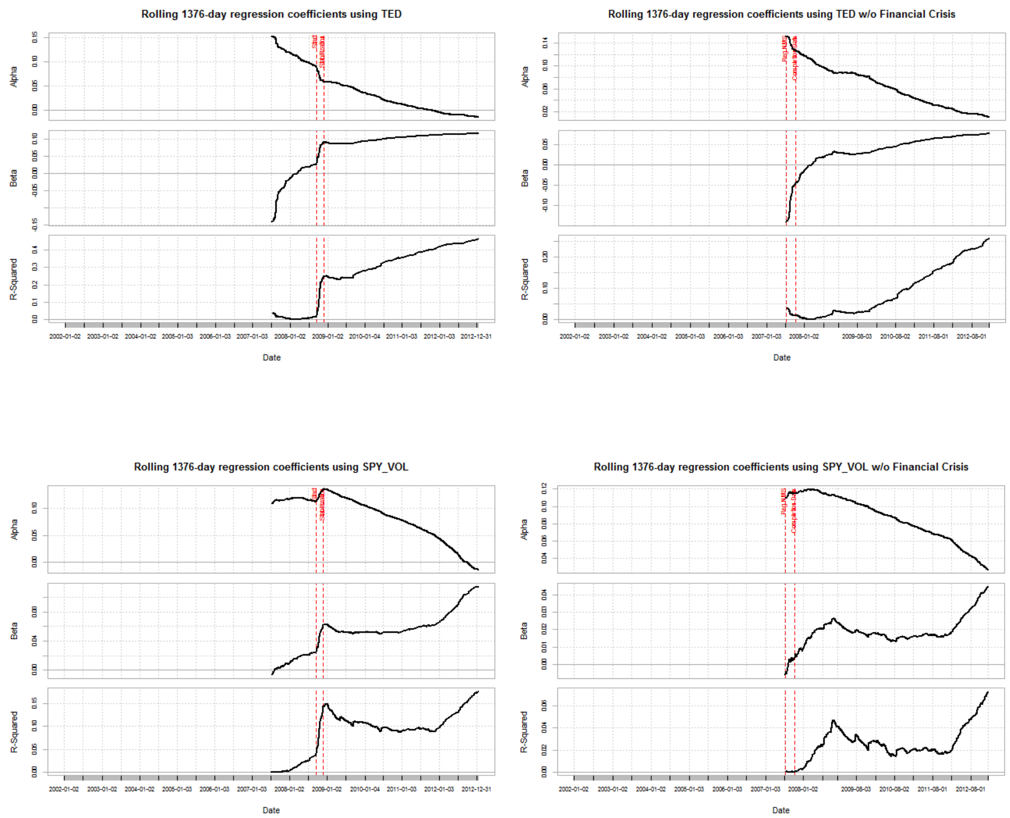

Figure 1. Rolling regression coefficients using TED and SPY_VOL. The dependent variable is the absolute size of premiums. The period indicated by red lines in left figures is the 50-days around Lehman Brothers bankruptcy while the period marked in red in the right side figures is the starting point and completion of the last phase of Reg. NMS.

As the completion of Reg. NMS is expected to be a shock to the linear projection of a dynamic system of ETF premiums (as is the financial crisis) we will use the Kalman filter to estimate the time-varying betas of the two most significant factors behind ETF premiums. Following this method we will reduce the noisiness to obtain a statically more reliable estimate. In addition, using the Kalman filter algorithm to obtain the beta estimates we will use the observed series to update the estimate to learn from previous and new states of nature (see Kalman 1960; Grewal & Andrews 2008). Figure 2 presents the time-varying beta estimates for TED and SPY_VOL using the Kalman filter method.

The figures show huge changes for both variables in time-varying beta estimates during the period from mid-2007 to 2009. The beta estimate for TED has been relatively close to zero during the whole period having experienced huge variation after Reg. NMS and during the financial crisis. The SPY_VOL beta shows different behavior as its time-varying beta experienced a radical up-side movement from 2005 to mid-2007 and falling rapidly after this point. This spiking point in time-varying SPY_VOL beta coincides moderately with the completion of Reg. NMS. The observed direction in beta estimate post-Reg. NMS has been falling. This might serve as a proof that post-Reg. NMS period indeed has been having characteristically larger trading volumes. The relationship with the rising trading volumes is inversely related to observed absolute size of ETF premiums, therefore leading to falling regression coefficient. This is in line with the argument that heightened HFT has some effects on ETF premiums by shrinking premiums efficiently via arbitrage process.

Moreover, the time-varying beta estimates show that most of the statistically significant explanatory power of TED spread which is shown in linear regressions is due to the short period during the financial crisis. One could argue that this verifies that TED spread can explain ETF premiums during the times of high market stress but has little statistical explanatory power to the actual level and sign of ETF premiums outside of such periods. The connection to HFT is thus not as meaningful as explained in the research design and shown by the regression analysis. TED serves as a proxy for market stress and can be used to predict ETF premiums in times of market stress, when the normal arbitrage mechanism is distorted.

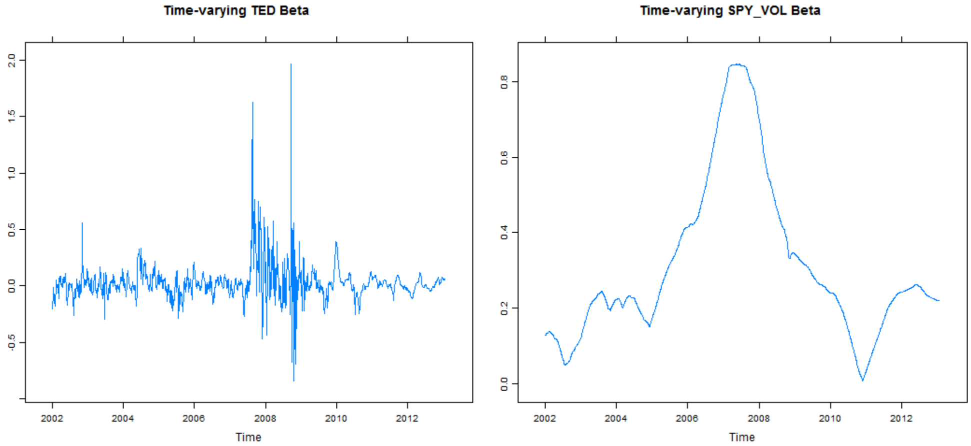

Figure 2. The time-varying betas using Kalman filters for TED and SPY_VOL as the independent variables and abs(ETF premium) as the dependent variable.

The results obtained by rolling regression analysis and Kalman filtered time-varying beta estimation show outcomes which are partly in line with the expectations. It was argued that TED spread as a proxy for arbitrage capital might be able to predict ETF premiums. Our findings reveal that such an explanatory power largely appears as an illusion in later times as it was only due to relatively small period during the financial crisis. Still, in such times it can predict widening ETF premiums. Davidson (2013) showed a relationship between prior stock market returns and daily ETF mispricing while our results indicate that this is only due to 50-days around the financial crisis, having very little meaning before that or in later times. Therefore this finding is against prior cross-sectional[16] empirical results.

In the research design we argued that prior levels of VIX can explain ETF premiums; this is also related to heightened volatility during the financial crisis where the arbitrage mechanism supposedly broke down and has near zero explanatory power if this era is removed. SPY_VOL on the other hand showed somewhat similar behavior as was expected: its regression beta twisted during the period of Reg. NMS completion and the factor has showed rising explanatory power since.

To see if this change in regression coefficient has been statistically significant, the fluctuating process of the linear regression residuals was computed using recursive

[16]It is worth noting again that this study aims only to explain the premiums related to SPY, and not the cross-sectional ETF universe.

residuals. The statistical significance at 95 % confidence interval was then estimated by a test based on the cumulative sum of recursive residuals (Rec-CUSUM) (see Brown et al 1975).

Figure 3 plots the Rec-CUSUM process for linear regression residuals using TED and SPY_VOL as the independent factors explaining the absolute size of SPY premiums. Structural change is considered to be statistically significant if the boundary levels are penetrated at some point. The figures verify that the implementation date of Reg. NMS has not been statistical significant and cannot therefore serve as an exhaustive structural break, although the CUSUM path for TED spread shows interesting behavior after that point. The figure also reveals that both variables have experienced a huge shift in their relation to ETF premiums after the financial crisis where their CUSUM path starts to deviate further away from the $\alpha = 0.05$ boundary levels and from the zero mean. This huge shift in empirical fluctuating process is difficult to explain qualitatively, but one explanation can be a notably calm period in SPY premiums after the financial crisis. This might be due to very efficient arbitrage trading in SPY premiums which would also explain the falling explanatory power when using TED spread as an independent variable.

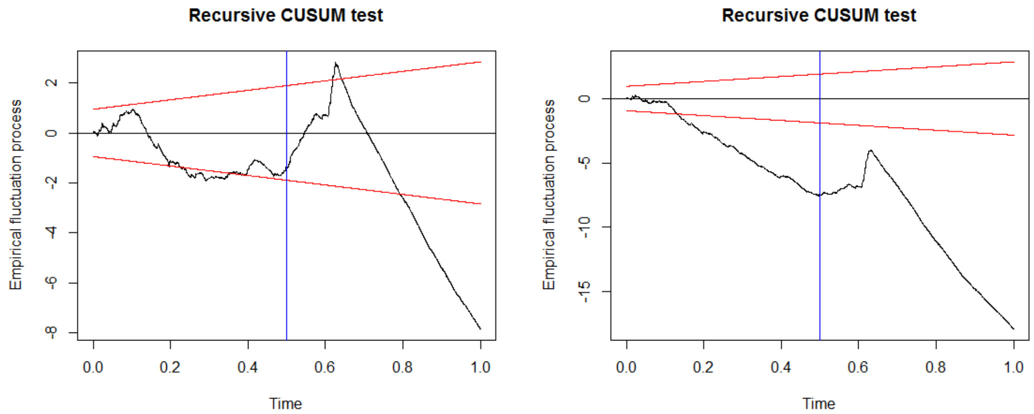

Figure 3. Recursive CUSUM test. Left figure shows the empirical fluctuation process for the linear relationship between TED spread and abs(premium). Right hand figure plots the same using SPY_VOL as independent variable. The blue line at t = 0.5 is the implementation date of Reg. NMS final phase.

8.3 ETF premium volatility modeling

The time period for ETF premium volatility modeling was chosen to represent the characteristics of post-Reg. NMS era. The in-the-sample model specification period is 09.07.2007 – 22.09.2011 (1051 observations) and the out-of-the-sample forecasting and model testing period is 23.09.2011 – 31.10.2013 (525 observations).

The exogenous variables included to the modeling process were the most statistically significant factors from the regression analysis in post-Reg. NMS era. Although CBY was dropped out immediately as the observed relationship with ETF premiums was qualitatively difficult to explain. After reviewing the GARCH model with possible candidates for exogenous variables, the chosen exogenous regressors are TED spread and the feature scaled daily SPY trading volume (SPY_VOL). These factors also have the most qualitatively meaningful role which follows tightly the research design. They also proved to be the most statistically significant regressors measured by their parameter standard errors.

The log series of daily SPY premiums shows significant autocorrelation. This was aimed to be removed by modeling of the mean process. The ACF and PACF for the AR(1) model residuals and squared residuals shows the existence of ARCH effects on the time-series. GARCH(1,1) model specification was started with ARMA(1,1)+GARCH(1,1) model including a list of exogenous variables. By dropping out the insignificant variables and model parameters we obtained a simple GARCH(1,1) with TED and SPY_VOL serving as exogenous variables in the variance equation while only TED showed statistical significance in the mean equation.

Models were also recalibrated using different distributions for the error terms: normal distribution, Student’s t-distribution, and skew Student’s t-distribution were tested. The Student’s t-distribution proved to give the best fit for the time-series. The final GARCH(1,1) with Student’s t-innovations and exogenous variables produced the following model (table 10):

Table 10. GARCH(1,1) model results.

Dependent Variable: log SPY premium		
Explanatory variables:	Estimate	Std. Error
Mean reg1 (TED)	-0.0145	0.0040
Omega	9.52E-11	5.13E-09
Alpha	0.1355	0.0453
Beta	0.8567	0.0405
Var reg1 (TED)	0.0003	0.0001
Var reg2 (SPY_VOL)	8.55E-05	2.58E-05
Shape	4.6587	0.8476
AIC	-2.0777	

The fitted SPY premium volatility time-series for the model calibration period is shown in figure 4. The out-of-the-sample model testing was conducted using the relevant exogenous factors and for comparison without such exogenous signals. The SPY premium time-series prediction against the actual observed series is shown in figure 5 while the rolling volatility predictions are presented in figure 6.

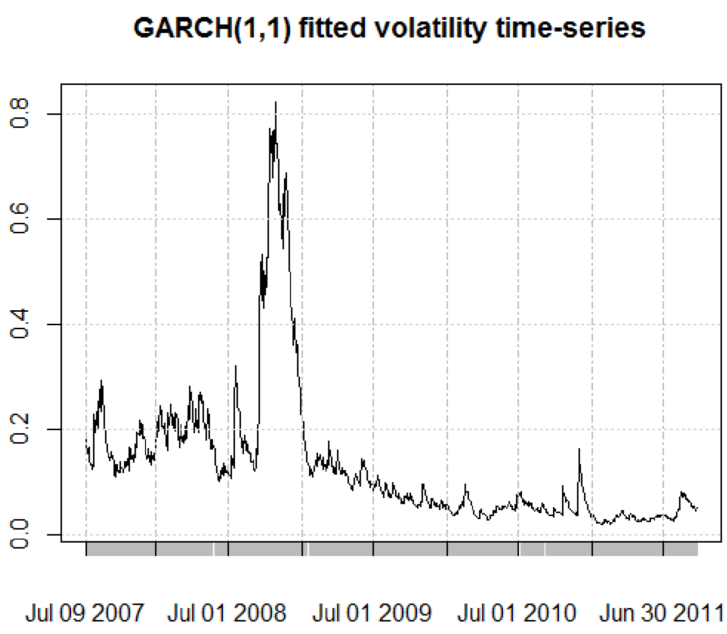

Figure 4. Fitted SPY premium volatility time-series 09.07.2007 – 22.09.2011.

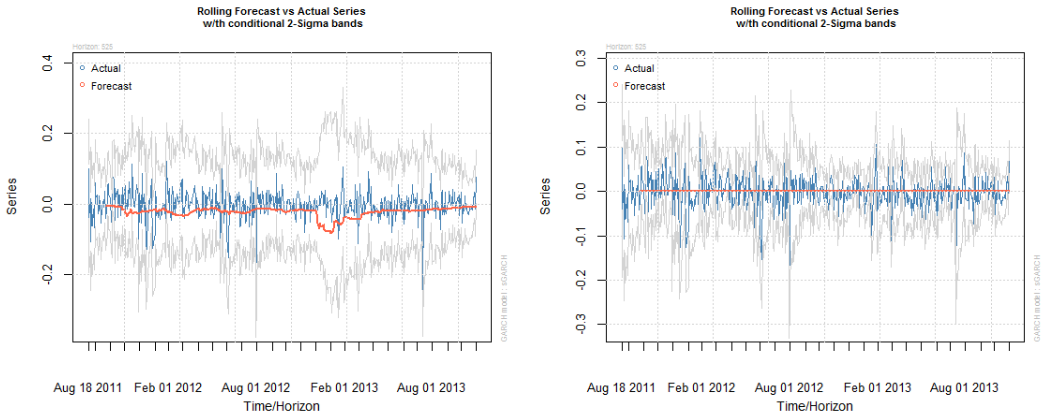

Figure 5. SPY premium time-series predictions 23.09.2011 – 31.10.2013. Left figure plots the predictions against the observed time-series using exogenous regressors while the right hand figure plots GARCH(1,1) without exogenous variables.

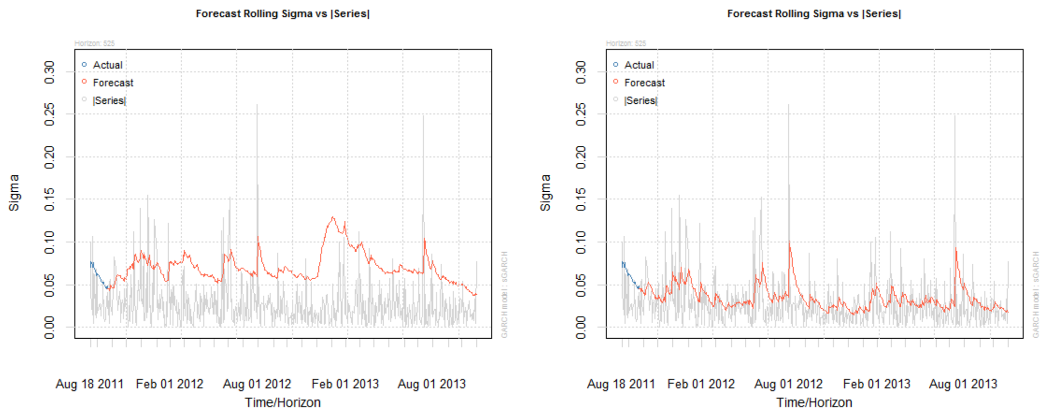

Figure 6. Rolling SPY premium volatility time-series predictions 23.09.2011 – 31.10.2013. Left figure plots the predictions against the observed time-series using exogenous regressors while the right hand figure plots GARCH(1,1) prediction without exogenous variables.

9 SUMMARY

Various studies have verbally pointed HFTs connection to ETF pricing process, leaving the in-depth analysis widely uncovered. This study starts by explaining the theoretical aspects of ETF arbitrage and by arguing that this trading strategy is mostly attractive to HFTs. In the empirical part we introduce some naive HFT activity proxies to a simple factor model explaining the observed SPDR trust (SPY) premiums to its NAV price during a period from 2nd of January 2002 to 15th of January 2013. In addition, various statistical and econometrical tools are employed to study the relationship between these factors and the SPY premiums. Namely these tools include regression analysis, rolling regressions, The Chow test, Kalman filter estimated time-varying betas, a test based on the cumulative sum of recursive residuals, and fitting a GARCH volatility model with the help of exogenous variables to predict SPY premiums.

Empirical results indicate that the absolute size of ETF premium is significantly related to endogenous ETF factors. In addition, the exogenous factors serving as a proxy for available arbitrage capital improve the explanatory power. Further analysis shows that the significant regression coefficients and explanatory power behind used factors is generated mainly due to the observations during the financial crisis. The Reg. NMS implementation failed to serve as an exhaustive structural break point in ETF pricing dynamics, but a detailed analysis on the relationship between two most important factors showed some movements that were in line with the expectations. These changes in regression coefficients were mostly statistically insignificant, although the post-Reg. NMS era has very low ETF premiums and higher trading volumes. This is in line with the idea that Reg. NMS made mushrooming HFT possible, and therefore high-frequency ETF arbitrage has become more efficient during this era. TED spread is significant in predicting ETF premiums during times of high market stress while ETF trading volume might serve as a naive factor for heightened HFT activity which is shrinking ETF premiums via arbitrage activity.

The main contribution of this study is related to the following issues: As ETF premiums can be significant in relation to their annual expense ratios investors can improve their trade execution by understanding the drivers behind ETF premiums. ETF premium modeling can also be useful in risk management and in investment decision making, while understanding HFTs' role in ETF mispricing adds to our incomplete knowledge on the effects of individual HFT strategies.

10 DISCUSSION

This study gets on with the research of individual HFT strategies and on their effects. The empirical result interpretation is mainly related to the risk-profile of arbitrageurs. The HFT activity around ETFs might be constrained by liquidity withdrawal, during market crisis, and in other periods of high volatility. Relatively little is known of the real HFT activity and how their trading behavior is related to factors such as used in this study to proxy their activity, but one can argue that these factors represent HFT risk-profiles at least in some level. There are times when HFT activity is reduced or completely paused and this may lead to widening ETF premiums. In addition, the high volatility and high cost of trading may cause HFTs to wait for a short amount of time (e.g. a trading day) until the ETF premium widens even more. High cost to finance short-term trading activities may introduce risks and other limits of arbitrage to arbitrageurs, making premiums last longer.

Previous studies have argued that TED spread as a proxy for arbitrage capital might be able to predict ETF premiums. Our findings reveal that such an explanatory power largely appears as an illusion in later times as it was only due to relatively small period during the financial crisis. Still, in such times it can predict widening ETF premiums. Davidson (2013) showed relationship between prior stock market returns and daily cross-sectional ETF mispricing, while our results show that when concentrating only to SPY this is due to 50-days during the financial crisis, having very little meaning before that or in later times. Similarly, in the research design we argued in line with previous papers that prior levels of VIX can explain ETF premiums. This is also related to heightened volatility during the financial crisis where the arbitrage mechanism supposedly broke down and has near zero explanatory power if this era is removed. SPY_VOL on the other hand showed somewhat similar behavior as was expected: its regression beta twisted around the period of Reg. NMS completion and the factor has showed rising explanatory power since.

The methodological choices used in this study leave a room for improvement. For example, the ETF premium modeling process is overly simplistic and could be improved by employing more sophisticated tools. This fundamental fragility is especially show in the chosen research data as we could only construct naive HFT proxies.

For example, ETF trade quotation data could be used to produce more reliable proxies for HFT activity around a certain ETF. Furthermore, intraday data and trade identifiers could be used to construct tick-by-tick ETF trades to find out more accurately the effects of HFT in ETF pricing process.

Even with it flaws, this study revealed various previously uncovered issues related to the factors behind ETF mispricing. In addition, this was the first paper, to our knowledge, to address the possible effects of Reg. NMS to ETF pricing process. The paper can be useful in future research and especially for idea formation purposes. Considering the current lack of empirical research on HFTs connection to ETF pricing, further papers on the topic are extremely desirable and valuable.

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APPENDICES

Appendix I List of factors and data sources

Available Arbitrageurs Capital:

TED Spread (TED) is defined as the difference between 3-month LIBOR and T-bill rates. Brunnermeier et al. (2009) explain the importance of TED spread as a premium that financial institutions would have to pay for their lending to finance their trading activities in relation to the true risk-free rate.
Source: http://www.federalreserve.gov/releases/h15/data.htm.

VIX Index (VIX) is defined as the Chicago Board Options Exchange Market Volatility Index. This serves as a proxy for available arbitrageurs' capital as higher volatility increases traders capital needs. Petäjistö (2011) and Davidson (2013) have documented the significance between VIX levels and ETF premiums. Source: http://finance.yahoo.com/q?s=^VIX.

Bond-oriented Risk Factors:

Yield Spread (YSPR) is defined as the difference between Moody's seasoned Baa corporate bond yield (BAA) and 10-year Treasury constant maturity rate (GS10). Source: http://www.federalreserve.gov/releases/h15/data.htm.

Corporate Bond Yield (CBY) is the difference between Moody's seasoned Baa corporate bond yield (BAA) and Moody's seasoned Aaa corporate bond yield (AAA). Source: http://www.federalreserve.gov/releases/h15/data.htm.

Fung-Hsieh Mutual Fund Risk Factors applicable at daily level:

FH1: *US Equities*: MSCI North American Equities [Datastream series: MSUSAM$(RI)].

FH2: *Non-US Equities*: MSCI non-US Equities [Datastream series: MSWXUS$(RI)].

FH3: *Emerging Market Equities*: MSCI Emerging Market index monthly total return [Datastream series: MSEMKF$(RI)].

FH4: *1-month Eurodollar Deposit Return*: One-month Eurodollar deposit rate of the previous month [Datastream series: ECUSD1M].

FH5: *Spot Gold*: Unofficial price for spot gold London morning fixing [Datastream series: GOLDBLN(UF)].

Source for above factors: THOMSON REUTERS DATASTREAM.

FH6: *TWEXMMTH*: Trade Weighted U.S. Dollar Index. Source: http://www.federalreserve.gov/releases/h10/Summary/indexn96_b.txt.

Kenneth French Industry Portfolios (Financial Industry Stress Factor):

Finance Industry Portfolio (MONEY). Finance industry value weighted returns. Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

ETF Endogenous Factors (HFT activity proxies):

Daily SPY volatility (SPY_S). A simple estimation of daily volatility calculated by using the true range of daily price variation. This is calculated as follows:

$$Vol_t = \frac{HI_t - LO_t}{Close_t}$$

where HI_t is the highest price during day t, LO_t is the lowest price in day t, and $Close_t$ is the closing price at day t. Source: Bloomberg.

SPY trading volume (SPY_VOL). A standardized measure of ETF daily trading volume with mean 0 and standard deviation of 1. A high daily value, say above one sigma, indicates higher than normal trading volume. This can serve as a simple proxy for heightened HFT activity as they generate majority of market trading volume. Source: Bloomberg.

Change in Shares (SHARES). The daily percentage change in amount of ETF shares outstanding. This serves as a measure of share creation/redemption process. Source: Bloomberg.

S&P 500 Endogenous Factors:

S&P 500 daily return (SP_R). Daily log return of S&P 500 index. Source: http://finance.yahoo.com/q?s=%5EGSPC.

Daily S&P 500 volatility (SP_S). A simple estimation of daily volatility calculated by using the true range of daily index variation. This is calculated as follows:

$$Vol_t = \frac{HI_t - LO_t}{Close_t}$$

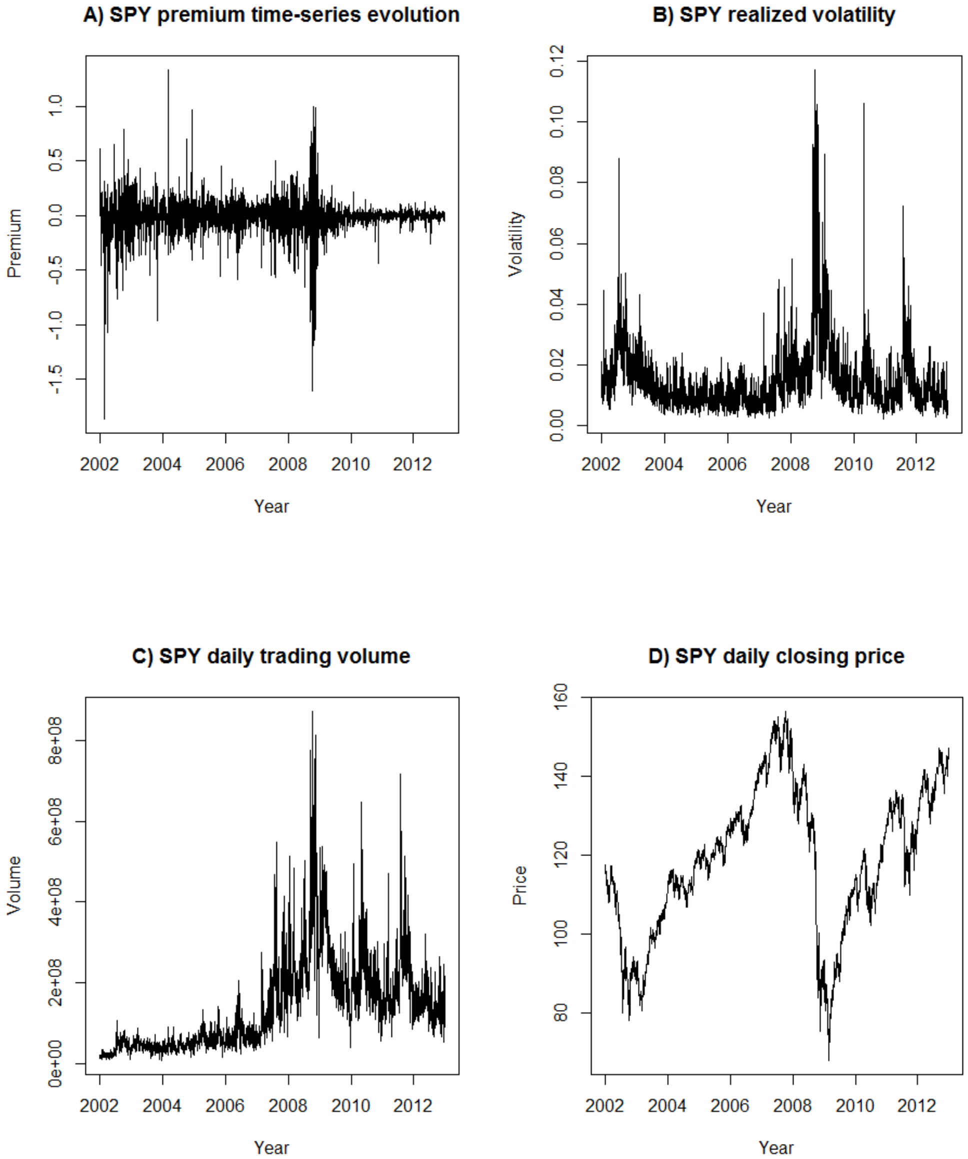
where HI_t is the highest point during day t, LO_t is the lowest point in day t, and $Close_t$ is the closing point at day t. Source:http://finance.yahoo.com/q?s=%5EGSPC.

S&P 500 trading volume (SP_VOL). A standardized measure of index daily trading volume with mean 0 and standard deviation of 1. A high daily value, say above one sigma, indicates higher than normal trading volume. This can serve as a simple proxy for heightened HFT activity as they generate majority of market trading volume. Source: http://finance.yahoo.com/q?s=%5EGSPC.

Appendix II Correlations between independent variables.

	TED	VIX	YSPR	CBY	FH1	FH2	FH3	FH4	FH5	FH6	MONEY	SPY_S	SPY_VOL	SHARES	SP_R	SP_S	SP_VOL
TED	1.00																
VIX	0.57	1.00															
YSPR	0.47	0.84	1.00														
CBY	0.59	0.78	0.91	1.00													
FH1	-0.05	-0.13	-0.02	-0.01	1.00												
FH2	-0.07	-0.15	-0.03	-0.02	0.56	1.00											
FH3	-0.07	-0.15	-0.02	-0.01	0.47	0.81	1.00										
FH4	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.02	1.00									
FH5	-0.01	-0.02	-0.01	0.00	-0.03	0.21	0.19	-0.01	1.00								
FH6	0.04	0.04	0.00	0.01	-0.12	-0.52	-0.35	-0.01	-0.44	1.00							
MONEY	-0.04	-0.11	-0.01	0.00	0.89	0.44	0.37	-0.03	-0.07	-0.08	1.00						
SPY_S	0.54	0.78	0.58	0.57	-0.12	-0.19	-0.19	-0.02	-0.02	0.08	-0.08	1.00					
SPY_VOL	0.54	0.48	0.45	0.43	-0.05	-0.11	-0.12	-0.01	-0.03	0.05	-0.05	0.43	1.00				
SHARES	0.04	0.02	0.01	0.00	-0.03	0.04	0.01	-0.03	0.03	-0.05	-0.04	0.00	0.02	1.00			
SP_R	-0.05	-0.13	-0.02	-0.01	0.99	0.55	0.46	-0.03	-0.03	-0.12	0.90	-0.11	-0.05	-0.03	1.00		
SP_S	0.53	0.79	0.60	0.57	-0.11	-0.19	-0.20	-0.02	-0.03	0.08	-0.07	0.95	0.45	0.01	-0.11	1.00	
SP_VOL	0.50	0.40	0.45	0.46	-0.01	-0.05	-0.06	-0.01	-0.01	0.04	-0.01	0.32	0.92	0.01	-0.01	0.34	1.00

Appendix III Figures of SPY time-series



A) shows the SPY premium time-series evolution during the time period used in the main part of this study. B) is the SPY realized daily volatility as measured by SPY_S. C) is the daily SPY trading volume, and D) the daily SPY closing price.

Appendix IV Regression results prior and after Reg. NMS

Regression results using actual level of premiums with divided time period. The dependent variable is the daily ETF premium. Panel A presents the results before the implementation of Reg. NMS. Panel B shows the time period post-Reg. NMS. Independent variables are dropped according to lowest absolute t-statistics from the regression run to the latter time period (2007-2013).

Panel A: Time period 2.1.2002 – 6.7.2007

	(1)	(2)	(3)	(4)
Intercept	-0.0035	0.0205 *	0.0210 *	0.0209 *
	(-0.75)	(2.34)	(2.38)	(2.36)
$MONEY_t$	0.0027	0.0023	0.0033	0.0037
	(0.62)	(0.52)	(0.68)	(0.74)
SPY_S_t		-1.9142 **	-1.9512 **	-1.9478 **
		(-3.20)	(-3.23)	(-3.23)
$FH2_t$			-0.2745	-0.3350
			(-0.48)	(-0.56)
$FH5_t$				0.1602
				(0.34)
N	1376	1376	1376	1376
Adj. R^2	0.00	0.01	0.01	0.01

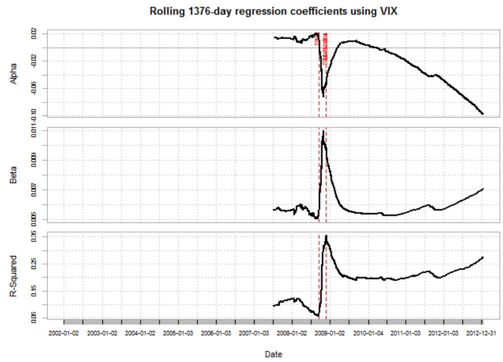
Panel B: Time period 9.7.2007 – 15.1.2013

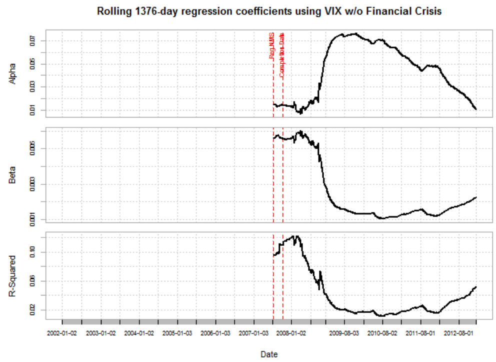
	(1)	(2)	(3)	(4)
Intercept	-0.0113 **	0.0267 ***	0.0217 **	0.0218 ***
	(-2.68)	(4.02)	(3.27)	(3.31)
$MONEY_t$	-0.0179 ***	-0.0190 ***	-0.0232 ***	-0.0245 ***
	(-10.86)	(-11.69)	(-12.94)	(-13.51)
SPY_S_t		-2.1844 ***	-1.8793 ***	-1.8372 ***
		(-7.34)	(-6.26)	(-6.15)
$FH2_t$			1.5907 ***	1.9220 ***
			(5.33)	(6.22)
$FH5_t$				-1.2028 ***
				(-3.89)
N	1376	1376	1376	1376
Adj. R^2	0.08	0.11	0.13	0.14

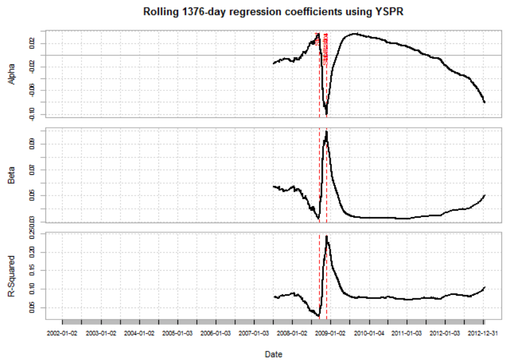
N = number of observations, *t*-values in parentheses,
* = 0.05 level of significance, ** = 0.01 level of significance, and *** = 0.001 level of significance.

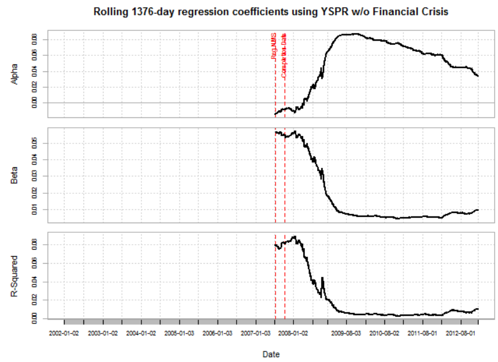
Appendix V Figures of rolling regression coefficients

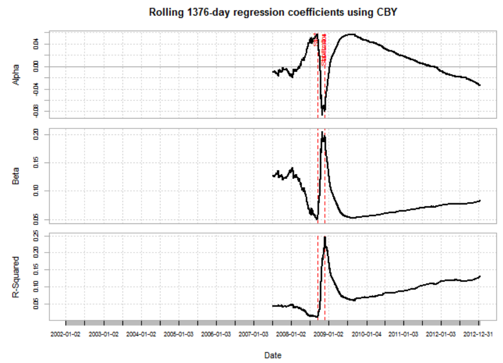
The rolling regression coefficients for the rest of the independent variables using abs(ETF premium) as the dependent variable. The period indicated by red lines in left figures is the 50-days around Lehman Brothers bankruptcy while the period marked in red in the right side figures is the starting point and completion of the last phase of Reg. NMS.

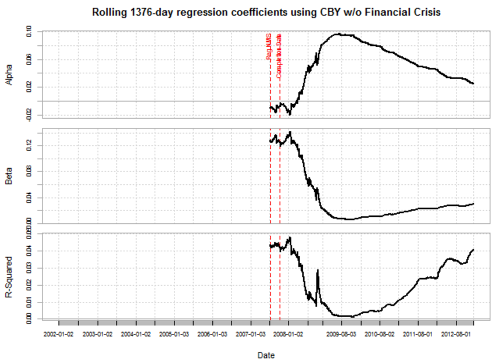


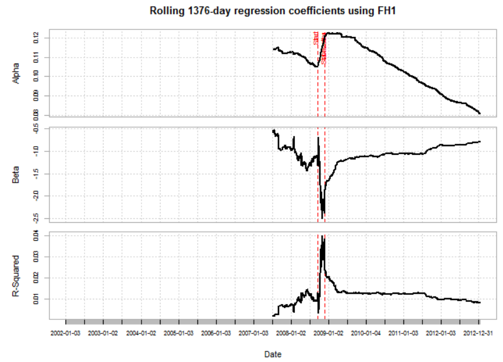


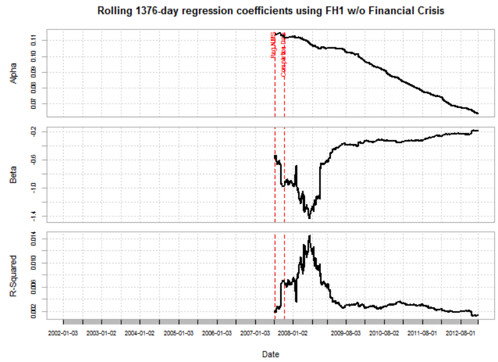


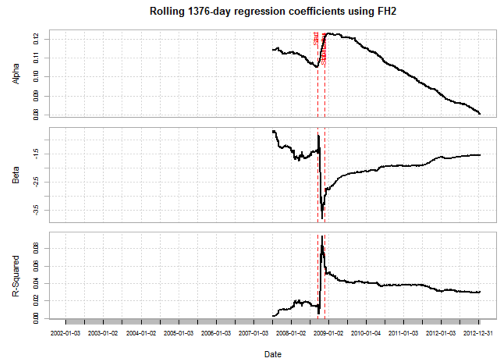


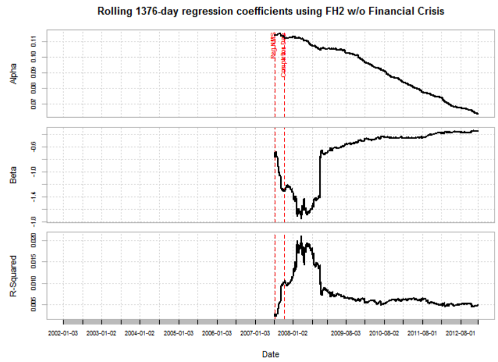


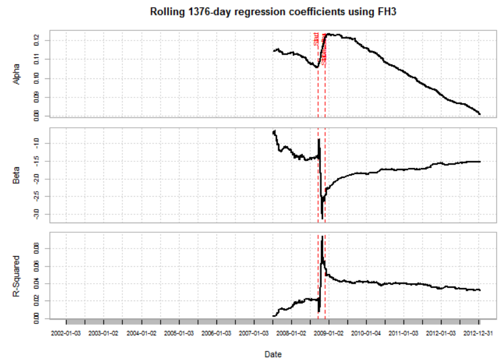


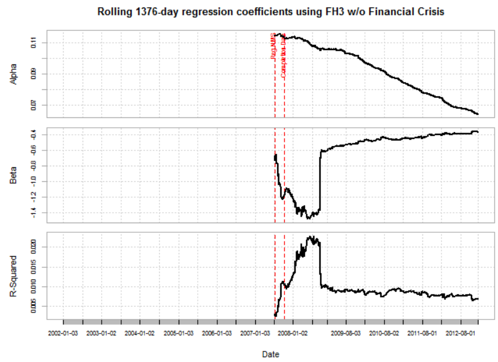

Rolling 1376-day regression coefficients using FH1
Alpha
Beta
R-Squared
Date

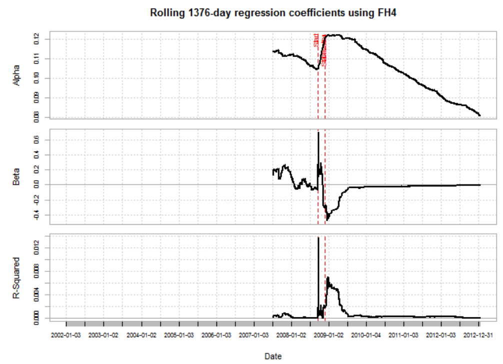

Rolling 1376-day regression coefficients using FH1 w/o Financial Crisis
Alpha
Beta
R-Squared
Date

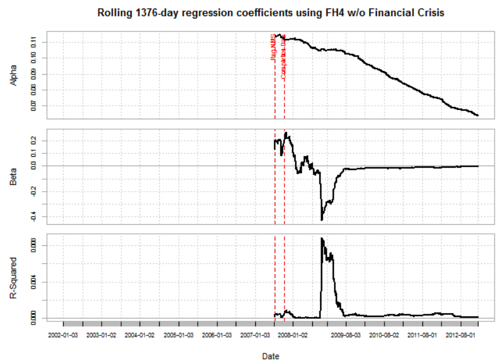

Rolling 1376-day regression coefficients using FH2
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using FH2 w/o Financial Crisis
Alpha
Beta
R-Squared
Date

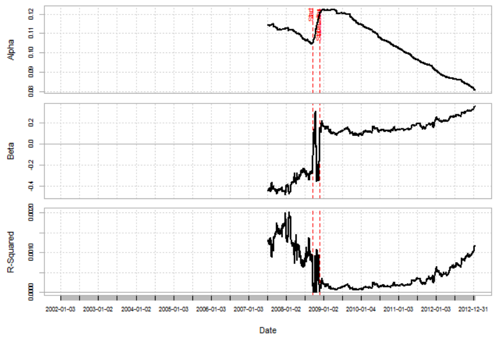

Rolling 1376-day regression coefficients using FH3
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using FH3 w/o Financial Crisis
Alpha
Beta
R-Squared
Date

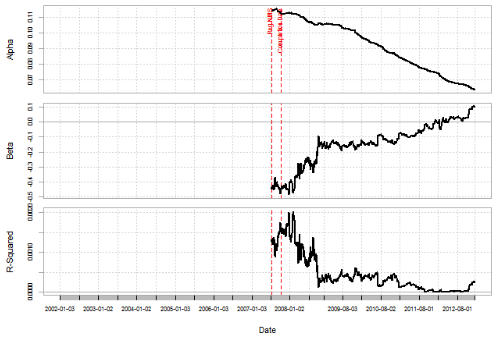

Rolling 1376-day regression coefficients using FH4
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using FH4 w/o Financial Crisis
Alpha
Beta
R-Squared
Date

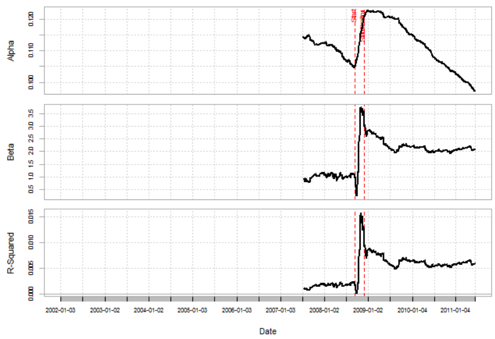
Rolling 1376-day regression coefficients using FH5



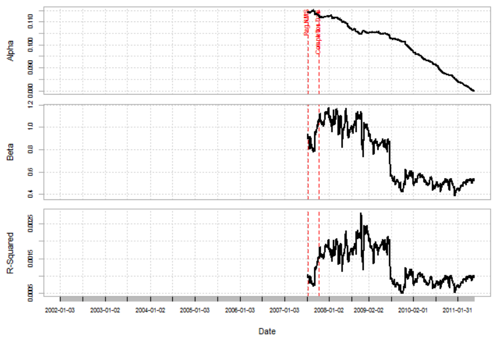
Rolling 1376-day regression coefficients using FH5 w/o Financial Crisis



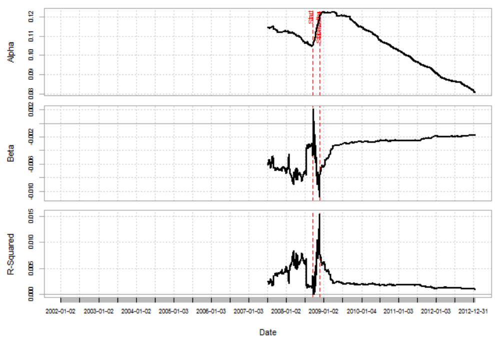
Rolling 1376-day regression coefficients using FH6



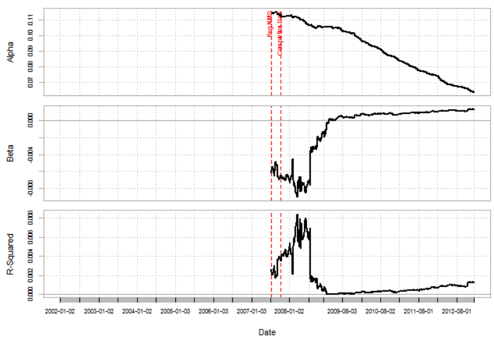
Rolling 1376-day regression coefficients using FH6 w/o Financial Crisis



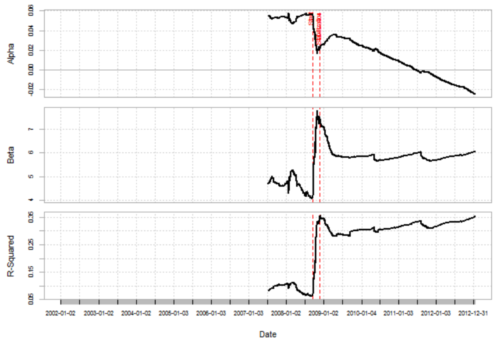
Rolling 1376-day regression coefficients using MONEY



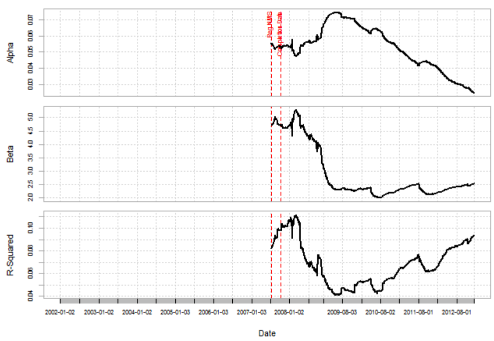
Rolling 1376-day regression coefficients using MONEY w/o Financial Crisis

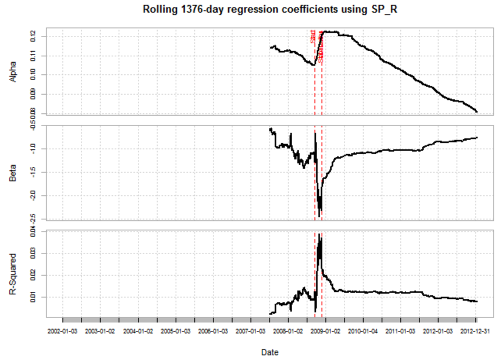


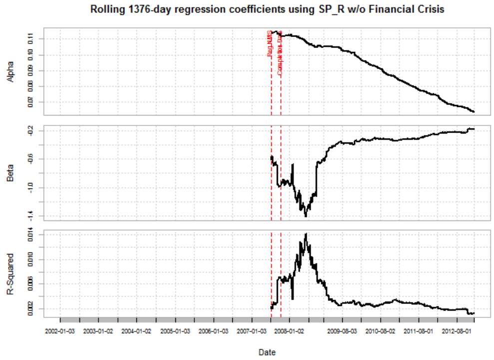
Rolling 1376-day regression coefficients using SPY_S

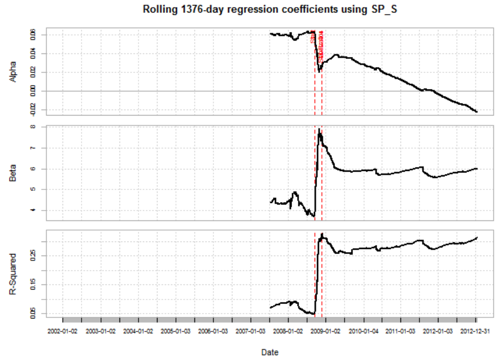


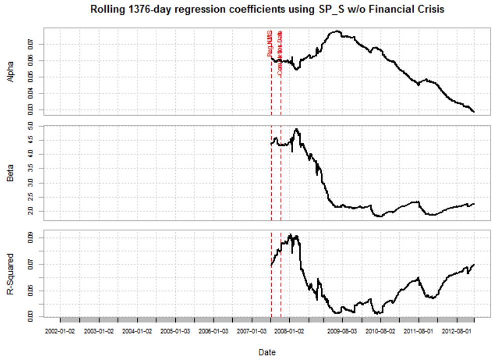
Rolling 1376-day regression coefficients using SPY_S w/o Financial Crisis

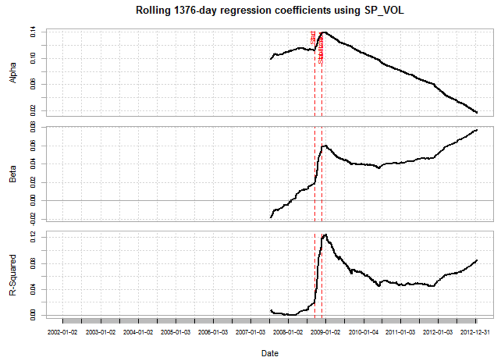


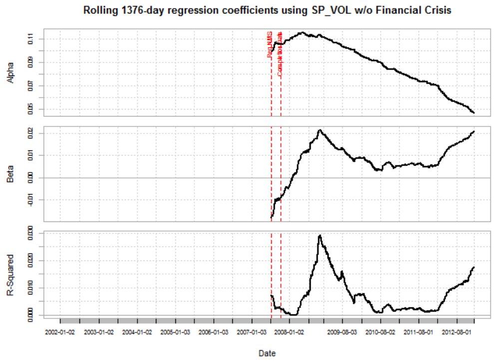

Rolling 1376-day regression coefficients using SP_R
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using SP_R w/o Financial Crisis
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using SP_S
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using SP_S w/o Financial Crisis
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using SP_VOL
Alpha
Beta
R-Squared
Date


Rolling 1376-day regression coefficients using SP_VOL w/o Financial Crisis
Alpha
Beta
R-Squared
Date