ETFs tracking the S&P 500:

Short-term demand and comovement

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Abstract

ETFs are an increasingly attractive vehicle for index investing, and part of ETF demand includes that from short-term investors. Using relative trading volume and relative liquidity, we study whether these proxies for ETF short-term demand increase the correlations of the underlying stocks. We test our hypotheses on the S&P 500 and find that increases in ETF trading activity and higher ETF relative liquidity is related to increasing constituent stock correlations. Further, we find the increase in correlations and ETF trading activity is also associated with return reversals, providing evidence that ETF trading activity imparts noise into underlying stock returns.

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Introduction

Modern portfolio theory started in the 1950s when Markowitz (1952) developed what we now know as the efficient frontier, the Pareto-optimal set of risk-return combination of portfolios of maximum return for any given mean-variance portfolio. This theory was extended by Sharpe (1964) and later Fama and French (1993), shaping how we think about investing through factors. These innovations, and others that have been developed from them, have changed the way we think about risk and have been incorporated into investment products. Specifically, this included the concept of the importance of return comovement within a portfolio as a measure of risk. Another important development was the idea that investors are better off, after fees, "buying the market" rather than picking individual stocks, as popularized by Malkiel (1973) in his book A Random Walk Down Wall Street. Soon after in 1976, John C. Bogle the founder of Vanguard launched the first index mutual fund, tracking the S&P 500 Index (Abner, 2016, p. 18).

State Street Global Advisor's SPDR S&P 500 fund (SPY) was the first exchange traded fund (ETF) launched in the United States in 1993 and remains the oldest and most successful ETF in the US (Ben-David, Franzoni, & Moussawi, 2017, p. 7). ETFs have seen enormous growth in the last two decades both in assets under management and in numbers of funds as can be observed from figure 1.1. ETFs are a financial instrument innovation that combines the ease and liquidity of trading shares like any other stock on an exchange and the benefits of investing in a diversified portfolio like a mutual fund. The proliferation of equity ETFs include those tracking major indexes and as well those created for factor and style investing, for example value and growth. Moreover, in 2014 the vast majority (approximately 99%) of US ETFs assets were passively managed (PwC publications, 2015, p. 19).

According to Investment Company Institute (2018), as of February 2018, the combined assets of US ETFs were $3.47 trillion in 1,878 ETFs, with almost $2 trillion in domestic equity. Over the year prior to February 2018, ETF assets increased $738.28 billion, or 27.1 percent, and of that growth, domestic equity ETFs increased $356.13 billion.

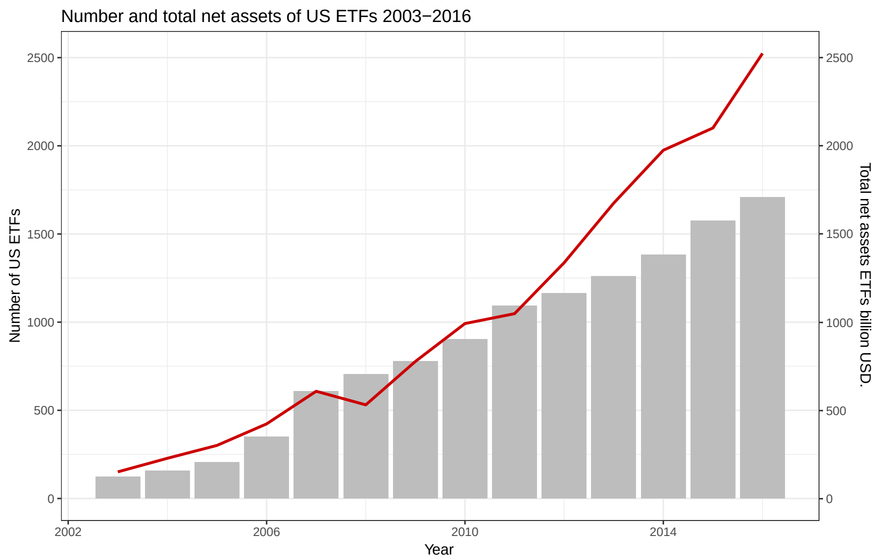


Figure 1.1: Number of ETFs (bars) left Y-axis and total net assets (line) right Y-axis. Only US registered ETFs from 2003 through 2016. Number of ETFs courtesy of Deutsche Bank (n.d.), total net assets from Investment Company Institute (n.d.).

Ben-David, Franzoni, and Moussawi (2017) report that in 2016 ETFs represented over 10% of the market capitalization of securities traded on US stock exchanges and over 30% of the overall daily trading volume. This is consistent with the data observed from figure 1.2 and 1.3. Furthermore industry experts project that ETF assets under management will nearly triple in the US and more than double globally over the next five years (Cox, 2016).

Despite its explosive growth, only recently has there been literature studying the effects of ETFs on the trading environment and its underlying basket of stocks. In the last few years, research has taken a closer look at what it means for stocks to be included on an index like the S&P 500 after the rise of ETFs. While some have shown the benefits of ETFs on the underlying stock though price discovery (Madhavan & Sobczyk, 2016), others have shown ETFs can have a negative impact on informational efficiency (Ben-David, Franzoni, & Moussawi, 2017; Israeli, Lee, & Sridharan, 2017).

Relatedly, others have shown that ETFs have exacerbated increasing comovement of stocks within an index (Da & Shive, 2017) that can be explained by ETF arbitrage activity (Da & Shive, 2017), and specifically by ETF demand shocks (Leippold, Su, & Ziegler, 2016), or ETF liquidity (Broman & Shum, 2018). The main mechanism by which ETF trading activity affects underlying stocks is through its arbitrage process, the creation and redemption of ETF shares to capitalize

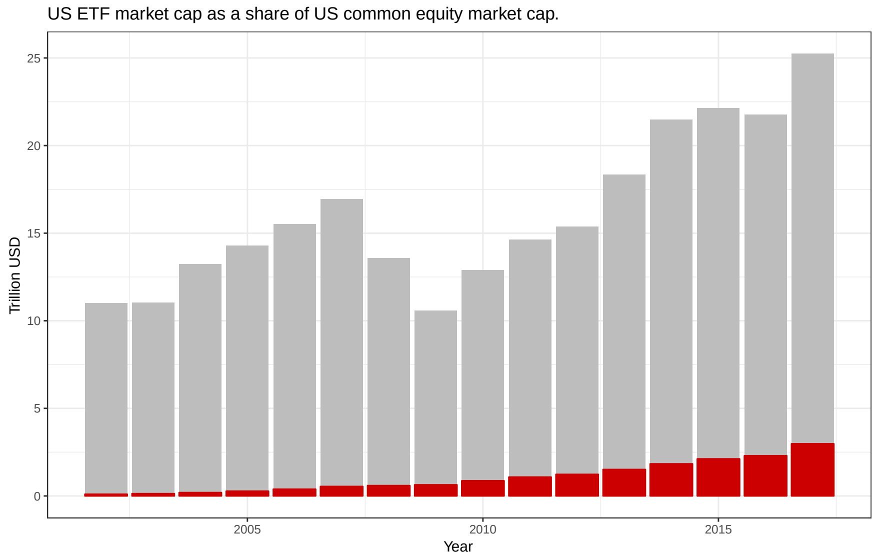


Figure 1.2: US ETF market capitalization (red) vs. US common equity market capitalization, the bars are not stacked. US ETF market capitalization is calculated as the monthly average market capitalization for US ETFs classified by share code 73 in the CRSP database (Center for Research in Security Prices, 2018h, pp. 81-2) US common equity market capitalization is calculated as the monthly average market capitalization for US common equity classified by sharecode 11 in the CRSP database (Center for Research in Security Prices, 2018h, pp. 81-2). All data is acquired from the CRSP monthly stock files (Center for Research in Security Prices, 2018e). The relative growth of ETFs is the important takeaway, where US Exchange traded funds today has over 10% of the market capitalization of US common equity. It is also important to note that a majority of ETFs hold common equity exclusively.

on the difference between ETF share price and its intraday net asset value (iNAV)[1]. While previous studies have examined the reasons behind the non-synchronous trading of ETF shares and its underlying stocks through demand and liquidity separately, no study has to date to the best of our knowledge has included both of these effects on stock correlations as we do here.

Broadly, the aim of this paper is to capture the effect of ETF demand, and specifically short-term demand, on their underlying stock correlations by studying the S&P 500 and ETFs that track the S&P 500. To do so, we form two hypotheses to separate the two theories behind increasing ETF demand or trading activity relative to the index, and that of ETF liquidity relative to the index constituent stocks as drivers of increasing comovement. Thus, the goal of this paper is to empirically test whether 1) an increase in relative ETF trading volume to the index trading volume is associated with an increase in index stock correlations, and 2) an increase in relative ETF liquidity to the underlying stocks' liquidity are related to increases in correlations among

[1] iNAV is sometimes also refereed to as the indicative net asset value (Abner, 2016, p. 220), but the two terms are used interchangeably in the literature.

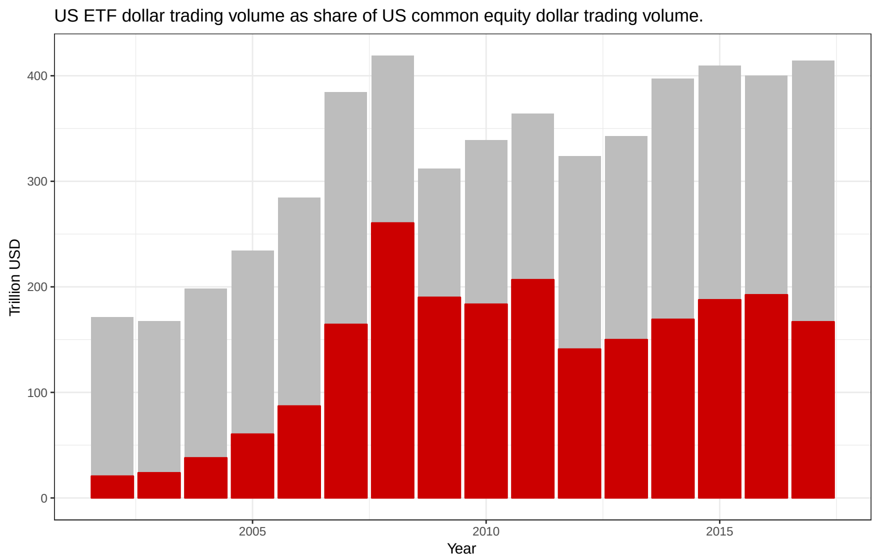


Figure 1.3: US ETF yearly dollar trading volume (red) vs. US common equity yearly dollar trading volume. Bars are not stacked. US ETF yearly trading volume is calculated as the sum of monthly dollar trading volume for US ETFs classified by share code 73 in the CRSP database conversly share code 11 for US common equity (Center for Research in Security Prices, 2018h, pp. 81-2). All data is acquired from the CRSP monthly stock files (Center for Research in Security Prices, 2018h). In itself this graph is not that important, but compared with figure 1.2, it becomes apparent that ETFs has a considerably higher turnover than common equity. This is important since one knows that a majority of ETFs consist off namely common equity.

the underlying stocks.

The first hypothesis is that a relative increase in trading volume between ETFs and its underlying stocks is associated with an increase in correlations among the stocks in the ETFs basket. Trading activity is measured by the daily trading volume and has been used both as proxy for demand (Leippold et al., 2016) and as a measure of liquidity (Hill, Nadig, & Hougan, 2015; Staer & Sottile, 2018) and therefore, we discuss trading volume in both respects. With respect to the demand aspect of trading volume, prior literature has shown that correlated demand can lead to increased correlations of the underlying assets (Greenwood, 2007; Barberis, Shleifer, & Wurgler, 2005). Because ETFs are created in baskets of typically 50,000 shares at a time, a creation unit, this trading activity could give rise to correlated price comovement. As a result, we should observe higher return comovement with increasing demand, as proxied by trading volume.

Our second hypothesis is that a relative increase in liquidity between ETFs and its underlying stocks is associated with an increase in correlations among the stocks in the ETFs basket. This hypothesis relies on a body of work providing evidence that higher liquidity stocks are preferred by short-term investors than lower liquidity stocks (Amihud & Mendelson, 1986; Ben-David, Franzoni, & Moussawi, 2017; Broman & Shum, 2018). Since short-term investors are defined by their higher turnover trading, such trading exerts price pressure on the ETF share price and triggers the arbitrage process. It follows that liquidity should be a proxy for short-term demand. However, liquidity is a multifaceted concept and defined in several ways. Here, we investigate ETF liquidity effects on correlation using the price impact measure of liquidity (Amihud, 2002), and the illiquidity of transaction costs (bid-ask spread). Trading volume, as discussed, represents another facet of liquidity and therefore we also examine trading volume as measure of liquidity in our analysis.

For both hypotheses, we use relative measures. This allows us to discuss ETF demand vis-à-vis underlying stock demand. In this sense, they encompass the non-synchronous trading relationship between the two that triggers the arbitrage process.

We test our hypotheses on the S&P 500 stocks and the three ETFs that track them, namely State Street's SPDR (SPY), BlackRock's iShares (IVV), and Vanguard's S&P 500 ETF (VOO). We find that our results are largely consistent with the view that ETF trading activity and short-term demand, as encompassed by both trading volume and liquidity, are related to correlations. Using the relative trading volume of ETFs to the total trading volume of the S&P 500, we find that it explains a lot of the variation of correlations, and is highly significant. The results show that 10% change in the trading ratio coincides with a .052 increase in average correlations.

We find a similar significant result in our other relative liquidity measure, but the relationship is not as strong as the trading ratio, as the results show that 10% increase in the aggregated relative liquidity measures is associated with a .001 increase in correlations. We conjecture that the trading ratio captures most of the short-term trading demand, since it is also a liquidity measure. Insofar as both measures capture short-term demand, we provide evidence to the argument that ETFs attract short-term traders and in doing so, increase the correlations among the underlying stocks.

To distinguish the effects of ETF short-term trading from ETF overall (net) demand broadly, we add ETF holdings percentage and an interaction term with the trading ratio. Holding percentage is defined as the ratio of the market capitalization of the three S&P 500 ETFs and the market capitalization of the S&P 500. Our findings show that overall ETF holdings percentage of the underlying market has no significance on average correlations. Even the interaction term of holdings percentage and the trading ratio has no significance. From this, we can see that the growth in ETFs are not significant in increasing correlations. Therefore, at least for the S&P 500, warnings about the enormous growth of ETFs seem to be overstated (Wurgler, 2010). However, it also lends support to our hypotheses that there is a part of ETF demand that does lend itself to increasing correlations, and that part is best explained by the presence of short-term traders.

We then address the question whether such increasing correlations are a result of increasing price discovery facilitated by ETFs or if they are incorporating a noise component in returns. There are two competing views regarding the price discovery effects of ETFs on the underlying stocks. The first is that ETF improve informational efficiency by being highly liquid (Madhavan & Sobczyk, 2016) and more quickly imparts fundamental information into the underlying stock prices (Glosten & Zou, 2016). The second view is that ETF demand also propagates non-fundamental demand such that it moves the prices of the underlying stocks away from intrinsic value (Israeli et al., 2017; Ben-David, Franzoni, & Moussawi, 2017).

To investigate whether our data shows that increasing correlations is related to non-fundamental moves in returns, we follow the methodology of Da and Shive (2017) and Leippold et al. (2016). If ETF demand propagates non-fundamental price pressure onto the underlying stocks, then the effects should be temporary and prices should revert soon thereafter. On the other hand, fundamental information represents information regarding intrinsic value and it should impart a more permanent effect on stock returns. Therefore, by regressing return reversals on correlations, we can observe whether correlations are excessive.

When we regress return reversals on our correlation measures, we find a positive and significant relationship. We go further and regress return reversals on our trading ratio variable and also find a positive and significant relationship to return reversals. This indicates that increases in both average correlation and the trading ratio coincide with non-fundamental movements in returns. This lends support to the argument that short-term traders of ETFs incorporate noise into the market as predicted by Greenwood (2007), Broman and Shum (2018) and Avramov, Chordia, and Goyal (2006) who show high liquidity stocks are associated with return reversals.

Interestingly, we do not find the same relationship with return reversals and relative liquidity. This means that although an increase in relative liquidity is associated with an increase in average correlation, we cannot say that it is related by non-fundamental demand. Further, our finding is robust to the measure of liquidity used, as composite measure or as individual measures. There are several possible explanations. The dataset used for our study only uses stocks from the S&P 500, compared to other studies that use data including stocks on other indexes. Moreover, perhaps the amihud measure and bid-ask spread are not adequate measures to capture liquidity for the ETFs studied here and the stocks on the S&P 500. In addition, we have already seen that although significant, they do not have much explanatory power in correlations.

What we can conclude from the results is that the trading ratio as a measure of trading activity of ETFs is associated with increasing correlations of the underlying stocks. To a lesser extent, we can also conclude that relative liquidity also increases correlations. Both of these findings affirm our hypotheses and is evidence that increases in short-term investor demand is associated with increases in correlations, but not long-term investor demand. The broader implications of increasing short-term trader demand is as relative trading activity and relative liquidity increases, investors of ETFs lose more of the diversification benefits of investing in the index. In other words, there is an increase in risk from investing in the S&P 500 as correlations increase and if such increasing risk cannot be diversified away, it adds to the market risk. Therefore, it may be that ETFs add a layer of systemic risk to the market. Furthermore, the increasing correlations are related to return reversals, indicating that the increasing correlations are incorporating noise into returns, and thus degrading the price discovery process by moving prices away from fundamental value.

1.1 The mechanics of ETFs

To understand how ETFs can affect its underlying stocks, it is important to understand their growth in the industry and how they function. In this section, we provide background information about ETFs and the mechanism that makes them unique financial instruments. The focus will be on physically replicating ETFs, which comprises most of the ETFs on the US market (Aramonte, Caglio, & Tuzun, 2017).

Fundamentally, ETFs are hybrid investments products. Like mutual funds, an investor buys shares in an ETF to own a proportionate interest in the pooled assets. They are like open-end mutual funds in that ETFs allow the creation and redemption of shares. Unlike mutual funds, the creation and redemption of an ETF shares is generally done "in-kind" and the ETF investor trades in or out a weighted underlying basket of securities for each share (Gastineau, 2010, p. 6) This process is the primary market for ETFs, the process of creation and redemption of ETFs shares. What makes them different from open-ended mutual funds is that these ETF shares are then publicly traded on the secondary market throughout the day like any publicly traded stock on an exchange as depicted in figure 1.4. This feature makes them more like close-end mutual funds whose shares are also traded publicly like a stock. However, close-end mutual funds issue a fixed number of shares to be traded whereas the number of shares outstanding for an ETF

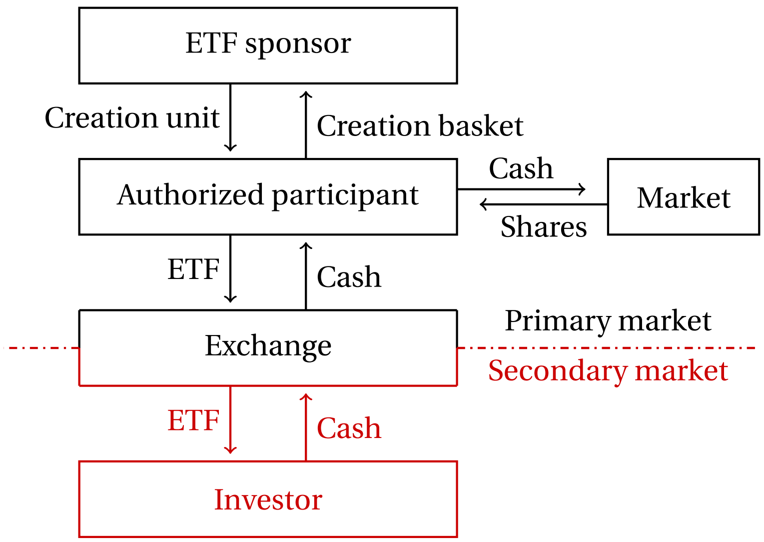


Figure 1.4: Market structure for creation of physically replicating ETF where figure the distinction between the primary and secondary market is highlighted. What is also important to note is that the authorized participants does not buy ETF shares from the ETF sponsor, but they trade a creation basket of shares + fee in-kind for a set number of ETF shares (creation unit). Oppositely APs can also redeem the basket of shares by delivering the same number of ETF shares as in a creation unit + a fee. Figure adapted from Ramaswamy (2011, p. 3)

changes with the creation and redemption of ETF shares (Abner, 2016, pp. 14-21).

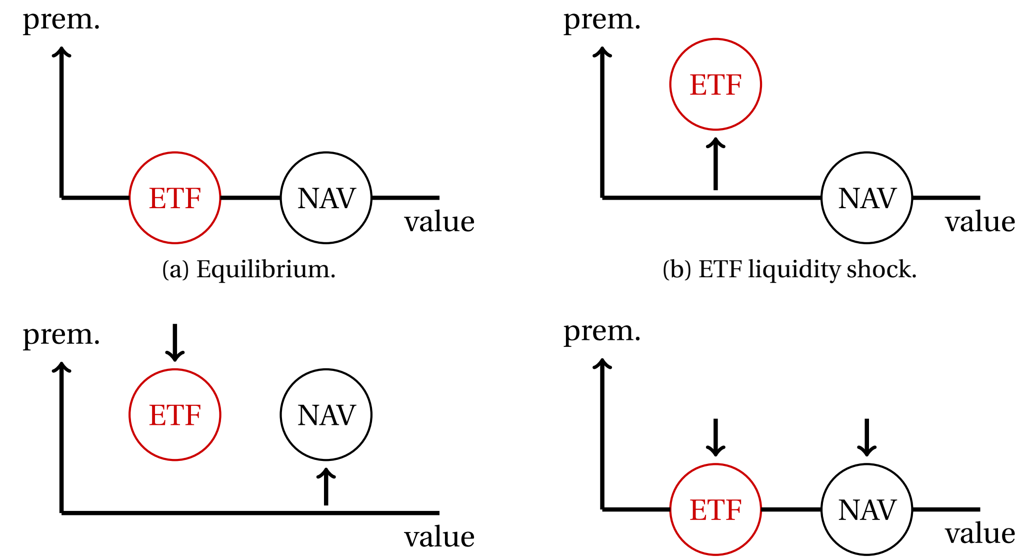
The secondary market for ETF shares function as for any other listed security. It is listed on an exchange and the price is determined by the market. Since ETFs represent pooled assets, the price of the ETF should be close to the value of the underlying assets. However, the market price of ETF shares often deviates from the intraday net asset value (iNAV) of the underlying stocks. To help keep the price close to the iNAV, the ETF sponsors publish the iNAV for each ETF every 15 seconds (Gastineau, 2010). When there is a large enough price discrepancy to overcome any transactions costs, investors will arbitrage the ETF and underlying stocks and the resulting price pressure brings the price of the ETF share and iNAV in line again. There are two types of market participants that stand to benefit from arbitraging the difference in ETF share price and NAV: Authorized Participants (APs) and secondary market arbitrageurs.

APs are a group of institutional investors and market makers authorized by the ETF issuer to trade directly with the ETF sponsor to create and redeem shares, or in other words, participate in the primary market for ETFs. They create or redeem ETFs shares "in-kind" with large blocks of weighted underlying stocks called creation baskets, which are published daily by the ETF sponsor. These creation baskets are traded in or out for a large block of ETF shares, called a creation unit, typically consisting of 50,000 ETF shares (Gastineau, 2010, p. 46).

Importantly, when there is a price discrepancy, the arbitrage process by the APs helps keep ETF share price in line with the iNAV as shown in figure 1.5. When the ETF share price is higher than NAV (sufficient enough to profit from arbitrage), APs will buy the creation basket of weighted underlying stocks to redeem a creation unit of ETF shares, and then sell the created ETF shares. By buying the lower priced stocks and selling the higher price ETF, the AP profits from the difference in price. This arbitrage process puts downward price pressure on the ETF price by increasing ETF shares in the market, and puts upward price pressure on the underlying stocks by decreasing the supply of those stocks in the market. The result is that ETF share price and NAV are in line. Conversely, when the ETF share price is lower than iNAV, APs will buy the ETF shares to trade in for a creation basket of underlying stocks. APs then sell the higher priced underlying stocks for a profit. Again, the buying of ETF shares will put upward price pressure on the ETF share price and downward pressure on the underlying stocks resulting in the convergence of ETF price and NAV.

The above argument raises the question of what drives ETF prices away from NAV. Fundamentally, asynchronous trading causes the price and NAV to move apart. But the reason for different trading activity could be a reflection of market forces creating different demands for the ETF with respect to its underlying stocks. Differences in demand would result in difference price pressures, triggering deviations between the ETF price and NAV such that there presents an arbitrage opportunity. There are several possible explanations why the market demand for ETF could be different than for the underlying stocks, for example differences in liquidity or taxation, among other possible explanations. We study the effects of differences in ETF demand here, specifically from short-term demand.

It is important to note that only APs have the ability to utilize the creation and redemption process as depicted in figure 1.6. They receive compensation only through the arbitrage process and through their market making activities in the secondary market from service fees they collect from clients who engage them to facilitate primary trades on their behalf. However, they have no legal obligation to create or redeem and though they generally are believed to take advantage of possible arbitrage opportunities, they are not obligated to do so. Therefore, in the scenario where all the APs withdraw from the primary market for an ETF at once, the creation and redemption mechanism for adjusting ETF share price will be frozen temporarily. In that case, the supply of ETF shares may be fixed in the short term and the price of the remaining ETF shares would be priced based on market forces. The price-NAV spread could increase more



(a) Equilibrium.

(b) ETF liquidity shock.

(c) The liquidity shock is propagated to the NAV making the NAV move away from the fundamental value, and the ETF price is moving towards the fundamental value.

(d) Reestablishment of equilibrium, where both the NAV and ETF price is back at their fundamental value.

Figure 1.5: Illustration of the arbitrage process adapted from Ben-David, Franzoni, and Moussawi (2017, p. 33). Where we first have an initial equilibrium as in 1.5a where the NAV and the ETF price is at their fundamental value. Then a liquidity shock is introduced forcing the ETF to rise in price thus introducing a premium in relation to the NAV 1.5b. Since this is an arbitrage possibility then these prices will move together until there are no premium 1.5c. Before both the ETF and the NAV moves back to their fundamental value 1.5d.

widely during this time, and arbitrage would only take place in the secondary market by secondary market arbitrageurs (Ben-David, Franzoni, & Moussawi, 2017, p. 10). In this sense, an ETF would then trade like a close-end mutual fund.

Arbitrage in the secondary market is a less effective mechanism in decreasing the price-NAV spread. Secondary market arbitrageurs will take a long or short position in the ETF and an opposite position in the main components of the index or other index-related trading instrument (e.g. futures or similar ETF) and wait for these prices to converge to realize a profit. These trades involve more risk because the spread may widen and because of uncertainty in time horizon for a payoff, if any (Marshall, Nguyen, & Visaltanachoti, 2013, p. 3486). In the case where all APs withdraw from the market at once, these risks are increased.

Another effect of the creation and redemption process unique to ETFs is low expense ratios. APs generally pay all the trading costs associated with buying the creation baskets and ETF shares,

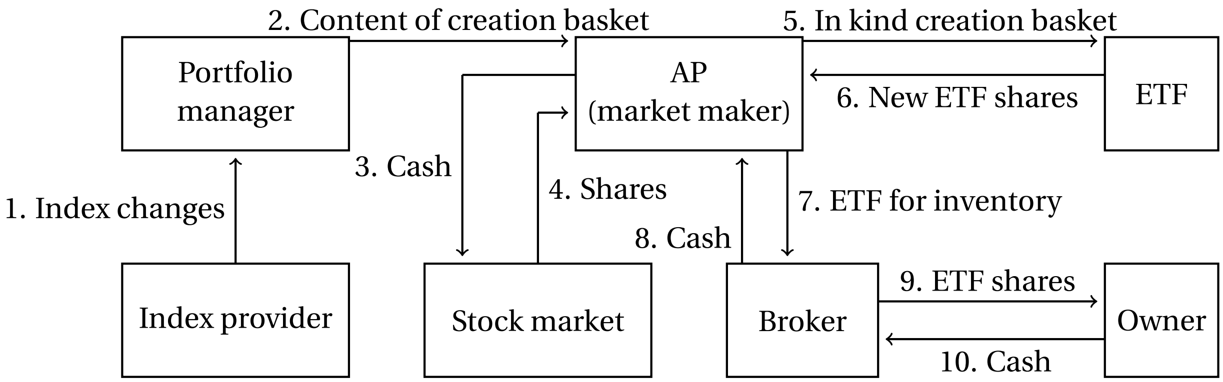


Figure 1.6: A closer look at the the ETF share creation process, where the steps before 5. is what precedes the creation of new ETF shares, thus expanding on figure 1.4. The figure is adapted from (Gastineau, 2010, p. 56), and the most important part is the APs, which can decide on the supply of new ETF shares, conversely they can also redeem ETF shares, then steps 10-3 is reversed.

and even pay an additional fee to the ETF provider for processing. Additionally, since ETFs have a limited amount of APs, sponsors have low operational costs. ETF sponsors have no transaction costs from investors trading on the secondary market. Moreover, ETFs that are not formed as unit investment trusts can lend out their securities for a fee, further decreasing ETF expenses. This feature creates a dual incentive for ETF sponsors to increase assets under management since they are not only incentivized by fees from investors (Blocher & Whaley, 2016, p. 24).

Literature review

Our paper studies the effects of ETF demand on its underlying stock correlations. In this regard, it joins other papers broadly on the subject of passive investing, and specifically on ETF trading effects on underlying stocks.

Passive index investing has been on the rise and there have been literature researching its effects on the stocks in the tracked index. Warning against the adverse effects of indexing, Wurgler (2010) argues that indexing can distort prices in the underlying securities. Examples of the such distortions can be seen in inclusion and exclusion effects, as shown by Morck and Yang (2001) which provide evidence to suggest a price premium for inclusion in the S&P 500. In the same vein, Sullivan and Xiong (2012) argue that the increase in index trading contributes to higher systematic equity market risk. The authors show that consistent with the increase of passive trading, equity betas have not only risen, but converged in recent years. Barberis et al. (2005) conduct an event study to show that inclusion on the S&P 500 increases the stock's beta to the S&P 500.

Other papers have studied the effects of ETFs specifically on the underlying stocks in its portfolio. There has been research that studied the impact ETFs have on price discovery, and whether they increase or distort informational efficiency. Lettau and Madhavan (2018) advance the view that ETFs reflect new information before the underlying assets, and therefore expedite price discovery. Glosten and Zou (2016) show empirically that ETFs increase the informational efficiency of stocks, particularly those with weak information environments. On the other hand, Israeli et al. (2017) shows that stocks owned by ETFs have higher trading costs, receive less analyst coverage, and exhibit lower informational efficiency measured by future earnings response coefficients. However, price dynamics may be nonlinear and may be affected by size of the market capitalization of the firms such that smaller firms have improved informational efficiency and larger firms have worse (Caginalp & DeSantis, 2017). Ben-David, Franzoni, and Moussawi

(2017) find that ETFs are a catalyst for liquidity trading and causes increased volatility to the underlying stock prices and that the increased volatility is associated with noise.

Our paper is part of the literature investigating the effects of ETFs on the correlations of the underlying basket of securities. Most notably, Da and Shive (2017) provided evidence collected from an extensive list of ETFs and their underlying stocks and find that the arbitrage process contributes to return comovement. They use daily data over a period from 2006 to 2013 to determine whether percentage of ETF ownership, intensity of the creation and redemption process, and ETF turnover have a positive relationship with the underlying stock correlations. Using a fixed effects model, they find that ETF turnover, and the interaction term between ETF turnover and ETF ownership percentage have a significant positive relationship with underlying stock correlations.

To further add to their analysis, they attempt to show increasing correlations with ETF activity within the S&P 500. However, we cannot use their results as guidance for our study of the S&P 500 because of an error in their research. "Specifically, we are focus on ETFs tracking the S&P 100 and the S&P 400 index. Both indices are value-weighted and together they form the S&P 500 index." (Da & Shive, 2017, p. 152). They cite that "There are three S&P 400 ETFs (offered by SPDR, Vanguard, and iShares accordingly)," (Da & Shive, 2017, p. 153). However, upon checking the constituent list of these S&P 400 ETFs from their respective providers, we note that they mistook the S&P 400 ETFs to track the bottom of the S&P 500 when they actually track the S&P 400 Midcap, an index with an entirely different set of stocks than the S&P 500. Therefore, their strategy of forming portfolios of 10% of the bottom S&P 100 (portfolio A) and a portfolio of 10% of the top of the S&P 400 (portfolio B) to control for similar fundamentals cannot inform our study.

Another paper that examines the relationship between stocks and correlations is by Leippold et al. (2016). This paper builds a theoretical framework of the effects of ETFs (and futures) on correlations. Their model is a rational equilibrium model and can be seen as an extension to Fremault (1991). Leippold et al. (2016) model allows for individual assets in the basket, thus making it possible to make predictions about the distinct behavior of ETFs and index futures. Their main prediction is that ETFs increase security return correlations both when trading activity incorporates information and when it can be regarded as noise. This holds under quite general conditions [1], and their model predicts that ETFs impact correlations more than futures

[1] More specifically the conditions for stock pairs is that these three features have the same sign: 1) expected payoffs of security pairs move in the same direction for a demand shock, 2) correlations of security price and the index, and 3) that trading cost relates to the index trading cost (Leippold et al., 2016, p. 23)

due to the arbitrage mechanism.

In addition, they provide an empirical analysis of ETFs and futures on correlations. Their main explanatory variables are index-related demand shocks, which is proxied by the residuals of their index-related trading ratios. They use the ARIMA residuals of these trading ratios as the explanatory variables in their regressions to capture an unexpected demand shock to index-related trading and find they have a significant positive effect on return correlations, and that this effect is larger for ETFs than futures. Finally, they examine whether the increased comovement is a result of price efficiency (fundamental price information) or otherwise (noise). To do this, they follow Da and Shive (2017) and examine the relationship between return reversals and correlations. They find, that the comovement is excessive, and therefore as least partly not caused by fundamentals. The authors also regress their proxy for index demand shocks against their aggregate measure of return reversal and also find a significant relationship, suggesting index trading activity is a significant driver of return reversals by including noise.

Adding to the literature on correlations and ETFs is Staer and Sottile (2018) who create a new measure of relative liquidity using volume to test arbitrage-induced trading pressure on underlying stock comovement with the ETF NAV using both intraday and daily data. They find that there is a strong, positive relationship between their measure, equivalent volume, and return comovement of the underlying stocks with the ETF NAV. They measure correlations using an approach based on dynamic conditional correlations, measured as the comovement of the stock's return and the ETF NAV return. This paper proxies liquidity with equivalent volume in order to investigate the relationship between liquidity and correlations, and they find that it increases comovement.

In addition to information efficiency, Glosten and Zou (2016) empirically finds that return comovement as measured by change in beta increases with ETF activity. Consistent with their findings, they find that increasing return comovement is, in part, a result of increased informational efficiency.

Da and Shive (2017), Leippold et al. (2016), Staer and Sottile (2018), Glosten and Zou (2016) are the research most similar to ours in that they all study ETF activity on correlations and finds a positive and significant relationship. Our methodology is most closely related Leippold et al. (2016) work, but we also extend the analysis in time and to include clientele effects in a broader study of ETF demand, which includes proxying short-term demand. We also use several measures of correlations for robustness and accuracy.

There has been some research conducted that have looked at ETF flows and their relationship on underlying stocks. Notably, Staer and Sottile (2018) finds that ETF flows are contemporaneous with index return and that the positive price impact of the flows reverts after a few days. Staer and Sottile (2018) study differs from Clifford, Fulkerson, and Jordan (2014) because it studies flows on returns, whereas Clifford et al. (2014) studies returns on flows. In their paper, they investigate investor motivations for investing in ETFs and find that ETF investors irrationally chase past returns. Broman and Shum (2018) find that relative liquidity predicts net flows, as well as inflows and outflows, positively and significantly.

Recent papers have focused on the liquidity of ETFs (Agrrawal, Clark, Agarwal, & Kale, 2014; Agarwal, Hanouna, Moussawi, & Stahel, 2017; Petajisto, 2017). Using their own measure of liquidity, Agrrawal et al. (2014) find that ETF liquidity has increased over time. We also add to the literature that ETFs attract short-term investors because of their high liquidity. Amihud and Mendelson (1986) find that low liquidity stocks are preferred by long-term investors, and therefore high liquidity stocks are preferred by short-term investors. Using institutional investor data, Broman and Shum (2018) test the hypothesis that liquidity facilitates trading and, in this regard, creates a liquidity clientele that have short-term trading horizons. They find that this is true, and predict that ETFs will continue to grow and facilitate short term trading since they are in all aspects more liquid than their underlying. Further, they find that the positive relationship between liquidity and fund flows reflects investors' preference for liquidity rather than arbitrage trades. We rely on this paper's findings to test whether this demand for liquidity affects comovement.

In addition, Israeli et al. (2017) show that uninformed traders prefer to trade ETFs and this in turn causes trading costs for the underlying stocks to increase. Ben-David, Franzoni, and Moussawi (2017) find indirect evidence that suggests that ETFs are used for liquidity trading and attract a new clientele of higher-turnover investors than those investing in only the underlying stocks. The impact of short-horizon traders has been long studied, for example by Stein (1987), and more recently, Cella, Ellul, and Giannetti (2013) find that the presence of short-horizon institutional investors exacerbates price drops during market turmoil because they exit the market. Campbell, Grossman, and Wang (1993) create a model that predicts high turnover stocks are associated with uninformed trading.

Because of their low costs and high liquidity, many investors use ETFs as an investment vehicle for shorting, a high turnover investment strategy. Stratmann and Welborn (2016) find that ETF short sale volume is a significant portion of total ETF trading volume. Madura and Ngo (2008) use short interest data to argue there is more short selling in ETFs than in common stocks. The result of these findings lend support to the argument that short-term investors are attracted to ETFs.

Hypothesis development

In this paper, we study the effects of ETF demand on the correlations among the underlying basket of stocks, as higher demand results in increased trading activity. In addition, because of the unique features of ETFs, we conjecture that part of ETF demand is from short-term traders. The consequences of this clientele effect may include increasing correlations as a result of their high turnover trading. In this section, we develop our hypotheses with the help of prior literature, outline how we plan to measure ETF demand, including short-term demand, and what we expect our results to show.

In frictionless markets with rational investors, prices move with fundamental information such that prices are an accurate reflection of intrinsic value. Therefore, any comovement in returns must be a result in comovement in the fundamentals. However, when market frictions are introduced, including limits to arbitrage, and irrational investors, comovement in returns may be from non-fundamental demand, giving rise to excess comovement (Broman, 2016). Clifford et al. (2014) show that investors in ETFs chase past returns as if the fund were actively managed, an irrational motive for investing in ETFs. Moreover, Israeli et al. (2017) argue that ETFs offer an attractive alternative for uninformed (or "noise") traders who would otherwise trade the underlying component securities.

Our main testable hypothesis is whether ETFs demand increases the correlations on their underlying basket of securities. Separately, we test whether such correlations are excessive, or non-fundamental. The demand for ETFs on the secondary market is reflected through trading activity that exerts price pressure on the ETF share price, driving it away from the ETF NAV. This triggers an arbitrage opportunity for the APs, which then create and redeem shares to profit from the price-NAV spread. As a result, the demand for ETFs propagates to their underlying stocks through the arbitrage channel. We posit such trading affects the correlations of the underlying securities since they are traded together as a basket of securities to be created or redeemed with the ETF sponsor.

Greenwood and Thesmar (2011) show that concentrated ownership or correlated liquidity demands increases price fragility and volatility, a result consistent with the category or habitat view of comovement. Such increases lead to increased excessive comovement, and in certain circumstances, arbitrageurs exacerbates such effects. Alternative to the fundamental view of comovement, the category view of comovement occurs when investors classify different securities into she same asset class and shift resources in and out of this class in correlated ways. Similarly, the habitat view of comovement occurs when investors restrict their trading to a given set of securities, and move in and out of that set in tandem. Barberis et al. (2005) find evidence to support the category and habitat view by measuring the change in betas to the S&P 500 before and after inclusion on the index in an event study and find they increase. Thus, we expect to see an increase in correlations with increasing ETF demand and trading activity.

Hypothesis 1: *An increase in trading volume for ETFs relative to their underlying stocks is associated with increases in correlations among the underlying stocks.*

To test Hypothesis 1, we examine the relationship between the demand for ETFs relative to the underlying stocks. We use daily trading volume as a proxy for demand since daily volume is a tally of the number of shares sold on a specific day of a stock. Thus, the ratio of ETF volume to underlying stock volume can be used to measure relative demand. Increases in the ratio represents a higher increasing demand for the ETFs with respect to the underlying shares, and vice versa. It should also be noted that volume is also used as measure of liquidity.

Furthermore, we argue that a part of the asynchronous trading in the secondary market between ETFs and the underlying stocks can be the result of a clientele effect. Specifically, our second hypothesis is that the difference in demand between ETF shares and the underlying stock shares is, in part, from short-term traders, traders with high turnover and shorter horizons than long-term investors. Amihud and Mendelson (1986) show low liquidity stocks, as measured by the bid-ask spread, is preferred by long-term investors. Conversely, high liquidity stocks are preferred by short-term investors. ETFs were constructed to be a liquid and convenient investment instrument, combining the ease and liquidity of trading on an exchange with the benefits of diversification.

In addition, the trading costs of ETFs, another dimension of liquidity, are lower than their basket of securities (Israeli et al., 2017; Broman & Shum, 2018). They offer an easy way to invest in different styles (Broman, 2016), to diversify (Ben-David, Franzoni, & Moussawi, 2017), and to sell short (Karmaziene & Sokolovski, 2015). Using their own measure of liquidity, Agrrawal et al. (2014) find that ETF liquidity has increased over time. ETFs are, on average, significantly more liquid than the basket of underlying securities in terms of bid-ask spread and turnover (Hill et al., 2015). Volume is another facet of liquidity and has been used in the ETF literature as a measure of liquidity (Staer & Sottile, 2018). Therefore, we include trading volume in our analysis of liquidity such that it also represents short-term demand.

As a result, in line with Amihud and Mendelson (1986) research, studies have found that the high liquidity of ETFs likely attracts short-term investors. Broman (2016) argues these short-term investors have correlated non-fundamental demands, such as inclusion on an index or investment style. Broman and Shum (2018) use institutional investor data to show that ETFs with high liquidity have higher short-term fund flows, greater short-term institutional ownership, and shorter institutional holding periods relative to their underlying baskets. Ben-David, Franzoni, and Moussawi (2017) also uses institutional investor data to show that ETF ownership of stocks attracts traders with higher turnover than for common stocks. They argue that ETFs are a catalyst for liquidity trading, and the effect of such trading is increased price volatility.

In similar fashion, Broman (2016) posits that retail investors are even more likely to attracted to ETFs for liquidity reasons because the transaction costs when investing in the underlying basket of securities are likely prohibitive (i.e. 500 weighted stocks for the S&P 500, or 1000 weighted stocks for the Russell 1000), and because ETFs have lower cost and more tax advantaged in the US relative to passive index mutual funds.

Additionally, because of their low costs and high liquidity, many investors may view ETFs as their preferred investment vehicle for making directional best on the index/market, a high turnover investment strategy. ETFs are popular vehicles for hedging market index movements, and short selling is an important aspect of ETF trading. One benefit of using ETFs for short sales is that they are not subject to the SEC's uptick rules, so investors can decide to short the shares no matter how great the downward pressure is on the shares. Using short sale data from Financial Industry Regulatory Authority (FINRA), Stratmann and Welborn (2016) find that ETF short sale volume is a significant portion of total ETF trading volume. Similarly, Madura and Ngo (2008) use short interest data to argue there is more short selling in ETFs than in common stocks.

Therefore, we expect short-term trader demand can be proxied by liquidity of the trading instrument as a result of short-term traders preferring more liquid assets. Understanding the drivers of ETF demand is important because of the potential spillovers to the underlying assets and to the market. According to Stein (1987), short horizon traders have adverse effects on information efficiency of prices and deters long-term investors. Cella et al. (2013) find that the presence of short-horizon institutional investors during market turmoil exacerbates price drops because these investors exit the market. Campbell et al. (1993) create a model that predicts high turnover stocks are associated with uninformed trading. Broman and Shum (2018) argue using institutional level data that ETFs attract short-term institutional investors and predict that would result in increased correlations of the underlying securities in similar investment styles. We test that prediction empirically here.

Hypothesis 2: *The higher liquidity of ETFs relative to its underlying stocks is associated with increases in correlations among the underlying stocks.*

Part of the ETF demand comes from short-term traders. Such demand can be proxied by the liquidity of the ETFs as a result of short-term traders preferring more liquid assets. To test Hypothesis 2, we use two measures of relative liquidity. The first is the Amihud measure of illiquidity (Amihud, 2002), which and is a well-accepted proxy for the price impact of trades. The second measure of liquidity is also a well-accepted proxy for the transaction costs of a trading a stock, the monthly average bid-ask spread. In addition, trading volume is another measure of liquidity, and therefore we also use the trading ratio in our analysis of liquidity. Using relative measures allows us to examine the relationship of ETFs to correlations vis-à-vis the underlying stocks.

Data

In this section, we will go into depth into how we obtained our data used for the empirical analyses to follow. All limitations of the data are noted, including quality and reliability, and our choices about how best to deal with limitations are discussed. We have decided to collect data from 2002 through 2017. The reason why 2002 is used as a starting point is because of the decision to decimalize most U.S. equity markets in the early 2000s, which was fully implemented in 2001 (Exchange Comittee on Decimals, 2000).

4.1 S&P 500

We have chosen to study the ETFs tracking the S&P500 and its constituent stocks. The S&P 500 index is the worlds best-known equity index. With a history that goes back to the 1920s, it is today considered to the best representation of the overall US equity market. The component stocks, weights, and methodology for inclusion is maintained by S&P Dow Jones Indices (2018d, 2018b, 2018a, 2018c). It is composed of 500 large-cap constituent companies and is considered to be a bellwether index for the US economy.

The objective of the index according to S&P Dow Jones Indices (2018d) is to measure the performance of the US market large-cap segment of the market. The selection of the component stocks is made by the autonomous S&P Index Committee. It chooses companies that fulfill the eligibility requirements as set forth by S&P Dow Jones Indices (2018d) to ensure that the index is representative of the US large-cap industry consisting of leading companies in leading industries.

An important limitation to our data is that the S&P 500 was initially a market capitalization weighted index, but switched to being a float-adjusted index in 2005 (Blitzer, 2013). This was perceived with skepticism, but for all practical purposes the this has not made much of a difference with over 97% of S&P 500 stocks in public float in 2013, thus the general float adjustment is minor (Blitzer, 2013). Float-adjusting weights are calculated by how many shares are made available for public trading rather than using the total shares outstanding (S&P Dow Jones Indices, 2018b). Shares that are excluded due to float-adjustment are for example closely held shares.

The fact that the S&P 500 is float-adjusted is important for our analysis because we use the weights of the index to calculate the weights of the ETF portfolios since the ETFs we study are physically replicating the S&P 500. Historical weights for the S&P 500 are not available to us, and neither are the (historical) public float amounts for each stock as used by S&P Dow Jones Indices (2018b) in their calculations. ETF portfolio holdings, at least for the SPY, the oldest and largest ETF in our study, are only filed semi-annually. Therefore, we choose to obtain weights based on market-capitalization using the price and shares outstanding at the end of the month.

4.2 S&P 500 tracking ETFs

There are currently three American ETFs which track the S&P 500 namely SPY, IVV and VOO. We collect their data from the CRSP database stock files on a daily and monthly frequency (Center for Research in Security Prices, 2018b). From the data retrieved from CRSP using each ETF's ticker as an identifier, we keep the the variables *ask*, *bid*, *price*, *retd*, *shrout*, *volume* and *vwretd*. These variables represent the closing ask, closing bid, closing price, returns included distributions, shares outstanding, volume and value weighted market return, their provenance are documented by Center for Research in Security Prices (2018h, pp. 13, 18, 73, 77, 82, 95 & 104).

It is important to note that these three ETFs are physically replicating the S&P 500. Therefore, we can get use the market cap weights of the S&P 500 as the weights for the same stocks in the ETF portfolio. This is done since the daily holding data is not readily available. Holdings data is based on the quarterly or semi-annual SEC filings, which is a snapshot in time. They do not timely reflect inclusions and deletions, therefore we argue that for the S&P 500 it is a better approximation to use the market capitalization weights, when the goal is to have the final dataset at a monthly time frame.

Additionally, ETFs are unique to mutual funds because they trade intraday like a stock and shares are created and redeemed at the end of day. Therefore, unlike most stocks, the shares outstanding for ETFs can change significantly from day to day. This value can be used to measure net fund flows in the primary market for ETFs, namely the net creation and redemptions by APs at end of day.

Table 4.1: Shares outstanding for SPY and IVV in thousands from 2013-01-22 to 2013-01-31 from both CRSP and the providers directly. As we can see from the the difference they are not the same. In unreported results we have computed the averages and the average daily difference is less than 0.01% of the shares outstanding. Therefore we deem the CRSP shares outstanding sufficient for weighting purposes.

date	SPY CRSP	SPY SPDR	diff. SPY	IVV CRSP	IVV iShares	diff. IVV
2013-01-22	868582	835332	33250	243950	246400	-2450
2013-01-23	868582	822182	46400	243950	246200	-2250
2013-01-24	868582	829432	39150	243950	245700	-1750
2013-01-25	868582	845532	23050	243950	243750	200
2013-01-28	868582	845632	22950	243950	243550	400
2013-01-29	868582	853032	15550	243950	243550	400
2013-01-30	868582	852632	15950	243950	243900	50
2013-01-31	852632	838882	13750	244100	244100	0

Unfortunately the CRSP does not update shares outstanding *shrout* for ETFs on a daily frequency. We have not been able to get official documentation for this, but we can empirically document it when we compare shares outstanding from CRSP for SPY and IVV with end of day data on shares outstanding published by the issuers SPDR and iShares respectively (State Street Global Advisors, 2018; iShares by Blackrock, 2018). To the best of our knowledge CRSP reports shares outstanding for ETFs as a kind of monthly average. A comparison for an arbitrary period from January 22nd to January 31st 2013 is presented as an example in table 4.1 and is representative of the discrepancies in the CRSP shares outstanding data.

In the ETF literature shares outstanding from CRSP has been used to calculate weights, but not deemed as precise enough to use for flows (Da & Shive, 2017, p. 140). Therefore we only use the shares outstanding data for the ETFs to calculate weights in relation to one of our liquidity measures and holding percentage. A reason to not use the shares outstanding data from the ETF providers is that State Street Global Advisors (2018) has only published data since mid-2006. Another interesting point is that Vanguard does not make their historical shares outstanding or NAV publicly available other than in their quarterly SEC reports.

However, since we our goal is to capture ETF demand and ETF short-term demand on the secondary market, net fund flows may not a good measure in that regard since it is a net measure of the effects from price pressure created from the secondary market onto the primary market.

Therefore, we instead use measures to proxy liquidity, a measure that has direct effects in the secondary market. Nevertheless, we note that it might have been useful to add the fund flows to our model, if only to separate the effect of relative trading on correlations and fund flows. However, we instead rely on Broman and Shum (2018) who find empirically that liquidity is a strong predictor of net flows, inflows, and outflows.

4.3 Individual constituents of the S&P 500

The first step in our empirical analysis begins with obtaining a comprehensive list of companies on the S&P 500 for each day from 2002 to 2017. The sample of individual constituents of S&P 500 from 2002 through 2017 is collected following the technical guidelines by Dobelman, Kang, and Park (2014). According to those guidelines, there are two main approaches in obtaining the S&P 500 constituent list from CRSP, which we have access to through Wharton Research Data Services (2018). We have applied both approaches for completeness and to be able to compare for best results.

The first approach is to access the Compustat index constituents database (Compustat - Capital IQ, 2018a), which is accessible through the browser (Wharton Research Data Services, 2018). We searched for the ticker i0003, which represents the S&P 500, specifying the relevant date range as 1.1.2002 to 31.12.2017. This returns a dataset with enough information to reliably recreate the constituents off the S&P 500 at any given time in the aforementioned time-frame (Dobelman et al., 2014, p. 9). The dataset is exemplified in table 4.2 and consist of one row for each continuous time-frame of trading days in which a company has been included in the index.

Table 4.2: Example of format of identifiers for the S&P 500 constituents dataset retrieved from Compustat (Compustat - Capital IQ, 2018a) for a sample of four companies for illustrative purposes. Irrelevant columns are excluded.

gvkey	from	through	conm	indextype	tic	co_conm	co_tic	co_cusip
24216	19981002		S&P 500 Comp-Ltd	LGCAP	I0003	AES CORP	AES	00130H105
1177	19760630		S&P 500 Comp-Ltd	LGCAP	I0003	AETNA INC	AET	00817Y108
30697	20040402	20100207	S&P 500 Comp-Ltd	LGCAP	I0003	AFFILIATED COMPUTER SERVICES	ACS	008190100
65886	20140701		S&P 500 Comp-Ltd	LGCAP	I0003	AFFILIATED MANAGERS GRP INC	AMG	008252108

Obtaining a unique identifier for share classes is important to use for CRSP searches because since 2014, there are more than 500 stocks in the S&P 500 as a result of the inclusion of multiple share classes from the same company. Traditionally a company could only be included in the

Table 4.3: Example format of the dsp500list from CRSP. Unique identifiers permno and start and ending dates, the original dsp500 list is subsetted such that only companies included in the sample period 2002 through 2017 is included.

permno	start	end
10078	19920820	20100128
10104	19890803	20171229
10107	19940607	20171229
10108	20020722	20050811
10137	20001211	20110225
10138	19991013	20171229

S&P 500 with a single share class. But since 2014 changes to the S&P 500 opened eligibility for the inclusion of multiple share-classes[1] from the same company (S&P Dow Jones Indices, 2014). For example, Alphabet's Class A and Class C trade as two separate stocks and have different weights on the index, but have the same *permco* in the data. This means that *permco* would be inappropriate in returning unique stock return data since it is a unique company identifier (Center for Research in Security Prices, 2018d). Instead, the *permno* are used as identifiers since they are unique down to the issue level and from there we obtain relevant returns from difference share classes from CRSP.

The dataset in table 4.2 does not include any unique identifier which can be used with the CRSP daily stock files (Dobelman et al., 2014, p. 9). Since the *cusip* included is the latest *cusip* and not the appropriate issue unique *ncusip* (Center for Research in Security Prices, 2018f). Therefore, the linking table between Compustat and CRSP is applied (Center for Research in Security Prices, 2018g), to establish the full sample of *permno* for the constituents at any given time (Center for Research in Security Prices, 2018d). Relying on the information published in the CRSP/Compustat merged database guide (Centre for Research in Security Prices, 2018) adjusting for any known inconsistencies[2] by hand. The dataset seen in table 4.2 is therefore enhanced with *permno*, and extra rows are added if constituents are identified with different *permno* for a single period of inclusion.

The second approach is to access the CRSP maintained list of index constituents for the S&P

[1]An interesting side note is the recent methodological change to the S&P 500 index where in July 2017 S&P Dow Jones Indices (2017) announced that new inclusions are no longer allowed to have multiple share-classes whereas existing constituents are grandfathered in.

[2]An example of such an inconsistency is for example due to mergers or other corporate actions (Center for Research in Security Prices, 2018c)

500 programmatically. This dataset is called the *dsp500list*[3] (Dobelman et al., 2014, p. 10) and is not accessible through browser searches, but is viewable in the database. Using the extensive guidelines provided for the WRDS cloud (Wharton Research Data Service, 2018), we connected through SSH. Once connected to the server we utilize command line access as a remote terminal to initialize an R session. We used the command line interactively to query for and extract the *dsp500list*. The dataset returned consists of *permno start date* and *ending date* for each companies inclusion in the S&P 500 as seen in table 4.3. The dataset is then subsetted such that it only includes constituents included between 2002 through 2017.

4.4 Daily returns of S&P 500 constituents

To get the daily returns for all S&P 500 constituents from Wharton Research Data Service there are two options: Compustat daily securities (Compustat - Capital IQ, 2018b) and the CRSP daily stock files (Center for Research in Security Prices, 2018a). The Compustat and CRSP files contain somewhat different data. Both databases have data on prices, but only the CRSP files provides returns. While calculating returns from prices is in theory not an issue, in practical application it is advantageous to retrieve the dataset containing returns, the CRSP dataset.

Four different datasets are retrieved, three using identifiers *gvkey*, *cusip* and *permno* from the Compustat index constituents, and one using *permno* from the *dsp500list*. All datasets are collected from 2002 through 2017 and are retrieved (Wharton Research Data Services, 2018). More specifically the *gvkey* are used to retrieve a sample from the Compustat daily securities database and the *cusip* and both *permno*'s are used to retrieve three samples from the CRSP daily stock files. Our four datasets are subsetted consistent with the dates of inclusion in the S&P 500 for the respective searched identifier.

When we compare the selected samples with what is used by CRSP themselves when calculating the S&P 500 index (Center for Research in Security Prices, 2018b). For the 4028 trading days from 2002 through 2017, the total observations in the sample is presented in table 4.4. The important thing to note is that the samples total observations, except for the one acquired using *cusip* is reasonably close to what CRSP itself reports. For the analysis we have chosen to use the sample acquired using the *dsp500list* since this has been shown to be the most accurate (Dobelman et al., 2014, p. 21). For the underlying securities we retrieve the variables *ask*, *bid*, *price*, *retd*,

[3]Abbreviation for the daily S&P 500 list, there is also a dataset called msp500list, which is the monthly list.

shrout and *volume*.

Table 4.4: Summary of the number of observations and daily constituents of S&P 500 for 4028 trading days from 2002-2017. Ind. total and ind. used is what CRSP reports in their index file (Center for Research in Security Prices, 2018b), gvkey is the sample acquired from Compustat, cusip is the sample acquired from CRSP using the original identifiers, which shows the necessity of applying the linking table from the CRSP/Compustat merged database to prevent bias (Centre for Research in Security Prices, 2018). The linking table is applied for the gvkey's to permno's and this represents the permno sample acquired from CRSP. Finally the dsp500list sample is the sample acquired from CRSP using the permno's from the dsp500list.

	ind. total	ind. used	gvkey	cusip	permno	dsp500list
n.	2017435	2017155	2017407	1973385	2017325	2017347
min.	498	496	498	481	498	498
1st q.	500	500	500	486.5	500	500
mean	500.85	500.78	500.85	489.92	500.83	500.83
3rd q.	500	500	500	491	500	500
max.	508	508	506	505	507	507

4.4.1 S&P 500 constituents return characteristics

Table 4.5: Summary statistics for net holding period returns and log returns both for the full sample and averages of individual series are presented.

	R_t	r_t	R_t pr. series	r_t pr. series
n.	2017347	2017347	2332	2332
min.	-0.942	-2.855	-0.179	-0.215
max.	1.024	0.705	0.202	0.178
1st q.	-0.0088	-0.0088	-0.0102	-0.0102
3rd q.	0.0097	0.0096	0.0106	0.0105
mean	0.00048	0.00021	0.00023	-0.00011
med.	0.00038	0.00038	0.00005	0.00004
sum	976.9	421.6	1.1	0.5
var.	0.0005	0.0006	0.0007	0.0007
sd.	0.0233	0.0237	0.0231	0.0234
skew.	0.5890	-3.4427	0.2855	-0.4783
kurt.	54.1	302.3	18.5	23.2

It is natural to start with discussing the nature of the underlying security returns. The returns we are using are the net holding period returns as defined by Center for Research in Security Prices (2018h, p. 101), where the daily returns R_t are calculated using (4.1) and represent the return at time t for purchasing the asset at time t^*. p_t and p_{t^*} is the last sale price or if not available the bid ask midpoint for time t and t^* respectively where $t^* < t$. f_t is a factor to adjust prices for any corporate events in time t and d_t is dividend amount in time t.

$$R_t = \frac{p_t f_t + d_t}{p_{t^*}} - 1 \tag{4.1}$$

Returns are one of the most heavily scrutinized types of financial data. Firstly we can inspect figure 4.1 which represents the cross section off all daily returns in the sample. From this we can highlight two facts about the returns, that they are both sharply peaked and heavy tailed, which by the look of it implies non-normality. This is consistent with well known stylized facts about empirical return (Cont, 2001, p. 226). Sample statistics for the full sample of holding period returns and log returns $r_t = \log(1 + R_t)$ are shown together with the average of the individual constituents return series in table 4.5. The point of non-normality will be important later when we discuss possible correlation measures.

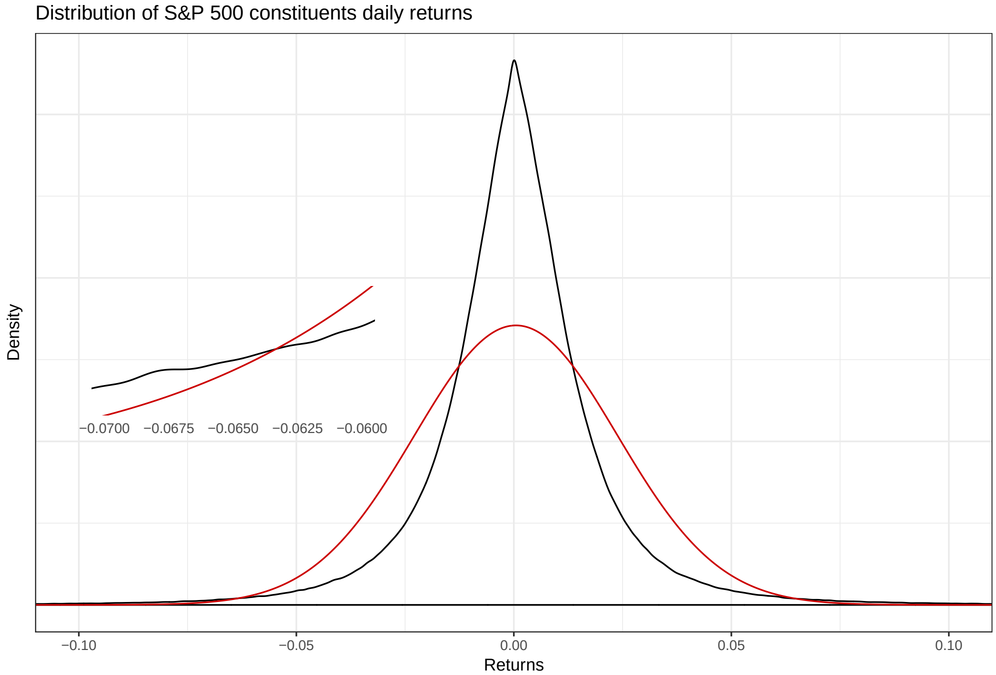


Figure 4.1: Distribution of S&P 500 constituents securities daily returns from 2002 through 2017. The distribution is compared to the normal distribution. The distribution of the returns is only showed in the range -10% to 10% for convenience purposes. The normal distribution is fitted with the first two moments of the full sample. And the corollary figure for log return is included in the appendix B.

4.5 Data for control variables

We also collect other data of interest and their provenance are discussed in the following. The data we have collected are mostly macroeconomic variables, which means that they are readily available from the Federal Reserve Bank of St. Louis (FRED) (Federal Reserve Bank of St. Louis, n.d.-a) database. FRED makes over 500,000 time series available from 86 sources (Federal Reserve Bank of St. Louis, n.d.-b). The data can be downloaded both as single files or accessed through their developer api. Practically we use the api provided by McTaggart, Daroczi, and Leung (2016) which allows us to access the FRED data from Quandl, which has the same nomenclature system as the FRED database (Quandl, n.d.). Here we retrieve: *CPIAUCSL* the consumer price index for all urban consumers as provided and discussed in detail in U.S. Bureau of Labor Statistics (2018), *INDPRO* industrial production, which is the G.17 series from Board of Governors of the Federal Reserve System (2018) and *TEDRATE* the ted spread which is the spread between the 3 month Libor based on USD and the 3 month Treasury Bill as calculated by Federal Reserve Bank of St. Louis (2018).

The VIX *VIXCLS* are available from the FRED database, but not through the Quandl api due to ownership of the underlying rights. Therefore we use another api to collect the VIX using the api wrapper available through Quantmod (Ryan & Ulrich, 2017). The underlying data series comes from Chicago Board Options Exchange (n.d.) where the methodology for the whole series has been calculated using the methodology presented in Chicago Board Options Exchange (2014) white paper.

The data-series discussed above has also been crosschecked against what FRED publishes to ensure consistency. And we have found no discrepancies indicating that the data quality is high contingent on trusting the FRED, a commonly used data source for economic research.

Methodology

The aim of this paper is to test empirically whether a relative increase in ETF demand is related to an increase in underlying stock correlations. Demand is proxied by trading activity, or trading volume. As explained earlier, short-term demand is proxied by liquidity. In this section, we introduce our variables of interest and explain how they are constructed. We also discuss our control variables and why we believe they are important to include. At the end of this chapter, we introduce our model and discuss our modeling approach.

5.1 Measure of correlation

We have decided to calculate multiple measures as the aggregate measure of correlation between the returns off S&P 500 constituent securities. Aggregating correlations down to one single number can mean that different measures can have different properties. Here, we compare the different measures of correlations and the grounds for why we use some of the different measures for empirical analysis. One important finding from this discussion is that the choice to value-weighting or equal weighting the correlations do not change the results. Therefore, although our data has limitations with respect to replicating the free-float weights of the S&P 500 and ETF portfolios exactly, we see that the difference between using equal weights or value weights is not significant. In addition we find that the measure used by Da and Shive (2017) *Fratio* is not necessarily a good proxy.

The choice of correlation measure is not trivial, and several measures have been adopted in the literature Shevlyakov and Oja (2016), Wilcox (2012) and specifically to ETFs' constituents' return Da and Shive (2017), Leippold et al. (2016). Our goal is to use a measure that is both robust and accurate in relation to what we are measuring, the pairwise correlation of index constituents returns.

5.1.1 Classic correlation measures

The three classic pairwise correlation measures are Pearson, Spearman and Kendall[1]. Whereas Pearson is the commonly used measure, the Spearman correlation and the Kendall Tau correlation coefficient are shown to be more robust to outliers in empirical analysis and do not depend as much on the distribution[2] of the data (Bonett & Wright, 2000, p. 24). All three measures calculate the correlation between two vectors. The reasoning for not just relying on Pearson is that as shown by Xu, Hou, Hung, and Zou (2013, p. 262) that when there are a tiny fraction of outliers then Spearman or Kendall could be better choices and that they serve complementary roles (Xu et al., 2013, p. 273).

5.1.2 Biweight midcorrelation

In addition to the classic correlation measures, we also calculate the biweight midcorrelation which is also less sensitive to outliers than the Pearson measure. We use it in addition to the robust Spearman and Kendall measures to compare whether our results are significantly changed as a result of choice of correlation measure. We calculate the biweight midcorrelation as implemented by Langfelder and Horvath (2012). A robust counterpart to Pearson correlation can be constructed by replacing the linear components with robust measures (Shevlyakov & Oja, 2016, pp. 140-3) as in equation (5.1) where it is possible to replace both location, ψ and $\sum_a^{max}$, with robust counterparts.

$$r_i(\psi) = \frac{\sum_a \psi(x_i - \hat{\boldsymbol{x}})\,\psi(y_i - \hat{\boldsymbol{y}})}{\sqrt{\sum_a^{max} \psi^2(x_i - \hat{\boldsymbol{x}}) \sum_a^{max} \psi^2(y_i - \hat{\boldsymbol{y}})}} \tag{5.1}$$

For each of the two vectors $\boldsymbol{x}$ and $\boldsymbol{y}$ with elements x_i and y_i, one can define two new vectors $\boldsymbol{u_x}$ and $\boldsymbol{u_y}$ using equation (5.2). Where the median is defined as $\operatorname{med}(\boldsymbol{x})$, the median absolute deviation as $\operatorname{mad}(\boldsymbol{x}) = \operatorname{med}|x_i - \operatorname{med}\boldsymbol{x}|$, and K is a constant.

[1] Formally the tau b statistic is used where possible ties are broken in the manner proposed by Kendall (1945)

[2] The shortcommings of Pearson correlation when applied to data having fat-tailed distributions or containing outliers, which is consistent with what we observe in our return data, is discussed by for example Shevlyakov and Oja (2016, p. 140).

$$\boldsymbol{u_i} = \frac{x_i - \text{med}(\boldsymbol{x})}{K\,\text{mad}(\boldsymbol{x})} \tag{5.2}$$

The constant K is set to 9[3] which is shown through simulation by Lax (1985, p. 740) to be the most efficient across three distributions with similar characteristics as security returns with a sample-size of $n = 20$, approximately the number of trading days in a month.[4] We define an indicator function as in (5.3), which is one if one minus the absolute value of u_i is greater than zero, otherwise it is set to zero.

$$I = \begin{cases} 1 & 1 - |u_i| > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.3}$$

Thereafter we can define weights as $w_i^x = \left(1 - u_i^2\right)^2 I\left(1 - |u_i|\right)$. This gives us the intuition that observations close to $\text{med}(\boldsymbol{x})$ are weighted higher and the weights approach zero when the the difference between x_i and $\text{med}(\boldsymbol{x})$ gets closer to $9\,\text{mad}(\boldsymbol{x})$ and is zero when the difference is larger. Thus the biweight midcorrelation ω between two vectors can be defined as in equation (5.4).

$$\omega = \frac{\sum_{i=1}^{n}\left(x_i - \text{med}(\boldsymbol{x})\right) w_i^x \left(y_i - \text{med}(\boldsymbol{y})\right) w_i^y}{\sqrt{\sum_{i=1}^{n}\left[w_i^x\left(x_i - \text{med}(\boldsymbol{x})\right)\right]^2}\sqrt{\sum_{i=1}^{n}\left[w_i^y\left(y_i - \text{med}(\boldsymbol{y})\right)\right]^2}} \tag{5.4}$$

5.1.3 Possible approximate measure

Another method for aggregating correlations into a single variable is to use the *Fratio*. This measure is an approximation proposed by Pollet and Wilson (2010, pp. 357-8), and shown to be a useful approximation for average correlation the rationale behind this measure is presented in appendix C. Approximate measures are used in varying degrees by both Da and Shive (2017), Leippold et al. (2016) in the ETF literature. Pollet and Wilson (2010)'s estimator of average correlation is shown in (5.5) and is used by Leippold et al. (2016), but as we can see it excludes the

[3] Albeit Veenstra, Cooper, and Phelps (2016) during an empirical test finds that a choice of $K = 13$ is optimal for portfolio optimization this is an inherently different application and therefore we have chosen to use $K = 9$. As to be consistent with the statistical literature (Wilcox, 2012, p. 455).

[4] Specifically the three distributions are: the normal distribution, a one-wild distribution where 19 datapoints $\sim N(0,1)$ and one datapoint $\sim N(0,100)$ and a slash distribution $Z = X/Y$ where $X \sim N(0,1)$ and $Y \sim U(0,1)$.

sum of square weights. In (5.5) the weights $w_{i,t}$ are the market capitalization of security i at time t divided by the total market capitalization of the portfolio at time t and $\hat{\rho}_{ij,t}$ is the Pearson correlation coefficient for security i and j at time t.

$$AC_t = \sum_{i=1}^{N} \sum_{i \neq j}^{N} w_{i,t} w_{j,t} \hat{\rho}_{ij,t} \tag{5.5}$$

Since we have a small sample of ETFs, we see no reason to rely on an approximation. For illustrative purposes we have included the *Fratio* when we discuss explicitly which measure to use, highlighting the fact that this might not be the most appropriate measure.

5.1.4 Calculation of measures

First the dataset is subsetted such that it only contains *permno*, *date* and *return*. For each sample month we will calculate a pairwise measure between non-overlapping monthly windows of returns. An important question is how to deal with the securities being included / deleted and such have missing returns. This can be illustrated in table 5.1 which illustrates how the monthly series of returns are coerced to a wide format with *date* as rows, *permno* as columns and *return* for security in the intersection. There are mainly two options on how to deal with the securities with missing return observations. Either one can use only the complete series or one can calculate measures using pairwise complete observations.

Table 5.1: Example of wide format where the upper right corner is shown, the first column contains dates while the rest contains the returns for an individual permno. NA represent missing values, which in most cases are due to additions or deletions. The NA's seen here is added for illustrative purposes only. Rounded for presentational purposes.

date	10078	10104	10107	10137	10138
20020102	0.0602	0.0123	0.01192	-0.0030	NA
20020103	0.02914	0.0937	0.0327	-0.0171	NA
20020104	0.0380	0.0105	-0.0048	-0.0110	NA
20020107	-0.0230	0.0026	NA	0.0028	0.0003
20020108	0.0235	0.0168	NA	-0.0085	-0.0022
20020109	-0.0251	0.0622	NA	0.0097	0.0091
20020110	-0.0037	-0.0024	NA	-0.0011	0.0101

For the correlation measures calculated using equal weights for each observation, we have used both the pairwise complete observations and the complete series. This is done so we can compare the two different methods of dealing with missing observations and see if the result differ. For the correlations measures that we have chosen to value weight according to end of month market capitalization of the constituent securities. Here only securities which have enough observations to calculate a correlation coefficient is used. So for example a security that is added to the index on the last trading day of the month and thus only has one day of eligible returns will not be used either for the calculation of weights or calculation of correlation measure[5].

For the calculation of the weights the dataset is first subsetted into long format where we have *date, permno, price* and *shares outstanding*. For the last trading day of each month we calculate market capitalizations for the individual securities i by multiplying the absolute value [6] of the closing price with the shares outstanding for that day. The total market capitalization is calculated as sum of the individual securities market capitalizations on the last trading day of each month. The weights are calculated as the market capitalization of the individual security over the total market capitalization. This means that for the last trading day of each month we have a vector of weights $\boldsymbol{w}_m$ consisting of weights w_i, which we for convenience can multiply with the transpose of itself to obtain a weight matrix $\boldsymbol{W}_m$

To calculate our correlation measures we start by calculating a correlation matrix for each year month m with the correlation measure chosen ρ, not to be confused with the specific Pearson correlation. $\boldsymbol{R}_{\rho,m}$ represents any of our correlation measures and is subsetted so we have a strictly upper triangular matrix $\boldsymbol{R}_{\rho,m,[i<j]}$ as shown in (5.6).

$$\boldsymbol{R}_{\rho,m} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1j} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{i1} & \rho_{i2} & \cdots & \rho_{ij} \end{bmatrix} \to \boldsymbol{R}_{\rho,m,[i<j]} = \begin{bmatrix} & \rho_{12} & \cdots & \rho_{1j} \\ & & \ddots & \vdots \\ & & & \rho_{ij-1} \\ & & & \end{bmatrix} \tag{5.6}$$

To find the average equal-weighted pairwise correlations for each month, we use (5.7) where N is the number of pairwise correlations in $\boldsymbol{R}_{\rho,m,[i<j]}$. For the equal weighted measures weights $\boldsymbol{w}_m$ are set to 1.

[5] Thus, making sure that all weights sum to 1.

[6] The absolute value is used since if no closing price is available CRSP reports the bid/ask average with a dash in front of it which otherwise would be interpreted as a negative (Center for Research in Security Prices, 2018h, p. 73).

$$\mathrm{ew}_{\rho,m} = \frac{\boldsymbol{w}_m^T \boldsymbol{R}_{\rho,m,[i<j]}\,\boldsymbol{w}_m}{N} \tag{5.7}$$

The value weighted measure which is shown in equation (5.8), it has been implemented with its vector and matrix representation. The weight matrix $\boldsymbol{W}_m$ is subsetted to a strictly upper triangular weight matrix $\boldsymbol{W}_{m,[i<j]}$, $\boldsymbol{e}$ is a vector of ones and $\circ$ represent the Hadamard product.

$$\begin{aligned}\mathrm{vw}_{\rho,m} &= \frac{2\sum_{i=1}^{N}\sum_{i<j}^{N} w_i w_j \rho_m}{1-\sum_{i=1}^{N} w_i^2} \\ &= \boldsymbol{e}^T\left(\left(\frac{\boldsymbol{W}_{m,[i<j]}}{\boldsymbol{e}^T\boldsymbol{W}_{m,[i<j]}\boldsymbol{e}}\right)\circ \boldsymbol{R}_{\rho,m,[i<j]}\right)\boldsymbol{e}\end{aligned} \tag{5.8}$$

The result is 12 measures of correlations, eight calculated with (5.7) and four with equation (5.8).

5.1.5 Which measure to use?

Table 5.2: Summary statistics of pairwise correlation measures for the constituents of S&P 500. From 2002 through 2017. The pairwise complete are calculated using pairwise complete vectors of returns while complete are calculated only using the securities that are complete for the full month in question. The *Fratio* are calculated in accordance with what presented by (Da & Shive, 2017, p. 144).

	min.	1st. q.	mean	3rd. q.	max.	sd.
pearson pair.	0.070	0.228	0.333	0.418	0.802	0.139
pearson comp.	0.069	0.228	0.334	0.420	0.802	0.139
vw. pearson	0.053	0.253	0.359	0.456	0.811	0.146
kendall pair.	0.056	0.165	0.247	0.310	0.632	0.103
kendall comp.	0.056	0.166	0.248	0.310	0.632	0.104
vw. kendall	0.046	0.181	0.263	0.341	0.635	0.108
spearman pair.	0.078	0.232	0.340	0.428	0.791	0.134
spearman comp.	0.079	0.233	0.341	0.428	0.791	0.135
vw. spearman	0.065	0.253	0.360	0.463	0.793	0.139
biweigh pair.	0.075	0.232	0.340	0.427	0.795	0.135
biweight comp.	0.076	0.232	0.341	0.427	0.795	0.135
vw. biweight	0.067	0.254	0.360	0.464	0.805	0.140
fratio	0.046	0.168	0.258	0.329	0.725	0.124

Here we compare the results of our monthly correlation measures and choose which ones to use as our dependent variable. When examining table 5.2, we can see that there is little difference between the measures. This might imply that the choice of measure is not of great importance, but on the other hand there are also some differences, especially when one looks at the magnitudes. When extending the analysis to also include correlations between the measures as depicted in figure 5.1 one can clearly see that qualitatively there are no differences between the measures.

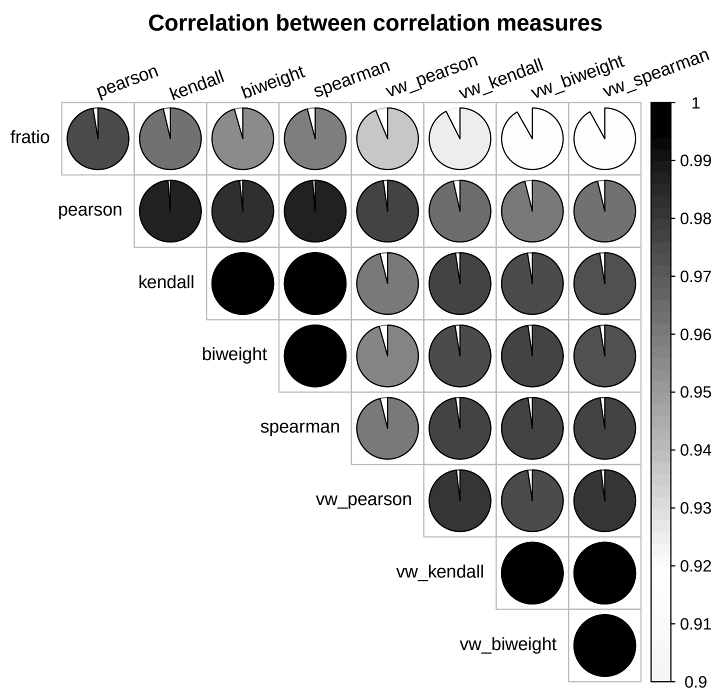


Figure 5.1: Correlation between correlation measures depicted between [0.9, 1], ordered by the angular values of the eigenvectors following Friendly (2002, p. 320-1). The non value weighted measures are equal weighted of the constituents correlations. For all correlation measures only securities with complete monthly returns are used for calculation. Qualitatively there are no difference if the pairwise complete observations are used to compute the measures, they all have a correlation > 0.98 with the used equal weighted measures.

Interestingly, there seems to be almost no difference if one uses the complete or only the pairwise complete. This is an important observation since it informs us that the deletion / addition of securities to the index is not important in regard to average pairwise correlations for the month. For simplicity, we discard the measures computed using the pairwise complete return vectors since they have similar values as their complete counterparts.

One can also see that an equal-weighted or value-weighted measures are quite similar, as depicted in figure 5.2. However, following literature we have chosen to focus on the value-weighted measures. In the end, we have chosen five measures of average pairwise correlation for our regression analysis: value-weighted Pearson, value-weighted Spearman, value-weighted Kendall, value-weighted biweight midcorrelation and equal-weighted biweight midcorrelation. The main parts of the empirical analysis will be carried out using measures based on the biweight midcorrelation since for example Wilcox (2012, pp. 454-5), recommends this usage of a robust correlation coefficients due the its higher breakpoint than classic sample estimators (Wilcox, 2012, p. 35).

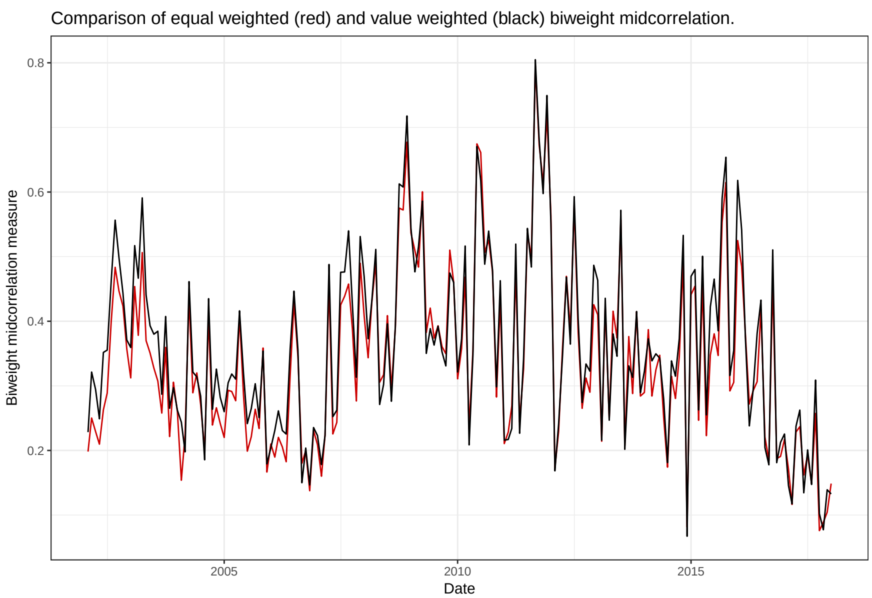


Figure 5.2: Equal weighted biweight midcorrelation vs. value weighted biweight midcorrelation. The results are similar for the other average correlation measures as well, thus there are no apparent differences in using equal weighted or value weighted measures. For theoretical correctness value weighted measures are used.

5.2 Trading ratio

The first independent variable of interest is the trading ratio which is used in the ETF literature by Leippold et al. (2016, p. 28) and in another iteration by Staer and Sottile (2018). It is defined as the ratio of dollar trading volume for ETFs to the dollar volume of the underlying assets. Trading volume is total amount of shares sold of a stock in a single day. As such, it is a measure of trading activity. The purpose of this variable is to proxy the demand for S&P 500 tracking ETFs in question relative to the demand for the underlying securities on the secondary market.

$$\text{Trading ratio} = \frac{\text{Total ETF dollar trading volume}}{\text{Total constituent securities dollar trading volume}} \tag{5.9}$$

The calculation is straight forward as shown in equation (5.10) where the ETFs active at any given time is denoted by s and the securities in the underlying basket denoted with subscript u and the dollar volume is calculated as $\text{dvol}_{i,d} = P_{i,d} * \text{vol}_{i,d}$. This equation gives us the monthly average trading volume between ETFs and the underlying stocks on the S&P 500.

$$\text{Trading ratio}_m = \frac{\sum_{d=1}^{D_{s,m}} \sum_{s=1}^{S_d} \text{dvol}_{s,d}}{\sum_{d=1}^{D_{u,m}} \sum_{u=1}^{U_d} \text{dvol}_{u,d}} \tag{5.10}$$

The underlying intuition behind the trading ratio is it describes nonsynchronous trading of ETFs relative to its underlying stocks as depicted in figure 5.3. This creates price pressure moving ETF share price away from its NAV, thereby triggering an arbitrage opportunity (Ben-David, Franzoni, & Moussawi, 2017). This mechanism has been illustrated earlier in figure 1.5. Trading activity is measured by the daily trading volume and has been used both as proxy for demand (Leippold et al., 2016) and as a measure of liquidity (Hill et al., 2015; Staer & Sottile, 2018) therefore, we discuss trading volume in both respects.

With respect to the demand aspect of trading volume, correlated demand can lead to increased correlations of the underlying assets (Barberis et al., 2005). Because ETFs are created and redeemed in baskets, this correlated trading activity could give rise to correlated price comovement. This could be a results of a certain class investors who prefer to invest in indexes such as the S&P 500, making ETFs that track them an attractive investment vehicle. Further, because of the liquidity of ETFs, short-term traders may be attracted to ETFs more than the underlying. Part of the nonsynchronous demand for ETFs is proposed to be caused by the correlated de-

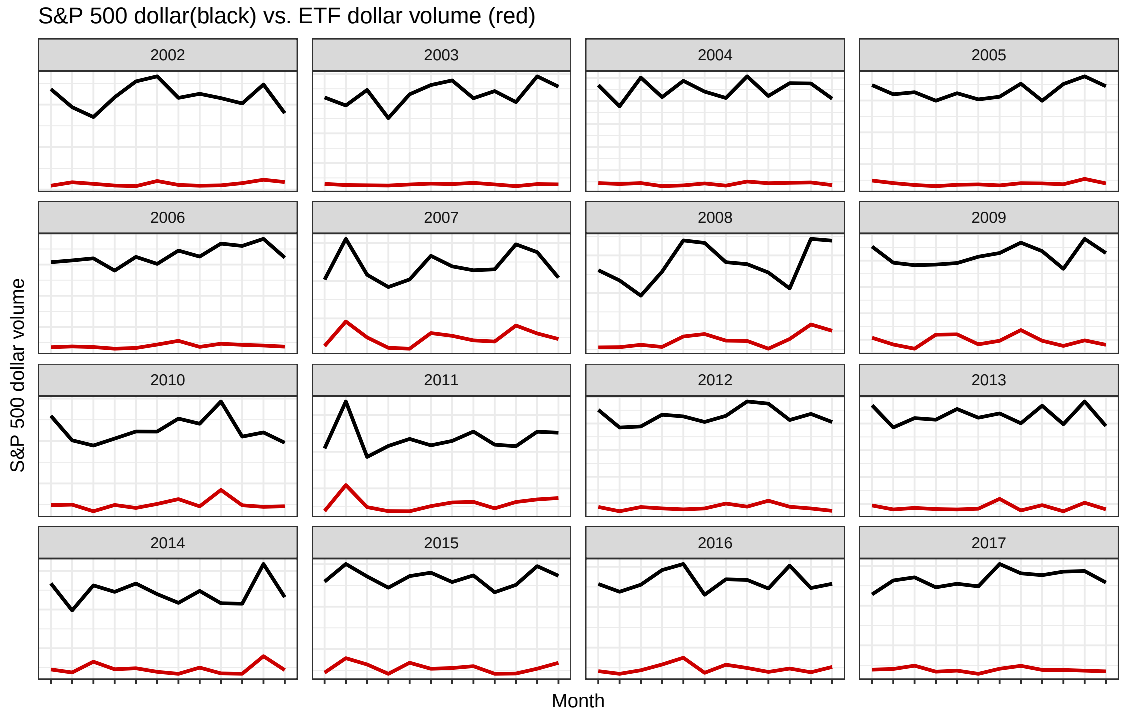


Figure 5.3: The ETF dollar volume (red) and S&P 500 dollar volume, depicted yearly using monthly data. This is the two variables we use to construct the trading ratio, where the rationale for dividing by the S&P 500 dollar volume is that it moves in tandem with the ETF dollar volume.

mand of short-term traders (Broman, 2016).This can cause differences in demand between the ETF and underlying stocks, and as ETF demand changes, this puts price pressure on the ETF share price triggering the arbitrage process. The APs then buy and sell large blocks of underlying stocks. As a result, we should observe higher return comovement with increasing relative demand, as proxied by trading ratio.

The trading ratio is depicted graphically in appendix D, and possible transformations will be discussed later. Finally it is should be noted that trading volume is used as a proxy for demand as well as liquidity (Amihud & Mendelson, 1986). As such, we can use it in our discussions of liquidity measures insofar as it also captures short-term trader demand.

5.3 Defining liquidity

Liquidity is a multifaceted concept, which we take into account in our approach to proxy liquidity, since our conjecture is that ETF short term demand intensifies the arbitrage process. In the literature multiple authors have documented commonality in liquidity, an example is Chordia, Roll, and Subrahmanyam (2000), which finds that there are common determinants of liquidity in the market. There is no one recognized view on the concept of liquidity communality or what causes it, both supply, demand, ownership and sentiment based explanations has been proposed (Karolyi, Lee, & van Dijk, 2012, p. 83).

The supply side view of liquidity as popularized by Brunnermeier and Pedersen (2009) states the determinant of the commonality in liquidity is market and funding liquidity. Alternatively, the demand side view of liquidity posits that the common determinant of liquidity is correlated trading activity (Chordia et al., 2000). In either case, the causes of commonality in liquidity is not critical to the analysis, but rather that there exists a common liquidity component that can be measured.

According to Goyenko, Holden, and Trzcinka (2009) who compares liquidity measures aggregated from daily data to and finds that measures aggregated from daily data to monthly and yearly frequencies generally do an adequate job of measuring liquidity. In the following we explicitly specify the construction of our liquidity measures, where we follow guidance from Amihud (2002), Karolyi et al. (2012), amongst others.

5.3.1 Amihud measure

A commonly used liquidity measure is the amihud illiquidity measure proposed by Amihud (2002), which follows the insights derived by Amihud and Mendelson (1986). This measure is used extensively both in the broader financial literature (Acharaya & Pedersen, 2005, p. 386) and in the ETF literature (Ben-David, Franzoni, & Moussawi, 2017, p. 17). It is generally regarded as one off the best daily proxies for the price impact of a trade, and it was found by Hasbrouck (2009, p. 1459) to be the best daily proxy when compared with high frequency liquidity measures. The amihud measure of illiquidity is defined as in equation (5.11) consistent with Amihud (2002, p. 34). For a single security i on day d it is defined as the absolute value of the return over the daily dollar volume $\mathrm{dvol}_{i,d} = P_{i,d} * \mathrm{Vol}_{i,d}$.

$$\text{amihud}_{i,d} = \frac{\left|R_{i,d}\right|}{\text{dvol}_{i,d}} \tag{5.11}$$

Because the amihud measure is a measure of illiquidity, we modify the amihud measure to make it more intuitively interpretable and increasing in liquidity as in equation (5.12). For each security i we take the monthly average, where m is the year month and $D_{i,m}$ represents the number of trading days consistent with Amihud (2002, p. 34). The modifications are that we add a constant, take natural logarithms because of possible outliers, and sign it. This is comparable to what is done by Karolyi et al. (2012, p. 88). In the ETF literature Broman and Shum (2018, p. 94) uses a similar measure, albeit without adding a constant which makes the measure numerically unfeasible when $R_{i,d} = 0$.

$$\text{amihud liquidity}_{i,m} = \frac{-1}{D_{i,m}} \sum_{d=1}^{D_{i,m}} \log\left(1 + \frac{\left|R_{i,d,m}\right|}{\text{dvol}_{i,d,m}}\right) \tag{5.12}$$

5.3.2 Proportional quoted spread

To measure transaction cost, which is a dimension of liquidity we use the proportional quoted bid ask spread as a proxy. Since we do not have access to the Trade and Quote (TAQ) database (NYSE Market Data, 2018), we use proportional quoted spreads calculated from closing daily data as noted by Chung and Zhang (2014, p. 95) to be among the top estimators compared to TAQ data. In the period from 2002 through 2009 Chung and Zhang (2014, p. 118) find that the proportional quoted bid ask spread performs well as a measure of transaction costs when aggregated to a monthly frequency. First we define the proportional quoted spread for security i on day d as in (5.13). Where the bid-ask spread is divided by the bid-ask midpoint for the daily close.

$$\text{PQSPR}_{i,d} = \left(\text{ask}_{i,d} - \text{bid}_{i,d}\right) / \left(\frac{\text{ask}_{i,d} + \text{bid}_{i,d}}{2}\right) \tag{5.13}$$

To make the measure more robust and numerically tractable we do some small modifications. We can start by defining a piecewise function as in (5.14) that accounts for negative spreads. We have decided to set the spread to one cent for the few times in which the spread crosses or is zero. This is done to make the measure numerically consistent, and is in agreement with what has been done by for example Ma, Anderson, and Marshall (2018, p. 34) and Chung and

Chuwonganant (2014, p. 478). Then we can define the $\text{PQSPR}_{i,m}$ for security i in year month m as in (5.15) where we add a constant, take the natural logarithm and sign it such that the measure is increasing in liquidity.

$$\text{spread}_{i,d,m} = \begin{cases} \text{ask}_{i,d,m} - \text{bid}_{i,d,m} & \text{ask}_{i,d,m} - \text{bid}_{i,d,m} > 0 \\ 0.01 & \text{otherwise} \end{cases} \tag{5.14}$$

$$\text{PQSPR}_{i,m} = \frac{-1}{D_{i,m}} \sum_{d=1}^{D_{i,m}} \log \left[1 + \text{spread}_{i,d,m} / \left(\frac{\text{ask}_{i,d,m} + \text{bid}_{i,d,m}}{2} \right) \right] \tag{5.15}$$

5.3.3 Relative measures

Following the idea presented by Broman and Shum (2018), we calculate the relative amihud measure and the relative proportional quoted spread between the ETFs and the underlying securities. The intuition here is that short term traders are driven by the relative liquidity of the ETF versus the underlying. We modify the measures proposed by Broman and Shum (2018, p. 95) since their measures are not numerically feasible. Therefore we leave the few days where ETF returns are equal to zero out, while we also leave out securities which have a daily volume of zero. In total this accounts for approximately 50 observations.

To implement the relative amihud measure we define $\text{ami}_{k,d}^{UND}$ and $\text{ami}_{i,d}^{ETF}$ according to equation (5.11) for all underlying securities k and our three ETFs i. To calculate the relative measure we use the value weighted underlying securities where the weights for each day are represented by $w_{k,d}$. Since we are only using three ETFs and since these are physically replicating the S&P 500 the weights calculated as market capitalization weights is an approximation of the holdings for each ETF. This means that we can define the measure for each month according to (5.16).

$$\text{relative amihud}_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D_{i,m}} \log \left(1 + \sum_{k=1}^{K} w_{k,d} * \text{ami}_{k,d}^{UND} / \text{ami}_{i,d}^{ETF} \right) \tag{5.16}$$

Underlying this is a the subtle assumption that the ETFs tracking the S&P 500 have homogeneous holdings. This allows us to calculate a weighted relative measure as in (5.17). $w_{i,d}$ is the market cap weight of ETF i on day d, thus D_m represents the number of trading days in a month[7].

$$\text{weighted relative amihud}_m = \frac{1}{D_m}\sum_{d=1}^{D_m}\log\left(1+\sum_{i=1}^{I} w_{i,d}\sum_{k=1}^{K} w_{k,d} * \text{ami}_{k,d}^{UND}/\text{ami}_{i,d}^{ETF}\right) \tag{5.17}$$

Similarly, to calculate the relative proportional quoted spread we calculate both a relative ETF measure for each ETF (5.18) and an aggregated weighted measure (5.19). We define the daily proportional quoted spread for each underlying or ETF for any given day according to equation (5.13) where the numerator is replaced by the result of equation (5.14). Thus, we define the daily proportional quoted spread for underlying securities k and ETFs i as $\text{PQSPR}_{k,d}^{UND}$ and $\text{PQSPR}_{i,d}^{UND}$ respectively.

$$\text{relative PQSPR}_d = \frac{1}{D_{i,m}}\sum_{d=1}^{D_{i,m}}\log\left(1+\sum_{k=1}^{K} w_{k,d} * \text{PQSPR}_{k,d}^{UND}/\text{PQSPR}_{i,d}^{ETF}\right) \tag{5.18}$$

$$\text{weighted relative PQSPR}_t = \frac{1}{D_m}\sum_{d=1}^{D_m}\log\left(1+\sum_{i=1}^{I} w_{i,d}\sum_{k=1}^{K} w_{k,d} * \text{PQSPR}_{k,d}^{UND}/\text{PQSPR}_{i,d}^{ETF}\right) \tag{5.19}$$

For all the relative liquidity measures we have added a constant and take the natural logarithm such that the measures are increasing in relative liquidity, thus ensuring consistency across our liquidity measures. Thus we have calculated a total of 14 liquidity measures, three using each of the equations (5.12), (5.15), (5.16) and (5.18) and one with each of equations (5.17) and (5.19). Since the interest for us is the change in liquidity we have also taken the difference off the already logged liquidity measures and summary statistics of both "raw" and differenced liquidity measures are added in appendix E for completeness.

5.3.4 Principal component of liquidity measures

Since liquidity is believed to be governed by mostly one single component it is appropriate to reduce the dimensions of liquidity measures (Korajczyk & Sadka, 2008). We reduce the dimen-

[7] SPY and IVV has perfectly overlapping daily trading data, but VOO is introduced in September 2009, obviously this is accounted for by the market capitalization weighting of the ETFs.

sionality by calculating principal components as done in the ETF literature, for example by Broman and Shum (2018, p. 96). The literature on principal components are vast and many faceted as exemplified by Jolliffe (2002) who recommends to ensure stationarity[8] before extracting the principal components to adhere to the inherent i.i.d. assumption. We cannot see that Broman and Shum (2018) account for any time dependency other than taking the logs before they extract the first principal components. In this regard our approach is slightly different since we difference the data. Another issue with calculating the principal components is that the VOO is introduced later than the other two ETFs. Here we have taken the pragmatic approach of calculating principal components before and after for the first three matrices in (5.20)[9].

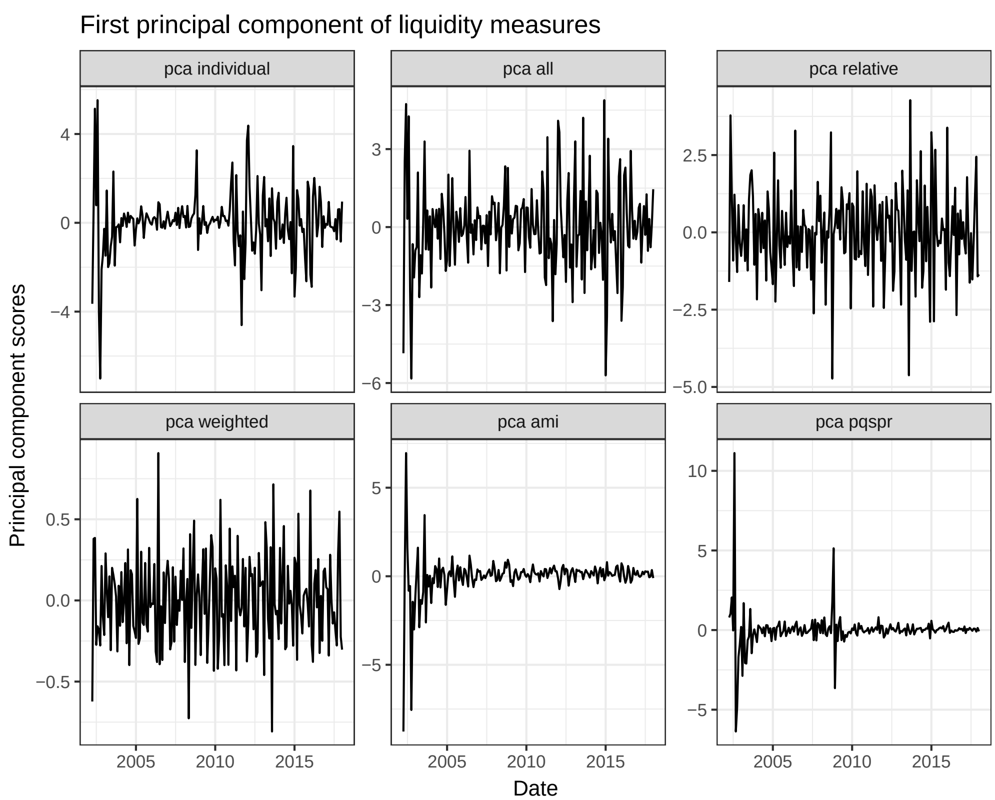


Figure 5.4: The extracted scores of the first principal component of different combinations of liquidity measures. Especially for ami and pqspr there seems to be some outliers in the start of the data causing inflated scores.

[8]There are multiple options to adhere to the inherent independence assumption, a first though would be to for example add lags and calculate dynamic principal component analysis (Vanhatalo, Kulahci, & Bergquist, 2017)

[9]To ensure that this approach gives results that are within reason we have for example looked at the correlation between the first and second principal components of the combined scores. Which is for all practical purposes zero, this informs us that there are no major discrepancies in what the first principal component captures from the different time periods.

Table 5.3: The variance explained by the first principal component for six different combinations of liquidity measures. The principal components are calculated on centered $\hat{\mu} = 0$ and scaled data $\hat{\sigma} = 1$ using singular value decomposition. The total is either the variance explained for the whole sample if appropriate or a weighted average of before and after the introduction of VOO.

	before VOO	after VOO	total
pca individual	0.463	0.403	0.436
pca all	0.278	0.311	0.293
pca relative	0.421	0.396	0.410
pca weighted			0.553
pca ami			0.697
pca pqspr			0.735

From a total of six combinations of liquidity measures, we extract the first principal component. The six distinct data matrices $\boldsymbol{X}_i$ is defined in (5.20) where $\|$ denotes concatenation, the notation is slightly deceptive since for example amihud liquidity$_i \|$PQSPR$_i$ represent the concatenation of a combined six vectors. Where the first difference of our liquidity measures are used in the construction of $\boldsymbol{X}_i$. We also normalize each series in $\boldsymbol{X}_i$, before the first principal components are calculated. The practical implementation follows Tsay (2010, p. 483-8), but calculations are done via singular value decomposition for computational efficiency and numerical stability.

$$
\begin{aligned}
\boldsymbol{X}_{\text{individual}} &= \text{amihud liquidity}_i \| \text{PQSPR}_i \\
\boldsymbol{X}_{\text{all}} &= \text{amihud liquidity}_i \| \text{PQSPR}_i \| \text{relative amihud}_i \| \text{relative PQSPR}_i \\
\boldsymbol{X}_{\text{relative}} &= \text{relative amihud}_i \| \text{ relative PQSPR}_i \\
\boldsymbol{X}_{\text{weighted}} &= \text{weighted relative amihud} \| \text{weighted relative PQSPR} \\
\boldsymbol{X}_{\text{ami}} &= \text{amihud liquidity}_{SPY} \| \text{amihud liquidity}_{IVV} \\
\boldsymbol{X}_{\text{PQSPR}} &= \text{PQSPR}_{SPY} \| \text{PQSPR}_{IVV}
\end{aligned}
\tag{5.20}
$$

The proportion of variance explained by the first principal components is shown in table 5.3. Here we can see that the scores of pca all explains less than 30% of the variance, thus being the least informative measure. Examining the time series plots of the scores that are shown in figure 5.4, informs us that the scores of *pca individual,pca ami* and *pca pqspr* are non-stationary. This leaves us with the relative measures and weighted measures as the appropriate scores to use in our subsequent analysis.

5.4 Control variables

Comovement in stock prices can be a result of macroeconomic and stock market factors. For example, during a market downturn, stock prices do precisely that, decrease in value at the same time. To control for possible market variations that could potentially affect stock correlations, we include in our model a set of financial market and macroeconomic variables. Since we are studying stocks and ETFs on the S&P 500, we limit our variables to US-specific indicators.

TED spread

When the economy is in a recession, stock prices tend to react accordingly and comove downward. To account for recessions or expansions, we include a variable for the TED spread, the difference between the three-month US Treasury bill and the three-month LIBOR rate. Historically, market observers have used the TED spread as an indicator for whether the economy is in a period of recession or expansion (Brunnermeier, 2009, p. 85). The three-month T-bill has traditionally been viewed as the risk-free rate while LIBOR reflects changing risk levels in interbank unsecured borrowing. In times of uncertainty, banks charge a higher fee, raising the LIBOR rate and investors tend to migrate to safer securities like Treasury bonds, pushing down the Treasury bond rate. As a result, the TED spread gauges the severity of a liquidity crisis (Brunnermeier, 2009, p. 85). Using a dynamic model Boudt, Paulus, and Rosenthal (2017, p. 154) finds empirical support that a TED spread above 48 basis points is indicative of economic crisis.

Industrial production

We use industrial production, another macroeconomic control variable, as a proxy for GDP growth rate. Chenery (1960, p. 624) stated that an "increase in per capita income in a country is normally accompanied by a rise in the share of industrial output." The advantage of using industrial production growth over GDP is that industrial production growth rate is reported on a monthly basis. With respect to stock returns, Schwert (1990) finds that production growth rates explain a large fraction of the variation in stocks. The National Bureau of Economic Research has the responsibility of making the official call whether the economy is in a recession and takes into account industrial production growth as one indicator of economic growth.

Inflation

Inflation is included as a control variable because it has been found to impact stock returns. Where inflation is the change in Consumer Price Index (CPI) is used to measure inflation and because it has been shown to have a similar impact on all stocks and thus increases correlations. Antonakakis, Gupta, and Tiwari (2017) find that although, in general, real stock returns and inflation are negatively correlated, but that the relationship is time-varying and at times of distress significantly positive.

VIX

Stock prices also tend to increase in correlations in times of high volatility (Longin & Solnik, 1995). To control for volatility in the market, we add the CBOE Volatility Index (VIX), a measure of market expectation of short term future volatility. We use this instead of historical volatilities since as noted by the creator of the VIX index Whaley (2009, pp. 103-4) it measures how much investors fear the downside in the market. Thus, it should have an inverse relationship with the average correlations. Interestingly, Whaley (2009, p. 103-4) also finds that the VIX inside a wide confidence band works quite well as a predictor for S&P 500 index returns.

Market return

It is important to control for market returns since for average correlations and returns are related as shown by (Pollet & Wilson, 2010, p. 380). Thus, we add the value weighted market return to our models.

5.5 Modeling

In the modeling section our goal is to model the relationship between the variables already presented. First we will start by presenting summary statistics of our variables and their timeplots. From this we can discuss appropriate transform of our variables. Then the proposed models will be presented.

5.5.1 Summary statistics and visual inspection

Table 5.4: Summary statistics for the variables available for modeling presented earlier. The provenance of the data used to construct measures or reasoning behind choosing them has been presented earlier in the text. Higher moments are added as to present better represent the distributions of the variables. Estimates are rounded for presentation.

	min.	1st. q.	mean	3rd. q.	max.	sd.	var.	skew.	ex. kurt.	n.
vw pearson	0.05	0.25	0.36	0.46	0.81	0.15	0.02	0.50	-0.05	192
vw spearman	0.06	0.25	0.36	0.46	0.79	0.14	0.02	0.49	-0.08	192
vw kendall	0.05	0.18	0.26	0.34	0.63	0.11	0.01	0.66	0.31	192
vw biweight	0.07	0.25	0.36	0.46	0.80	0.14	0.02	0.47	-0.11	192
ew biweight	0.08	0.23	0.34	0.43	0.80	0.14	0.02	0.61	0.12	192
trading ratio	0.03	0.11	0.17	0.22	0.37	0.07	0.00	0.18	-0.50	192
pca individual	-7.02	-0.41	0.00	0.46	5.52	1.45	2.10	-0.25	4.86	190
pca all	-5.83	-0.89	0.00	0.80	4.88	1.70	2.89	-0.01	1.42	190
pca relative	-4.73	-0.88	0.00	0.86	4.28	1.41	1.99	-0.03	0.88	191
pca weighted	-5.47	-0.63	0.00	0.58	4.47	1.05	1.11	0.00	5.56	191
vwretd	-0.18	-0.01	0.01	0.03	0.11	0.04	0.00	-0.77	2.11	192
ted spread	0.12	0.21	0.43	0.46	3.15	0.42	0.18	3.37	13.95	192
vix	9.5	13.4	19.3	22.9	59.9	8.4	70.0	1.9	4.6	192
ind pro	87.1	95.4	99.5	103.5	107.3	4.9	24.2	-0.5	-0.8	192
cpi	177.7	199.3	215.7	234.7	247.9	20.5	419.3	-0.3	-1.2	192

With the creation of the variables in mind we now take a closer look at them and present summary statistics and figures depicting the variables of interest. The summary statistics are depicted in table 5.4, and the cross sectional distributions are added and discussed in appendix F.

For us it is more interesting to view the time series plots as depicted in figure 5.5. This is done to enhance the understanding of the data before more formal tests are conducted. The five first

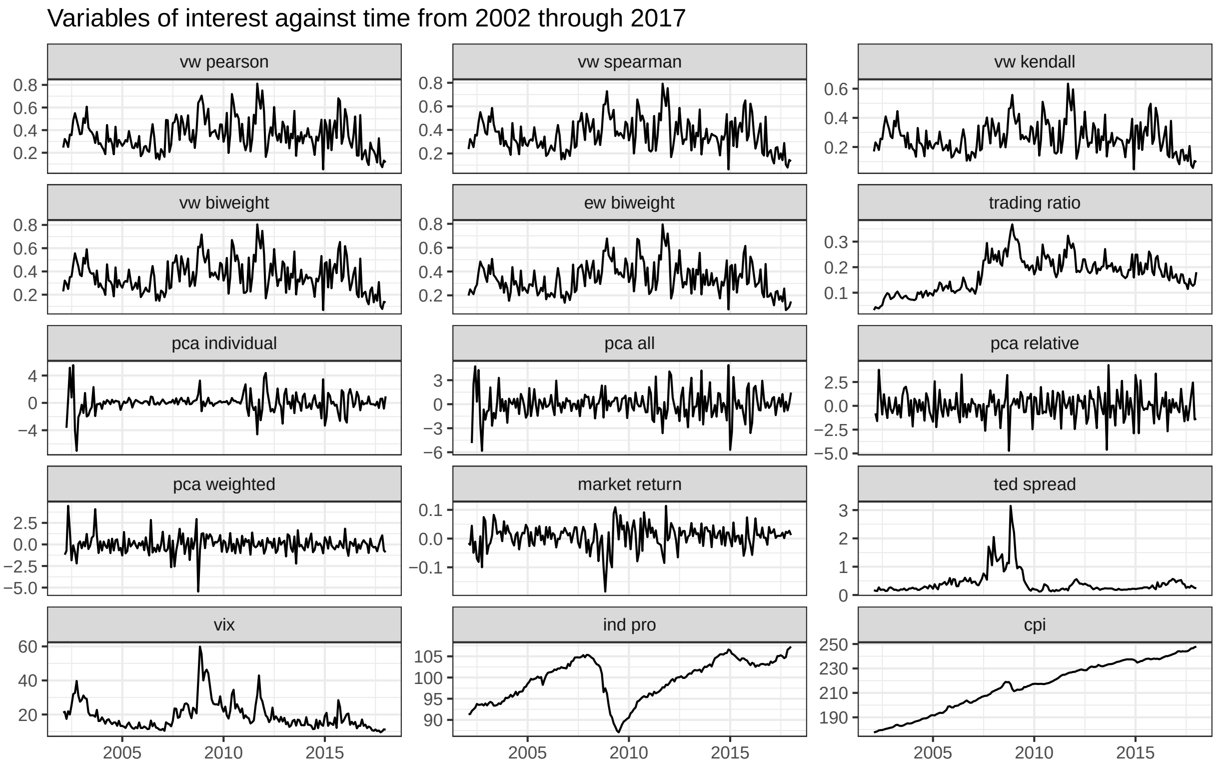


Figure 5.5: Time plots of the variables available for modeling for the full sample available early 2002 through 2017. Interestingly one can see that the correlation measures as discussed earlier is almost the same, especially when contrasting the value weighted and equal weighted biweight mid correlation this can be seen. As for our liquidity measures only those deemed reasonable to use has been included. These are the only variables which have been transformed, the provenance of the variables are discussed in depth in the data section.

plots, which are of the correlations measures confirm what we have seen earlier, that there does not seem to be much of a difference between them.

The trading ratio seems to sharply increase during the financial crisis, where a possible explanation could be as Karmaziene and Sokolovski (2015) has shown is connected with SEC 2008 short sale ban of financial securities and the create to lend mechanism of ETFs. More specifically they showed that short interest in SPY significantly increased during the financial crisis, as market participants could synthetically short the banned stocks through ETFs (Karmaziene & Sokolovski, 2015, p. 24-5).

More interestingly is what we can see from our liquidity measures, where both the relative and weighted have some spikes where one would expect, especially the negative spikes in relation to the financial crisis. The same patterns can also be seen in the control variables. Thus this is a feature of the data in, which we will have to inspect more closely in the following to find the appropriate transformations and feasible econometric approach.

5.5.2 Unit root and stationarity testing

Since we can infer from figure 5.5 that there might be issues relating to unit roots and non-stationarity, we want to formally test for this to be informed of appropriate transformations. We employ a test that look for covariance stationarity which formally according to Tsay (2010, p. 30) requires the a series has constant: mean μ, variance σ_y^2 and covariance γ_s. We also employ unit-root tests, which tests that the series has a unit root and as such the characteristic polynomial is not invertible.

Following the advice of Pfaff (2008, p. 105) we apply multiple tests, which has different usages and interpretations. Three examples of such tests and their results are given in table 5.5 where we have tested the series in question in their untransformed form. The first test employed is the KPSS-test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), which tests the null hypothesis of stationarity against the alternative of a unit root, thus taking a conservative approach (Pfaff, 2008, p. 103). We specify the test to test for level stationarity as proposed by Kwiatkowski et al. (1992, pp. 161-2), where the lag truncation parameter is chosen by truncating $3 * \frac{\sqrt{n}}{13}$. From this test we can see that can reject the null of stationarity for the *trading ratio*, *vix*, *industrial production* and *cpi*.

The second test employed is the Augmented Dickey Fuller test (Dickey, 1976, pp. 366-73), that tests the null of the existence of a unit root against the alternative of no unit root. The interesting thing to note is that this test results are not consistent across different correlation measures. On the other hand for the *trading ratio*, *vix*, *industrial production* and *cpi* the results are consistent thus it seems that these variables will have to be transformed.

We employ a third and last test the Phillips-Perron test (Phillips & Perron, 1988) since the first two are not conclusive and does not agree on how we should transform some of the variables. This test, makes a correction to the ADF-test to account for heterogeneity and weak dependence. Where the hypotheses are the same as the ADF test. The test results is that we cannot reject the null for *industrial production* and *cpi*.

Following the advice given by Pfaff (2008, p. 105), we place more weight on the KPSS-test since both the ADF-test and the PP-test places unit root null. From this we can infer that the *trading*

Table 5.5: We test for level stationarity for each off the timeseries, where we present the number of appropriate differences for each test, the test statistic and the p-value are according to the 5% level. Where the critical values used in the KPSS test is 0.463 as reported by Kwiatkowski, Phillips, Schmidt, and Shin (1992, p. 166), and the p values is interpolated. The critical value for the ADF test is between -3.45 and -3.42 at the 5% level as reported by Dickey (1976, p. 53), but only for $n = 100$ and $n = 250$, which interestingly differs slightly from the critical values provided by Fuller (1976, p. 373), revealing an error, since the later references the first. The PP test relies on the same critical values as the ADF test (Phillips & Perron, 1988, p. 345).

	KPSS			ADF			PP		
series	d. kpss	kpss stat.	kpss p.	d. adf	adf stat.	adf p.	d. pp	pp stat.	pp. p.
vw pearson	0	0.36	0.095	1	-3.36	0.063	0	-116.1	0.010
vw spearman	0	0.32	0.100	0	-3.44	0.050	0	-110.0	0.010
vw kendall	0	0.31	0.100	0	-3.54	0.040	0	-108.6	0.010
vw biweight	0	0.33	0.100	1	-3.42	0.053	0	-111.2	0.010
ew biweight	0	0.45	0.058	1	-3.18	0.093	0	-96.4	0.010
trading ratio	1	1.95	0.010	1	-2.41	0.405	0	-23.3	0.032
pca individual	0	0.11	0.100	0	-7.00	0.010	0	-152.6	0.010
pca all	0	0.06	0.100	0	-7.78	0.010	0	-186.8	0.010
pca relative	0	0.03	0.100	0	-7.43	0.010	0	-216.4	0.010
pca weighted	0	0.06	0.100	0	-6.36	0.010	0	-204.7	0.010
market return	0	0.11	0.100	0	-5.76	0.010	0	-169.9	0.010
ted spread	0	0.45	0.054	1	-2.48	0.377	0	-24.4	0.024
vix	1	0.58	0.025	1	-2.99	0.162	0	-26.5	0.016
ind pro	1	1.62	0.010	2	-2.84	0.224	1	-5.4	0.807
cpi	1	4.82	0.010	1	-1.84	0.644	1	-7.5	0.687

ratio, *vix*, *industrial production* and *cpi* has a unit root. Thus, we will have to transform these variables appropriately as to avoid spurious results (Enders, 2014, pp. 198-9). Although there are different options on how to transform the variables, we have chosen to use the log differences, which is an approximation for percentage change. The alternative approaches are regular differences and detrending. Therefore we take the log difference of the *trading ratio*, *cpi*, *industrial production* and *vix*. A summary of the cross sectional of the transformed variables can be seen in table 5.6, and in the following we will denote the log differences with Δ[10].

We have also looked at possible structural breaks which collaborates with the above discussion where the visualization of the test are added in appendix H-J. This for the most part confirm of our earlier tests, and therefore we will continue with the transformed variables. Another in-

[10]We have chosen not to multiply the log differences by 100 to represent percentages, but rather keep the decimal form.

Table 5.6: Summary transformed variables

	min.	1st. q.	mean	3rd. q.	max.	sd.	var.	skew.	ex. kurt.	n.
Δtrading ratio	-0.454	-0.108	0.009	0.105	0.448	0.173	0.030	0.124	-0.192	191
Δholding percentage	-0.215	-0.020	0.010	0.034	0.262	0.061	0.004	0.388	3.418	191
Δcpi	-0.018	0.000	0.002	0.003	0.014	0.003	0.000	-1.381	9.283	191
Δind pro	-0.044	-0.002	0.001	0.004	0.017	0.007	0.000	-2.141	10.468	191
Δvix	-0.486	-0.110	-0.0034	0.103	0.853	0.196	0.038	0.583	1.632	191

teresting relationship depicted is the 3-dimensional density between our biweight correlation measure, trading ratio and time as shown in appendix K. This seems to provide suggestive evidence of a changing relationship between correlations and trading ratio and informs us how important it is to look at sub-sample regressions.

5.5.3 Are pairwise correlation autoregressive?

Table 5.7: Example of autoregressive and moving average models fitted to the measure of biweight midcorrelation. Using standard evaluation criteria we find that the ar(3) model is the "best" model, thus informing us that there are an autoregressive component in our dependent variable. As seen from the rightmost column where a ar(3) model is fitted to the correlation measure based on Pearson. The coefficients does not change, in unreported results we have also checked the other correlation measures and the ar(3) models is for all of them the best or second best model when comparing information criterions.

	ar(1)	arma(1,1)	ar(3)	ar(3) pearson
intercept	0.36	0.35	0.35	0.35
	(0.02)	(0.03)	(0.02)	(0.03)
ar1	0.47	0.84	0.35	0.35
	(0.06)	(0.07)	(0.07)	(0.07)
ar2			0.09	0.04
			(0.07)	(0.07)
ar3			0.22	0.28
			(0.07)	(0.07)
ma1		−0.51		
		(0.11)		
AIC	−251.5	−260.6	−262.1	−246.6
AICc	−251.4	−260.4	−261.8	−246.3
BIC	−241.7	−247.6	−245.8	−230.4
Log Likelihood	128.7	134.3	136.0	128.3

First we can start by thinking about the process that governs the evolution of our correlation measures. Therefore it is natural to start examining this series, we know from the stationarity tests that it is right on the border of being integrated of order one. To better understand the autocorrelation structure of our correlation measure we examine the acf and pacf of the measure based on the biweight midcorrelation depicted in appendix G, which show some kind of autoregressive component. A lower order ar-model might be appropriate. To consider this formally we test this using the algorithm proposed by Hyndman and Khandakar (2008, pp. 10-2). We allow for a non-zero mean comparing models using AIC, BIC and AICc. Examples of relevant models are presented in table 5.7. The two best models are the arma(1,1) model and the ar(3) model. Where the importance of this is that it informs us that there seems to be an autoregressive component in our correlation measure. The results are similar for all our correlation measures, but there is some disagreement if it is governed by an AR(3) process or an ARMA(1,1). This is important since it informs us how many lags of the dependent variable to include in our final models.

5.6 Regression models

To model the relationship we can start by thinking about the relationships between the variables. The proposed models attempts to capture how ETF demand increases comovement between securities in the basket. In the following we will present seven different models given in equation (5.23)-(5.29). For presentational simplicity we start by defining $\boldsymbol{X}$ as a matrix of our control variables as an m x n matrix, concatenated from our control variables and consists off Δ*cpi*, Δ*industrial production*, Δ*VIX*, *TED spread*, and *market return*.

$$\boldsymbol{X} = \Delta\text{cpi}_m \| \Delta\text{industrial production}_m \| \Delta\text{VIX}_m \| \text{TED spread}_m \| \text{market return} \tag{5.21}$$

Similarly we define a matrix $\bar{\boldsymbol{\rho}}$ consisting off three lags of our correlation measure $\bar{\rho}$ consistent with what we have found to be appropriate earlier where the subscript indicating which correlation measure it is, is dropped for simplicity. Thus, in its general form $\bar{\boldsymbol{\rho}}$ is an m by three matrix consisting of $\text{dependent}_{m-1}, \ldots, \text{dependent}_{m-3}$.

$$\bar{\boldsymbol{\rho}} = \bar{\rho}_{m-1} \| \bar{\rho}_{m-2} \| \bar{\rho}_{m-3} \tag{5.22}$$

Now we can specify the regression models where we put a correlation measure denoted with

$\bar{\rho}_m$ on the left hand side, and we follow the convention of letting m represent year month. For simplicity we have dropped the subscript i representing different correlation measures. Since this will be explicitly made clear in the presentations of the models and the same goes for the time period. All our models includes both controls and lags of the dependent variable. For each of the models we add different independent variables of interest. In the following we also adopt the convention that ϕ_i represents the coefficients related to the trading ratio and β_i represents coefficients related to liquidity measures. Furthermore for simplicity Δ is dropped. The first model (5.23), uses the trading ratio, the first principal component of our relative measure of liquidity.

$$\bar{\rho}_m = \alpha + \phi * \text{trading ratio}_m + \beta * \text{relative liquidity}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m \tag{5.23}$$

The second model (5.24) is excactly the same as the first model, but we change the measure of liquidity to be the first principal component of our weighted relative liquidity measure.

$$\bar{\rho}_m = \alpha + \phi * \text{trading ratio}_m + \beta * \text{weighted liquidity}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m \tag{5.24}$$

In the third model (5.25) we explore the possibility of adding a lag of the trading ratio. We also change back to using the first principal component of our relative liquidity measure since this is what we believe is the best liquidity measure available to us.

$$\begin{aligned}\bar{\rho}_m = &\alpha + \phi_1 * \text{trading ratio}_m + \phi_2 * \text{trading ratio}_{m-1} + \beta * \text{relative liquidity}_m + \\ &\boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m\end{aligned} \tag{5.25}$$

In the fourth model (5.26) we remove our liquidity measure, thus including only the trading ratio as a variable of interest. Similarly in model five (5.27) we do not include the trading ratio, but do include relative liquidity.

$$\bar{\rho}_m = \alpha + \phi * \text{trading ratio}_m + \beta * \text{relative liquidity}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m \tag{5.26}$$

$$\bar{\rho}_m = \alpha + \beta * \text{relative liquidity}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m \tag{5.27}$$

In the sixth model (5.28) we include another variable as an interaction term with the trading ratio and that is holding percentage[11], which is the sum of our three ETFs market capitalization over the sum of the underlying stocks market capitalization. This representing how much of the underlying stocks the three ETFs own in any given month. We use the log differenced holding percentage since it is increasing across time, thus this is meant to test if how much of the underlying shares the ETF holds are important.

$$\begin{aligned}\bar{\rho}_m = \alpha + \phi_1 * \text{trading ratio}_m + \phi_2 * \text{trading ratio}_m * \text{holding percentage}_m + \\ \xi * \text{holding percentage}_m + \beta * \text{relative liquidity}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m\end{aligned} \tag{5.28}$$

The seventh model (5.29) is a variant of what (Leippold et al., 2016) presents as their main model. The demand shock is represented as the residuals for a fitted ARIMA model. In our case we fitted the best ARIMA model which is an AR(2) model fitted to the differenced trading ratio as shown in appendix M. Albeit there are differences in the model specification between what we estimate and what they have estimated, the models are similar enough that we believe this could be a way of affirming our approach. Thus this works as a robustness check for our approach of using the log differenced trading ratio as our main independent variable. We also use a different sample period, thus including the recent low correlation environment. Therefore we deem it to be interesting in its own to see if the relationships they have previously found still exists.

$$\bar{\rho}_m = \alpha + \phi * \text{trading ratio ARIMA residuals}_m + \boldsymbol{\gamma} * \boldsymbol{X} + \boldsymbol{\Theta} * \bar{\boldsymbol{\rho}} + \varepsilon_m \tag{5.29}$$

[11] Holding percentage has not been introduced earlier, but we calculate it formally at the end of each month as $\sum_{i=1}^{n} \text{market capitalization}_i / \sum_{j=1}^{p} \text{market capitalization}_j$ where n represents the number of ETFs and p represents the number of underlying securities, following Da and Shive (2017, p. 144). For completeness a time-plot of ETF holding percentage is included in appendix L, and we have chosen to log difference it.

Empirical results

In this section, we report our regression results from our models as described, along with several iterations of the model to examine how the relationship may change. The goal is to assess how the effect of interest, correlations, varies with our variables of interest, trading ratio and relative liquidity. We interpret and compare the results from each model, discussing their implications to our hypothesis, prior literature, and to the broader market.

6.1 Main models

We start our analysis by introducing our regression results presented in table 6.1. Model 1 is our model from (5.23) and contains both our variables of interest meant to proxy demand, trading ratio and relative liquidity. The results show that trading ratio is significant at the 1% level. Since the trading ratio is log differenced, the interpretation of the regression result for correlations on trading ratio is that a 10% increase in the trading ratio coincides with a .052 increase in correlations.

The relative liquidity variable likewise shows a significant positive relationship with correlations at the 1% level. The interpretation of the relative liquidity coefficient is that an 1 unit increase in the aggregated relative liquidity measures is associated with an 0.01 increase in correlations. Because we are using a composite measure of relative liquidity, it should be noted that an increase in a composite measure is a net percentage increase in the component measures, relative amihud and bid-ask spread. Therefore, a net increase in relative liquidity could possibly mean that there was a decrease in one measure, but it was offset by the other for a net positive result. Since we are using the first principal component to aggregate multiple relative liquidity measures it is hard to interpret what a 1 unit increase actually is.

Table 6.1: Regression results from 2002 through 2017, Model 1 through Model 7 are the models presented in (5.23) to (5.29). The dependent variable are our measure calculated from the biweight midcorrelation, and all models are estimated using ordinary least squares. Robust standard errors are presented in parenthesis and are estimated following Newey and West (1987), where the automatic lag length selection as proposed by Newey and West (1994) has been used. Significance at the 10%,5% and 1% level are denoted with *, **,*** stars respectively.

dependent variable:	Full sample from 2002 through 2017						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.52^{***}	0.53^{***}	0.56^{***}	0.53^{***}		0.50^{***}	
	(0.04)	(0.04)	(0.04)	(0.04)		(0.05)	
Δtrading ratio$_{m-1}$			0.27^{***}				
			(0.05)				
Δholding percent						0.09	
						(0.11)	
Δtrading ratio x Δholding percent						0.44	
						(0.60)	
trading ratio ARIMA residuals							3.08^{***}
							(0.23)
relative liquidity	0.01^{***}		0.01^{**}		0.02^{***}	0.01^{***}	0.01^{***}
	(0.00)		(0.00)		(0.01)	(0.00)	(0.00)
weighted liquidity		0.02^{***}					
		(0.01)					
Δcpi	-3.22^{**}	-3.34^{***}	-3.20^{**}	-3.55^{***}	-4.26^{**}	-2.97^{**}	-0.95
	(1.32)	(1.28)	(1.42)	(1.33)	(1.84)	(1.42)	(1.70)
Δind pro	-1.57	-1.70	-1.82^{*}	-1.31	-1.42	-1.36	-1.86^{**}
	(1.10)	(1.14)	(0.99)	(0.98)	(1.34)	(1.03)	(0.83)
Δvix	0.04	0.05	0.06	0.04	0.07	0.04	0.02
	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
ted spread	-0.01	-0.01	-0.01	-0.01	-0.03^{**}	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
market return	-0.18	-0.19	-0.07	-0.23	-1.09^{***}	-0.20	-0.17
	(0.18)	(0.19)	(0.19)	(0.20)	(0.30)	(0.19)	(0.20)
dependent$_{m-1}$	0.63^{***}	0.63^{***}	0.38^{***}	0.59^{***}	0.39^{***}	0.62^{***}	0.44^{***}
	(0.05)	(0.05)	(0.07)	(0.05)	(0.08)	(0.05)	(0.05)
dependent$_{m-2}$	0.12^{**}	0.12^{**}	0.35^{***}	0.14^{**}	0.13^{*}	0.12^{**}	0.18^{***}
	(0.05)	(0.05)	(0.07)	(0.06)	(0.08)	(0.05)	(0.05)
dependent$_{m-3}$	0.11^{***}	0.11^{***}	0.15^{***}	0.13^{***}	0.17^{***}	0.12^{***}	0.27^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
intercept	0.06^{***}	0.06^{***}	0.05^{**}	0.06^{**}	0.14^{***}	0.05^{**}	0.05^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
R^2	0.73	0.74	0.77	0.72	0.48	0.74	0.77
Adj. R^2	0.72	0.72	0.75	0.71	0.46	0.72	0.76
RMSE	0.07	0.07	0.07	0.08	0.10	0.07	0.07
Num. obs.	189	189	189	189	189	189	189

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The results from Model 1 lends support to our first hypothesis that higher relative demand as proxied by trading volume coincides with higher correlations. It also provides evidence for our second hypothesis, that the higher relative liquidity of ETFs is also associated with increased correlations. Insofar as these relative liquidity measures proxy short-term demand, we can say that this supports the argument that short-term demand is related to increased correlations. Recall that trading volume is also used as a measure of liquidity, and that liquidity is a multi-faceted concept defined in many different ways (i.e. price impact, transactions costs, turnover). As a result, it may be that the trading ratio captures much of the short-term demand. To explore further we compare Model 1 with its various iterations.

To show that our measure of relative liquidity is robust to different liquidity measures, we use the first principal component of our weighted average relative liquidity measures. The results of Model 2 show how similar the results are whether using a weighted measure or our relative measure, and confirms our liquidity measure result from Model 1.

Model 3 results exemplifies our previous point that our measure of aggregated relative liquidity perhaps does not capture short-term demand as well as the trading ratio. By adding a lagged variable of the trading ratio, relative liquidity loses some its significance, but is still significant at the 5% level. This supports the conjecture that the amihud measure and the bid-ask spread are appropriate measures, but perhaps only separate a small amount of short-term demand from trading volume, at least for the ETFs we study here. In that regard, the results show that trading ratio is the main driver of explanatory force behind increasing correlations, incorporating the bulk of short-term demand.

When trading ratio is the only variable of interest, as in Model 4, table 6.1 shows that it does not change the relationship between trading ratio and correlations much, and only slightly affects R^2 from Model 1. When removing the liquidity measure, the R^2 decreases from .73 to .72, meaning that the liquidity measure explains a small part of variations in correlations. On the other hand, in Model 5 when trading ratio is removed and only relative liquidity is left, the R^2 decreases from .73 to .48. This conveys that relative liquidity is a weaker explanatory variable for correlations, albeit significant, and that the trading ratio has much explanatory power in observed correlations.

What can be concluded from Models 1-5 is that trading ratio as a measure of demand and of liquidity has a strong relationship with underlying stock correlations and explains much of the variation of those correlations. It can be argued that high turnover traders are probably better captured by the trading ratio than our other measures of liquidity. Despite the fact that the amihud measure and bid-ask spread are commonly used to measure liquidity, they might not be adequate measures for completely separating short-term demand from the trading ratio for the ETFs we study here. Although to a lesser extent than trading ratio, relative liquidity does have significant explanatory power in observed correlations of the underlying stocks, and perhaps could be better in models that study other less liquid indexes. As such, it is not as strong an explanatory variable as the literature would predict, at least for the S&P 500, but the results provides support that they are related to correlations (Broman & Shum, 2018). In this regard, our first hypothesis that trading ratio would capture demand and also short-term demand is supported by the findings. To a lesser extent, our findings regarding the significant relationship between relative liquidity and correlations also support our second hypothesis, but we see that much of the short-demand is most likely captured by trading ratio.

In Model 6, we add ETF ownership holding percentage, holding percent, calculated as the ratio between the market capitalization of ETFs and the market capitalization of the S&P 500. We also add an interaction term between holding percentage and trading ratio. This allows us to better understand the drivers of underlying stock correlations by comparing short-term demand to net demand over time, or the sum of shares outstanding over time. Since our findings show that trading ratio is capturing much of the short-term demand, we add ETF ownership holding percentage as a proxy for separating long term overall demand and the demand captured by trading ratio, which we believe is a proxy for short-term demand. A positive relationship with holding percentage and correlations would show that the more investors buy ETF shares and create a net positive demand, the more we observe an increase in correlations and furthermore, this effect should be separate from the effect of ETF trading activity. A positive relationship with the interaction term would mean that effects of trading ratio on correlations are greater when there is ETF growth.

However, as table 6.1 shows, there is no significance in holding percent in relation to correlations, and also not in the interaction term between holding percent and trading ratio. Importantly, Model 6 shows that the growth in ETF demand alone does not affect the underlying stock correlations. Rather, it is the relative trading volume and liquidity that are important. This further adds to our analysis because it shows that although both long-term investors and short-term traders are attracted ETFs, it is the high-turnover traders, as proxied by trading ratio and relative liquidity, that are the main drivers of increasing correlations. In other words, those that "buy-and-hold" ETF shares do not matter. This makes sense in terms of our hypotheses because we have argued that correlated trading and high turnover trading are the main drivers behind increases correlation. From the results we see that it is the intensity of trading that is related to increasing correlations. Therefore, although prior literature has warned against the negative effects of growth the in ETFs and passive investing (Wurgler, 2010; Israeli et al., 2017), our results show that such arguments with respect to correlations should be distinguished to the growth of short-term trader demand for ETFs, not overall demand.

We estimate Model 7 as a check for our results consistency with prior literature. Since Leippold et al. (2016) also empirically tests the same ETFs as we do on the S&P 500 index, we find it appropriate to replicate a variation of their model, using a dataset that both starts later and extends an additional 5 years. In their model, they use the residual of a seasonal ARIMA model of the trading ratio to proxy a demand shock. Interestingly the usage of a seasonal model is something we cannot find evidence for as seen in the fitted model in appendix M, and also goes against Rompotis (2010) findings that does not find any evidence of seasonality in ETF trading. We would not expect any seasonal patterns in the S&P 500 constituent securities since dollar volume as we have shown in the earlier discussion of the trading ratio, there does not seem to be evidence of seasonality either in the numerator or the denominator. Comparing our results to theirs, we observe that we were able to obtain a positive and significant result, just as in Leippold et al. (2016). The magnitudes are different, but that may be a result of differing time periods of data, having a different measure of correlation, and having a different set of control variables. What is important to note is that our results do not change whether we use the trading ratio to proxy demand or its residual to proxy a demand shock. Both variables are highly significant and positive in their relationship to increasing correlations.

To further add to our discussion and for the accuracy of our results, we point to the control variables with consistently significant results across the models in table 6.1, inflation and the lagged dependent variables. Both results are consistent with what we would expect. The variable measuring inflation, Δcpi, is significant in Models 1-6 and where it is significant it is negative, as we would expect. This means that an increase in inflation is associated with decreasing correlations, and vice versa. As discussed in the rationale for adding inflation to the model, inflation tends to have the same effect on all stocks. In times of high inflation, the purchasing power of money decreases, and there is less spending, thus signifying a deteriorating economic climate. Further, the lagged dependent variable is significant in all models also as we would expect, as earlier tests show that correlations have an autoregressive component. Furthermore the other control variables are generally not significant, but all has the expected sign except for the *TED spread*.

6.2 Alternative correlation measures

As discussed earlier in the chapter on methodology, different correlation measures may influence the regression results as they exhibit slight differences. To highlight that our results are robust to the correlation measures used, we refer to the estimated results in table 6.2. They generally show that there are only minor discrepancies for different iterations of Model 1 using different correlation measures. Comparing the models shows that all the results remain similar, except in the case of the value-weighted Pearson. Recall from our earlier discussion that the Pearson measure is the most often used but is also more sensitive to outliers in the data. This can be taken as validation for our approach of careful consideration regarding the choice of measure. Relying solely on a measure based on Pearson would have given us a different conclusion in relation to our second hypothesis. In total this strengthens our findings because our results are not significant just because of our choice off a single measure of correlation, but is shown to hold for different measures.

Table 6.2: In this tables all the models are defined as in (5.23). But they are estimated using different is the usage of different correlation measures. Model 1 is the same as Model 1 in 6.1, but the others have a different dependent variable. Sample from 2002 through 2017. Standard errors are presented in parenthesis and they are calculated consistent with Newey and West (1987) and the lags selected according to Newey and West (1994). Significance at the 10%,5% and 1% level are denoted with *, **,*** stars respectively.

dependent variable:	vw biweight	ew biweight	vw pearson	vw spearman	vw kendall
	Model 1	Model 2	Model 3	Model 4	Model 5
Δtrading ratio	0.52^{***}	0.47^{***}	0.54^{***}	0.51^{***}	0.39^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
relative liquidity	0.01^{***}	0.01^{***}	0.01	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δcpi	-3.22^{**}	-3.16^{**}	-3.84^{**}	-3.46^{**}	-2.70^{**}
	(1.32)	(1.26)	(1.68)	(1.34)	(1.05)
Δind pro	-1.57	-1.49^{*}	-1.25	-1.40	-1.01
	(1.10)	(0.89)	(1.05)	(1.10)	(0.84)
Δvix	0.04	0.06	0.08^{*}	0.06	0.04
	(0.05)	(0.04)	(0.05)	(0.04)	(0.03)
ted spread	-0.01	-0.01	0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
market return	-0.18	-0.12	-0.04	-0.14	-0.12
	(0.18)	(0.20)	(0.18)	(0.18)	(0.14)
dependent$_{m-1}$	0.63^{***}	0.68^{***}	0.58^{***}	0.64^{***}	0.63^{***}
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
dependent$_{m-2}$	0.12^{**}	0.14^{**}	0.14^{***}	0.12^{**}	0.12^{**}
	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
dependent$_{m-3}$	0.11^{***}	0.08^{*}	0.13^{***}	0.10^{**}	0.10^{**}
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
intercept	0.06^{***}	0.05^{**}	0.05^{**}	0.06^{***}	0.04^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R^2	0.73	0.75	0.72	0.74	0.74
Adj. R^2	0.72	0.73	0.70	0.73	0.72
RMSE	0.07	0.07	0.08	0.07	0.06
Num. obs.	189	189	189	189	189

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.3 Before and after financial crisis

When we discussed the reasoning behind including our control variables, much of the motivation was controlling for volatility in market conditions or macroeconomic factors indicating a market downtown. Such factors have been seen to increase correlations. For the same reason, we have decided to subset the sample into three time periods: before, during, and after the recession. The rationale behind this is to test if the financial crisis is the driver of the result as discussed in chapter 5. Nationa Bureau of Economic Research (2018) defines the recession to be from December 2007 through June 2009. But, what they define is the recession, such a choice of time frame would be inappropriate for us since our study are concerned with the financial markets and not the broad economy as such. The financial markets where hit by the sub-prime crisis in the summer of 2007 and the U.S. stock market peaked in 2007. Therefore we have chosen to define the financial crisis as from October 2007 through June 2009. Doing so allows us to discern how the ETF trading ratio and relative liquidity relationship with correlations has changed over time, and how our overall results compare to the different time periods.

Table 6.3 show regression results from before and after the financial crisis for models of the form presented in (5.23) and (5.26) to (5.28). The important interpretation is that this lends support for our initial findings that the trading ratio captures most of ETF trading activity and demand. We do not report the estimated models from during the recession since the time frame is to short and thus suffers from low degrees of freedom. This might also be an issue in the period before the recession, but since we have around 5 times as many observations as we have regressors, this seems to be in line with what is recommended from the literature Ḟor completeness models of other time periods are also estimated, where 6 years rolling windows are presented in the appendix N, which show that the coefficients are mostly stable.

When we look at table 6.3 Model 4, we see that in the earlier period holding percent is significant at the 5% level and adding it to the model slightly increases the R^2 from .69 to .72 compared to Model 1. Interpreting the data, we see that a 10% increase in holding percent is related to a 0.027 increase in average correlation. Comparing these results to Model 8, where we see that neither holding percent or the interaction term between trading ratio and holding percentage are significant.

What we can interpret from these results is most likely the evolution of ETFs. The time period included in the "Before financial crisis" results are from 2002-2006. During this period, ETFs were only just gaining traction, as we have seen for example in figure 1.1. During the inception

Table 6.3: In this tables Model 1 and 4-6 from table 6.1 and as defined in (5.23) and (5.26)-(5.28). The full sample is subsetted to both the period before and after the financial crisis. The dependent variable is based on our biweight midcorrelation measure. Standard errors are presented in parenthesis and they are calculated consistent with Newey and West (1987) and the lags selected according to Newey and West (1994). Significance at the 10%,5% and 1% level are denoted with *, **,*** stars respectively.

dependent variable:	Before financial crisis				After financial crisis			
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Δtrading ratio	0.40^{***}	0.40^{***}		0.38^{***}	0.60^{***}	0.61^{***}		0.57^{***}
	(0.06)	(0.06)		(0.06)	(0.06)	(0.06)		(0.06)
relative liquidity	0.01		0.01	0.01	0.01^{*}		0.02^{*}	0.01^{**}
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
Δholding percent				0.27^{**}				0.25
				(0.13)				(0.15)
Δtrading ratio x Δholding percent				0.48				1.19
				(0.74)				(0.97)
Δcpi	−0.16	−0.15	0.29	1.78	0.07	−0.24	−4.71	0.92
	(1.98)	(1.85)	(3.07)	(1.89)	(2.94)	(2.84)	(4.00)	(3.24)
Δind pro	−1.61	−1.68	−2.47	−0.94	−1.92	−1.67	0.47	−1.65
	(1.72)	(1.66)	(1.94)	(1.58)	(1.25)	(1.31)	(2.75)	(1.23)
Δvix	0.16^{**}	0.15^{**}	0.18^{*}	0.16^{***}	-0.10^{*}	-0.10^{*}	-0.15^{*}	-0.12^{**}
	(0.07)	(0.07)	(0.10)	(0.06)	(0.05)	(0.06)	(0.08)	(0.05)
ted spread	0.02	0.02	−0.01	0.02	-0.08^{*}	-0.08^{**}	-0.22^{***}	-0.09^{*}
	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.08)	(0.05)
market return	0.30	0.24	−0.50	0.30	-1.14^{***}	-1.32^{***}	-2.47^{***}	-1.29^{***}
	(0.26)	(0.26)	(0.35)	(0.24)	(0.36)	(0.31)	(0.61)	(0.32)
dependent_{m-1}	0.66^{***}	0.65^{***}	0.47^{***}	0.62^{***}	0.64^{***}	0.59^{***}	0.31^{***}	0.63^{***}
	(0.08)	(0.08)	(0.11)	(0.11)	(0.07)	(0.07)	(0.10)	(0.06)
dependent_{m-2}	0.07	0.07	0.18^{*}	0.04	0.18^{***}	0.20^{***}	0.18^{*}	0.19^{***}
	(0.10)	(0.10)	(0.10)	(0.11)	(0.06)	(0.05)	(0.10)	(0.06)
dependent_{m-3}	0.16^{***}	0.17^{***}	0.10	0.21^{***}	0.06	0.09^{*}	0.20^{***}	0.08^{*}
	(0.06)	(0.05)	(0.08)	(0.07)	(0.05)	(0.05)	(0.07)	(0.04)
intercept	0.02	0.02	0.10^{**}	0.02	0.08^{***}	0.08^{***}	0.21^{***}	0.08^{**}
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)
R^2	0.69	0.69	0.45	0.72	0.81	0.80	0.52	0.81
Adj. R^2	0.64	0.64	0.36	0.65	0.79	0.78	0.48	0.79
RMSE	0.06	0.06	0.09	0.06	0.07	0.07	0.11	0.07
Num. obs.	66	66	66	66	99	99	99	99

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

of an ETF, there is rapid growth and liquidity may depend more on shares outstanding. One can also commonly see institutional investors tapping into the implied liquidity during ETF inceptions (Abner, 2016, pp. 107-8). In total, however, holding percent over the entirety of the data is insignificant, suggesting that amount of the underlying securities held by an ETF does not matter.

We again look at the control variables with significant results. Looking at the variable for the VIX, Δvix, the relationship in the models "Before financial crisis" is positive, but negative in the models "After the financial crisis". We would expect to see a positive relationship between volatility and correlations. Also, the TED spread variable, *ted spread*, is also negative in those models where we would expect to see a positive relationship. However, this might be explained by the post-recession era having artificially low interest rates such that it keeps LIBOR artificially low even during times of market downturn. On the other hand, *market return* is negative as we would expect. In total, we conclude that our results are mostly similar to our main models in table 6.1, but that there are some discrepancies.

6.4 Discussion

In total, the results show that increasing correlations are indeed related to increasing relative trading volume, and to a lesser extent, relative liquidity as measured by the amihud measure and bid-ask spread. These results largely do not change when different measures of correlations or liquidity are used in the regressions. Insofar as they together reflect ETF short-term demand, we can say that increasing ETF short-term demand is associated with increasing correlations. We now address the implications of increasing correlations coinciding with increasing ETF short-term demand.

One main implication of increasing correlations is the effect it has on portfolio diversification. A well-diversified portfolio reduces price / return variability, or risk, in large part by reducing its average covariances while maintaining expected return (Brealey, Myers, & Allen, 2014). Diversification works because prices of different stocks do not move exactly together. If stocks started to increasingly move together, some of the benefits of diversification are lost, and as a consequence the portfolio risk increases.

Here, the portfolio is the stocks in the S&P 500, and increasing correlations are increasing the risk of investing in the index. Investors who buy S&P 500 tracking ETFs as an easy way to invest with the benefits of diversification must realize that the short-term demand for ETFs might change the advantages of diversification. Moreover, if the risk caused by ETF short-term demand cannot be diversified away, then it would increase the market (systemic) risk (Brealey et al., 2014). The selection criteria for inclusion into the S&P 500 as published by S&P Dow Jones Indices (2018d) does not account for correlations as part of eligibility, but we cannot ascertain exactly what the index committee uses to measure "market representativeness". Perhaps, as correlations increase even further, index providers may consider possible adverse effect of ETFs on their constituent stocks.

In addition, the S&P 500 is the index that many consider to be the best-known representative of the overall large cap US equities. If the increased risk from increasing correlations is not reflective of the large-cap US market in general, it then follows that the S&P 500 may not be as accurate a proxy for the US large-cap stock market as one may believe.

From the perspective of a market participant our results show how important it is to understand the changing complexity of the market. ETFs are one of the financial innovations that have changed a part of the market ecosystem and is continuously changing it. This complexity can be exhibited through the complex dynamic between ETF and futures being used for long and short positions, a relationship further complicated by the cross arbitrage between E-minis and S&P 500 tracking ETFs (Menkveld & Yueshen, 2018, p. 25). This illustrates how important ETFs have become in the financial system and why it is important to study and understand their broad market implications, particularly in regard to possible new risks they introduce and how they change market complexities.

As discussed, understanding the drivers of ETF demand is important because of the potential spillovers to the underlying assets and to the market. Our results provide evidence for the hypothesis that ETFs attract short-term traders. According to Stein (1987), short horizon traders have adverse effects on information efficiency of prices and deters long-term investors. Cella et al. (2013) find that the presence of short-horizon institutional investors during market turmoil exacerbates price drops because these investors exit the market. Furthermore, Campbell et al. (1993) create a model that predicts high turnover stocks are associated with uninformed trading. Therefore, if short-term traders are associated with noise, then some of the consequences of noise traders in ETFs may include decreased price efficiency and increased transaction costs of the underlying stocks (Israeli et al., 2017).

Information efficiency describes the process and expediency of fundamental information being imparted into prices. All non-fundamental changes in prices degrades price discovery because prices are not a true measure of company value. Comovement in returns as a result of non-fundamental demand degrades price discovery because it moves prices away from fundamental values, and examples of trading on non-fundamental demand would be trading for liquidity or hedging purposes. Correlated non-fundamental only increases non-fundamental comovement (Greenwood & Thesmar, 2011; Barberis et al., 2005). Thus, increasing correlations has the potential of decreasing the price discovery process. This leads us to investigate whether the increasing correlation are excessive.

6.5 Excessive correlations

Having identified a positive relationship between increasing comovement in returns and ETFs trading activity and liquidity, the question is whether these comovements are excessive. In frictionless markets with rational investors, the only comovement in asset returns is due to comovement in fundamental values. When market frictions are introduced ETFs may propagate non-fundamental demand to the underlying securities, giving rise to excessive correlations. To test this hypothesis we closely follow the methodology presented by Leippold et al. (2016, p. 37-9), which is an adaptation of the approach used by Da and Shive (2017, p. 159-64).

If ETF trading propagates non-fundamental demand onto underlying prices, those movements in prices should revert. (Ben-David, Franzoni, & Moussawi, 2017, p. 44). Conversely, if price movements were based on fundamentals then underlying demand for ETFs would impound a permanent change, thus we would not observe reversals of returns. The hypothesis is that the demand for ETFs as represented by the trading ratio does not only contain information about the market, but also a noise component. Therefore for every underlying stock i in the S&P 500 at month end in year month m with available days d we estimate the regressions in (6.1), where $r_{i,d,m}$ is the return. Defining the month end market capitalization weights vector as $\boldsymbol{w}_m$ with elements $w_{i,m}$ and the vector of coefficients $\boldsymbol{\gamma}_m$ with elements $\hat{\gamma}_{i,m}$ we can capture the aggregate return reversal in a given month as $\bar{\gamma}_m$. This measures average underlying autocorrelations coefficients for the underlying securities.

$$\begin{aligned} r_{i,m,d} &= \alpha_{i,m} + \gamma_{i,m} r_{i,m,d-1} + \epsilon_{i,m,d} \\ \bar{\gamma}_m &= \boldsymbol{w}_m^T \boldsymbol{\gamma}_m \end{aligned} \tag{6.1}$$

The idea behind using return reversals is that this enables us to regress $\bar{\gamma}_m$, the return autocorrelation coefficient, on our three main variables of interest: a measure of average correlation, trading ratio and a liquidity measure and a lagged variable of itself to correct for autocorrelation. The explicit models estimated are presented in (6.2). For all the following models, we expect a significant and negative coefficient on β_1 relating the variable of interest to our autocorrelation measure, meaning that return reversals are larger in magnitude when our variables of interest are higher. These predictions are in accordance with Avramov et al. (2006, p. 2365)'s empirical results, where they find volume-based and liquidity-based measures to be significant in explaining return reversals.

$$
\begin{aligned}
\bar{\gamma}_m &= \alpha_m + \beta_1 \bar{\rho}_m \ + \beta_2 \bar{\gamma}_{m-1} + \epsilon_m \\
\bar{\gamma}_m &= \alpha_m + \beta_1 \text{trading ratio}_m \ + \beta_2 \bar{\gamma}_{m-1} + \epsilon_m \\
\bar{\gamma}_m &= \alpha_m + \beta_1 \text{pca relative}_m \ + \beta_2 \bar{\gamma}_{m-1} + \epsilon_m
\end{aligned}
\tag{6.2}
$$

Table 6.4: Results of regressing return reversals $\bar{\gamma}_m$ on correlations, ETF activity as represented by the trading ratio and liquidity. Newey-West standard errors are calculated and lags selected following Newey and West (1987, 1994). Estimation is done for the full sample from early 2002 through 2017, results are robust to different subsets of the data. The results presented are qualitatively similar using different correlations measures and $\bar{\rho}_m$ is the value weighted biweight midcorrelation. The liquidity measure is the first principal component of the our relative liquidity measures, results are not sensitive to the choice of liquidity measure.

	Correlation	ETF	Liquidity
intercept	-0.011	-0.031^{*}	-0.063^{***}
	(0.016)	(0.016)	(0.007)
$\bar{\rho}_m$	-0.148^{***}		
	(0.040)		
trading ratio$_m$		-0.195^{**}	
		(0.086)	
pca relative$_m$			0.003
			(0.004)
$\bar{\gamma}_{m-1}$	-0.010	-0.007	0.012
	(0.071)	(0.072)	(0.073)
R^2	0.067	0.027	0.003

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

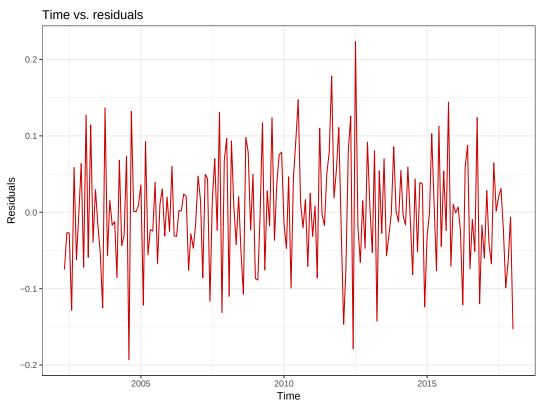
The results are presented in table 6.4 and we note that the coefficients on average correlations and trading ratio are negative and significant at the 0.01 and 0.05 percent level respectively, while liquidity is not significant. The results are interesting since they provide evidence linking return reversals to correlations and index trading activity. This suggests that return comovement is excessive, or incorporates noise from non-fundamental trading. It also lends support to the hypothesis that ETF short-term demand is imparting noise into underlying returns, as exhibited by the relationship between ETF activity and return reversals. Perhaps for correlated demand from short term investors as predicted by Barberis et al. (2005), Broman (2016). These results are qualitatively similar to the results found by both Leippold et al. (2016), Da and Shive (2017). In addition, it confirms the findings and theoretical predictions of Campbell et al. (1993), which relates high volume to uninformed trading.

While both correlations and trading activity incorporate a noise component, our liquidity measure does not. It is intriguing that we do not observe the same relationship with our measure of relative liquidity as we do with correlations and ETF activity. Since our measure of relative liquidity is a proxy for short-term demand for ETFs, we cannot say that such demand is associated with return reversals. In other words, this does not provide support that short-term trader demand as measured by liquidity imparts noise into the underlying stock returns. This result is not in line with our prediction and contradicts the findings of Avramov et al. (2006, p. 2392-3), that find liquidity is associated with return reversals.

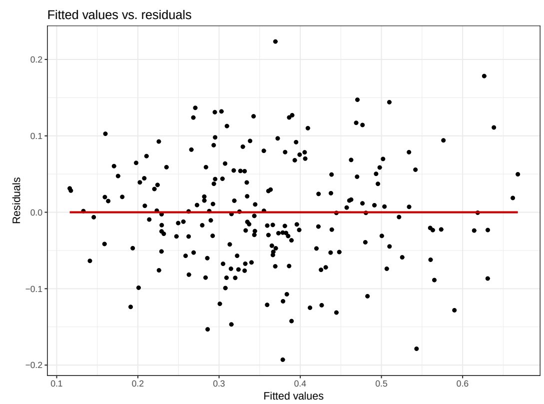
There are some possible explanations for our results showing no relationship between liquidity and return reversals. While we are studying only some of the most liquid securities, prior literature germane to the subject of liquidity and return autocorrelation have used broader universes, which might be an explanation of the result. In addition, since we use the first principal component of the changes in the relative proportional bid ask spreads as a measure, it might be impaired by the fact that the bid ask spreads in underlying securities have tightened more than for ETF which often exhibit end of day close spreads at 1 cent. This implies that this measure might not capture the desired effect on return reversals since liquidity is such a multifaceted concept. Furthermore it might be the case that the amihud measure and bid-ask spread is adequate in capturing short-term demand for the S&P 500.

6.6 Robustness checks

The subseting off our sample and also the usage of other correlation measures are possible ways to check for robustness. But there are also more formal tests for robustness. In this section we will introduce some of the test we have done, where the results will only be presented for Model 1 from table 6.1. The idea behind conducting robustness tests is to ensure that our modeling strategy is sound such as our models do not suffer from misspecification.



(a) Time vs. residuals



(b) Fitted values vs. residuals

Figure 6.1: Here we have plotted the time vs. residuals 6.1a, from which we can see that there does not appear to be for example any clustering, or other patterns of interest. For the fitted values vs. residuals 6.1b, there does not seem to be any strange patterns suggesting heteroscedasticity or possible non-captured non-linearities.

First it is natural to inspect the residuals, which are presented in figure 6.1. This suggests that the residuals are nicely distributed. Formally this can be tested with a normality test. Here we have employed the Jarque-Bera test as explicitly shown in table 6.5, and this confirms normally distributed residuals.

Table 6.5: Tests for normality of residuals, Jarque-Bera test the null of normality by using the skewness and excess kurtosis (Tsay, 2010, p. 10).

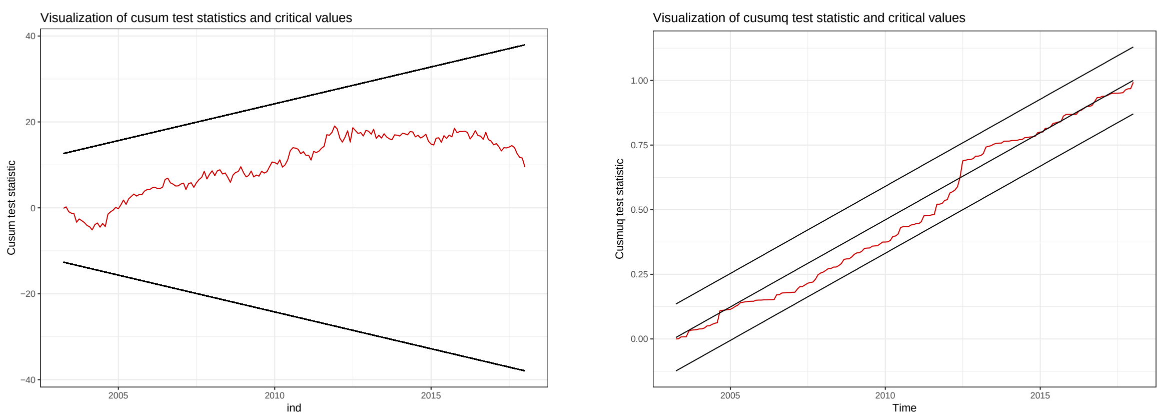
test	statistic	p value
Jarque-Bera	0.308	0.857

As we can see from figure 6.1a there might be some autocorrelation in the residuals. We have formally tested for this using a Breusch-Goodfrey test and at the same time we have also performed a Teräsvirta test for non-linearity as presented in table 6.6. The first makes us reject the null of no serial correlation, while we in the latter cannot reject the null of linearity in the residuals. This means that the first test informs our choice and usage of standard errors calculated following Newey and West (1987, 1994) throughout all our regressions, while the second is evidence against misspecification of functional form.

Table 6.6: We have tested for autocorrelation in the residuals using a Breusch-Godfrey test (Breusch, 1978), that tests the null of auto correlation in the residuals, thus we have to reject the null. We have also performed a Teräsvirta test (Teräsvirta, Lin, & Granger, 1993) that test for non-linearity, and we can see that we cannot reject the null linearity in the residuals.

test	statistic	p value
Breusch-Godfrey	40.66	5.59E-05
Teräsvirta	4.05	0.132

The most pressing assumption we cannot test for formally is the exogeneity assumption in regards to the trading ratio specifically and also the other regressors. One critical assumption for our approach is that we have not omitted a relevant variable. Another is possible problem we have chosen to specify our model contemporaneously and have not been able to find good candidates for instruments for the trading ratio, it might be the case that our modeling suffers from problems in relation to endogeneity. But, since our regressions shows similar results as (Leippold et al., 2016), with what they have deemed a sound identification strategy this is in itself support for our approach.



(a) Cusum

(b) Cusumq

Figure 6.2: Cusum test 6.2a and cusumq test 6.2b employed to the residuals and the recursive residuals respectively. For the implementation we have followed Turner (2010), and used the critical values for the a 5% level test for both. Where the confidence intervals is constructed using $a = 0.948$ for the cusum test and $c_0 = 0.12944$ As we can see from both tests the red line does not cross the black lines, which is the critical values where we for the cusum test tests at the 5% level using $a = 0.948$

Since we are weary off the chance for structural breaks in our models. This motivates us to employ formal tests for structural breaks. Where we have chosen to use the cusum and cusumq test, which has complementary properties. Where the cusum test is better at detecting structural breaks in the intercept, while the cusumq test is better at detecting breaks in the coefficients (Turner, 2010, p. 1049). The test has been implemented following Turner (2010). From figure 6.2 we can see the results of both the cusum and cusumq test and we can see that the red line does not exceed the critical values. This means that the residuals from Model 1 do not show signs of structural breaks. The implications from this is that we cannot see evidence for changing coefficients across time.

Conclusion

ETFs have grown dramatically over the past decades. Using the S&P 500 stocks and the ETFs that track it, this paper has presented empirical results that show increases in ETF trading activity and liquidity is associated with increases in the correlations of the underlying stocks. As such, they lend support to our two hypotheses. Insofar as ETF trading volume and liquidity capture short-term demand, this presents evidence for a short-term clientele effect affecting index constituent return comovement. However, our findings show that our measure of relative liquidity has a weak explanatory relationship to correlations, albeit significant. We interpret this as indicative that trading ratio is capturing most of the short-term demand that relative liquidity is also meant to proxy. Therefore, we add to our model ETF ownership holding percent in order to separate long-term demand from short-term demand that we believe is encompassed by the trading ratio.

However, our analysis shows that the growth in net demand for S&P 500 ETFs is not significant to increases in correlations of the constituent stocks. Moreover, the interaction term between holding percent and trading ratio is also not significant. The interpretation of the results is that ETF net growth has no effects on correlations, and the effects of the trading ratio is not greater with changes in total ETF ownership percentage of the underlying stocks. Importantly, what we conclude is that if relative trading volume and relative liquidity are separating the short-term demand from long-term demand captured by holding percent, then the results are evidence that it is primarily short-term demand driving correlations and not "buy-and-hold" investors in ETFs.

Further, we test our findings to see whether increasing comovement is a result the expedient relaying of fundamental information into underlying stock or whether they are propagating noise. Some papers have shown that because of ETF liquidity, they improve price discovery because they impart fundamental information into prices faster than the underlying stocks. On the other hand, others have shown that the same ETF liquidity also attracts short-term traders, traders associated with noise trading. To test these two conjectures, we regress return reversals on our estimated correlations. The intuition behind this methodology is that returns exhibit reversals with non-fundamental trading, but do not otherwise. This follows the line of theory that fundamental changes in value have a more permanent change in returns whereas non-fundamental changes in prices causes prices to revert.

Interestingly, correlations have a positive and significant relationship with return reversals. Regressing return reversals on the trading ratio also produces a positive and significant relationship. The importance of such a finding is that it suggests that both correlations and trading activity are related to non-fundamental movements and that ETF trading activity imparts a noise component into correlations and returns. As a result, ETFs short-term trading activity degrades the price discovery process of the underlying stocks, distorting prices away from intrinsic value. These findings are consistent with the category or habitat view of comovement where correlated non-fundamental demand increases excessive correlation. It is also evidence that short-term investors with their high-turnover investment strategies impound noise into returns.

However, though relative liquidity coincides with correlations, and correlations coincides with return reversals, relative liquidity alone does not show the same significant relationship with return reversals. This brings into question the adequacy of relative liquidity capturing enough short-term trading activity, at least for the S&P 500. Alternatively, it could be that trading based on high liquidity is not related to noise and based on fundamentals, but this conjecture goes against prior literature findings.

Using different measures of correlations and liquidity, we find that our results are robust even in different time periods. However, even after careful consideration of the model, we cannot preclude the possibility of misspecification, for example omitted variable bias. For this reason, we do not claim causality in our results since we do not have a control group or an exogenous shock feasible for our study.

The implications from the findings is that there is an increase in risk from investing in the S&P 500 index as a result of increasing ETF trading activity and liquidity. Therefore, as ETF trading activity increases, the ETF investor loses more of the diversification benefits from investing in the index. If such increasing risk cannot be diversified away, the effects from ETF trading activity could add to systemic risk.

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Appendices

Appendix A

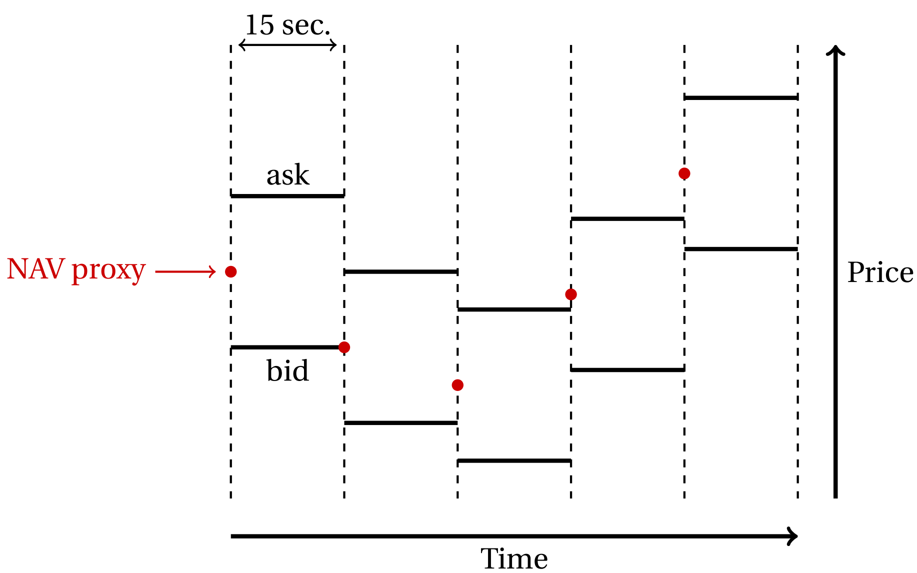


Figure A.1: Using the intraday NAV (iNAV) to proxy bid and asks is naive, some market participant continuously calculate iNAV or use bid-ask quotes that changes much more quickly than depicted in the illustration adapted from (Gastineau, 2010, p. 201). The problem with this is that the quotes used for iNAV published every 15 seconds in principle does not reflect the most recent information available in the marketplace, thus one can understand how there is an arms race to be better informed.

Appendix B

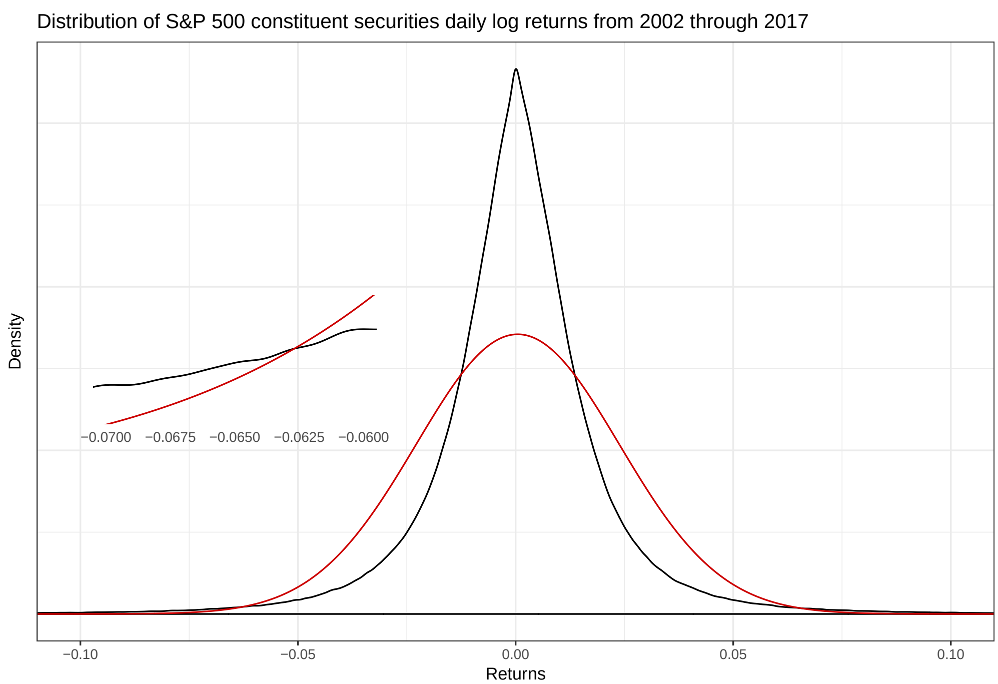


Figure B.1: Distribution of S&P 500 constituents securities daily returns from 2002 through 2017. The distribution is compared to the normal distribution. The distribution of the returns is only showed in the range -10% to 10% for convenience purposes. The normal distribution is fitted with the first two moments of the full sample.

Appendix C

The product of average correlation and average stock return variance is used by Pollet and Wilson (2010) in a regression as presented in (C.1), where $\hat{\sigma}^2_{s,t}$ is the portfolio variance and the average variance is estimated as $AV_t = \sum_{i=1}^{N} w_{i,t}\hat{\sigma}^2_{i,t}$

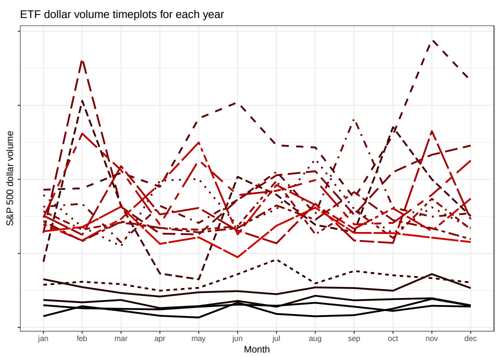
$$\hat{\sigma}^2_{s,t} = \beta_0 + \beta_1 \left(AV_t * AC_t\right) + \epsilon_t \tag{C.1}$$

From this Pollet and Wilson (2010, p. 370) present an interesting empirical result. The reported result has an R^2 of 97.69%, meaning that the product of average correlation and average return variance explains almost all of the variation in portfolio variance. As such, this prompts Da and Shive (2017, p. 144) to rearrange the model in (C.1) and define the Fratio (C.2), or average correlations of stock in a portfolio, as the variance of the average daily returns in the portfolio over the average of the variance of the returns of securities in the portfolio.

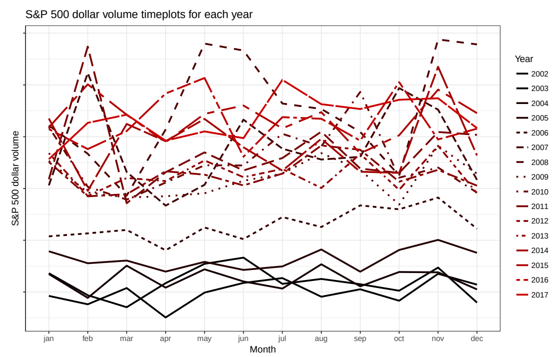
$$\text{Fratio}_t = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{1}{N^2}\hat{\rho}_{ij,t}\hat{\sigma}_{i,t}\hat{\sigma}_{j,t}}{\frac{1}{N}\sum_{i=1}^{N}\hat{\sigma}^2_{i,t}} \tag{C.2}$$

The rationalization Da and Shive (2017) uses for leaving out the weights is that Pollet and Wilson (2010, pp. 372-4) mention in their unreported results that they do not find a qualitative differences in using value-weighted or equal-weighted measures of average correlation.

Appendix D



(a) ETF dollar volume



(b) S&P 500 Dollar Volume

Figure D.1: D.1a represents the ETF dollar volume for each year, conversely D.1b represents the S&P 500 dollar volume for each year. Thus showing the numerator and denominator that has been used to calculate the trading ratio as depicted in D.2

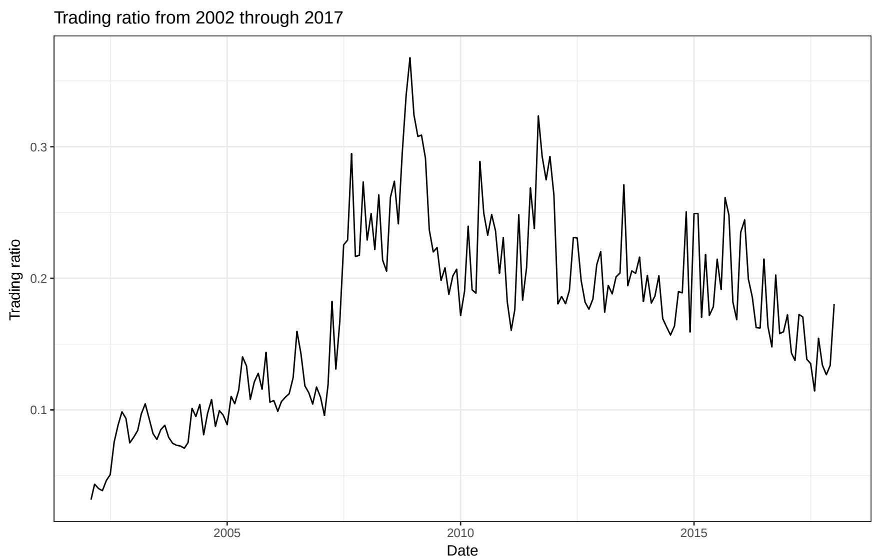


Figure D.2: Trading ratio from February 2002 through 2017. By the look of the series it looks like the a transformation of the trading ratio might be appropriate.

Appendix E

Table E.1: Summary statistics of the liquidity measures. A higher number means more thus interestingly one can see for the individual ETFs that SPY generally are more liquid, VOO was first introduced later so here interestingly enough it clearly

	min.	1st. q.	mean	3rd. q.	max.	sd.	n. na
amihud liquidity$_{SPY}$	-5.5E-10	-7.9E-11	-8.6E-11	-4.1E-11	-2.3E-11	9.8E-11	0
amihud liquidity$_{IVV}$	-1.0E-07	-6.6E-09	-9.6E-09	-1.5E-09	-5.7E-10	1.9E-08	0
amihud liquidity$_{VOO}$	-1.5E-07	-9.4E-09	-1.2E-08	-2.5E-09	-1.2E-09	2.2E-08	104
PQSPR$_{SPY}$	-4.2E-04	-9.3E-05	-9.1E-05	-5.6E-05	-3.8E-05	5.8E-05	0
PQSPR$_{IVV}$	-0.00211	-0.00029	-0.00027	-0.00010	-0.00004	0.00033	0
PQSPR$_{VOO}$	-0.00042	-0.00021	-0.00016	-0.00009	-0.00005	0.00009	104
relative amihud$_{SPY}$	3.714	5.026	5.298	5.611	6.259	0.478	0
relative amihud$_{IVV}$	0.342	1.259	1.690	2.160	3.009	0.623	0
relative amihud$_{VOO}$	0.095	0.515	1.162	1.763	2.416	0.676	104
weighted relative amihud	3.536	4.795	5.032	5.332	6.067	0.429	0
relative PQSPR$_{SPY}$	1.515	1.640	1.981	2.132	3.540	0.468	0
relative PQSPR$_{IVV}$	0.689	1.237	1.411	1.533	2.933	0.337	0
relative PQSPR$_{VOO}$	0.614	0.873	1.079	1.291	1.573	0.248	104
weighted relative PQSPR	1.442	1.548	1.899	2.037	3.493	0.468	0

Table E.2: Summary of differenced liquidity measures.

	min.	1st. q.	mean	3rd. q.	max.	sd.	n. na	n. diff.
amihud liquidity$_{SPY}$	-2.1E-10	-6.8E-12	4.9E-12	1.4E-11	2.5E-10	3.3E-11	2	2
amihud liquidity$_{IVV}$	-4.6E-08	-5.7E-10	3.1E-10	6.0E-10	5.4E-08	8.0E-09	1	1
amihud liquidity$_{VOO}$	-2.4E-08	-8.1E-10	2.7E-09	1.1E-09	7.5E-08	1.3E-08	106	2
PQSPR$_{SPY}$	-9.7E-05	-2.4E-06	1.2E-06	4.2E-06	9.7E-05	1.5E-05	1	1
PQSPR$_{IVV}$	-1.5E-03	-1.7E-05	2.0E-06	2.0E-05	7.8E-04	1.6E-04	1	1
PQSPR$_{VOO}$	-1.4E-04	-1.2E-05	3.3E-06	2.3E-05	1.0E-04	3.9E-05	105	1
relative amihud$_{SPY}$	-0.878	-0.195	0.011	0.239	1.079	0.301	1	1
relative amihud$_{IVV}$	-0.808	-0.185	0.012	0.205	0.801	0.283	1	1
relative amihud$_{VOO}$	-0.541	-0.085	0.026	0.194	0.543	0.245	105	1
weighted relative amihud	-0.894	-0.189	0.009	0.218	0.816	0.280	1	1
relative PQSPR$_{SPY}$	-0.719	-0.033	-0.007	0.031	0.833	0.132	1	1
relative PQSPR$_{IVV}$	-0.720	-0.077	-0.007	0.079	0.524	0.165	1	1
relative PQSPR$_{VOO}$	-0.319	-0.062	0.009	0.080	0.324	0.107	105	1
weighted relative PQSPR	-0.710	-0.039	-0.009	0.028	0.807	0.126	1	1

Appendix F

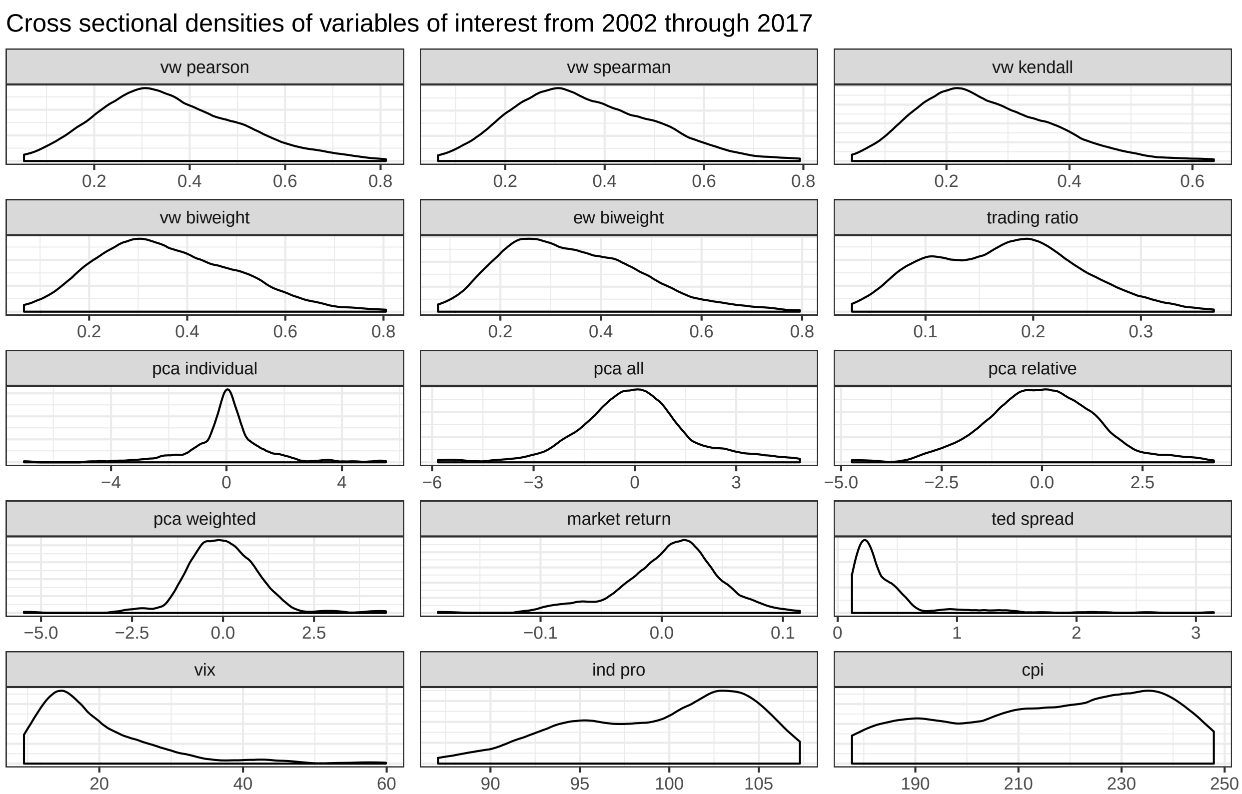


Figure F.1: Cross sectional distributions for variables of interest available for modeling for the full sample from early 2002 through 2017. The individual densities uses the Epanechnikov kernel $k(u) = \frac{3}{4}\left(1-u^2\right)\mathbb{1}(|u| \leq 1)$ (Epanechnikov, 1969) and we choose bandwidth according to the standard deviation of the smoothing kernel.

From F.1 we can clearly see that our correlations measures are quite similar, but we can see that the pairwise correlation measure using kendall is slightly different than the others. Both by being slightly more right skewed and slightly more peaked. The four other correlation measures are more or less identical. The only other difference to note is the difference between the value weighted and the equal weighted biweight midcorrelation, where the latter slightly more right skewed and peaked than its value weighted counterpart. While we have not formally tested for differences between them, from examining both the cross sectional densities and the summary statistic there does not seem to be much differences between the correlation measures. And as discussed earlier and depicted in figure 5.1, the correlation between the correlation measures are generally very high.

For our four chosen liquidity measures, there are not that much to be noted since the values of the first principal components are hard to interpret numerically. But, we can note from figure F.1, that both the measure calculated from individual liquidity measures and the measure calculated for weighted relative measures are peaked. Also it is interesting to note the heavy-tailedness, thus informing us that "extreme" event occur more often than if the measures had been normal distributed.

For what we earlier has deemed as control variables, note that the market return is distributed as expected, with a slight left skew and while also being peaked. The *ted spread* is right skewed and the maximum is almost five standard deviations away from the mean, thus informing us that a transformation might be appropriate.

Appendix G

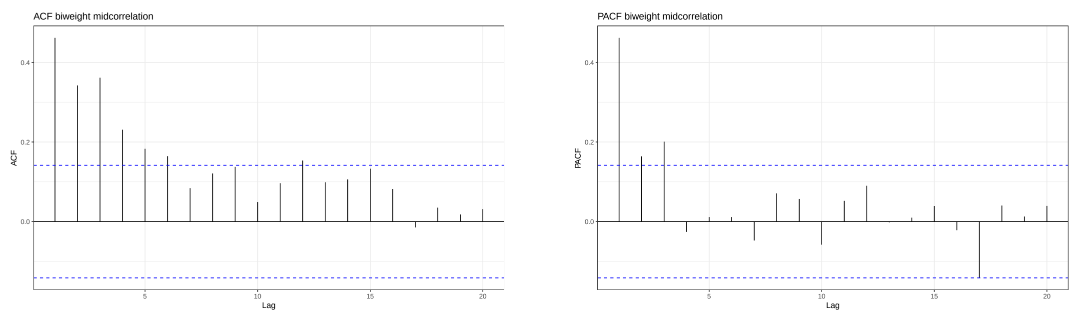


Figure G.1: ACF of biweight midcorrelation (left) and PACF of biweight midcorrelation. This informs us about the structure of the autocorrelation in our dependent variable, which we need to take into consideration when modeling.

Appendix H

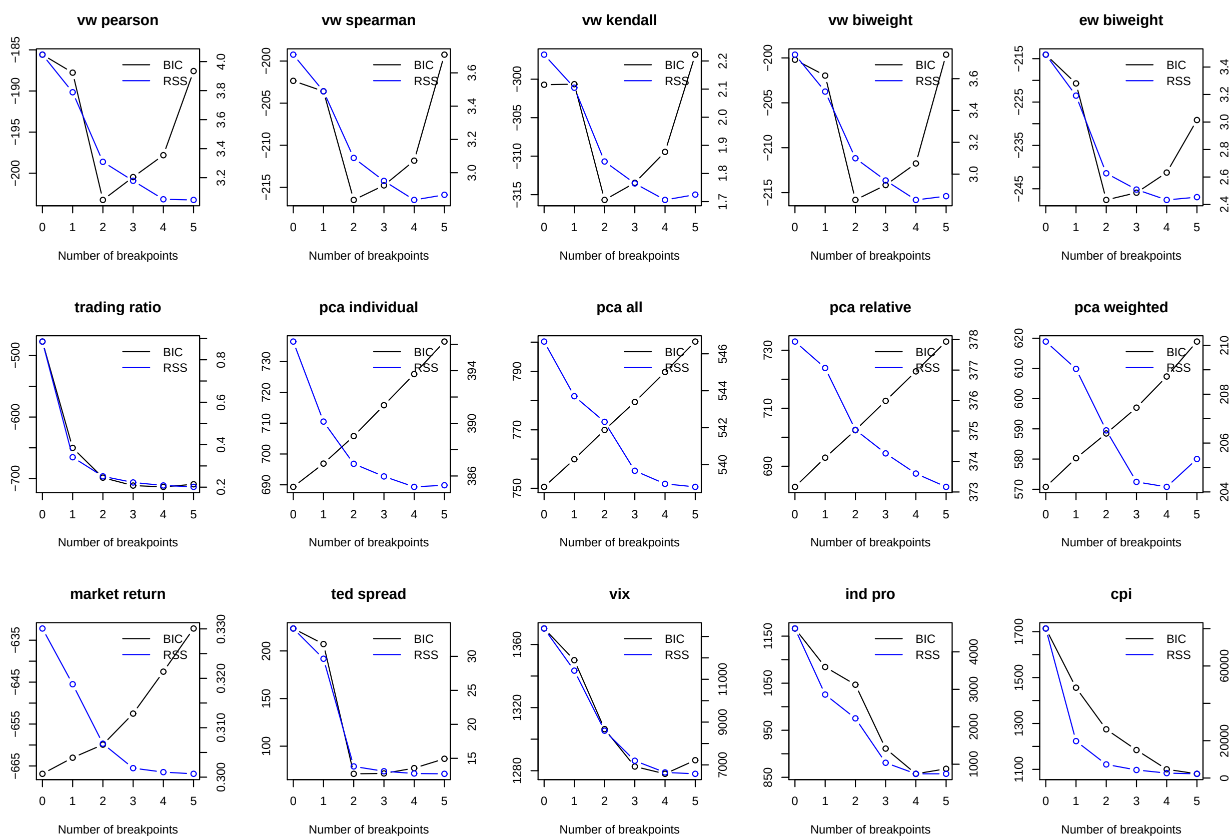


Figure H.1: Number of breakpoints, as estimated by minimizing the residual sum of squares using the procedure described and implemented by Zeileis, Kleiber, Krämer, and Hornik (2003, pp. 112-3). This suggest there are breakpoints in our dependent variable.

Appendix I

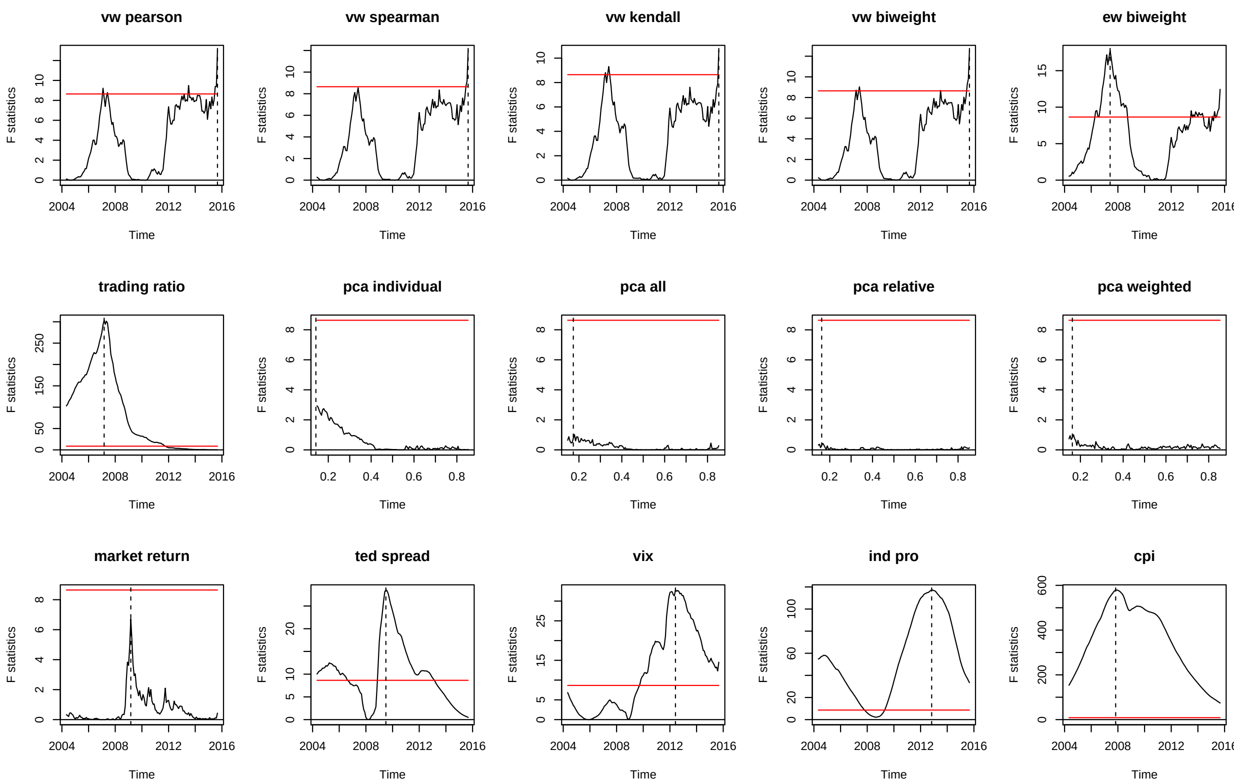


Figure I.1: Testing for breakpoints in I(1) series as proposed by Hansen (1992). The test is done by regressing the series on a constant removing the first and last 15% of the sample as adviced. If the F statistic is exceeding the boundary this has to be seen as evidence for a structural break, thus the mean is changing (Zeileis, Kleiber, Krämer, & Hornik, 2003, p.115).

Appendix J

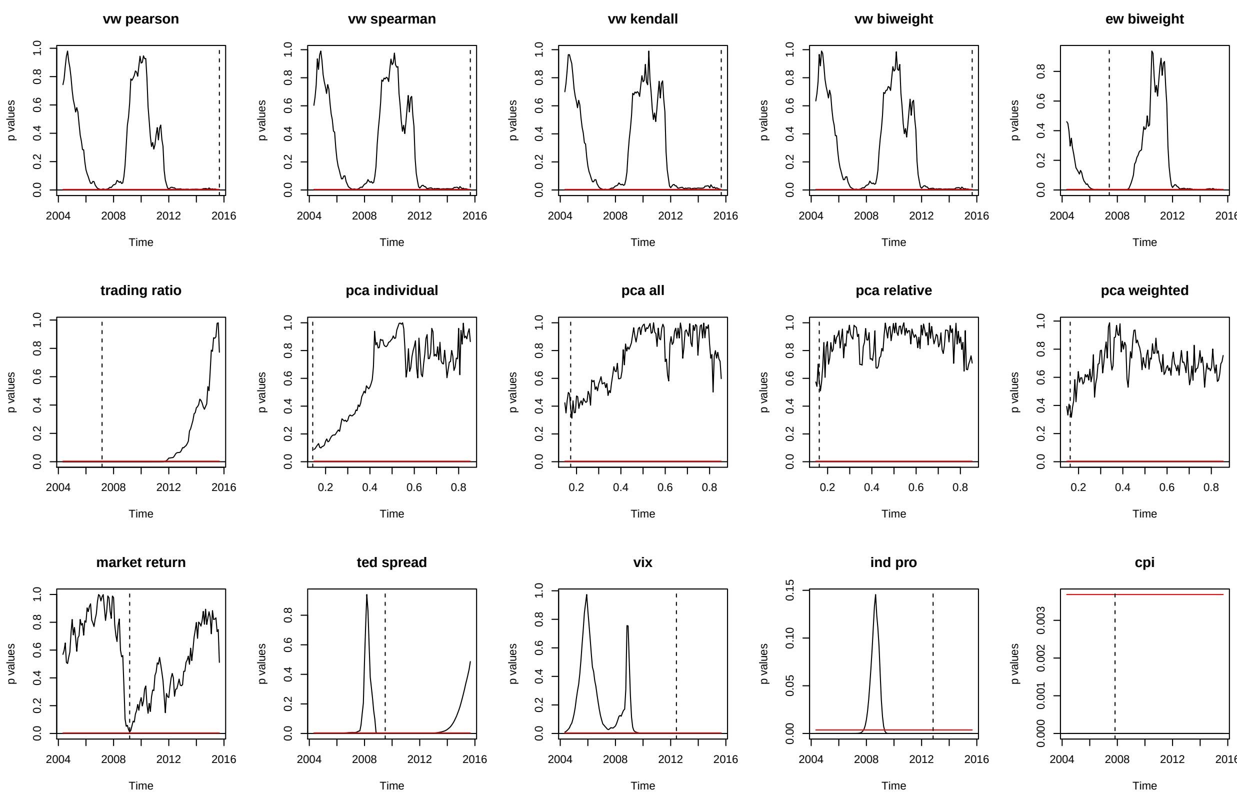
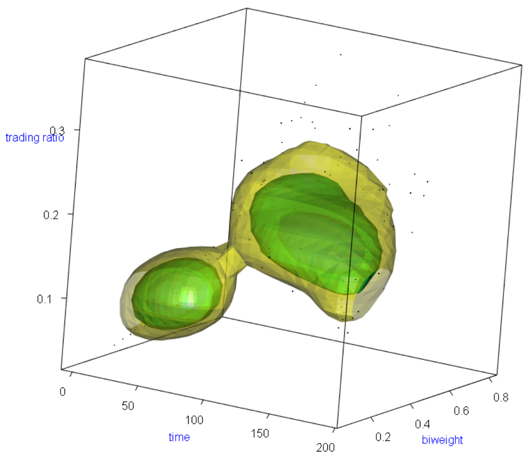
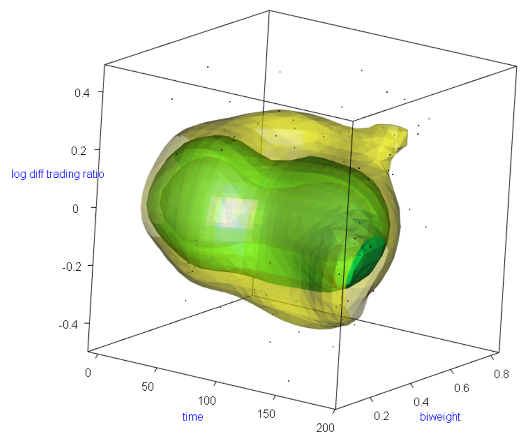


Figure J.1: P values for the test in I.1, and basically if the p value is lower than the red line, then this is evidence of a structural break in the series (Zeileis, Kleiber, Krämer, & Hornik, 2003, p. 115). Thus, we can see that there are some evidence of structural breaks in our series, but this mostly coincides with our unit root / stationarity tests. Thus, it does not change our view on the variables we have chosen to transform. This result is also different from the result depicted in H.1, and we can see there are only slight evidence for breakpoints in our correlation measures. Thus this informs us about the importance of estimating our models for multiple time periods.

Appendix K



(a) 3-d density trading ratio, biweight midcorrelation and time.



(b) 3-d density log differenced trading ratio, biweight midcorrelation and time.

Figure K.1: To visualize the changing density between our measure based on biweight midcorrelation and trading ratio, we have calculated how their estimated densities changes over time. The implementation is from Bowman and Azzalini (2014), where the implementation are described in detail by Bowman and Azzalini (1997), to the best of our knowledge the isosurfaces are calculated using a marching cubes algorithm along the line of what is presented by Chernyaev (1995). This is interesting since it visualize how the density changes where there in figure K.1a there seems to be a change in the relationship over time, which is not present in figure K.1b.

Appendix L

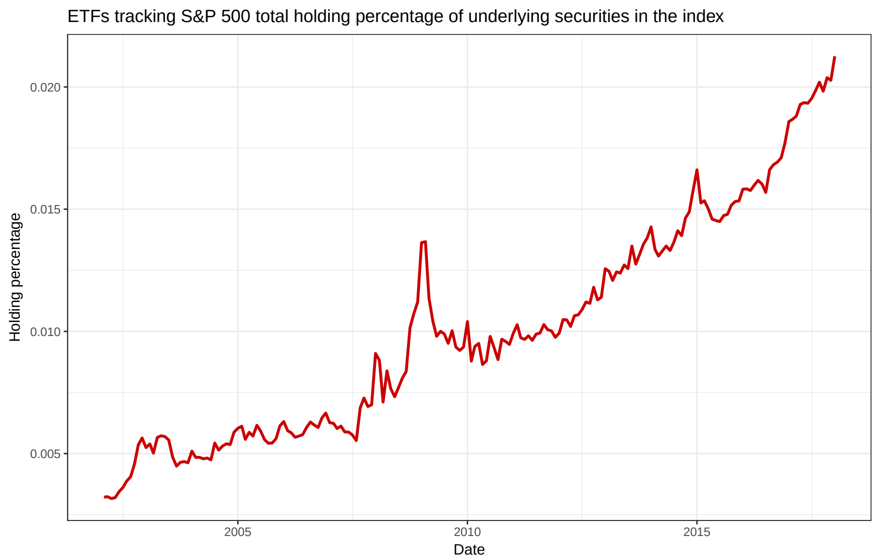


Figure L.1: ETFs tracking the S&P 500 total holding percentage of the underlying securities in the index. Calculated using end of month figures.

Appendix M

Table M.1: Alternative ARIMA models fitted to the trading ratio and then be able to use the residuals as done by Leippold, Su, and Ziegler (2016, p. 29), which mentions that they specifically use a seasonal ARIMA model, but only mentions that the AIC and BIC are available from the authors. Thus, we do not know what kind of model they have fitted. But what we do know, is that in our sample there are no evidence of any seasonality in the trading ratio, while no seasonal models is shown below in our sample an ARIMA(2,1,0) is seen to be the best model in our sample. Their main argument is that the residuals represents unexpected demand shocks to the ETFs. To the contrary we are under the belief that this is captured by the trading ratio itself, thus there are no need for further complications. Comparing models using the residuals and just the plain log differenced trading ratio does not show any qualitative different results. On the other side Leippold, Su, and Ziegler (2016) does have a different model specification, thus we cannot say with certainty that the differences are not due to some other factor.

	ar(2)	arma(1,4)	ma(4)	ma(1)	ar(1)
ar1	−0.41	0.67			−0.32
	(0.07)	(0.18)			(0.07)
ar2	−0.28				
	(0.07)				
ma1		−1.08	−0.40	−0.43	
		(0.19)	(0.07)	(0.07)	
ma2		0.13	−0.12		
		(0.12)	(0.07)		
ma3		0.29	0.18		
		(0.11)	(0.08)		
ma4		−0.23	−0.15		
		(0.07)	(0.07)		
AIC	−791.80	−791.67	−790.24	−787.77	−778.56
AICc	−791.67	−791.21	−789.91	−787.71	−778.50
BIC	−782.04	−772.15	−773.97	−781.27	−772.06
Log Likelihood	398.90	401.83	400.12	395.89	391.28

Appendix N

Table N.1: Subsample from 2002-2007 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2002 through 2007						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.39^{***}	0.40^{***}	0.39^{***}	0.39^{***}		0.37^{***}	
	(0.06)	(0.07)	(0.05)	(0.06)		(0.05)	
Δtrading ratio$_{m-1}$			0.39^{***}				
			(0.05)				
Δholding percent						0.34^{***}	
						(0.11)	
Δtrading ratio x Δholding percent						0.39	
						(0.48)	
trading ratio ARIMA residuals							2.83^{***}
							(0.50)
relative liquidity	0.00		0.00		0.00	0.00	0.01
	(0.01)		(0.00)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.00					
		(0.01)					
Δcpi	0.78	0.64	-0.93	0.75	1.61	3.03^{*}	0.99
	(1.55)	(1.86)	(1.36)	(1.72)	(2.40)	(1.79)	(2.19)
Δind pro	-0.83	-0.89	-1.28	-0.90	-1.62	-0.16	-0.57
	(1.67)	(1.81)	(1.02)	(1.91)	(1.76)	(1.55)	(1.69)
Δvix	0.13^{*}	0.13^{*}	0.09	0.13^{*}	0.16^{**}	0.14^{**}	0.07
	(0.07)	(0.07)	(0.05)	(0.07)	(0.07)	(0.06)	(0.07)
ted spread	0.01	0.01	0.02	0.01	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
market return	0.15	0.13	0.04	0.12	-0.67^{*}	0.21	-0.24
	(0.29)	(0.29)	(0.21)	(0.30)	(0.38)	(0.28)	(0.25)
dependent$_{m-1}$	0.66^{***}	0.67^{***}	0.19^{**}	0.66^{***}	0.46^{***}	0.60^{***}	0.44^{***}
	(0.10)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)	(0.06)
dependent$_{m-2}$	0.02	0.02	0.43^{***}	0.02	0.14	0.01	0.09
	(0.13)	(0.10)	(0.07)	(0.11)	(0.09)	(0.11)	(0.08)
dependent$_{m-3}$	0.19^{***}	0.19^{***}	0.20^{***}	0.20^{***}	0.16^{**}	0.24^{***}	0.28^{***}
	(0.06)	(0.06)	(0.06)	(0.05)	(0.07)	(0.07)	(0.05)
intercept	0.03	0.03	0.04^{**}	0.03	0.09^{***}	0.03^{*}	0.05^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
R^2	0.68	0.68	0.83	0.68	0.46	0.72	0.71
Adj. R^2	0.63	0.63	0.80	0.63	0.38	0.66	0.66
RMSE	0.07	0.07	0.05	0.07	0.09	0.06	0.06
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.2: Subsample from 2003-2008 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Full sample from 2003 through 2008						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.34^{***}	0.35^{***}	0.39^{***}	0.34^{***}		0.30^{***}	
	(0.07)	(0.07)	(0.05)	(0.07)		(0.08)	
Δtrading ratio$_{m-1}$			0.35^{***}				
			(0.07)				
Δholding percent						0.16^{*}	
						(0.08)	
Δtrading ratio x Δholding percent						0.82^{***}	
						(0.25)	
trading ratio ARIMA residuals							2.45^{***}
							(0.44)
relative liquidity	0.01^{*}		0.00		0.01^{*}	0.01^{**}	0.01^{**}
	(0.01)		(0.00)		(0.01)	(0.01)	(0.00)
weighted liquidity		0.01					
		(0.01)					
Δcpi	−3.08	−3.10	-3.76^{**}	−3.13	−2.66	−2.76	−2.04
	(2.23)	(2.04)	(1.82)	(2.15)	(2.39)	(2.38)	(2.48)
Δind pro	-2.00^{**}	-2.02^{*}	-2.57^{**}	-1.74^{**}	-2.21^{**}	-1.46^{*}	-1.82^{**}
	(1.00)	(1.08)	(0.97)	(0.73)	(0.83)	(0.86)	(0.90)
Δvix	0.13^{**}	0.13^{*}	0.14^{**}	0.11	0.15^{*}	0.13^{**}	0.13^{*}
	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.06)	(0.07)
ted spread	0.02	0.01	0.01	0.02	−0.00	0.02	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
market return	−0.11	−0.15	−0.04	−0.19	-0.89^{**}	−0.13	0.15
	(0.29)	(0.31)	(0.29)	(0.36)	(0.41)	(0.27)	(0.31)
dependent$_{m-1}$	0.53^{***}	0.52^{***}	0.18^{**}	0.50^{***}	0.36^{***}	0.48^{***}	0.32^{***}
	(0.13)	(0.12)	(0.08)	(0.11)	(0.11)	(0.14)	(0.08)
dependent$_{m-2}$	0.03	0.03	0.37^{***}	0.03	0.11	0.05	0.07
	(0.10)	(0.10)	(0.07)	(0.11)	(0.08)	(0.12)	(0.09)
dependent$_{m-3}$	0.15^{*}	0.15^{*}	0.17^{***}	0.17^{**}	0.15^{*}	0.16^{*}	0.24^{***}
	(0.08)	(0.08)	(0.05)	(0.07)	(0.09)	(0.08)	(0.07)
intercept	0.09^{***}	0.09^{***}	0.08^{***}	0.09^{***}	0.14^{***}	0.09^{***}	0.10^{***}
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.74	0.73	0.84	0.73	0.61	0.75	0.78
Adj. R^2	0.69	0.69	0.81	0.69	0.55	0.70	0.74
RMSE	0.07	0.07	0.05	0.07	0.08	0.07	0.06
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.3: Subsample from 2004-2009 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2004 through 2009						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.39^{***}	0.40^{***}	0.44^{***}	0.39^{***}		0.36^{***}	
	(0.07)	(0.07)	(0.05)	(0.05)		(0.04)	
Δtrading ratio$_{m-1}$			0.32^{***}				
			(0.07)				
Δholding percent						0.07	
						(0.06)	
Δtrading ratio x Δholding percent						0.81^{***}	
						(0.23)	
trading ratio ARIMA residuals							2.50^{***}
							(0.43)
relative liquidity	0.01		0.00		0.01	0.01^{**}	0.01^{**}
	(0.01)		(0.00)		(0.01)	(0.00)	(0.00)
weighted liquidity		0.01^{***}					
		(0.00)					
Δcpi	−3.90	−3.78	-4.12^{**}	-4.11^{*}	−3.48	−3.76	−2.73
	(2.83)	(2.69)	(1.92)	(2.15)	(3.53)	(3.22)	(2.46)
Δind pro	-1.49^{**}	-1.73^{**}	-1.98^{**}	−1.32	-1.25^{***}	-1.15^{**}	-1.34^{*}
	(0.71)	(0.65)	(0.86)	(0.86)	(0.40)	(0.44)	(0.71)
Δvix	0.13^{**}	0.14^{**}	0.17^{***}	0.12^{**}	0.21^{***}	0.12^{***}	0.16^{**}
	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.07)
ted spread	0.01	0.01	0.01	0.02	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
market return	0.18	0.17	0.31^{*}	0.16	−0.32	0.14	0.45^{*}
	(0.15)	(0.16)	(0.16)	(0.17)	(0.26)	(0.11)	(0.23)
dependent$_{m-1}$	0.60^{***}	0.61^{***}	0.31^{***}	0.59^{***}	0.41^{***}	0.57^{***}	0.43^{***}
	(0.14)	(0.13)	(0.10)	(0.12)	(0.06)	(0.09)	(0.08)
dependent$_{m-2}$	−0.04	−0.03	0.28^{***}	−0.04	0.03	−0.04	0.07
	(0.08)	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)	(0.09)
dependent$_{m-3}$	0.21^{***}	0.19^{**}	0.23^{***}	0.22^{***}	0.19^{**}	0.23^{***}	0.35^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.06)	(0.07)
intercept	0.07^{**}	0.08^{**}	0.06^{**}	0.07^{**}	0.13^{***}	0.07^{***}	0.04^{*}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
R^2	0.74	0.75	0.82	0.74	0.58	0.75	0.77
Adj. R^2	0.70	0.70	0.79	0.70	0.52	0.70	0.73
RMSE	0.07	0.07	0.06	0.07	0.09	0.07	0.06
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.4: Subsample from 2005-2010 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2005 through 2010						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.46^{***}	0.48^{***}	0.50^{***}	0.45^{***}		0.44^{***}	
	(0.05)	(0.05)	(0.05)	(0.05)		(0.07)	
Δtrading ratio$_{m-1}$			0.23^{***}				
			(0.07)				
Δholding percent						−0.00	
						(0.08)	
Δtrading ratio x Δholding percent						0.49	
						(0.34)	
trading ratio ARIMA residuals							2.52^{***}
							(0.39)
relative liquidity	0.01^{**}		0.01^{*}		0.01	0.01^{**}	0.01^{***}
	(0.01)		(0.00)		(0.01)	(0.01)	(0.00)
weighted liquidity		0.02^{***}					
		(0.01)					
Δcpi	-4.92^{**}	-4.77^{**}	-4.93^{***}	-5.17^{**}	−5.35	-4.98^{**}	−3.09
	(2.10)	(1.81)	(1.73)	(1.99)	(3.26)	(2.34)	(2.11)
Δind pro	−1.51	−1.78	−1.75	−1.16	−1.13	−1.40	-1.66^{*}
	(0.98)	(1.26)	(1.16)	(0.83)	(0.76)	(0.91)	(0.93)
Δvix	0.10^{*}	0.11^{*}	0.12^{**}	0.10	0.16^{*}	0.09^{*}	0.11^{*}
	(0.05)	(0.06)	(0.05)	(0.06)	(0.09)	(0.05)	(0.06)
ted spread	−0.01	−0.02	−0.01	−0.01	−0.02	−0.01	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
market return	−0.12	−0.12	−0.00	−0.12	-0.73^{*}	−0.14	0.08
	(0.22)	(0.23)	(0.22)	(0.23)	(0.42)	(0.23)	(0.26)
dependent$_{m-1}$	0.72^{***}	0.72^{***}	0.48^{***}	0.67^{***}	0.52^{***}	0.72^{***}	0.54^{***}
	(0.11)	(0.10)	(0.14)	(0.11)	(0.11)	(0.12)	(0.10)
dependent$_{m-2}$	−0.07	−0.05	0.17^{*}	−0.03	−0.07	−0.08	0.01
	(0.08)	(0.07)	(0.09)	(0.09)	(0.07)	(0.07)	(0.08)
dependent$_{m-3}$	0.19^{***}	0.17^{**}	0.21^{***}	0.20^{***}	0.26^{***}	0.20^{**}	0.33^{***}
	(0.07)	(0.07)	(0.05)	(0.07)	(0.07)	(0.08)	(0.06)
intercept	0.07^{***}	0.08^{***}	0.06^{**}	0.07^{**}	0.13^{***}	0.07^{**}	0.05^{**}
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
R^2	0.80	0.81	0.83	0.79	0.60	0.80	0.80
Adj. R^2	0.77	0.77	0.79	0.76	0.54	0.76	0.77
RMSE	0.07	0.06	0.06	0.07	0.09	0.07	0.07
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.5: Subsample from 2006-2011 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2006 through 2011						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.56^{***}	0.59^{***}	0.60^{***}	0.54^{***}		0.55^{***}	
	(0.09)	(0.08)	(0.07)	(0.07)		(0.09)	
Δtrading ratio_{m-1}			0.27^{***}				
			(0.08)				
Δholding percent						0.02	
						(0.07)	
Δtrading ratio x Δholding percent						0.16	
						(0.42)	
trading ratio ARIMA residuals							2.88^{***}
							(0.39)
relative liquidity	0.02^{***}		0.01^{**}		0.01	0.02^{***}	0.01^{***}
	(0.01)		(0.00)		(0.01)	(0.01)	(0.00)
weighted liquidity		0.02^{***}					
		(0.01)					
Δcpi	-5.11^{**}	-4.80^{***}	-5.06^{***}	-5.59^{***}	-7.02^{**}	-5.10^{**}	-2.90
	(1.98)	(1.78)	(1.83)	(2.08)	(3.34)	(2.00)	(2.61)
Δind pro	-1.02	-1.46	-1.39	-0.55	0.24	-0.91	-1.31
	(1.05)	(1.29)	(1.14)	(1.05)	(1.39)	(0.95)	(1.00)
Δvix	0.10^{**}	0.11^{**}	0.13^{**}	0.11^{*}	0.11	0.10^{**}	0.11^{**}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)	(0.05)	(0.05)
ted spread	-0.02	-0.03	-0.02	-0.02	-0.04^{**}	-0.02	-0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
market return	-0.05	-0.06	0.05	-0.08	-0.95^{**}	-0.06	0.14
	(0.21)	(0.21)	(0.23)	(0.22)	(0.43)	(0.22)	(0.25)
dependent_{m-1}	0.76^{***}	0.77^{***}	0.50^{***}	0.69^{***}	0.45^{***}	0.76^{***}	0.55^{***}
	(0.09)	(0.07)	(0.10)	(0.07)	(0.11)	(0.10)	(0.07)
dependent_{m-2}	0.04	0.05	0.31^{***}	0.08	0.06	0.04	0.10
	(0.10)	(0.08)	(0.10)	(0.09)	(0.13)	(0.10)	(0.07)
dependent_{m-3}	0.11	0.09	0.14^{**}	0.13^{*}	0.22^{***}	0.12	0.31^{***}
	(0.09)	(0.07)	(0.06)	(0.07)	(0.07)	(0.09)	(0.06)
intercept	0.06^{**}	0.06^{**}	0.04	0.06^{*}	0.16^{***}	0.06^{*}	0.03
	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)	(0.03)	(0.03)
R^2	0.81	0.82	0.84	0.79	0.56	0.81	0.82
Adj. R^2	0.78	0.79	0.80	0.76	0.50	0.77	0.79
RMSE	0.07	0.07	0.07	0.07	0.11	0.07	0.07
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.6: Subsample from 2007-2012 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2007 through 2012						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.56^{***}	0.58^{***}	0.63^{***}	0.54^{***}		0.54^{***}	
	(0.09)	(0.09)	(0.09)	(0.08)		(0.10)	
Δtrading ratio$_{m-1}$			0.30^{***}				
			(0.09)				
Δholding percent						0.02	
						(0.11)	
Δtrading ratio x Δholding percent						0.46	
						(0.74)	
trading ratio ARIMA residuals							2.82^{***}
							(0.41)
relative liquidity	0.02^{**}		0.01^{**}		0.01	0.02^{**}	0.02^{***}
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.02^{**}					
		(0.01)					
Δcpi	-6.53^{**}	-5.98^{**}	-5.47^{*}	-7.63^{***}	-11.27^{***}	-6.58^{**}	-4.42
	(2.63)	(2.63)	(2.98)	(2.36)	(2.21)	(2.69)	(3.44)
Δind pro	-1.32	-1.62	-1.74	-0.75	-0.35	-1.15	-1.59
	(1.41)	(1.53)	(1.41)	(1.26)	(1.87)	(1.22)	(1.22)
Δvix	0.01	0.02	0.06	-0.01	0.03	0.00	0.03
	(0.09)	(0.09)	(0.06)	(0.09)	(0.11)	(0.09)	(0.08)
ted spread	-0.02	-0.03	-0.02	-0.02	-0.04^{**}	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
market return	-0.20	-0.22	0.01	-0.28	-1.08^{***}	-0.24	-0.03
	(0.23)	(0.25)	(0.22)	(0.25)	(0.40)	(0.24)	(0.26)
dependent$_{m-1}$	0.68^{***}	0.68^{***}	0.45^{***}	0.59^{***}	0.34^{***}	0.68^{***}	0.50^{***}
	(0.12)	(0.11)	(0.11)	(0.10)	(0.08)	(0.13)	(0.08)
dependent$_{m-2}$	-0.03	-0.01	0.25^{**}	0.00	-0.02	-0.03	0.05
	(0.09)	(0.08)	(0.12)	(0.09)	(0.13)	(0.10)	(0.07)
dependent$_{m-3}$	0.10	0.09	0.13^{**}	0.12^{*}	0.16^{*}	0.10	0.29^{***}
	(0.06)	(0.06)	(0.06)	(0.07)	(0.09)	(0.06)	(0.05)
intercept	0.13^{**}	0.13^{***}	0.10^{**}	0.15^{***}	0.27^{***}	0.13^{**}	0.09^{*}
	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
R^2	0.69	0.70	0.73	0.68	0.45	0.70	0.73
Adj. R^2	0.64	0.65	0.68	0.63	0.37	0.63	0.69
RMSE	0.08	0.08	0.08	0.09	0.11	0.09	0.08
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.7: Subsample from 2008-2013 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2008 through 2013						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.73^{***}	0.75^{***}	0.78^{***}	0.73^{***}		0.66^{***}	
	(0.06)	(0.06)	(0.07)	(0.07)		(0.09)	
Δtrading ratio$_{m-1}$			0.28^{**}				
			(0.12)				
Δholding percent						0.03	
						(0.17)	
Δtrading ratio x Δholding percent						1.87	
						(1.69)	
trading ratio ARIMA residuals							3.50^{***}
							(0.32)
relative liquidity	0.01^{***}		0.01^{***}		0.02^{*}	0.02^{**}	0.02^{***}
	(0.01)		(0.00)		(0.01)	(0.01)	(0.00)
weighted liquidity		0.02^{***}					
		(0.01)					
Δcpi	-5.54^{*}	-4.99	-4.57	-6.40^{**}	-10.96^{***}	-6.28^{*}	-2.80
	(3.08)	(3.01)	(3.90)	(3.00)	(2.88)	(3.44)	(4.36)
Δind pro	-2.38^{***}	-2.68^{***}	-2.38^{***}	-1.83^{**}	-1.26	-2.04^{***}	-2.31^{***}
	(0.87)	(0.89)	(0.86)	(0.73)	(1.72)	(0.76)	(0.85)
Δvix	0.02	0.05	0.09	0.01	0.03	-0.02	0.07
	(0.09)	(0.09)	(0.07)	(0.10)	(0.12)	(0.12)	(0.07)
ted spread	-0.03^{*}	-0.04^{**}	-0.03	-0.03	-0.06^{**}	-0.04^{*}	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
market return	-0.01	-0.02	0.21	-0.09	-1.20^{**}	-0.19	0.25
	(0.21)	(0.22)	(0.22)	(0.28)	(0.46)	(0.32)	(0.26)
dependent$_{m-1}$	0.69^{***}	0.69^{***}	0.47^{***}	0.60^{***}	0.35^{***}	0.68^{***}	0.48^{***}
	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)	(0.10)	(0.08)
dependent$_{m-2}$	0.13	0.14^{*}	0.35^{***}	0.19^{**}	0.08	0.14^{*}	0.18^{**}
	(0.09)	(0.08)	(0.13)	(0.07)	(0.14)	(0.07)	(0.08)
dependent$_{m-3}$	-0.01	-0.01	0.04	0.00	0.08	-0.00	0.23^{***}
	(0.03)	(0.03)	(0.04)	(0.04)	(0.07)	(0.04)	(0.05)
intercept	0.10^{**}	0.10^{*}	0.08	0.11^{**}	0.26^{***}	0.11^{**}	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.76	0.77	0.78	0.75	0.45	0.77	0.78
Adj. R^2	0.72	0.73	0.74	0.71	0.36	0.72	0.75
RMSE	0.08	0.08	0.07	0.08	0.12	0.08	0.07
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.8: Subsample from 2009-2014 the models have the exact same specification as those estimated in table 6.1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
dependent variable:	Subsample from 2009 through 2014						
biweight midcorrelation Δtrading ratio	0.68^{***}	0.69^{***}	0.77^{***}	0.70^{***}		0.60^{***}	
	(0.06)	(0.06)	(0.06)	(0.06)		(0.09)	
Δtrading ratio$_{m-1}$			0.40^{***}				
			(0.08)				
Δholding percent						0.22	
						(0.18)	
Δtrading ratio x Δholding percent						2.17^{*}	
						(1.29)	
trading ratio ARIMA residuals							3.55^{***}
							(0.20)
relative liquidity	0.02^{**}		0.02^{***}		0.03^{**}	0.02^{**}	0.02^{***}
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.04^{**}					
		(0.02)					
Δcpi	1.98	1.53	5.56	1.68	−7.57	2.72	4.55
	(3.94)	(4.06)	(4.46)	(4.20)	(5.24)	(4.41)	(4.01)
Δind pro	−0.74	−1.14	0.35	−0.71	2.43	0.16	−0.21
	(1.59)	(1.50)	(1.41)	(1.80)	(3.42)	(1.64)	(1.27)
Δvix	−0.01	0.00	0.02	0.03	-0.16^{*}	−0.05	0.01
	(0.12)	(0.12)	(0.08)	(0.11)	(0.09)	(0.13)	(0.09)
ted spread	0.01	−0.00	0.07	0.05	0.01	0.01	0.13^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.11)	(0.05)	(0.04)
market return	−0.30	−0.34	−0.06	−0.44	-1.86^{***}	−0.59	−0.09
	(0.34)	(0.32)	(0.27)	(0.36)	(0.47)	(0.39)	(0.29)
dependent$_{m-1}$	0.77^{***}	0.76^{***}	0.45^{***}	0.64^{***}	0.37^{***}	0.73^{***}	0.52^{***}
	(0.08)	(0.08)	(0.10)	(0.10)	(0.12)	(0.09)	(0.07)
dependent$_{m-2}$	0.08	0.10	0.37^{***}	0.15^{**}	0.09	0.10	0.10
	(0.09)	(0.08)	(0.10)	(0.07)	(0.15)	(0.09)	(0.08)
dependent$_{m-3}$	−0.01	−0.01	0.04	0.00	0.07	−0.00	0.18^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)
intercept	0.06^{*}	0.06^{*}	0.03	0.07	0.21^{***}	0.07	0.04
	(0.04)	(0.04)	(0.03)	(0.05)	(0.06)	(0.04)	(0.04)
R^2	0.77	0.78	0.82	0.74	0.40	0.78	0.83
Adj. R^2	0.73	0.74	0.78	0.70	0.31	0.74	0.80
RMSE	0.07	0.07	0.07	0.08	0.12	0.07	0.06
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.9: Subsample from 2010-2015 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2010 through 2015						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.63^{***}	0.65^{***}	0.72^{***}	0.66^{***}		0.58^{***}	
	(0.05)	(0.06)	(0.06)	(0.06)		(0.06)	
Δtrading ratio$_{m-1}$			0.33^{***}				
			(0.07)				
Δholding percent						0.35	
						(0.25)	
Δtrading ratio x Δholding percent						2.07^{*}	
						(1.20)	
trading ratio ARIMA residuals							3.35^{***}
							(0.20)
relative liquidity	0.02^{**}		0.02^{**}		0.03^{***}	0.02^{**}	0.02^{**}
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.04^{**}					
		(0.02)					
Δcpi	1.10	1.26	3.89	−0.02	−7.04	2.39	3.64
	(4.03)	(3.06)	(5.18)	(3.51)	(5.10)	(4.50)	(4.36)
Δind pro	−1.61	−2.05	−1.45	−1.71	2.78	−1.43	-2.17^{*}
	(1.41)	(1.47)	(1.45)	(1.42)	(3.09)	(1.26)	(1.16)
Δvix	−0.09	−0.06	−0.06	−0.10	−0.10	-0.10^{**}	-0.09^{*}
	(0.05)	(0.06)	(0.04)	(0.07)	(0.07)	(0.05)	(0.05)
ted spread	−0.01	0.01	0.02	−0.02	−0.12	−0.01	0.09
	(0.11)	(0.07)	(0.12)	(0.09)	(0.17)	(0.08)	(0.11)
market return	-0.90^{**}	-0.80^{**}	−0.62	-1.20^{***}	-2.10^{***}	-1.03^{***}	-0.72^{*}
	(0.43)	(0.38)	(0.43)	(0.35)	(0.45)	(0.33)	(0.42)
dependent$_{m-1}$	0.70^{***}	0.72^{***}	0.44^{***}	0.60^{***}	0.35^{***}	0.68^{***}	0.47^{***}
	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.07)
dependent$_{m-2}$	0.15^{*}	0.14^{*}	0.40^{***}	0.18^{***}	0.19^{*}	0.15^{*}	0.18^{**}
	(0.08)	(0.07)	(0.09)	(0.06)	(0.10)	(0.08)	(0.07)
dependent$_{m-3}$	−0.03	−0.03	0.01	0.02	0.08	−0.01	0.17^{***}
	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
intercept	0.09^{**}	0.08^{***}	0.06^{*}	0.10^{***}	0.21^{***}	0.08^{***}	0.06^{*}
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)
R^2	0.80	0.80	0.83	0.77	0.49	0.81	0.85
Adj. R^2	0.76	0.77	0.79	0.74	0.41	0.77	0.82
RMSE	0.07	0.07	0.07	0.08	0.12	0.07	0.06
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.10: Subsample from 2011-2016 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2011 through 2016						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.62^{***}	0.62^{***}	0.69^{***}	0.64^{***}		0.57^{***}	
	(0.07)	(0.07)	(0.08)	(0.07)		(0.08)	
Δtrading ratio$_{m-1}$			0.27^{***}				
			(0.09)				
Δholding percent						0.16	
						(0.29)	
Δtrading ratio x Δholding percent						2.65^{**}	
						(1.21)	
trading ratio ARIMA residuals							3.36^{***}
							(0.33)
relative liquidity	0.01		0.01^{**}		0.03^{**}	0.01	0.01^{*}
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.02					
		(0.02)					
Δcpi	1.96	1.53	5.43	1.47	−6.47	2.73	5.17
	(3.39)	(2.86)	(4.71)	(2.81)	(5.21)	(3.83)	(3.47)
Δind pro	−2.26	−2.33	−2.29	−1.76	0.37	−1.80	−2.28
	(1.78)	(1.96)	(1.58)	(1.76)	(3.28)	(1.85)	(1.51)
Δvix	-0.13^{**}	-0.11^{*}	-0.11^{**}	-0.14^{**}	-0.15^{*}	-0.14^{**}	-0.13^{**}
	(0.06)	(0.06)	(0.05)	(0.06)	(0.08)	(0.05)	(0.05)
ted spread	−0.08	−0.08	−0.08	-0.09^{*}	-0.18^{*}	−0.08	−0.04
	(0.05)	(0.06)	(0.07)	(0.05)	(0.10)	(0.06)	(0.06)
market return	-1.20^{**}	-1.23^{**}	-0.88^{*}	-1.49^{***}	-2.49^{***}	-1.26^{**}	-0.94^{*}
	(0.54)	(0.59)	(0.50)	(0.48)	(0.65)	(0.51)	(0.49)
dependent$_{m-1}$	0.61^{***}	0.59^{***}	0.41^{***}	0.54^{***}	0.24^{*}	0.61^{***}	0.41^{***}
	(0.11)	(0.12)	(0.09)	(0.11)	(0.13)	(0.09)	(0.09)
dependent$_{m-2}$	0.16^{**}	0.16^{***}	0.36^{***}	0.17^{***}	0.21^{*}	0.16^{**}	0.18^{***}
	(0.06)	(0.06)	(0.11)	(0.05)	(0.11)	(0.07)	(0.07)
dependent$_{m-3}$	0.05	0.06	0.08	0.09^{**}	0.14^{*}	0.06	0.25^{***}
	(0.05)	(0.05)	(0.05)	(0.04)	(0.08)	(0.05)	(0.07)
intercept	0.10^{**}	0.11^{**}	0.08^{*}	0.12^{**}	0.24^{***}	0.10^{**}	0.08^{*}
	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.04)	(0.05)
R^2	0.78	0.77	0.80	0.76	0.46	0.79	0.81
Adj. R^2	0.74	0.73	0.76	0.73	0.38	0.74	0.78
RMSE	0.08	0.08	0.07	0.08	0.12	0.08	0.07
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table N.11: Subsample from 2012-2017 the models have the exact same specification as those estimated in table 6.1.

dependent variable:	Subsample from 2012 through 2017						
biweight midcorrelation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Δtrading ratio	0.50^{***}	0.50^{***}	0.53^{***}	0.51^{***}		0.50^{***}	
	(0.07)	(0.06)	(0.09)	(0.06)		(0.06)	
Δtrading ratio$_{m-1}$			0.12				
			(0.11)				
Δholding percent						0.20	
						(0.22)	
Δtrading ratio x Δholding percent						-0.36	
						(1.41)	
trading ratio ARIMA residuals							2.97^{***}
							(0.33)
relative liquidity	0.01		0.01		0.02^{*}	0.01^{*}	0.01
	(0.01)		(0.01)		(0.01)	(0.01)	(0.01)
weighted liquidity		0.02					
		(0.02)					
Δcpi	-2.02	-2.50	-1.13	-2.35	-5.68	-1.57	1.71
	(3.58)	(3.66)	(4.11)	(3.70)	(4.77)	(3.83)	(3.48)
Δind pro	-2.41^{*}	-2.42	-2.55^{**}	-1.59	-3.35	-2.80^{**}	-2.97^{**}
	(1.24)	(1.50)	(1.21)	(1.37)	(2.67)	(1.33)	(1.12)
Δvix	-0.17^{***}	-0.15^{**}	-0.15^{***}	-0.19^{***}	-0.20^{**}	-0.18^{***}	-0.18^{***}
	(0.05)	(0.06)	(0.05)	(0.04)	(0.08)	(0.05)	(0.05)
ted spread	-0.07	-0.06	-0.06	-0.07	-0.18^{**}	-0.08	-0.08
	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)
market return	-1.75^{***}	-1.73^{***}	-1.52^{**}	-2.12^{***}	-3.10^{***}	-1.85^{***}	-1.65^{**}
	(0.62)	(0.64)	(0.73)	(0.44)	(0.72)	(0.56)	(0.64)
dependent$_{m-1}$	0.46^{***}	0.45^{***}	0.37^{***}	0.40^{***}	0.13	0.45^{***}	0.28^{***}
	(0.06)	(0.06)	(0.10)	(0.04)	(0.12)	(0.06)	(0.07)
dependent$_{m-2}$	0.21^{***}	0.21^{***}	0.30^{***}	0.23^{***}	0.19^{**}	0.20^{***}	0.22^{***}
	(0.05)	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.05)
dependent$_{m-3}$	0.12^{*}	0.13^{*}	0.14^{*}	0.17^{***}	0.19^{*}	0.12^{*}	0.28^{***}
	(0.07)	(0.07)	(0.07)	(0.06)	(0.10)	(0.07)	(0.08)
intercept	0.11^{***}	0.11^{***}	0.10^{**}	0.11^{***}	0.25^{***}	0.11^{***}	0.11^{**}
	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)
R^2	0.76	0.76	0.77	0.75	0.52	0.76	0.79
Adj. R^2	0.72	0.72	0.72	0.71	0.44	0.71	0.75
RMSE	0.07	0.07	0.07	0.07	0.10	0.07	0.07
Num. obs.	69	69	69	69	69	69	69

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix O

Table O.1: Model where the log difference of our dependent variables is used instead of in levels. The standard errors are calculated according to Newey and West (1987, 1994). All regressions in this table is specified as model 1 from table 6.1, thus we can see that the results are remarkably similar. On consideration, which could be of interest in a model like this is the issue of cointegration since, the dependent variable is specified as being intergrated of order 1, thus making an error correction model a possibility.

dependent variable:	vw biweight Model 1	ew biweight Model 2	vw pearson Model 3	vw spearman Model 4	vw kendall Model 5
Δtrading ratio	1.61^{***}	1.52^{***}	1.76^{***}	1.60^{***}	1.68^{***}
	(0.17)	(0.16)	(0.20)	(0.17)	(0.18)
relative liquidity	0.05^{**}	0.05^{***}	0.03^{*}	0.05^{***}	0.05^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Δcpi	-7.48^{*}	-7.57^{*}	-9.14^{*}	-8.49^{**}	-8.66^{**}
	(4.20)	(4.50)	(4.68)	(4.08)	(4.16)
Δind pro	-6.20^{**}	-5.31^{**}	-5.73	-5.58^{*}	-5.58^{*}
	(2.95)	(2.28)	(3.52)	(3.02)	(3.08)
Δvix	0.19	0.22^{*}	0.23	0.22	0.23
	(0.14)	(0.14)	(0.16)	(0.14)	(0.15)
ted spread	-0.02	-0.02	-0.01	-0.02	-0.02
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
market return	0.17	0.17	0.50	0.25	0.26
	(0.57)	(0.58)	(0.59)	(0.58)	(0.60)
Δdependent$_{t-1}$	-0.39^{***}	-0.34^{***}	-0.43^{***}	-0.39^{***}	-0.38^{***}
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Δdependent$_{t-2}$	-0.22^{***}	-0.17^{***}	-0.22^{***}	-0.21^{***}	-0.20^{***}
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Δdependent$_{t-3}$	-0.12^{***}	-0.10^{**}	-0.07^{*}	-0.12^{***}	-0.11^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
intercept	0.01	0.01	-0.00	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
R^2	0.74	0.74	0.72	0.74	0.74
Adj. R^2	0.72	0.72	0.71	0.73	0.73
RMSE	0.24	0.22	0.27	0.24	0.24
Num. obs.	188	188	188	188	188

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$