ETF ownership and the volatility of U.S. stocks

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Abstract

This thesis explores the effect ownership by exchange traded funds have on the volatility of their underlying securities. We build upon the research conducted by Ben-David, Franzoni and Moussawi (2017a) and first replicate the results presented by them that ownership by exchange traded funds increase volatility. Building on the replicated results, we extend their research by replicating their findings in a larger sample covering practically all publicly traded stocks in the U.S. market. Furthermore, we group the ETFs according to investment style and investigate how ownership by various types of funds may contribute to volatility differently. In all three tests conducted we find a positive and significant relation between a security's volatility and ETF ownership. Additionally, we find that the different groups of funds contribute differently to the volatility of securities.

Keywords: Exchange traded funds, volatility, arbitrage

JEL classification codes: G12, G13, G14.

Abbreviations:

ETF: Exchange traded fund

AUM: Assets under management

PERMNO: Permanent Number Variable Name

Fundno: Fund number

Market Cap: Market capitalization

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1. Introduction

Almost 10 years have passed since the global financial crisis of 2008 hit the world, and since then the financial markets have changed drastically. New regulations, ultra-low interest rates with quantitative easing and financial innovation have all reshaped the financial market. In the midst of this ever changing market we find a fairly new investment vehicle, the exchange traded fund (ETF). The ETF, similar to an open-end mutual fund in the sense that it gives the owner of an ETF-share a claim on the underlying assets, but different because it is traded publicly like a share of common stock, was first introduced in the U.S.1993, and has after a slow start, become one of the fastest growing investment vehicles, representing over 10% of the market capitalization of securities traded in the U.S (Ben-David et al. 2017b). This feat has been achieved in under 20 years. And it is not hard to understand why ETFs have become so popular. They are cheap, offering low transaction cost and management fees for investments otherwise associated with high costs. They offer easy access to financial products previously only offered to high net worth individuals and institutional investors, like pension funds and hedge funds. They also offer access to otherwise time-consuming investment strategies like index tracking.

We research the relationship between the volatility of the underlying securities of ETFs and the aggregated ownership by ETFs in those securities. By aggregating the holdings of a large sample of U.S. ETFs and calculating how large their ownership is in each individual security, we can draw conclusions regarding how the ownership by ETFs relate to the volatility of these securities. We draw inspiration from Ben-David, Franzoni and Moussawi (2017a) who show that ETF ownership relate to higher volatility and build upon their research by first replicating their findings in a larger sample and then showing that all types of ETFs are not alike. Our findings show that how an ETF affects volatility is related to its investment style. We construct three groups of ETFs (Core, Industry & Other) and show that Core contribute to lower volatility while Industry and Other contributes to higher volatility with statistical significance.

With the growing market share that ETFs now hold of total U.S. assets, the different types of ETFs offered in the market has increased drastically. Today there are ETFs offering access to various themes of assets, like physical commodities, illiquid, hard-to-invest-in, emerging market small cap securities and corporate bonds. Alongside there are more traditional ETFs offering index tracking and investment strategies like equity income portfolios and growth stock portfolios. In aggregate, there are over 1,700 ETFs offered in the U.S. today compared to 349 ten years ago (Bloomberg, 2018).

However, with the growing popularity in ETFs together with the interesting attributes offered by ETFs, regulators and researcher alike have started to look into the possible problems arising from increased trading in ETFs. Lower liquidity in the underlying securities (Petajisto, 2017), a transmission mechanism for nonfundamental shocks (Malamud, 2015), an increase in stock return synchronicity reported by Israeli, Lee and Sridharan (2017) and the increase in volatility of underlying securities with increasing ETF ownership, presented by Ben-David et al. (2017a). There is a long-standing conversation about the relation between derivatives and their underlying securities. ETFs has become one of the largest types of derivatives in the market which increase the interest of how they affect the market and their underlying securities. We continue the research of Ben-David et al. (2017a) on the relationship between ETF ownership and increased volatility. First, we replicate the findings of Ben-David et al. (2017a) on the S&P 500 index. Then, we expand the experiment, by including all publicly traded securities in the US market in our model, producing results in line with Ben-David et al (2017a). Lastly, after concluding that there is a significant increase in the volatility of underlying securities with increasing ETF ownership, we explore different ETF-types and if these different types of ETFs contribute differently to the volatility. By dividing the sample of ETFs into three groups based on their investment style we find significant differences between the three groups contribution to the volatility of the underlying securities.

Exchange traded funds (ETFs) are investment entities that issue securities that trade continuously on public exchanges (Ben-David et al (2017b), structured as open-end investment companies. The most common purpose for an ETF is to track equity indices, i.e. S&P 500 and Dow Jones Industrial Average. ETFs have low transaction costs and high intraday liquidity which have made them an increasingly popular investment vehicle. Table 1 illustrates the overall rise of index investments in recent years, both in the form of ETFs and mutual funds. As we can see, index ETFs have experienced the largest growth among all types of funds. Active ETFs are starting to emerge although they are still a very small portion of total ETF AUM.

Table 1. The table shows AUM in billions of U.S. dollars. Index funds include both traditional index funds and smart-beta index funds. Source:(Ben-David et al., 2017b)

US Equity Funds

	Year	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*
ETFs	*Index*	31	63	79	92	131	184	220	283	384	290	436	566	612	756	1 013	1 233	1 235	1 329
	Active	0	0	0	0	0	0	0	1	2	11	11	12	12	11	13	20	23	24
Mutual Funds	*Index*	335	327	308	255	365	444	486	592	666	479	660	824	857	1 025	1 433	1 706	1 689	1 806
	Active	2 633	2 586	2 322	1 709	2 325	2 688	2 918	3 299	3 532	2 324	2 999	3 497	3 350	3 663	4 774	5 066	4 976	5 044

ETFs can track virtually any type of asset. The most popular ETFs are those that replicate indices, such as the world's largest ETF, SPDR S&P 500 ETF, more commonly known as SPY, which mirrors the S&P 500 index. But there are also ETFs tracking commodities, bonds, currencies, real estate, or other baskets of assets following investment strategies like equity income portfolios. The portfolios of ETFs can be related to a specific theme, holding a narrower scope of investments compared to the typical index replicating ETF, for example in a specific type of commodity or a selected industry. Additionally, actively managed ETFs (ETMFs) have recently emerged in which managers actively pick securities in an attempt to generate alpha. By investing in ETFs, investors are given access to markets, industries, and assets that previously would have required large amounts of capital and effort to create diversified portfolios within. Hence, ETFs provide a way for investors to more easily create diversified portfolios due to lower capital requirements for investments in ETFs.

Because of the liquidity of ETFs, low transaction cost and the vast variation, ETFs have become a popular instrument not only for institutional investors and private investors but also for trading. These special traits ETFs have, attract short-term horizon noise traders as shown by Broman (2016).

The increasing inflow of capital into exchange traded funds in recent years and their high attractiveness for various type of market participants raises interest for investors and regulators alike, to examine the effects the relatively new investment vehicle has on their underlying securities and the capital markets.

1.1 Purpose

Recent research of Ben-David et al. (2017a) shows a relation between higher ETF ownership and the volatility of securities in the S&P 500- and Russell 3000 index. However, all ETFs are not the same as they have widely varying investment strategies. ETFs can invest in specific sectors or industries, have different strategies like equity income or mirror broader indices. The purpose of this thesis is to broaden the research of Ben-David et al. (2017a) by observing, not only the S&P 500 and Russell 3000, but the complete U.S. equity market, and furthermore test whether different types of ETFs contribute differently to the increased volatility suggested by Ben-David et al. (2017a).

1.2 Research Questions

1.2.1 Volatility in the complete U.S. equity market

Can we find the same significant results on the complete U.S. equity market as Ben-David et al. (2017a) find in their paper?

Can we first replicate the findings of Ben-David et al. (2017a) on an S&P 500 sample and then on the complete U.S. equity market?

1.2.2. Volatility by type of ETF

Are there differences in the contribution to volatility depending on what type of ETF is holding the security?

1.3 Thesis Organization

The remainder of this thesis starts with the literature review in section II, providing further theoretical background. In section III, the methodology is presented describing the empirical process, our hypotheses, and regression models. Then in section IV the data collection and data begin with a description of how all data is retrieved, followed by a discussion of how we have formulated our variables and summary statistics. In the results in section V, we show the answers to the various hypotheses, discuss limitations and robustness, to finally conclude the thesis in section VI. At the end, there is an appendix of all tables which are referenced throughout the thesis.

2. Literature review

The literature review is divided into three parts. The section I discusses index- and passive investing, starting in the Mutual funds industry. The section II cover ETFs and ETF arbitrage. Section III covers volatility.

2.1 Index- and Passive Investments

In the financial market, there is a wide array of products and solutions created and designed to meet the demand of investors seeking ways to invest their capital. Equity, bonds, commodities and real estate among other things can all be traded on their respective markets, in funds, through futures, options, or other types of derivatives. Equity mutual funds have been a popular choice among investors, with a substantial rise in AUM since the beginning of the 1990s (Sullivan & Xiong, 2012).

In the mutual fund industry, there are two main styles fund managers practice, passive or active. The strategy of a passive mutual fund follows the efficient market hypothesis described by Fama (1970), in which the main idea is that securities should be efficiently priced and only change in price when new information is presented to the market. In contrast, an active mutual fund's goal is to generate abnormal returns compared to the market return (Grindblatt & Titman, 1989), either through market timing, superior stock picking skills possessed by the funds managers, speed advantages or superior private information obtained by the managers. Roughly this could be translated into that an active fund manager objective is to "beat the market". However, most evidence throughout the literature points to the presence of an efficient market, particularly in the case presented by Carhart (1997). Carhart (1997) presented results which show that the persistence in mutual fund performance does not reflect superior stock picking skills by the fund's managers. Still, as of end 2016, active mutual funds in the US market represent approximately two thirds of the 6.8 trillion US dollars invested in equity held by mutual funds (Ben-David et al. 2017b).

However, passive investments are on the rise and have been for some time. Over the last 17 years, the average annual growth rate of assets invested in passive investments has been about twice that of actively managed assets (Sullivan & Xiong 2012).

Within mutual funds, the index fund is one of the typical investment products. The objective of an index-linked investment such as an index fund, is defined by Wurgler (2010): *"as an investment focused on a predefined and publicly known set of stocks"*. For example, the Vanguard 500 index fund's objective is to mimic the return of the S&P 500 index, the leading market index gauge of large-cap US equities.

2.2 Exchange traded funds

As an investment vehicle, ETFs is a fairly new invention. Introduced in the US market during mid-1990s (Ben-David et al., 2017b), ETFs have over the last ten years increased in popularity, according to (Madhavan 2014; Sullivan & Xiong 2012) and have fundamentally changed the mutual fund industry. From 2000, when assets under management (AUM) in ETFs covering US equities totaled $70 billion (Madhavan, 2014), the increase in AUM until recently has been staggering. In mid-2014, AUM stood at $1.7 trillion (Madhavan, 2014), a yearly average[1] increase of 23.69%. For reference, the yearly average increase of AUM in active mutual funds[2] was 4.9%.

What can describe the increasing popularity of this newly created investment product, that in a sense is like an open-end mutual fund, which offer unlimited share creation and redemption, but do not offer its shares on a public exchange? Ben-David et al. (2017b) argue that low transaction costs and access to high intraday liquidity are the main reasons for the popularity of ETFs. Sullivan and Xiong (2012) mention the increasing popularity of index trading, and that the diversification possibilities in various market segments offered through ETFs are key elements of rising ETF popularity. Additionally, Ben-David et al. (2017a) argue that investment strategies that only were accessible to institutional investors before the introduction of ETFs (i.e. short selling and the use of leverage) are now accessible for retail investors and this access can also explain the growing interest in ETFs.

Offering low transaction cost, which is an important aspect for passive investors and thus making ETFs a popular choice among these investors, ETFs have also attracted short horizon traders (Ben-David et al., 2017b) and "noise" traders (Israeli et al., 2017) due to the low cost and high liquidity. Short horizon traders tend to use ETFs to make directional bets on various markets (Broman & Shum, 2018; Stratmann & Welborn, 2012). A noise trader is in the words of Black (1986, p.531): *"Noise trading is trading on noise as if it were information. People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading. Perhaps they think the noise they are trading on is information. Or perhaps they just like to trade"*. According to Ben-David et al. (2017a) rising evidence points to that these noise traders play a significant role in creating non-fundamental demand shocks, where fundamental information is not the main information these transactions are based on. Malamud (2015) also show that the creation/redemption mechanism the APs use to exploit arbitrage between an ETFs price and the collective price of its underlying securities, explained below, can temporarily propagate liquidity shocks to the ETFs underlying securities.

Another possible effect of increasing popularity in ETFs is decreasing informational efficiency of the ETFs underlying securities. Israeli et al. (2017) find that increasing ETF ownership in securities lowers the informational efficiency by measuring the securities' future earnings

[1] Geometric.
[2] Calculated with values form table 1 in Ben-David et al. (2017b).

response coefficient and finding it significantly lower for securities with high ETF ownership. These findings are in line with Stein (1987) who argues short-term speculators lower the informational efficiency of prices. Da and Shive (2018) report a strong relationship between ETF activity and return co-movement of the underlying securities in the ETF. The co-movement reduces some of the diversification benefits that ETFs promotes (Da & Shive, 2018). Additionally, regarding the consequences of increasing index trading through ETFs, research by Sullivan and Xiong (2012) show that rising AUM in index-based investments increase commonality among the index constituents and this can lead to a rise in systematic market risk.

2.3 ETF arbitrage

ETFs mirror the price of a basket of securities intraday through a mechanism called the creation-redemption mechanism which allows market-makers to arbitrage through creating or redeeming shares in a fund. Similarly to mutual funds, ETFs consist of fund shares which can be created and redeemed at the end of each trading day at the current per share net asset value (NAV) defined as the fund's assets, minus potential liabilities, divided by the number of shares. In contrast to mutual funds, these shares are created or redeemed only with market-making firms called authorized participants (APs). APs have the option to not only, as all market participants, trade ETF shares in the secondary market but they also have the option to purchase or redeem shares at NAV with the issuer at the end of the trading day. Under no arbitrage, this mechanism keeps the price of the ETF in the secondary market within a range equal to the transaction cost away from the intraday NAV as arbitrageurs continuously trade any mismatches in ETF price and NAV by buying either the ETF or the underlying basket of securities and short selling the other (Madhavan, 2014). Marshall, Nguyen, and Visaltanachoti (2013) presented empirical proof of the existence of this ETF arbitrage.

Interestingly, as ETFs have grown larger questions arise whether price changes in NAV are moving the price of the ETF, or in fact changes in ETF price due to non-fundamental price shocks (such as those created by noise and liquidity traders) affect the price of the underlying basket of securities. That is, if the trading of the ETF moves the intraday NAV and not the other way around. Da and Shive (2018) find that the APs arbitrage activity related to ETF trading creates non-fundamental price shocks to the underlying stocks they hold. Also, Ben-David et al. (2017a) provides examples where liquidity shocks from ETFs to the underlying securities do increase volatility. The previously uncertain area of how ETFs affect the financial markets is becoming increasingly explored and the relationship between ETF arbitrage and increased volatility in underlying stocks is increasingly established.

2.4 Volatility

The research on ETF ownership and the effect it has on security prices is related to the question if there is a possible correlation between ETF ownership and volatility. Volatility is a measurement of the degree of variation in a price series over time (Berk & DeMarzo, 2017) and a natural next step in ETF ownership research after researching the security price itself. Ben-David et al. (2017a) test if an increase in the ETF ownership of the underlying securities lead to an increase of volatility in the underlying securities. With the stated hypothesis that ETFs are a catalyst for liquidity trading and that the ensuing price shocks propagate to the underlying securities through arbitrage, Ben-David et al. (2017a) test if higher ETF ownership create higher volatility in the ETFs underlying securities, all else equal. The result from Ben-David et al. (2017a) show that a shock (increase) in ETF ownership shift the volatility of the median stock in the S&P 500 to a place between the 55th and 64th percentiles.

3. Methodology

3.1 Analysis model

To answer our two research questions, we conduct a series of OLS regressions. For the volatility of each stock, *i*, at time, *t*, we run four different regressions. Regression (1) and (2) are stated below. Regression (1) is using the total ETF ownership and controls while regression (2) accounts for lagged volatility to deal with the autocorrelation in volatility due to volatility clustering discussed previously.

(1)

$$Volatility_{it} = \alpha + \beta_1 ETF\ ownership_{All_{it}} + Controls + \varepsilon_{it}$$

(2)

$$\begin{aligned} Volatility_{it} = \alpha + \beta_1 ETF\ ownership_{All_{it}} + Controls + \beta_{10} Volatility_{i,t-1} \\ + \beta_{11} Volatility_{i,t-2} + \beta_{11} Volatility_{i,t-3} + \varepsilon_{it} \end{aligned}$$

Controls:

$$Controls = \log(MktCap)_{i,t-1} + \frac{1}{Price_{i,t-1}} + Amihud_{i,t-1} + Book\ to\ Market_{i,t-1} + Gross\ Profitability_{i,t-1} + Past\ 12\ month\ return_{i,t-1}$$

Regressions (3) and (4) are similar to (1) and (2) in their construct. Now we have divided the ETF ownership into groups depending on their investment styles by Lipper classification. This division is described in the data section below.

(3)

$$Volatility_{it} = \alpha + \beta_1 ETF\ ownership_{Industry_{it}} + \beta_2 ETF\ ownership_{Core_{it}} + \beta_3 ETF\ ownership_{Other_{it}} + Controls + \varepsilon_{it}$$

(4)

$$Volatility_{t} = \alpha + \beta_1 ETF\ ownership_{Industry_{it}} + \beta_2 ETF\ ownership_{Core_{it}} + \beta_3 ETF\ ownership_{Other_{it}} + Controls + \beta_{10} Volatility_{i,t-1} + \beta_{11} Volatility_{i,t-2} + \beta_{11} Volatility_{i,t-3} + \varepsilon_{it}$$

The first two regressions aim to replicate the findings of Ben-David et al. (2017a) on two different samples. First, the S&P 500 under almost the same time span used in their thesis. Second, on the full sample used in this thesis with a longer time span and broader range than that of Ben-David et al. (2017a). The latter two regressions aim to answer research question number two. Breaking the effect of ETF ownership up in the Lipper classification groups described earlier to see their different contributions to volatility. This is only done on the large sample.

All control variables are lagged once, since we wish to study the effect of ETF ownership in period *t* on the volatility in the following period, $t + 1$. In regression (2) and (4) respectively we lag volatility up to three times due to the strong autocorrelation.

3.2 Hypothesis formulation

To answer our research questions, we formulate three hypotheses that we test with our regressions stated above on two different samples. S&P 500 and our large sample of ETF holdings.

- *Hypothesis 1:* ETF ownership has a statistically significant effect on the volatility of securities in the S&P replication sample.
- *Hypothesis 2:* The effect of ETF ownership proposed in hypothesis one can be found in our large sample of ETF holdings.
- *Hypothesis 3:* There are statistically significant differences in volatility contribution depending on ETF type.

4. Data collection and data

4.1 Data collection

We collect all ETFs traded on U.S. exchanges which only hold equities, excluding leveraged, synthetic, commodity and bond ETFs. We include ETFs with a geographical focus on the United States with a minimum AUM of $100M. In total, the selection includes 380 funds with a total AUM of $1.91 trillion (Bloomberg, 2017-12-29). In the total US ETF-market ($2.7 trillion), including bonds, synthetic and leveraged ETFs, our sample covers 70.4%. The funds in the sample varies between a low AUM of $44 million to a high of $277.5 billion. For more statistics on the sample of funds, see Table 2 below for statistics and List 1 in the appendix for a list of all the funds in the sample.

We collect monthly holding data for each individual ETF in the sample over a period of 11 years and 7 months between January 31, 2006 and December 31, 2017 using the Wharton research data services CRSP Mutual Fund database. This date is chosen because this is when CRSP started reporting the market value of each security holding held by the ETF. To keep track of each unique security that the ETFs hold, we use the CRSP PERMNO, a number reported by CRSP that never changes over a security's lifespan, even if the company's name or ticker changes. Using the list of PERMNOs, we collect monthly prices and number of shares outstanding for each security from CRSP Monthly Security file database. The data is collected during the sample period which is used to calculate monthly market capitalization for each security.

The data used to calculate realized volatility are the daily closing prices for each security. They are collected from CRSP during the period January 1, 2006 to December 31, 2017 for each security held by the sample of ETFs. The daily prices are adjusted for stock splits using the cumulative factor to adjust price (CFACPR) provided by CRSP.

4.1.1 Control variable data

For the variables logged market capitalization and inverse security price, the same dataset previously described to calculate market capitalization is used. To calculate the Amihud illiquidity measure, daily security prices and daily trading volume is collected from CRSP daily stock file for each stock in the sample. Data collected to calculate the Book-to-Market ratio (B/M-ratio) and Gross Profitability variables are taken from Compustat's fundamentals database. In Compustat, we collect quarterly data on each security's total assets, deferred taxes and investment tax credits, total liabilities, total value of preferred stocks, revenue and cost of goods sold.

4.1.2 Lipper Classifications

To test if different ETF-types contribute differently to the underlying securities volatility we must classify the ETFs in the sample. To do this, we use Lipper classification names. It is a system used to classify mutual funds and ETFs based on their prospectus and the funds holding-composition, which is provided by Thomson Reuters Lipper Alpha Insight. We collect the classification names for all ETFs in our sample through CRSPs Mutual Funds Fund Summary database, in total 32 different classification names. All classification names can be seen in Table 3 in the appendix.

We divide the different classifications into three groups which we name Core, Industry and Other. The Core group consist of classifications focusing on passive- and index investing, recall from the literature review. This group consist of the fewest number of funds but with the largest part of the total assets under management, see Table 2. The industry group contain funds with a focus on certain industrial sectors, everything from commodities and utility to healthcare and technology. This group contain the largest number of funds but holds the lowest amount of assets, with almost three times lower average AUM, see Table 2. We can also observe that the average number of holdings in each fund is much lower in these funds, which could be explained by the specific allocation focus these types of funds pursue. In the final group, called Other, the funds not matching into the Industry or Core categories are placed. Particularity these are funds focusing on specific strategies. For example, value and growth investment strategies or equity income strategies where securities with high cash dividends are of special interest. This group is between Industry and Core categories in terms of total AUM, number of ETFs and average holdings.

With this separation of the ETFs into three separate groups based on investment style and type, we can conduct regressions to test our second research question regarding if different types of ETFs contribute differently to volatility.

Table 2 – Summary statistics for each classification group

The table describes all ETFs and each Lipper classification group of ETFs mentioned in the above section where AUM is assets under management and Holdings represent the number of individual stocks held by the ETFs in the sample.

	All	Core	Industry	Other
Number of ETFs	380	107	146	128
Total AUM (mUSD)	1 920 190	1 013 474	361 099	545618
Avg. AUM (mUSD)	5 053	9 561	2 473	4 263
Median AUM (mUSD)	815	754	815	886
Min AUM (mUSD)	44	47	44	63
Max AUM (mUSD)	277 542	277 542	34 728	58 262
Average Holdings	326	669	90	310
Median Holdings	126	450	54	207
Min Holdings	1	11	20	1
Max Holdings	3 624	3 624	404	1 535

4.2. Variables

4.2.1 Realized volatility

Realized variance as a concept was introduced by Barndorff-Nielsen and Shephard (2002). Derived from realized variance, realized volatility is used to measure price variability.

We use daily price data derived from CRSP on all stocks held by the ETFs to compute the realized volatility. We compute monthly realized volatility for each security based on daily returns as:

$$r_i = \log(P_d) - \log(P_{d-1})$$

$$RV_{t,i} = \sum_{i,t=1}^{N_{i,t}} r_i^2$$

$$RVol_{t,i} = \sqrt{RV_{t,i}}$$

Where the realized volatility, RVol, for each security, i, at month *t* is the root of realized variance RV. The realized variance for each security is calculated by summarizing the daily returns squared for each security for each month. Daily return (r_i) is calculated by using logarithmic difference in accordance with all calculation of returns throughout the thesis.

Because of autocorrelation in volatility due to the presence of volatility clustering described earlier, we include three lags of the realized volatility variable as explanatory variables in each regression.

4.2.2 ETF ownership

Before we calculate ETF ownership we process the holding data. Some ETFs do not only hold individual stocks but also hold other ETFs or other funds as well. We have removed a number of these by removing holdings with names containing: “ETF”, “FUND” or similar as well as three holdings we have identified as ETFs.

In the beginning of our sample’s time span ETFs were relatively new and only reported their holdings of individual securities quarterly. Recently, most ETFs report holdings monthly. Because of the quarterly reports of holdings, we forward fill the ETF holdings in order to have a value for each month in all cases where the holdings are not reported. This means that when a fund only reports quarterly holdings we assume the holdings market value to be the same for the two consecutive months until the next reported market value.

We calculate the market capitalization each month for each security by multiplying share price with shares outstanding for each consecutive month. Aggregating the value held in each security by each ETF and dividing it with the security's market capitalization we calculate ETF ownership. The ETF ownership in a single security, *i*, at month, *t*, is calculated as:

$$ETFownership_{i,t} = \frac{\sum_{j=1}^{J} AUM_{j,i,t}}{MktCap_{i,t}}$$

Where *J* is the set of individual ETFs, *j*. AUM is the assets under management by ETF *j* in stock *i* at the end of month *t.* MktCap is the market cap of security *i* at the end of month *t*.

We winsorize the ETF ownership variable at the 99th percentile. Winsorizing is a statistical transformation where extreme values, in this case the one percent most extreme values, in the distribution are replaced by the value of the percentile of choice. In our case we do this at the one percent level, replacing all values above the 99th percentile with the value at the 99th percentile. We only do this for the right tail of the distribution because some large values would be driving our regression leading to no proper description of the mean, which is the purpose of our OLS regression. The smallest numbers in our distribution cannot be considered extreme values as they simply represent no ETF ownership.

Tale 5 shows summary statistics of all regression variables. The ETF ownership variable represents ownership in each separate stock held by the 380 sample ETFs. We observe a maximum of 51% and minimum of 0% with a mean of 8.5% of securities market cap held by ETFs. Ben-David et al. (2017a) note that in their 2015 sample 7.05% of stocks market cap in the S&P 500 were held by ETFs. Our findings of 8.5% mean is only considering equity ETFs over the period 2006 - 2017 for over 7 819 stocks. Because we have a shorter historical perspective and wider scope of stocks, which may not be as heavily focused by ETFs as S&P 500 companies, compared to Ben-David et al. (2017a) we don't see it as surprising that we find a lower mean holding compared to Ben-David et al. (2017a).

4.2.3 Logged market Capitalization

The logged market capitalization variable is used to control for the effect firm size has on volatility. The sizes of firms vary widely across the dataset, from the largest security, Apple, which was valued at $882 billion (Bloomberg, 2017-11-30) to InspireMD, which was valued at

$1.045 Million (Bloomberg, 2017-11-30). We use the natural logarithm of the market cap to narrow the range in the market capitalization sample since there is a large variation from the largest to the smallest market capitalization. By using a logged variable the range is between 8 and 27, instead of a range of around 882 billion. We expect the logged market capitalization control variable to have a negative effect on a security's monthly volatility, since historical data show that larger companies tend to have a lower standard deviation in volatility compared to smaller companies (Berk & DeMarzo, 2017).

$$Logged\ Market\ Capitalization_{i,t} = \log\left(Market\ Cap_{i,t}\right)$$

The variable is the natural logarithm of the market cap for each security, *i*, for each month, *t*, in the sample. The market cap is calculated using the monthly closing price and shares outstanding for each security as reported by CRSP.

4.2.4 Inverse price

The Inverse price variable is used to control if a security's share price contributes to the volatility of that security. The reason for using inverse price as a control variable is the significant difference in share prices between different stocks. For example, from the Berkshire Hathaway share price of $297 600 (Bloomberg, 2017-12-29) to securities with prices less than a dollar or even down to a couple of cents. The rationale is that securities with low prices are easier for investors to access which could create more liquidity in these "low-price" securities compared to "expensive" securities that only wealthy private investors and institutional investors have access to. The extra liquidity created by the low price can have an impact on the volatility of securities through noise traders. We expect this control variable to have an increasing effect on a security's volatility.

$$Inverse\ Price_{i,t} = \frac{1}{P_{i,t}}$$

The price variable used is CRSP's "price alternate" (ALTPRC) which is an alternate monthly price derived from daily prices, it contains the last non-missing price in each month.

4.2.5 Amihud

The Amihud-variable is a measurement of a security's illiquidity. The absolute daily return for each security is divided with the security's daily dollar trading volume, aggregated monthly.

We use this measurement as a control variable to check if presence of illiquidity in a security influence the security's volatility. The Amihud-ratio is calculated as (Amihud 2002):

$$A_{i,t} = \sum_{j=1}^{d_t} \frac{|r_{i,j}|}{dvol_{i,j}}$$

We calculate the returns using the difference of the natural logarithm of daily price data retrieved from CRSP. Dollar volume is calculated by multiplying each trading day's volume by the daily closing price. Using this calculation process, days which have either no return nor volume produce an infinite or error value. These days are replaced with not a number (NaN) and hence disregarded in the following monthly summarization.

4.2.6 Past 12-month return

It is well documented that stock return volatility is positively related to trading volume (Bae, Chan, & Ng, 2004) and we control for this effect by including the 12-month past return. We calculate 12-month return for each security, *i*, each month, *t*, using monthly closing prices from CRSP.

$$12\ month\ return_{i,t} = \log(price_{i,t}) - \log(price_{i,t-12})$$

4.2.7 Book-to-Market ratio

$$Book\ Equity_{i,t} = Total\ asset_{i,t} - (Total\ libilities_{i,t} + Preferred\ Stocks_{i,t}) + Deferred\ Tax\ Credit\ and\ Investment\ Tax\ Credit_{i,t}$$

$$Market\ Capitalization_{i,t} = Price_{i,t} \times Shares\ outstanding_{i,t}$$

$$Book\ to\ market\ ratio_{i,t} = \frac{Book\ Equity_{i,t}}{Market\ Capitalization_{i,t}}$$

The variables used to create the book-to-market ratio are reported quarterly. Since our explanatory variable, ETF ownership, is reported as monthly data we forward fill the two missing months in each quarter. In this process, the missing months in each quarter are replaced with the value of the last quarterly reported data in the series. Because these variables originate from companies' financial statements, we reason that forward filling is the appropriate method to fill in the missing months in each quarter. We assume that a company's financial statement is stable and constant between two reporting quarters and that this makes it possible to use forward filling.

We winsorize the data at the 99th percentile on the upper and lower tail of the distribution for the same reason and by the same method as mentioned previously in the sub-section describing calculation of the ETF-share variable.

4.2.8 Gross profitability

The gross profitability measure, presented by Novy-Marx (2013) is used as a standard predictor of returns (Ben-David et al., 2017a). It is a measure of a company's profitability when the cost of goods sold are stripped away and then divided by its assets. It can be seen as the gross return on assets.

Gross profitability is calculated in a similar fashion as the book-to-market ratio. Gross profitability is also reported quarterly but we use backward propagation to fill missing values. We fill the missing months regarding gross profitability backward since we reckon the quarterly reported profitability is a better representation of the past few months rather than the future. By performing backward filling in this way we avoid making any predictions of any future profits.

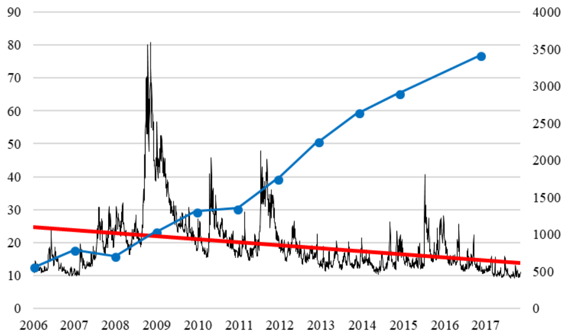
We winsorize the gross profitability, as with earlier variables, at the 99th and 1st percentile on the upper and lower tail of the distribution respectively. See summary statistics of all variables in Table 4 in the appendix.

4.2.9 Time

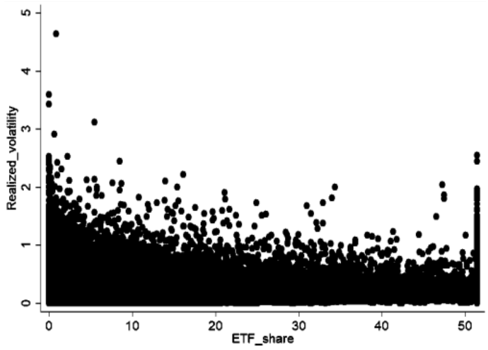
In table 6, panel A, we see the CBOE Volatility index (VIX), left axis, and global ETF assets, right axis (CBOE, 2018). VIX measures the volatility implied by S&P 500 index options and is a popular measure of stock market volatility. The red line is a fitted linear trend of the VIX index. Recent years has been a historic period of low volatility, with decreasing volatility during the time of our sample. At the same time, global ETF assets has increased dramatically from approximately $500 billion to $3 500 billion. On a macro level, it would not be not surprising that we find negative correlation between ETF ownership and volatility since they trend in opposite directions during the sample space. Panel B show a scatterplot of our dependent variable, realized volatility, and main explanatory variable, total ETF ownership. A negative trend which would be expected from the macro trends in panel A is apparent. However, contrary to the fitted line in panel A, volatility is not continuously downward sloping but instead consist of many shorter up- and downtrends. Simply controlling for time as a variable in our regression would not be a proper representation of the reality. To properly account for cross-sectional differences we use time fixed effects to account for the differences in volatility & ETF ownership dependent on time.

Table 6 – Macro trends and ETF ownership

Panel A – VIX index and global ETF assets



Panel B – ETF ownership and realized volatility



4.3 Descriptive Statistics

In Table 4 we present descriptive statistics for our first research question, to replicate the result presented by Ben-David et al (2017a). Testing if ETF ownership impacts the volatility of the ETFs underlying securities on a sample of the S&P 500 companies.

In Table 5, we present summary statistics for our main research question, to see if there is an effect on securities volatility depending on the level of ETF ownership. The sample includes all stocks held by our sample of ETFs which is close to the whole investable U.S. equity market, as opposed to the S&P 500 replication above.

In both tables, the mean, minimum, maximum and standard deviation of the dependent, explanatory and control variables are presented. Looking at the mean of the monthly realized volatility, we see that it is significantly higher for the larger sample than the S&P 500 sample. This is likely due to the higher number of small sized companies in the larger sample which tend to have a higher average volatility than large companies (Berk and DeMarzo 2017). We can see that the large sample includes many smaller sized securities since we observe a significantly lower mean on the logged market capitalization variable in the larger sample, average size of 657.5 million USD compared to 1.41 billion USD in the S&P 500 sample.

The lower mean of logged market capitalization can also explain the mean of ETF ownership and the difference between the two samples. Since there are fewer ETFs covering the largest indices in which all US securities are represented (i.e. Russell 3000 and Vanguard Total stock Index) than ETFs covering popular indices like the S&P 500, the average ETF ownership is lower in the larger sample. For reference, the S&P 500 is not only a popular index for ETFs to track, it is also the index which SPY, the single largest ETF by AUM, is tracking. The ETF market's focus on funds like SPY make the higher mean of ETF ownership in the S&P 500 sample compared to the larger sample natural.

Considering the Amihud illiquidity measurement, an explanation of the higher mean in the large sample compared to S&P 500 can be the lower daily dollar turnover in small sized companies. The securities of large sized companies like those included in the S&P 500 have significantly higher daily turnover and thus we observe a lower mean for the Amihud variable.

Table 4. Summary statistics, S&P 500 regression

	N	Mean	Std Dev	Min	Max
Realized volatility	40 067	0.087	0.065	0.002	1.414
ETF ownership (%)	40 067	11.086	5.046	0.918	51.413
1/Price	40 067	0.034	0.036	0.001	0.952
log (Mktcap ($))	40 067	23.372	1.067	18.891	27.344
Amihud	40 067	0.000	0.000	0.000	0.000
Past 12-month return	40 067	0.111	0.624	-0.991	57.976
Book-to-Market	40 067	0.559	0.461	-1.492	4.211
Gross profitability	40 067	0.072	0.061	-0.268	0.631

Table 5. Summary Statistics

	N	Mean	Std Dev	Min	Max
Realized volatility	604 044	0.130	0.110	0.000	4.642
ETF ownership (%)	599 297	8.474	8.998	0.000	51.413
ETF ownership, Core (%)	556 099	5.497	5.284	0.000	30.363
ETF ownership, Industry (%)	397 440	1.492	2.706	0.000	15.106
ETF ownership, Other (%)	527 103	2.361	2.666	0.000	15.941
1/Price	601 146	0.147	0.529	0.000	58.824
log (Mktcap ($))	604 044	20.304	1.986	8.560	27.506
Amihud	604 028	0.005	0.153	0.000	65.637
Past 12-month return	579 056	0.168	1.630	-0.999	217.012
Book-to-Market	543 368	0.661	0.666	-1.492	4.211
Gross profitability	539 382	0.061	0.086	-0.268	0.631

5. Results

5.1 Hypothesis 1 – Replication of results in the S&P 500 sample

First, we attempt to replicate the results of Ben-David et al. (2017a) and answer our first research question. Table 7 below shows the result of the two OLS regressions that we run to replicate the test of Ben-David et al. (2017a) on the S&P 500 sample. In regression (1), where lagged volatility is not included we observe an increased volatility by 0.03% for every 1% increase of ETF ownership at a 10% significance level.

In regression (2) we add three months of lagged volatility. We find an R^2 of 0.72 in regression (2) which is a significant increase compared to regression (1). We're glad that the ETF ownership variables remain significant, and even reaches a higher level of significance, as it is a sign that any persistent factors that drive volatility do not linearly explain the differences captured by the added lagged volatility variables.

We find similar results as Ben-David et al. (2017a) although not as strong of an effect. This could have several possible explanations, derived from the limitations we have regarding sample size, sample time range and control variables used. These are explained in detail below in the limitation section.

We successfully replicate a positive significant effect of ETF ownership on stock volatility in a similar sample as Ben-David et al. (2017a) which is the first step of our method. Next, we look for the same effect in the large sample.

Table 7. Replication Regression, S&P 500

The table shows estimates from ordinary least squares (OLS) regressions of monthly realized volatility on ETF ownership and controls. Regressions (2) include lagged volatility. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between May 31, 2006 and December 31, 2017.

Dependent variable:	Monthly realized volatility (t)	
Sample:	S&P 500	
	(1)	(2)
ETF ownership	0.00063*	0.00030***
	(1.72)	(4.43)
log(mktcap(t-1))	-0.11***	-0.001***
	(-4.03)	(-3.08)
1/Price (t-1)	0.361***	0.079***
	(7.36)	(6.27)
Amihud (t-1)	0.892	-0.297
	(0.40)	(-0.68)
Book-to-Market (t-1)	0.013***	0.002**
	(3.59)	(2.24)
Past 12-month return	-0.003	-0.002*
	(-1.38)	(-1.94)
Gross profitability	-0.033**	0.002
	(-2.22)	(0.49)
Volatility (t-1)		0.353***
		(20.25)
Volatility (t-2)		0.217***
		(14.44)
Volatility (t-3)		0.212***
		(13.83)
Time Fixed Effects	Yes	Yes
Observations	50 132	50 132
R^2	0.514	0.720

5.2 Hypothesis 2 – Effect of ETF ownership in a large sample

Regression (1) and (2) of Table 8 below presents estimates of total ETF ownership and control variables in the large sample.

In regression (1), not including lagged volatility, we estimate a positive coefficient of ETF ownership at the one percent significance level. We also find statistical significance at the one percent level for all control variables. The inverse price, Amihud, past 12-month return and B/M-ratio have positive effects on volatility while we estimate logged market cap and gross profitability having a decreasing effect on volatility. The R^2 is quite low at 0.353. More of the variance in the model is explained by previous volatility, see regression (2) below.

In regression (2), when adding lagged volatility (t-1,-2,-3) the coefficient on ETF ownership become smaller but remains positive at the one percent significance level and the R^2 increases to 0.522. This indicates that a large portion the effect on monthly volatility is due to volatility in previous months. For the same reasons as with the previous hypothesis we are glad that the variables remain significant. We argue that an R^2 of 0.522 it is an acceptable level of explanation of variance in the model. Ben-David et al. (2017a) show an R^2 of 0.643, among other things they include several control variables that we do not which can explain the difference, see the limitations section below. All control variables are statistically significant. Inverse price and Amihud have positive effects while log market cap, B/M-ratio, past 12-month return, and gross profitability have negative effects.

To conclude, we find a statistically significant positive relation between volatility and ETF ownership in the large sample.

Table 8. OLS Regressions, Stock Volatility and ETF Ownership

The table shows estimates from ordinary least squares (OLS) regressions of monthly realized volatility on ETF ownership and controls. The panel is divided in two sections. The first section, columns (1) and (2), are estimates of our first regression on total ETF ownership. The second section, columns (3) and (4) are estimates of the second regression with the three different group explanatory variables. Regressions (2) and (4) respectively include lagged volatility. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between May 31, 2006 and December 31, 2017.

Dependent variable:	Monthly realized volatility (t)			
Sample:	All		Classification	
	(1)	(2)	(3)	(4)
ETF ownership (all)	0.00079***	0.00023***		
	(11.04)	(9.40)		
ETF ownership (core)			-0.00050**	-0.00018*
			(-2.12)	(-1.91)
ETF ownership (industry)			0.00152***	0.00069***
			(5.90)	(7.47)
ETF ownership (other)			0.00331***	0.00088***
			(7.64)	(4.70)
log(mktcap(t-1))	-0.018***	-0.005***	-0.020***	-0.005***
	(-24.75)	(-32.05)	(-25.95)	(-33.21)
1/Price (t-1)	0.034***	0.022***	0.028***	0.018***
	(7.42)	(9.16)	(7.11)	(7.89)
Amihud (t-1)	0.012***	0.005***	0.012***	0.005***
	(4.26)	(3.05)	(4.24)	(3.11)
Book-to-Market (t-1)	0.01***	-0.001**	0.010***	0.000**
	(10.46)	(-3.85)	(-3.01)	(-2.01)
Past 12-month return (t-1)	0.001***	0.001***	-0.001***	-0.000***
	(3.17)	(-3.50)	(-2.95)	(-3.09)
Gross profitability (t-1)	-0.028***	-0.023***	-0.017***	-0.019***
	(-4.68)	(-9.10)	(-3.01)	(-7.66)
Volatility (t-1)		0.274***		0.275***
		(73.47)		(73.04)
Volatility (t-2)		0.182***		0.183***
		(45.04)		(44.66)
Volatility (t-3)		0.189***		0.188***
		(54.78)		(54.76)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	556 773	556 773	558 819	558 819
R^2	0.353	0.522	0.348	0.519

5.3 Hypothesis 3 – ETF-style effect on volatility

In regression (3) and (4) of table 8 above, the total ETF ownership tested in hypothesis 2 is divided in the three groups; Core, Industry and Other. We test if they have different relations to volatility among them compared to the effect found for total ETF ownership.

We find with varying statistical significance, 1% for Industry and Other, 10% for Core, that they do contribute differently, in both regression (3) and (4). We estimate that increased Core ETF ownership contribute to lower volatility while increased ownership by Industry- and Other ETFs relate to higher volatility.

We have statistical significance at the five percent level for all variables in both regression (3) and (4) except that we find Core ETF ownership to have 10% significance in regression (4). In both regressions, logged market cap, past 12-month return, gross profitability and time have one percent significant negative relation to volatility while inverse price, Amihud and B/M-ratio has a positive relation. In regression (4) we have an R^2 of 0.519. It is similar to that of regression (2) which we find reasonable since it is the same data explaining the variance, just that ETF ownership is divided into different groups.

Recall from Table 2 in the data collection that the Core-group stands over 50% of the total ETF AUM. The world's largest ETFs such as the SPY and VOO, that replicate the S&P 500 index represent a large portion of this group. In these funds, most of the ETF trading described in the introduction takes place and around 20% of the value is short sold. That these funds are traded so frequently and hold a lot of speculative positions would suggest higher volatility in accordance with ideas presented by Atkins and Dyl (1997) that there is a relation between higher volatility and short holding times of securities. However, we find a negative relationship of ETF ownership on volatility. This could be related to the increased indexing in financial markets which some argue are decreasing volatility. Since Core funds are mainly replicating broad indices it would make sense if that was the case. Further research must be conducted to answer this question, see the section about further research in the conclusion below.

We find that Industry fund ownership relate to higher volatility. Industry funds are narrower and focus on a certain type of securities while Core ETFs are generally replications of broad market indices. Following the reasoning above, these funds must differentiate from the macro trend compared to Core ETFs following broad market indices. The found effect could be explained by the more speculative nature of these funds. Instead of buying a whole index, when buying an industry ETF an investor takes a more specific position in, for instance, only oil related securities. The narrower scope and speculative nature of these ETFs may contribute to more concentrated ETF ownership during shorter time periods increasing volatility due to the ETF arbitrage channel described in the introduction.

We estimate that Other-type funds relate positively to volatility. Other contains mostly value- and growth funds. They are, like Industry, of a narrow nature and suitable for speculating in a narrower scope of stocks compared to the indices replicated by Core-ETF. So, Other ETFs could be increasing volatility according to the same reasoning as Industry-ETFs. In addition, growth funds tend to be more volatile by nature which might contribute to this effect as well.

5.4 Control variable coefficient results

The below descriptions of our results regarding the control variables are general throughout our, in total six, regressions in terms of coefficient sign unless specifically stated otherwise. We describe what we estimate and an analysis of the meaning of those estimates for each control variable. Statistical significance varies throughout the regressions and are stated specifically for each regression.

5.4.1 Inverse Price

We estimate a significant positive effect of inverse price on volatility at the one percent level. Meaning that a lower stock price is related to higher volatility. This is in accordance with our expectations and can be explained by several reasons. Stocks with lower stock prices are available to a greater number of investors and can be traded more frequently than a high-priced counterpart. High trading volume and low transaction costs are known to be related to higher volatility (Atkins & Dyl, 1997). Stocks with very low stock prices experience high percentage changes in price whenever there is significant trading in the stock. Especially among small illiquid companies that tend to have low stock prices. The nature of these stocks causes them to have high volatility in many cases (Berk & DeMarzo, 2017).

5.4.2 Amihud

The Amihud illiquidity measure has two factors that affect its value, recall from the variable description:

$$A_{i,t} = \sum_{j=1}^{d_t} \frac{|r_{i,j}|}{dvol_{i,j}}$$

A high Amihud measure would be caused by a high absolute return or a low trading volume. We estimate a significant positive effect of Amihud on volatility. This is in accordance with earlier reasoning that small illiquid stocks tend to experience high return percentage-wise and trade under low dollar volumes compared to large stocks, for example in the S&P 500. For stocks that are trading under high volume, high return volatility is related to trading volume causing there to be more trading in the stock generating volatility.

However, in the S&P 500 sample when accounting for lagged volatility we estimate a negative coefficient for the Amihud illiquidity measure, suggesting volatility is higher for more liquid stocks. Professor Yakov Amihud (2014) states that higher volatility may be a sign of a liquid and well-functioning market in the sense that as new information moves the market in a direction, a liquid market sets the correct price quicker than an illiquid market. This leads to higher volatility in the liquid market as the full price move of the new information is integrated in the market during a shorter period than the equivalent illiquid market.

5.4.3 Past 12-month return

We estimate slightly negative or close to zero economic effect of the past 12-month return control variable with one percent significance in the large sample but insignificant in the S&P 500.

5.4.4 Book to Market

The control variable book to market ratio (B/M-ratio) is calculated as the value of a company's assets if all liabilities are "paid off" divided by the market value of the company. Usually, a high B/M-ratio would indicate a value-company, with a lot of valuable assets not reflected in its market value. These are typically companies with a lot of physical assets such as property, machinery and inventory. Examples of industries that generally have a high B/M-ratio are consumer goods, manufacturing and energy. If the B/M-ratio is low it indicates a growth-company, which normally have fewer valuable assets but a high market value reflecting its future potential. These companies typically have a lot of patents and intangible assets which, by accounting standards, are harder to estimate. So, instead of having a lot of assets on its books in terms of value, these companies' future potential is reflected in their market value. Examples of industries with traditionally a lot of growth companies are pharmaceutical, technology and biotech. We expect the B/M-ratio variable to have a negative effect on volatility because value companies, i.e. high B/M-ratio, would have a more stable price, especially in times of a downturn in the market, compared to growth companies that tend to fluctuate more. However, we consitently find B/M-ratio to have almost no, or slightly positive, economic effect at a 5% level.

5.4.5 Gross Profitability

We estimate a negative effect in all significant regressions of Gross Profitability. We expect this control variable to have a negative effect on the realized volatility because a high gross profitability measurement is an indication that a company is well-managed. We argue that a well-managed company should be more stable and thus be less volatile than a company with low gross profitability and hence be less well-managed.

5.4.6 Logged market capitalization

The logged market capitalization variable is used in the regression to control for the size of each company. We expect it to have a negative effect on a security's monthly volatility because larger companies tend to fluctuate less than smaller company, stated by Perez-Quiros and Timmermann (2000) and Berk and DeMarzo (2017, p.323). This implies, all else equal, that a security with a high market cap will have a lower realized volatility than a security with a low market cap. This is what we find in our estimates presented in table 7 and 8 above, where all coefficients for logged market capitalization are negative, leading to a negative effect on realized volatility of an increase in market cap.

6. Limitations

In reconstructing the S&P 500 regression by Ben-David et al. (2017a) we have limitations regarding sample size, sample range, and variables used. The data used by Ben-David et al. (2017a) range from January 2000 to December 2015, as described in the data collection section we start collecting data from May 2006. In regard to the number of funds of which we have collected stock holdings, we only have 380 funds compared to 454 funds in the sample by Ben-David et al. (2017a). We also exclude the Bid-Ask-spread as a control variable, which is used by Ben-David et al. (2017a). The most significant limitation however, is probably the different way we calculate the dependent variable volatility. We use realized volatility on the monthly level and Ben-David et. al (2017a) use daily volatility.

When calculating ETF ownership, we removed several cases where an ETF holds another ETF or fund. There is a possibility that we have not removed all instances of this issue and a few ETFs or similar instruments may still be included in our sample.

7. Robustness

We take several steps to test for robustness and the OLS assumptions in our regressions. We start by testing if any of the variables show time trends. We do this by regressing each variable on a time variable for each stock, *i*, and month, *t*, using the regression equation:

$$Y_{i,t} = \alpha_0 + \alpha_1 t + \varepsilon_{i,t}$$

The results are presented in Table 9, see appendix. We can clearly see that all variables except the Amihud measurement are significant, which means there is a time trend present in the data. To adjust for this time trend, we include Time as a control variable in all regression models. The variable Time is explained earlier in the thesis under the control variables chapter.

To control for heteroscedasticity, we use the built-in function in the Stata software, called robust, to deal with any violations to the heteroscedasticity OLS-assumption.

To test the data for highly persistent variables, especially in the lagged realized volatility variables, we examine the correlation matrix looking for the first order autocorrelation. If we find the first order correlation such that:

$$corr\,(Y_t, Y_{t-1}) > 0.9 \quad or \quad corr\,(Y_t, Y_{t-1}) < -0.9$$

we would suspect a highly persistent variable. When examining the correlation matrix, we find that no variable show signs of high persistence.

Lastly, we test for serial correlation in the error term. By first running the regression of total ETF ownership on volatility in the large sample, we save the residuals (error terms, ε). After lagging all residuals, we perform a new regression:

$$\begin{aligned}\hat{\varepsilon}_{i,t} &= p\hat{\varepsilon}_{i,t-1} + \gamma_1 ETF\ ownership_{All_{it}} + \gamma_k Controls_{it} \\ &+ Volatility_{i,t-1} + \beta_{11} Volatility_{i,t-2} + \beta_{11} Volatility_{i,t-3} + U_t\end{aligned}$$

and test the null hypothesis:

$$H_0\!: p = 0$$

If the t-statistic for *p* is significant we reject the null hypothesis and prove that the data is serial correlated in the error term. We find that this is the case for our data, reject the null hypothesis, and therefore plan to perform a Newey-West standard error test, due to time restraints we have not had the time before this hand in (2018-05-20). It will be tested before the final seminar. We also intend to perform a Breusch-Godfrey test to test the serial correlation in the error term.

8. Conclusion

Throughout this thesis we answer two research questions. First, if we can replicate the findings of Ben-David et al. (2017a) that ETF ownership is related to volatility on a similar sample as them, as well as the complete U.S. market. Second, if there are differences in the effect ETF ownership has on volatility depending on what ETF-type is holding the securities. We divide the ETFs into three groups based on their investment and allocation style.

In the regression replicating Ben-David et al. (2017a) on their S&P 500 sample, we find a positive and significant effect that ETF ownership increase volatility by 0.03% for every 1% increase of ETF ownership. It can be discussed whether this effect is economically significant, since it only represents a 0.27% change of the sample mean. The results from our large regression, covering all investable stocks in the U.S., is a positive and significant effect on volatility from ETF ownership of 0.023% at a 1% significance level. This can also be discussed if it is of economic significance. It corresponds to a sample mean increase of 0.13%.

Our final regression, of the whole U.S. market volatility on ETF ownership divided into groups, show significant coefficients for all the ETF groups We estimate a negative effect on volatility of the Core group, which implies index-style ETFs decrease volatility by 0.018%. Industry and Other on the other hand show positive effects from ETF ownership on volatility. Industry had an effect of 0.069% and Other had an effect of 0.088%, which is high compared to previous coefficients throughout this thesis.

We contribute to the literature in two ways. First, we expand the work of Ben-David et al. (2017a) and show that the positive relation between ETF ownership and volatility in securities exist in a larger sample, covering practically the complete investable universe of U.S. stocks. Second, we show that ETFs contribute to the volatility of said securities differently depending on the type of ETF. Namely, Core-type ETFs relate to lower volatility while Industry- and Other-type ETFs relate to increased volatility.

There are some limitations to our research. There are possible errors in the data collection process and handling of the data. By only using CRSP through WRDS there are some gaps in the original data that we could have filled if we had more time by collecting data from other databases and merging the datasets to create a more complete sample. The sample time period and size are two limitations we are aware of. We could, for example, have chosen a wider timeframe and collected more holding data. There is also a limitation in the sense that the results are statistically significant, but one could argue that some of the coefficients are not economically significant, which a larger sample and more complete sample potentially could fulfil.

We see two areas where further research should be conducted. First, further research should be conducted to investigate the nature of holders of various ETF-types to answer questions regarding if holders of different ETF-types behave differently regarding position size, holding term et cetera. With this knowledge, it could be determined with greater certainty why different ETF-types contribute differently to volatility.

Research should also be conducted on a broader level regarding if increasing investments in ETFs can be connected to the rising popularity to invest in indices. Sullivan and Xiong (2012) finds that increasing investments into index funds contribute to higher systematic risk in the equity market. There is a possibility that the positive effect ETF ownership has on the volatility of the underlying securities, found by Ben-David et al. (2017a) and by us in this thesis, in fact is the increasing systematic market risk that index funds contributes with according to Sullivan and Xiong (2012).

9. Bibliography

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10. Appendix

Table 3. Lipper Classification Names

Core	Industry	Other
Large-Cap Core Funds	Basic Materials Funds	Alternative Active Extension Funds
Mid-Cap Core Funds	Consumer Goods Funds	Alternative Long/Short Equity Funds
Multi-Cap Core Funds	Consumer Services Funds	Equity Income Funds
S&P 500 Index Funds	Energy MLP Funds	Equity Leverage Funds
Small-Cap Core Funds	Financial Services Funds	Large-Cap Growth Funds
	Global Health/Biotechnology Funds	Large-Cap Value Funds
	Global Science/Technology Funds	Mid-Cap Growth Funds
	Health/Biotechnology Funds	Mid-Cap Value Funds
	Industrials Funds	Multi-Cap Growth Funds
	Natural Resources Funds	Multi-Cap Value Funds
	Real Estate Funds	Small-Cap Growth Funds
	Science & Technology Funds	Small-Cap Value Funds
	Telecommunication Funds	Specialty/Miscellaneous Funds
	Utility Funds	

Table 11. Correlations in the large sample

Panel A - Regression (1) & (2)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Realized volatility (%)	(1)	1.0000										
ETF ownership (%)	(2)	-0.0723	1.0000									
1/Price	(3)	0.3195	-0.0288	1.0000								
log(Mktcap($))	(4)	-0.3832	0.1764	-0.3513	1.0000							
Amihud	(5)	0.0544	-0.0202	0.0728	-0.0541	1.0000						
Book-to-Market	(6)	0.1346	0.0143	0.1120	-0.2561	0.0328	1.0000					
Gross profitability	(7)	-0.0723	0.0050	-0.0442	0.0755	0.0007	-0.1925	1.0000				
Past 12-month return	(8)	-0.0132	-0.0105	-0.0417	-0.0102	-0.0058	-0.0622	0.0053	1.0000			
Realized volatility (t-1)	(9)	0.5963	-0.0754	0.3210	-0.3872	0.0529	0.1469	-0.0709	-0.0077	1.0000		
Realized volatility (t-2)	(10)	0.5481	-0.0731	0.3149	-0.3881	0.0470	0.1571	-0.0685	0.0019	0.6000	1.0000	
Realized volatility (t-3)	(11)	0.5239	-0.0706	0.3055	-0.3867	0.0514	0.1614	-0.0673	0.0101	0.5491	0.6037	1.0000

Panel B - Regression (3) & (4)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Realized volatility (%)	(1)	1.0000												
ETF ownership, Core (%)	(2)	-0.0523	1.0000											
ETF ownership, Industry (%)	(3)	0.0222	0.3331	1.0000										
ETF ownership, Other (%)	(4)	-0.0280	0.8856	0.2974	1.0000									
1/Price	(5)	0.2724	0.0659	0.0574	0.0637	1.0000								
log(Mktcap($))	(6)	-0.3656	-0.0350	0.0373	-0.0198	-0.3033	1.0000							
Amihud	(7)	0.0211	-0.0049	-0.0032	-0.0052	0.0391	-0.0183	1.0000						
Book-to-Market	(8)	0.1236	0.1031	0.0465	0.1088	0.1022	-0.2035	0.0118	1.0000					
Gross profitability	(9)	-0.0669	0.0278	-0.1732	0.0478	-0.0486	0.0823	0.0080	-0.2225	1.0000				
Past 12-month return	(10)	-0.0272	-0.0190	-0.0092	-0.0210	-0.0324	-0.0126	-0.0021	-0.0696	0.0023	1.0000			
Realized volatility (t-1)	(11)	0.6071	-0.0480	0.0210	-0.0285	0.2867	-0.3743	0.0214	0.1410	-0.0657	-0.0209	1.0000		
Realized volatility (t-2)	(12)	0.5592	-0.0468	0.0204	-0.0302	0.2749	-0.3753	0.0193	0.1548	-0.0636	-0.0119	0.6100	1.0000	
Realized volatility (t-3)	(13)	0.5357	-0.0475	0.0211	-0.0260	0.2682	-0.3737	0.0284	0.1605	-0.0619	-0.0030	0.5610	0.6128	1.0000

Table 10. Correlations in the S&P 500 sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Realized volatility (%)	(1)	1,0000										
ETF ownership (%)	(2)	-0,0997	1,0000									
1/Price	(3)	0,4038	0,0269	1,0000								
log(Mktcap($))	(4)	-0,3020	-0,3228	-0,3689	1,0000							
Amihud	(5)	0,3658	0,0116	0,4893	-0,4513	1,0000						
Book-to-Market	(6)	0,2432	0,0712	0,3401	-0,1973	0,1706	1,0000					
Gross profitability	(7)	-0,0711	-0,0832	-0,1070	-0,0003	-0,0110	-0,4713	1,0000				
Past 12-month return	(8)	-0,1830	0,0616	-0,1120	0,0604	-0,1278	-0,0616	0,0199	1,0000			
Realized volatility (t-1)	(9)	0,7581	-0,1346	0,4143	-0,3091	0,4197	0,2460	-0,0664	-0,1876	1,0000		
Realized volatility (t-2)	(10)	0,6960	-0,1260	0,4165	-0,3086	0,3865	0,2682	-0,0698	-0,1753	0,7466	1,0000	
Realized volatility (t-3)	(11)	0,6152	-0,1209	0,4084	-0,3088	0,3478	0,2765	-0,0717	-0,1602	0,6347	0,7376	1,0000

Table 4. Summary Statistics for the large sample

	N	Mean	Std Dev	Min	Max
Realized volatility (%)	604 044	0.130	0.110	0.000	4.642
ETF ownership (%)	599 297	8.474	8.998	0.000	51.413
ETF ownership, Core (%)	556 099	5.497	5.284	0.000	30.363
ETF ownership, Industry (%)	397 440	1.492	2.706	0.000	15.106
ETF ownership, Other (%)	527 103	2.361	2.666	0.000	15.941
1/Price	601 146	0.147	0.529	0.000	58.824
log (Mktcap ($))	604 044	20.304	1.986	8.560	27.506
Amihud	604 028	0.005	0.153	0.000	65.637
Past 12-month return	579 056	0.168	1.630	-0.999	217.012
Book-to-Market	543 368	0.661	0.666	-1.492	4.211
Gross profitability	539 382	0.061	0.086	-0.268	0.631

Table 5. Summary statistics, S&P 500 sample

	N	Mean	Std Dev	Min	Max
Realized volatility (%)	40 067	0.087	0.065	0.002	1.414
ETF ownership (%)	40 067	11.086	5.046	0.918	51.413
1/Price	40 067	0.034	0.036	0.001	0.952
log(Mktcap ($))	40 067	23.372	1.067	18.891	27.344
Amihud	40 067	0.000	0.000	0.000	0.000
Past 12-month return	40 067	0.111	0.624	-0.991	57.976
Book-to-Market	40 067	0.559	0.461	-1.492	4.211
Gross profitability	40 067	0.072	0.061	-0.268	0.631

Table 9. Time trend test, large sample

Regressor:	Time
Dependent variable:	
Realized volatility	-0,114***
	(-93,27)
ETF ownership (all)	30,340***
	(293)
ETF ownership (core)	23,117***
	(417,8)
ETF ownership (industry)	5,486***
	(163)
ETF ownership (other)	9,000***
	(299)
1/Price	-0,057***
	(-10,04)
log(Mktcap)	1,755***
	(66)
Amihud	-0,003
	(-1,41)
Book-to-Market	0,062***
	(7,86)
Past 12-month return	-0,045***
	(-43)
Gross profitability	0,553***
	(29)
Volatility (t-1)	-0,112***
	(-93,11)
Volatility (t-2)	-0,114***
	(-94,7)
Volatility (t-3)	-0,112***
	(-93,37)

List 1. Sample ETFs

Below is a complete list of all ETFs that constitute our sample of which we have calculated the aggregated holdings to construct our ETF ownership variables in combination with their respective Lipper classification.

AdvisorShares Wilshire Buyback ETF
AI Powered Equity ETF
Alerian MLP ETF
Alps Equal Sector Weight ETF
ALPS Medical Breakthroughs ETF
Alps Sector Dividend Dogs ETF
Barron's 400 ETF
Cambria Core Equity ETF
Cambria Shareholder Yield ETF
Consumer Discretionary Select Sector SPDR Fund
Consumer Staples Select Sector SPDR Fund
Davis Select US Equity ETF
Deep Value ETF
DeltaShares S&P 400 Managed Risk ETF
DeltaShares S&P 500 Managed Risk ETF
Direxion All Cap Insider Sentiment Shares
Direxion NASDAQ-100 Equal Weighted Index Shares
Energy Select Sector SPDR Fund
Fidelity Dividend ETF for Rising Rates
Fidelity MSCI Consumer Discretionary Index ETF
Fidelity MSCI Consumer Staples Index ETF
Fidelity MSCI Energy Index ETF
Fidelity MSCI Financials Index ETF
Fidelity MSCI Health Care Index ETF
Fidelity MSCI Industrials Index ETF
Fidelity MSCI Information Technology Index ETF
Fidelity MSCI Materials Index ETF
Fidelity MSCI Real Estate Index ETF
Fidelity MSCI Telecommunications Services Index ETF
Fidelity MSCI Utilities Index ETF
Fidelity NASDAQ Composite Index Tracking Stock
Financial Select Sector SPDR Fund
First Trust Capital Strength ETF
First Trust Cloud Computing ETF
First Trust Consumer Discretionary AlphaDEX Fund
First Trust Consumer Staples AlphaDEX Fund
First Trust Dorsey Wright Focus 5 ETF
First Trust Dow Jones Internet Index Fund
First Trust Dow Jones Select MicroCap Index Fund
First Trust Energy AlphaDEX Fund
First Trust Equity Opportunities ETF
First Trust Financials AlphaDEX Fund
First Trust Health Care AlphaDEX Fund
First Trust Industrials/Producer Durables AlphaDEX Fund
First Trust Large Cap Core AlphaDEX Fund
First Trust Large Cap Growth AlphaDEX Fund
First Trust Large Cap Value AlphaDEX Fund
First Trust Materials AlphaDEX Fund
First Trust Mid Cap Core AlphaDEX Fund
First Trust Mid Cap Growth AlphaDEX Fund
First Trust Morningstar Dividend Leaders Index Fund
First Trust Multi Cap Growth AlphaDEX Fund
First Trust NASDAQ ABA Community Bank Index Fund
First Trust NASDAQ Bank ETF
First Trust NASDAQ Cybersecurity ETF
First Trust NASDAQ Technology Dividend Index Fund
First Trust NASDAQ-100 Equal Weighted Index Fund
First Trust NASDAQ-100 Ex-Technology Sector Index Fund
First Trust NASDAQ-100 Technology Sector Index Fund
First Trust Natural Gas ETF
First Trust North American Energy Infrastructure Fund
First Trust NYSE Arca Biotechnology Index Fund
First Trust RBA American Industrial Renaissance ETF
First Trust Rising Dividend Achievers ETF
First Trust S&P REIT Index Fund
First Trust Small Cap Core AlphaDEX Fund
First Trust Small Cap Growth AlphaDEX Fund
First Trust Technology AlphaDEX Fund
First Trust Utilities AlphaDEX Fund
First Trust Value Line Dividend Index Fund
First Trust Water ETF
FlexShares Morningstar US Market Factor Tilt Index Fund
FlexShares Quality Dividend Defensive Index Fund
FlexShares Quality Dividend Index Fund
Global X MLP & Energy Infrastructure ETF
Global X MLP ETF
Global X S&P 500 Catholic Values ETF
Global X Scientific Beta US ETF
Global X SuperDividend US ETF
Goldman Sachs ActiveBeta US Large Cap Equity ETF
Guggenheim Defensive Equity ETF
Guggenheim Mid-Cap Core ETF
Guggenheim Raymond James SB-1 Equity ETF
Guggenheim S&P 500 Equal Weight Consumer Staples ETF
Guggenheim S&P 500 Equal Weight Energy ETF
Guggenheim S&P 500 Equal Weight ETF
Guggenheim S&P 500 Equal Weight Financials ETF
Guggenheim S&P 500 Equal Weight Health Care ETF
Guggenheim S&P 500 Equal Weight Industrials ETF
Guggenheim S&P 500 Equal Weight Materials ETF
Guggenheim S&P 500 Equal Weight Technology ETF
Guggenheim S&P 500 Equal Weight Utilities ETF
Guggenheim S&P 500 Pure Growth ETF
Guggenheim S&P 500 Pure Value ETF
Guggenheim S&P 500 Top 50 ETF
Guggenheim S&P MidCap 400 Equal Weight ETF
Guggenheim S&P MidCap 400 Pure Growth ETF
Guggenheim S&P MidCap 400 Pure Value ETF
Guggenheim S&P SmallCap 600 Pure Growth ETF
Guggenheim S&P SmallCap 600 Pure Value ETF
Guggenheim S&P Spin-Off ETF
Health Care Select Sector SPDR Fund
Horizons NASDAQ 100 Covered Call ETF
Industrial Select Sector SPDR Fund
InfraCap MLP ETF
Innovator IBD 50 ETF
IQ Chaikin US Large Cap ETF
IQ Chaikin US Small Cap ETF
iShares Cohen & Steers REIT ETF
iShares Core Dividend Growth ETF
iShares Core High Dividend ETF
iShares Core S&P 500 ETF
iShares Core S&P Mid-Cap ETF
iShares Core S&P Small-Cap ETF
iShares Core S&P Total US Stock Market ETF
iShares Core S&P US Growth ETF
iShares Core S&P US Value ETF
iShares Core US REIT ETF
iShares Dow Jones US ETF
iShares Edge MSCI Min Vol USA ETF
iShares Edge MSCI Multifactor USA ETF
iShares Edge MSCI USA Momentum Factor ETF
iShares Edge MSCI USA Quality Factor ETF
iShares Edge MSCI USA Size Factor ETF
iShares Edge MSCI USA Value Factor ETF
iShares Micro-Cap ETF
iShares Morningstar Large-Cap ETF
iShares Morningstar Large-Cap Growth ETF
iShares Morningstar Large-Cap Value ETF
iShares Morningstar Mid-Cap ETF
iShares Morningstar Mid-Cap Growth ETF
iShares Morningstar Mid-Cap Value ETF
iShares Morningstar Small-Cap ETF
iShares Morningstar Small-Cap Growth ETF
iShares Morningstar Small-Cap Value ETF
iShares Mortgage Real Estate ETF

iShares MSCI KLD 400 Social ETF
iShares MSCI USA Equal Weighted ETF
iShares MSCI USA ESG Select ETF
iShares Nasdaq Biotechnology ETF
iShares North American Natural Resources ETF
iShares North American Tech ETF
iShares North American Tech-Software ETF
iShares PHLX Semiconductor ETF
iShares Residential Real Estate ETF
iShares Russell 1000 ETF
iShares Russell 1000 Growth ETF
iShares Russell 1000 Value ETF
iShares Russell 2000 ETF
iShares Russell 2000 Growth ETF
iShares Russell 2000 Value ETF
iShares Russell 3000 ETF
iShares Russell Mid-Cap ETF
iShares Russell Mid-Cap Growth ETF
iShares Russell Mid-Cap Value ETF
iShares Russell Top 200 ETF
iShares Russell Top 200 Growth ETF
iShares Russell Top 200 Value ETF
iShares S&P 100 ETF
iShares S&P 500 Growth ETF
iShares S&P 500 Value ETF
iShares S&P Mid-Cap 400 Growth ETF
iShares S&P Mid-Cap 400 Value ETF
iShares S&P Small-Cap 600 Growth ETF
iShares S&P Small-Cap 600 Value ETF
iShares Select Dividend ETF
iShares Transportation Average ETF
iShares US Aerospace & Defense ETF
iShares US Basic Materials ETF
iShares US Broker-Dealers & Securities Exchanges ETF
iShares US Consumer Goods ETF
iShares US Consumer Services ETF
iShares US Energy ETF
iShares US Financial Services ETF
iShares US Financials ETF
iShares US Healthcare ETF
iShares US Healthcare Providers ETF
iShares US Home Construction ETF
iShares US Industrials ETF
iShares US Insurance ETF
iShares US Medical Devices ETF
iShares US Oil & Gas Exploration & Production ETF
iShares US Oil Equipment & Services ETF
iShares US Pharmaceuticals ETF
iShares US Real Estate ETF
iShares US Regional Banks ETF
iShares US Technology ETF
iShares US Telecommunications ETF
iShares US Utilities ETF
John Hancock Multifactor Large Cap ETF
John Hancock Multifactor Mid Cap ETF
JPMorgan Diversified Return US Equity ETF
Legg Mason Low Volatility High Dividend ETF
Materials Select Sector SPDR Fund
Nationwide Maximum Diversification US Core Equity ETF
Nationwide Risk-Based US Equity ETF
Oppenheimer Large Cap Revenue ETF
Oppenheimer Mid Cap Revenue ETF
Oppenheimer Small Cap Revenue ETF
Oppenheimer Ultra Dividend Revenue ETF
O'Shares FTSE Russell Small Cap Quality Dividend ETF
O'Shares FTSE US Quality Dividend ETF
PowerShares Aerospace & Defense Portfolio
PowerShares Buyback Achievers Portfolio
PowerShares Dividend Achievers Portfolio
PowerShares DWA Healthcare Momentum Portfolio
PowerShares DWA Industrials Momentum Portfolio
PowerShares DWA Momentum Portfolio
PowerShares DWA SmallCap Momentum Portfolio
PowerShares DWA Technology Momentum Portfolio
PowerShares Dynamic Biotechnology & Genome Portfolio
PowerShares Dynamic Building & Construction Portfolio
PowerShares Dynamic Large Cap Growth Portfolio
PowerShares Dynamic Large Cap Value Portfolio
PowerShares Dynamic Leisure & Entertainment Portfolio
PowerShares Dynamic Market Portfolio
PowerShares Dynamic Pharmaceuticals Portfolio
PowerShares Dynamic Semiconductors Portfolio
PowerShares Dynamic Software Portfolio
PowerShares FTSE RAFI US 1000 Portfolio
PowerShares FTSE RAFI US 1500 Small-Mid Portfolio
PowerShares High Yield Equity Dividend Achievers Portfolio
PowerShares KBW Bank Portfolio
PowerShares KBW High Dividend Yield Financial Portfolio
PowerShares KBW Premium Yield Equity REIT Portfolio
PowerShares KBW Regional Banking Portfolio
PowerShares NASDAQ Internet Portfolio
PowerShares Russell 1000 Enhanced Equal Weight Portfolio
PowerShares Russell 1000 Equal Weight Portfolio
PowerShares Russell 1000 Low Beta Equal Weight Portfolio
PowerShares Russell Midcap Pure Growth Portfolio
PowerShares Russell Top 200 Pure Growth Portfolio
PowerShares S&P 500 BuyWrite Portfolio
PowerShares S&P 500 ex-Rate Sensitive Low Volatility Portfolio
Powershares S&P 500 High Beta Portfolio
PowerShares S&P 500 High Dividend Low Volatility Portfolio
Powershares S&P 500 Low Volatility Portfolio
PowerShares S&P 500 Quality Portfolio
PowerShares S&P MidCap Low Volatility Portfolio
PowerShares S&P SmallCap Financials Portfolio
PowerShares S&P SmallCap Health Care Portfolio
PowerShares S&P SmallCap Industrials Portfolio
PowerShares S&P SmallCap Information Technology Portfolio
PowerShares S&P SmallCap Low Volatility Portfolio
PowerShares Water Resources Portfolio
PowerShares WilderHill Clean Energy Portfolio
Principal US Mega-Cap Multi-Factor Index ETF
Principal US Small-Cap Multi-Factor Index ETF
ProShares Large Cap Core Plus
ProShares Russell 2000 Dividend Growers ETF
ProShares S&P 500 Dividend Aristocrats ETF
ProShares S&P MidCap 400 Dividend Aristocrats ETF
Real Estate Select Sector SPDR Fund
RiverFront Dynamic US Dividend Advantage ETF
Schwab 1000 Index ETF
Schwab Fundamental US Broad Market Index ETF
Schwab Fundamental US Large Company Index ETF
Schwab Fundamental US Small Company Index ETF
Schwab US Broad Market ETF
Schwab US Dividend Equity ETF
Schwab US Large-Cap ETF
Schwab US Large-Cap Growth ETF
Schwab US Large-Cap Value ETF
Schwab US Mid-Cap ETF
Schwab US REIT ETF
Schwab US Small-Cap ETF
SPDR Dow Jones REIT ETF
SPDR NYSE Technology ETF
SPDR Portfolio Large Cap ETF
SPDR Portfolio Mid Cap ETF
SPDR Portfolio S&P 500 Growth ETF
SPDR Portfolio S&P 500 High Dividend ETF
SPDR Portfolio S&P 500 Value ETF
SPDR Portfolio Small Cap ETF
SPDR Portfolio Total Stock Market ETF
SPDR Russell 1000 Low Volatility Focus ETF
SPDR Russell 1000 Momentum Focus ETF
SPDR Russell 1000 Yield Focus ETF
SPDR S&P 400 Mid Cap Growth ETF
SPDR S&P 400 Mid Cap Value ETF
SPDR S&P 500 Fossil Fuel Reserves Free ETF
SPDR S&P 600 Small Cap ETF
SPDR S&P 600 Small Cap Growth ETF
SPDR S&P 600 Small Cap Value ETF
SPDR S&P Aerospace & Defense ETF
SPDR S&P Bank ETF
SPDR S&P Biotech ETF

SPDR S&P Capital Markets ETF
SPDR S&P Dividend ETF
SPDR S&P Health Care Equipment ETF
SPDR S&P Homebuilders ETF
SPDR S&P Insurance ETF
SPDR S&P Metals & Mining ETF
SPDR S&P Oil & Gas Equipment & Services ETF
SPDR S&P Oil & Gas Exploration & Production ETF
SPDR S&P Pharmaceuticals ETF
SPDR S&P Regional Banking ETF
SPDR S&P Retail ETF
SPDR S&P Semiconductor ETF
SPDR S&P Telecom ETF
SPDR S&P Transportation ETF Trust
SPDR SSGA Gender Diversity Index ETF
SPDR SSGA US Large Cap Low Volatility Index ETF
SPDR SSGA US Small Cap Low Volatility Index ETF
Technology Select Sector SPDR Fund
USAA MSCI USA Value Momentum Blend Index ETF
Utilities Select Sector SPDR Fund
ValueShares US Quantitative Value ETF
VanEck Vectors BDC Income ETF
VanEck Vectors Biotech ETF
VanEck Vectors Morningstar Wide Moat ETF
VanEck Vectors Mortgage REIT Income ETF
VanEck Vectors Oil Services ETF
VanEck Vectors Pharmaceutical ETF
VanEck Vectors Semiconductor ETF
Vanguard 500 Index Fund; ETF Shares
Vanguard Consumer Discretionary Index Fund; ETF Shares
Vanguard Consumer Staples Index Fund; ETF Shares
Vanguard Dividend Appreciation Index Fund; ETF Class Shares
Vanguard Energy Index Fund; ETF Class Shares
Vanguard Extended Market Index Fund; ETF Shares
Vanguard Financials Index Fund; ETF Shares
Vanguard Growth Index Fund; ETF Class Shares
Vanguard Health Care Index Fund; ETF Class Shares
Vanguard High Dividend Yield Index Fund; ETF Shares
Vanguard Industrials Index Fund; ETF Class Shares
Vanguard Information Technology Index Fund; ETF Class Shares
Vanguard Large-Cap Index Fund; ETF Shares
Vanguard Materials Index Fund; ETF Shares
Vanguard Mega Cap Growth Index Fund; ETF Shares
Vanguard Mega Cap Index Fund; ETF Shares
Vanguard Mega Cap Value Index Fund; ETF Shares
Vanguard Mid-Cap Growth Index Fund; ETF Shares
Vanguard Mid-Cap Index Fund; ETF Shares
Vanguard Mid-Cap Value Index Fund; ETF Class Shares
Vanguard REIT Index Fund; ETF Shares
Vanguard Russell 1000 Growth Index Fund; ETF Shares
Vanguard Russell 1000 Index Fund; ETF Shares
Vanguard Russell 1000 Value Index Fund; ETF Shares
Vanguard Russell 2000 Growth Index Fund; ETF Shares
Vanguard Russell 2000 Index Fund; ETF Shares
Vanguard Russell 2000 Value Index Fund; ETF Shares
Vanguard Russell 3000 Index Fund; ETF Shares
Vanguard S&P 500 Growth Index Fund; ETF Shares
Vanguard S&P 500 Value Index Fund;ETF Shares
Vanguard S&P Mid-Cap 400 Growth Index Fund; ETF Shares
Vanguard S&P Mid-Cap 400 Index Fund; ETF Shares
Vanguard S&P Mid-Cap 400 Value Index Fund; ETF Shares
Vanguard S&P Small-Cap 600 Growth Index Fund; ETF
Vanguard S&P Small-Cap 600 Index Fund; ETF Shares
Vanguard S&P Small-Cap 600 Value Index Fund; ETF Shares
Vanguard Small-Cap Growth Index Fund; ETF Class Shares
Vanguard Small-Cap Index Fund; ETF Shares
Vanguard Small-Cap Value Index Fund; ETF Class Shares
Vanguard Telecommunication Services Index Fund; ETF Shares
Vanguard Total Stock Market Index Fund; ETF Class Shares
Vanguard Utilities Index Fund; ETF Shares
Vanguard Value Index Fund; ETF Shares
VictoryShares US 500 Enhanced Volatility Wtd Index ETF
VictoryShares US 500 Volatility Wtd Index ETF
VictoryShares US EQ Income Enhanced Volatility Wtd Index ETF
VictoryShares US Large Cap High Div Volatility Wtd Index ETF
Vident Core US Equity Fund
WisdomTree CBOE S&P 500 PutWrite Strategy Fund
WisdomTree US Dividend ex-Financials Fund
WisdomTree US Earnings 500 Fund
WisdomTree US High Dividend Fund
WisdomTree US LargeCap Dividend Fund
WisdomTree US MidCap Dividend Fund
WisdomTree US MidCap Earnings Fund
WisdomTree US Quality Dividend Growth Fund
WisdomTree US SmallCap Dividend Fund
WisdomTree US SmallCap Earnings Fund
WisdomTree US SmallCap Quality Dividend Growth Fund
WisdomTree US Total Dividend Fund
Xtrackers Russell 1000 Comprehensive Factor ETF
PowerShares QQQ Trust, Series 1
SPDR Dow Jones Industrial Average ETF Trust
SPDR S&P 500 ETF Trust
SPDR S&P MidCap 400 ETF