# Are Passive Exchange-Traded Funds a Catalyst for Market Instability?

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To cite this article: Alves, Carlos, Diogo Gomes. 2023. Are Passive Exchange-Traded Funds a Catalyst for Market Instability?, European Review of Business Economics III(1): 43-64.
DOI: https://doi.org/10.26619/ERBE-2023.3.1.3.

## ABSTRACT

Exchange-traded funds (ETFs) figure prominently as a notable outcome of financial innovation, offering a cost-efficient avenue for acquiring a diversified portfolio and enabling frequent trading. However, the significant expansion of the ETF market has raised concerns among investors and regulators. The heightened liquidity and passive characteristics of indexed ETFs have the potential to lead to synchronized movements in stock prices and noise trading, thereby impacting underlying securities through arbitrage. This research examines the influence of the escalating ownership of passive ETFs on US stocks and its potential to destabilize the market. Utilizing the constituents of the S&P 500 index, our findings supported the pivotal role of passive ETF ownership in shaping price volatility and systematic risk. Moreover, the study reveals compelling evidence suggesting that issuer concentration in the underlying index may act as an additional factor contributing to systematic risk.

**Keywords:** ETF; Exchange-Traded Funds; Passive Investment; Volatility; Systematic Risk
**JEL Codes:** G11, G23, G28, G50

## I. Introduction

Exchange-traded funds (ETFs) combine the benefits of diversification and simplicity of index investing while maintaining the high liquidity and accessibility common in individual stocks. In addition, this financial instrument has contributed significantly to enhancing the accessibility of otherwise out-of-reach markets for the regular retail investor.

While initially ETFs were seen as an ideal investment vehicle for long-term buy-and-hold investors, the reality is that the high liquidity and low transaction costs characteristic of ETFs made them an extremely attractive financial instrument for high-frequency traders, which account for a significant share of the daily volume traded. ETFs account for over 30% of all trading on the US stock market (Wigglesworth, 2017). Among these investors, noise or uninformed traders harm the well-functioning markets and can destabilize the underlying securities through the ETF arbitrage channel (Ben-David et al., 2014). Authorized participants (APs) have a crucial role in this process by profiting from price differences between the ETF and its underlying basket of securities. If ETF shares are traded at a premium to the net asset value, APs can sell ETF shares on secondary markets. They can then acquire the underlying securities and form ETF units by delivering them in creation baskets at the close of the day. Conversely, suppose ETF shares are trading at a discount. In that case, APs can purchase ETF shares on secondary markets, redeem creation units at the end of the day, and subsequently sell the underlying securities they have obtained through this process (for more details about the function of an ETF and the role of APs see, among others, Ben-David et al., 2017; Hill et al., 2015; Lettau & Madhavan, 2018; Pagano et al., 2019)

Simultaneously, there has been an extensive debate on whether the passive nature of this instrument is beneficial for the market. Evidence indicates that the stock pricing mechanism cannot easily distinguish price changes caused by an event pertinent to one asset from information that relates only to other assets when learning from ETF prices (Bhattacharya & O'Hara, 2018). By promoting index investing, passive ETFs could increase asset pair correlation among index constituents, leading to an upsurge in systematic risk.

Despite this, ETF trading is expected to keep growing at a remarkable pace, with PwC, in a recent survey, indicating that by 2026, ETF assets under management (AuM) will double and reach a total of 20 trillion dollars on a global scale (PWC, 2021). Hence, any potential repercussions in the markets from this surge in popularity could reach even higher magnitudes. To further illustrate the importance of this topic, several representatives of financial institutions and regulators have started to alert investors worldwide to the hidden dangers of the rise in passive ETF investing following several events and empirical evidence that have confirmed some of the regulators' concerns (Bhattacharya & O'Hara, 2018; Pagano et al., 2019).

Current literature on ETFs is still in its early days, predominantly because the most significant share of the upswing in the ETF market occurred during the last two decades. Nevertheless, this analysis is mainly related to the research from Ben-David et al. (2014), Ben-David et al. (2017) and Hansson and Perers (2018), who investigated the impact of ETF ownership on individual stock volatility in the US equity market.

In this context, Glosten et al. (2021) discovered that ETFs, due to their heightened liquidity compared to the underlying securities, offer investors a more accessible means of exposure to the systematic risk component of assets rather than their idiosyncratic component. This streamlined access facilitates the discovery of prices related to the systematic element and hinders that of the idiosyncratic element. Additionally, Da and Shive (2018) have observed an association between ETFs and increased co-movement in the returns of the stocks within an index. They attribute this phenomenon to the heightened trading activity in the corresponding ETF when investors receive news related to the index, impacting the underlying securities through arbitrage, and rendering them more responsive to index-related news than news linked to idiosyncratic factors. Another contributing factor is the potential attraction of sentiment-driven noise traders to ETFs, whose collective trading behavior may influence the relevant stock index. If this holds, the augmented co-movement in security prices may signify a more straightforward transmission of noise trading shocks rather than a swifter revelation of fundamental information regarding systematic risk (Pagano et al., 2019). Also, Sullivan and Xiong (2012) further investigated the influence of ETF ownership on the underlying securities, confirming the detrimental relation evidenced through a rise in price co-movement, pairwise asset correlation, and beta at the individual and aggregate perspectives.

In this paper, we explore the aftermath of an increase in the concentration of capital in indexed ETFs, measured by the stock's passive ETF ownership percentage, on price volatility and systematic risk at the stock level. Intuitively, we study the US perspective as it has the most saturated ETF market (Pagano et al., 2019), reaching conclusions relevant to markets worldwide. We use the primary sample of the S&P 500 index constituents and the passive plain-vanilla ETFs that hold these stocks from 2010 to 2020.

To the best of our knowledge, this segment has not been further explored in previous research. Thus, it complements the current evidence on this topic, including chiefly different ETF styles in their analyses. Furthermore, by implementing a different methodology and applying it to a more recent timeframe, this empirical research aims to focus on the implications of indexing related to the proliferation of passive ETFs, considering that the average percentage ownership in S&P 500 index stocks more than doubled from the beginning of 2010.

The structure of this paper is as follows. Section II presents the relevant literature and develops the hypotheses. Then, section III describes the data and methodology used, section IV presents the empirical results, and section V concludes.

## II. Literature review and hypotheses

### *A. The Emergence and Development of Passive Investment*

In 1976, Vanguard's founder, Jack Bogle, introduced the world to the first index fund available to retail investors. This financial innovation would create a new paradigm in the financial world and propel massive growth in the passive investing industry.

Passive or index investing refers to financial instruments, such as indexed mutual funds or ETFs, which track a specific index by either fully replicating the index, known as full replication or by holding a sample of the stocks that include it, referred to as partial replication.

Initially, indexing served as a tool to represent the performance of an economy. It was first introduced in the US in the 1800s with the Dow Jones Transportation Average and later with the creation of the Dow Jones Industrial Average, representing the railroads and industrial segment in the US, respectively. Both indexes, although modified, are still used today and belong to an increasing list of market-tracking indexes.

Indexes introduced a new challenge for the asset management industry since they served as a performance benchmark for active fund managers. This led to findings exposing actively managed funds, which, on average, were proven to underperform the broad-based indexes they focused on. Such discoveries questioned the managers' ability to effectively choose winners in an industry heavily reliant on substantial management fees (e.g., Carhart, 1997; Malkiel, 2017; Stambaugh, 2014).

Following these findings, the mutual fund industry has provided new ways of investing. A pioneer when it came to index investing and considered the father of passive investing, Jack Bogle created the Vanguard 500 fund, which tracked the S&P 500 index. This first retail index fund was initiated in 1976 and has grown to over $380 billion in assets. Indexed funds introduced a simple and efficient way in which individual and institutional investors could gain exposure to a diversified basket of financial assets, challenging active fund managers by offering a cost-effective alternative.

Institutional funds invest on behalf of final investors through open-ended funds, such as mutual funds and ETFs, and close-ended funds. This form of investing has played a growing role in the US financial system, illustrated by institutional investors increasingly dominating the US market.

According to the ICI report (2021), while in 2000, assets under the management of investment funds represented $7.2 trillion, at the end of 2020, US institutional investors managed around $30 trillion in assets. They invested on behalf of more than 105 million US retail investors. While 23% of assets within US households are invested in funds in 2020, compared to only 3% in 2000, this share is expected to keep rising, partly explained by the ageing of the US population and the reliance on individual retirement accounts (IRAs) and defined contribution plans (D.C.) in these funds.

Indexed funds, including mutual funds and ETFs, are on the frontline of this trend and, in the US, have grown into a $9.9 trillion industry in 2020 (ICI, 2021). While in 1980, actively managed funds represented nearly the full share of total assets allocated in funds, the reality has shifted drastically and, in 2018, passive exceeded active US-equity funds AuM, standing at 54% of the total equity mutual fund market in the US in 2021 (Seyffart, 2021).

In their research, Sullivan and Xiong (2012) show that from 1993 to 2010, passive funds have increased at double the growth rate of active funds, at 26% and 13%, respectively. More recently, according to ICI (2021), while assets allocated to funds have overall continued to increase, the share of active funds, in contrast, decreased over the last years, implying that some of the outflows from actively managed equity mutual funds have shifted to both indexed mutual funds and, to a higher degree, indexed ETFs.

In short, stimulated and encouraged by academic literature that demonstrated that active management was globally a destroyer of value rather than a creator of wealth, institutional investors expanded their offer of passive investment alternatives, particularly funds and ETFs indexed to market benchmarks. Based on this expansion, index-linked passive investment is the predominant form of investment in the US today.

### *B. The Debate About Passive versus Active Management*

The debate between the pros and cons of active versus passive investing has intensified over recent years. Two simple ideas stand behind these investment strategies. On the one hand, active investors believe that there is an added value behind the security selection process of professional managers and attempt to beat the returns of their market benchmarks by a margin greater than the management fee. Conversely, passive investors want to take part in the market returns by buying and holding an index fund with considerably lower fees due to its passive nature.

At their core, passive investment vehicles benefit from supporting a substantial share of the academic literature. This is because they have essential characteristics for an efficient investment vehicle, such as a built-in diversification tool and low transaction fees, which, according to French (2008) are symptoms of a more efficient market. Furthermore, one could argue that the trend from active to passive investing is backed by market efficiency theory, described by Fama (1970), since passive investing is the rational choice if an investor believes that the market incorporates all available information and, therefore, there would be little value in trying to beat the market on a consistent basis (Stambaugh, 2014).

To strengthen this argument further, the available data on stock market returns supports the passive investing theory. A French (2008) study concluded that a passive investor would, on average and under reasonable assumptions, achieve a return higher of 67 basis points compared to an active investor between 1980 and 2006.

More recently, Malkiel (2017) showed that, in 2016, two-thirds of active managers on large-cap stocks in the US underperformed the S&P 500 index. The evidence was even more robust for small-cap stocks, where 85% of active managers underperformed their correspondent small-cap index. In the same research, when extended to 15 years, around 90% of active managers underperformed the market benchmark in three geographic areas: the US, international, and emerging markets.

The same author argues that, in an efficient market, active managers would underperform their passive counterparts, on average, by the amount of the management fees charged. At the same time, some investors profit, and others will incur losses on the same scale, resulting in a zero-sum game. The intuition for this lies in the proposition that, under conditions of market efficiency, all stocks have implicit in their price all available information at any given time, and no investor should be able to predict the future consistently. With the introduction of transaction and management fees, the strategy shifts to a negative-sum game in which active investors underperform the market, on average, by the fees charged. In practice, this idea is consistent with the conclusion by Malkiel (2017), which provided evidence that the underperformance from active investors concerning the market index was in line with the average management fee charged during the same period.

The authors developed an extensive literature review on this topic. Treynor and Mazuy (1966) contributed to this area of research with one of the most relevant findings. They concluded that only one in a 57-fund sample demonstrated significant timing abilities. Furthermore, similar results were also reached, using different funds and time samples (e.g., Connor & Korajczyk, 1988; Cumby & Glen, 1990; Fabozzi & Francis, 1979; Henriksson & Merton, 1981), strengthening the overall skepticism from most of the academics when it comes to the added value brought by active-fund managers to the financial industry. Finally, Carhart's (1997) findings did not support the existence of stock-picking skills from the portfolio managers of mutual funds.

However, not all findings hurt active investors' prospects. A recent study concluded that active funds outperformed the market if one included only the bearish periods between 2005 and 2020 (Molander & van Loo, 2020). This conclusion supports the idea that active investing in bear markets may be an added benefit because active managers can allocate capital to more crisis-proof securities upon the release of macroeconomic news. In contrast, passive investors follow a strict investing strategy delimited by the index, regardless of what is happening in the market.

ESG (Environmental, Social, and Governance) considerations are an additional factor in favor of active investors worth noting. Despite the growing popularity of ESG-themed indexes, most capital in passive investing remains concentrated in broad-based indexes like the S&P 500. This concentration in traditional indexes may impede the shift towards ethical investing, as the nature of these indexes' channels additional funds to institutions that might otherwise face investor reluctance due to the nature of their business.

### *C. Background on Exchange-Traded Funds*

ETFs have led to a rise in passive investing. While mutual funds introduced the idea of indexing, ETFs quickly surged as the most popular passive investment vehicle in the US and are set to overtake mutual funds on a global scale.

In 1993, the S&P Depository Receipt (SPDR), known as Spider, was created, and it is the first ETF tracking the S&P 500 index. Almost three decades later, ETFs have grown in size, diversity, scope, complexity, and market significance (Pagano et al., 2019). According to ICI (2021), since 2000, total assets under ETFs in the US have increased from $66 billion to $5.4 trillion in 2020, with the number of ETFs going from 80 to 2,296 in the same period. The US ETF market leads this industry with a 69% share of the global ETF market, mainly concentrated on large-cap US stocks (ICI, 2021).

By definition, ETFs are an investment vehicle that holds a specific basket of financial securities, including equities, bonds, commodities, currencies, or even hybrids (Alves, 2014). Similar to mutual funds, ETFs can be either actively or passively managed. However, the active share of total assets under management is relatively small.

As this research focuses on the detrimental effects of indexing, we will refer to the term ETFs as solely indexed ETFs during the remaining empirical research, which considers over 95% of the ETF market (Marquit & Curry, 2022).

In particular, passive ETFs, like indexed mutual funds, attempt to replicate the performance of a specific index. Nevertheless, the main differentiating factor that makes ETFs an attractive financial instrument for investors is the way they trade. Whereas mutual funds trade outside a stock exchange, and all orders are executed once a day at the same price, ETFs trade intraday on a regular stock exchange and can, similarly to stocks, be short-sold and bought on margin (Petajisto, 2017). This implies that ETFs have higher liquidity than any other passive vehicle, leading to lower transaction costs and adding the inexistence of active management fees to lower overall expense ratios. Also, ETFs can be more tax-effective since, contrary to mutual funds, they are often redeemable (Securities and Exchange Commission, 2021). Redeeming in kind means that, instead of using cash, some investors can acquire ETF shares by exchanging them for the underlying securities (Securities and Exchange Commission, 2021).

To illustrate the differential of costs, while hedge funds charged on average a 1.4% management fee at the end of 2020, a number which has decreased significantly during the last decade due to the pressure of passive vehicles, expense ratios in ETFs can go as low as 0.03%, as is the case of the popular Vanguard S&P 500 ETF, VOO (Picker, 2021).

Even though ETFs are traded on a regular exchange, only APs, usually large-broker dealers (Hill et al., 2015), can participate in the primary market, where the ETF manager issues a share, and the APs deliver the baskets of predefined securities in the tracked index in exchange, acting as market-makers. Similarly, APs can redeem the ETF share by exchanging it with the underlying securities with the issuer.

APs also serve as an arbitrage mechanism, keeping in check any differences between the ETF price and the net asset value (NAV) of its underlying securities. Israeli et al. (2017) explain that if an ETF trades above its NAV, APs will choose to deliver the basket of securities in exchange for the overpriced ETF share, generating new ETF shares and exerting pressure for the ETF price to decrease to its NAV.

On the other hand, if the ETF is trading below the NAV, authorized participants will buy the ETF share, redeem it for the basket of underlying assets and sell these securities in the secondary market to take advantage of their higher NAV (Petajisto, 2017). This means that APs will buy the cheapest asset and short-sell the more expensive one between the ETF and its underlying securities, exerting pressure for the prices to converge by holding this position until they do (Ben-David et al., 2014). Individual investors can trade with the APs on the secondary market.

The most popular index covered in the ETF segment is, by far, the S&P 500. As the name implies, the index contains stocks corresponding to a list of 500 companies quoted on the New York Stock Exchange (NYSE) and the NASDAQ in the proportion of their market capitalization, according to different parameters, such as market capitalization, liquidity, and its representation within the industry it belongs to. It is widely used as a benchmark for the US economy, and 14 different ETFs cover it with nearly $1 trillion in assets, including the largest ETF in the world, the SPDR S&P 500, with over $410 billion in assets.

ETFs bridge the gap between the trading convenience of a stock and the diversifying benefits of mutual funds (Israeli et al., 2017). Moreover, as global coverage increases, ETFs allow investors to invest in markets that would otherwise be unreachable for some investors (Bhattacharya & O'Hara, 2018).

### *D. Exchange-Traded Funds and Market Volatility*

Although initially perceived as an optimal financial vehicle for long-term, buy-and-hold investors, ETFs have exhibited notable deviations from this concept (Ben-David et al., 2014). The evidence indicates a substantial shift. ETF trading now constitutes over one-third of the total trading volume in the US market, attracting considerable attention from short-term, high-frequency investors (Pagano et al., 2019). This trend is exemplified by the most active funds frequently trading at volumes surpassing their market capitalization daily (Petajisto, 2017).

Israeli et al. (2017) define noise or uninformed traders as those who, due to non-fundamental motives, would be better off refraining from trading. The existence of noise traders is widely discussed in financial academia, with Black (1986) suggesting motivations such as a false sense of information or deriving utility from trading. Ben-

David et al. (2014) found that, on average, ETFs trade at a bid-ask spread 20 basis points lower than the equivalent portfolio of underlying stocks, partially attributed to market makers and their adjustments for adverse selection issues.

Broman (2016) and Krause et al. (2014) provide evidence suggesting that these characteristics attract short-horizon noise traders, leading to a migration from underlying securities to ETFs. Over time, this shift may reduce liquidity in underlying stocks, discouraging informed traders from researching individual securities and lowering price efficiency (Israeli et al., 2017). Bradley and Litan (2010) indicates that ETFs undermine traditional price discovery processes and pose a source of systemic risk. Andrei and Hasler (2015) also show that investors' attention to news and learning uncertainty determines the stock return variance and risk premia.

Arbitrage mechanisms can place significant price pressure on underlying securities when ETF prices deviate from the NAV (Ben-David et al., 2014). Petajisto (2017) empirically confirms substantial deviations between ETF prices and NAV, fluctuating by approximately 200 basis points despite arbitrage activities. Ben-David et al. (2014) asserts that over 50% of the daily volume of the S&P 500 SPDR ETF is attributed to arbitrage trading, representing a significant channel of noise propagation to underlying securities. In his empirical research, Malamud (2015) proves that the creation/redemption of ETF shares through the arbitrage channel is a shock propagation channel that can cause persistent price dislocations. This idea is in accordance with Stein (1987), who alerted us to the consequences of speculators in price inefficiency and welfare reduction.

As ETF ownership increases, corresponding securities may experience decreased individual-level liquidity, contributing to a drop in stock-level liquidity (Israeli et al., 2017). Bhattacharya and O'Hara (2018) argue that the indexing nature of ETFs may create market fragility and elevate systemic risk, as idiosyncratic shocks to one asset can affect non-correlated assets through the ETF pricing channel, increasing systematic risk.

Along these lines, Grossman and Stiglitz (1976) posit that the market is a self-correcting mechanism, suggesting a cyclical relationship between active and passive investment strategies. Israeli et al. (2017) find that ETF ownership is positively related to higher trading costs, lower benefits from information acquisition, lower response coefficients in future earnings, and a decline in analyst coverage of the firm.

Studies by Ben-David et al. (2014), Hansson and Perers (2018), and Glosten et al. (2021), demonstrate that the impact of ETFs on the liquidity of underlying securities varies across markets and industry-type ETFs. While ETFs may enhance information efficiency in weak information environments, they could exacerbate volatility and reduce price efficiency in well-covered markets.

Hansson and Perers (2018) corroborate the findings of Ben-David et al. (2014), showing a positive relationship between ETF ownership and the volatility of the underlying securities in the US equity market. Focusing on leveraged ETFs, Ivanov and Lenkey (2018) find ETF ownership to be an insignificant variable in explaining price volatility. Finally, studies by Da and Shive (2018) and Sullivan and Xiong (2012) highlight the potential harmful effects of increased ETF investing in well-functioning financial markets, including heightened co-movement between asset pairs and increased systematic risk, particularly in small and illiquid stocks.

### *E. Hypotheses*

The review of the literature carried out in the previous paragraphs has made clear the increased importance of passive investment and the prominence of ETFs in this context. In particular, the literature shows that ETFs have deviated from their initial perception as long-term investments, with over one-third of the US market trading volume now attributed to ETFs, drawing attention from short-term, high-frequency investors. The rise of noise traders, attracted by ETF characteristics, may reduce liquidity in underlying stocks, lowering price efficiency, and posing systemic risks. Arbitrage deviations between ETF prices and NAV contribute to significant noise propagation. At the same time, increased ETF ownership is linked to higher trading costs and reduced information benefits, impacting liquidity and systemic risk across markets and industry-type ETFs. Studies indicate potential harmful effects, including increased co-movement and systematic risk, particularly in small and illiquid stocks.

In this context, Bhattacharya and O'Hara (2018) argue that passive ETFs propel systemic risk since they encourage investing through a basket of securities. This means that ETFs can potentially increase asset pair correlation due to an idiosyncratic shock affecting one asset's ability to impact another independent asset that belongs to the same index through the arbitrage channel. This is one of the major concerns for market regulators and practitioners because, ultimately, it increases the probability of an event having a snowball effect with systemic implications. The evidence also indicates that an increase in the equity market free float concentration in passive ETFs is likely to lead to higher systematic risk, measured by the stock's correlation to the market or beta, which would align with Sullivan and Xiong (2012). Therefore, this paper posits the following hypothesis:

**H1:** Passive ETFs are positively associated with systematic risk at the stock level.

Additionally, this is in line with Ben-David et al. (2014), who concluded that ETF ownership was positively related to individual stock volatility between 2000 and 2012, considering all US-based equity ETFs, since ETFs are a natural choice for noise traders who look for high liquidity securities to trade at a high frequency. As ETFs own a more significant share of the equity market free float, we expect that this will have a destabilizing effect on the underlying securities, leading to an increase in individual stock volatility. Therefore, this paper posits the following hypothesis:

**H2:** Passive ETFs are positively associated with volatility at the stock level.

## III. Data, methodology and variable definition

### A. Sample and data source

The period and frequency analyzed consist of a 10-year period spanning the first quarter of 2010 to the first quarter of 2020 on a quarterly frequency. The data is from Thomson Reuters DataStream. The period was not extended to the most recent data available because we did not wish to consider the effect of the COVID-19 pandemic on the US equity market.

The first step in the data collection process was to define the filtering criteria from which the stocks analyzed would be retrieved. Ben-David et al. (2014) limited the ETFs to those originating from the US instead of constraining the origin of the stocks. However, to meet our research criteria, it is more adequate to consider ETFs, whether they originate in the US or not, since non-US ETFs with US stock holdings can impact the stability of US stock prices. Therefore, in this research, only the stock origin is filtered using the S&P 500 index constituents, whereas ETF origin is not restrained.

In addition to the natural technical limitations that would be involved in using a much larger and representative sample of stocks, one other relevant reason for choosing the S&P 500 index was that the US ETF market is mainly concentrated on large-cap US stocks, and, in theory, the adverse effects should be more transparent with this sample. By focusing on the S&P 500 index constituents, we primarily move past issues such as including low liquidity and low ETF coverage stocks as a substantial amount of our sample, which could dilute the unfavorable effects that this research looks to quantify. The intuition for this is that the AuM and the number of ETFs covering the more popular and concise indexes, such as the S&P 500, are higher than for more extensive broad indexes that include significantly more securities (Hansson & Perers, 2018).

Following this, the first step in the data collection process was to retrieve the historical constituents of the S&P 500 index every quarter for the chosen period.

The descriptive statistics and the Pearson's correlation coefficients are reported in the Appendix.

### B. Methodology

In this empirical investigation, panel data is utilized instead of time-series or cross-sectional data, as the objective is to scrutinize the evolution of various variables in relation to individual stocks over time, constituting both the entity and time variables for regression analysis.

When examining a panel dataset, three principal alternatives were considered: pooled ordinary least squares (POLS), fixed effects model (FEM), and random effects model (REM). However, it became evident from the outset that the POLS model would not be suitable, as it is designed for datasets where all entities exhibit similar behavior, which is not the case for stocks within a broad index like the S&P 500. Despite this, a Breusch-Pagan test was conducted. As expected, the choice came down to FEM or REM for this dataset. Ultimately, the Hausman test confirms that the fixed-effects model is the most appropriate for this dataset[1].

## C. *Variable definition*

*C.1. Passive ETF ownership*

The variables used in the study are identified and described in Appendix 1 (Table A.1). For the main independent variable, as selected by previous research (Ben-David et al., 2014), we used the percentage of total AuM of all ETFs on a specific stock, which is referred to as ETF ownership.

First, using Thomson Reuters Datastream, we collected and added the AuM that the selected ETFs have on each of the S&P 500 constituents each quarter. Due to equipment constraints, there was the need to limit data size, which ultimately led to using the top 100 ETFs ranked by their holdings on each stock.[2] The set of 100 ETFs that invest the most in one S&P500 stock may differ from the set of 100 ETFs that invest the most in another S&P500 stock.

In theory, this limitation would have a more significant impact as we reached more recent periods because the ETF market has been increasing at a fast pace in both total ETF AuM and the number of ETFs covering each stock (ICI, 2021). Furthermore, stocks with the lowest Herfindahl-Hirschman Index (HHI) are more likely to have a substantial amount of data left out because this indicates that, within the top 100 ETFs, ETF AuM are more evenly distributed, which could imply that some relevant ETFs were left out. On the other hand, for the stocks with higher HHI value within the top 100 ETFs, the total amount of ETF AuM is already highly concentrated within the top few ETFs and, therefore, it is unlikely that any ETF outside the top 100 would have any meaningful data that is not considered in this study.

Since we are simply interested in the detrimental effects of indexed ETFs, we solely consider the ETFs whose investing style is defined as "indexing" by Thomson Reuters

[1] The results have not been included to save space but are available upon request.

[2] In theory, this limitation would be more impactful as we get to more recent periods because the ETF market has been increasing at a fast pace in both total ETF AuM and the number of ETFs covering each stock (ICI, 2021). Furthermore, stocks with the lowest Herfindahl-Hirschman Index (HHI) are more likely to have a substantial amount of data left out because this indicates that, within the top 100 ETFs, ETF AuM are more evenly distributed, which could imply that some relevant ETFs were left out. On the other hand, for the stocks with higher HHI value within the top 100 ETFs, the total amount of ETF AuM is already highly concentrated within the top few ETFs and, therefore, it is unlikely that any ETF outside of the top 100 would have any meaningful data that is not considered in this study. To attempt to estimate the magnitude of this effect, we consider the last period available, the last quarter of 2021, and compare what percentage of ETF ownership is left out for the top and bottom three stocks by their HHI index value. As expected, for the top three stocks by HHI value, we do not consider, on average, about 0.5% of total ETF ownership, whereas for the more susceptible bottom three stocks, we leave out around 1.0%. From this, we can infer that, on average, during the whole period analyzed, we expect to have left out below 1.0% of total ETF ownership with this methodology. Therefore, the conclusions, even though not representing the entire population of indexed ETFs owning S&P 500 stocks, should nonetheless yield relevant and representative results.

Datastream and discard any actively managed ETFs. In theory, we expect this alteration from the previous research to yield more robust results since actively managed ETFs do not share some of the characteristics that make passive ETFs a natural choice for noise traders, such as the lack of management fees.

*Equation 1: ETF AuM*

$$ETF\ AuM_{i,t} = \sum ETF_{r,i}$$

To calculate passive ETF AuM for stock $i$ at time $t$, we add the assets for the top 100 ETFs with respect to holdings of that stock. In the equation, $r$ stands for the order rank of each ETF going from 1 to 100.

*Equation 2: ETF Ownership*

$$ETF\ Ownership_{i,t} = \frac{ETF\ AuM_{i,t}}{Market\ Capitalization_{i,t}}$$

Following this, we obtain the passive ETF ownership variable by dividing the ETF AuM, previously calculated for stock $i$ and time $t$, by the corresponding market capitalization.

*C.2. Risk measures*

To obtain stock volatility, we first collected the daily closing prices for each stock for ten years through Thomson Reuters Datastream. Following this process, we calculate the daily returns. Using those returns, we compute quarterly volatility using the regular standard deviation formula.

The beta (i.e., the systematic risk measure) was retrieved each quarter from Thomson Reuters Datastream. In particular, the available beta is a historical beta calculated with a rolling 5-year period of monthly frequency logarithmic changes, updated quarterly.

*C.3. Control variables*

Following the calculation of the main dependent and independent variables of this research, we then introduce several control variables to isolate the effect that we aim to capture from other factors that could impact stock price volatility and beta.

This empirical research applies the same control variables to the tests corresponding to both hypotheses. We include controls for liquidity, industry, ETF issuer concentration, and size, all retrieved through Thomson Reuters Datastream.

The link between liquidity and volatility is widely documented in the literature (Atkins & Dyl, 1997). Intuitively, a highly liquid stock should attract noise traders to a higher degree (Hansson & Perers, 2018). A common way to address this link is by using stock price as a control variable. In general, a high stock price is less liquid than a low stock price since it requires more funds to acquire stock with a higher price and vice versa. The price used in this work is the closing price on the last day of the quarter.

We then look at the possible relationship between industry and price instability. Growth companies tend to be more volatile than established ones (Perez-Quiros & Timmermann, 2000). This research considers this relation by introducing the price-to-book value. To ensure that every variable value has a relevant economic meaning, we eliminate the values for this variable in which the ratio is negative.

Bhattacharya and O'Hara (2020) introduce the idea of an issuer concentration effect that we consider in this model. The author explains that the issuance market is dominated by essential issuers that often depend on only a few authorized participants, which could act as an additional source of risk. However, intuitively, we argue that theoretically the opposite effect could also take place. Stocks that have their passive ownership dispersed through several issuers have a higher possibility of having a rise in pairwise correlation with a larger basket of securities since they are exposed to several issuers that could track different indexes. To account for these effects, we included the HHI in the model as a measure of ETF issuer dispersion on the passive ETF ownership of each stock.

Currently, there is a lack of evidence on the effects of ETF issuer concentration on market stability (Bhattacharya & O'Hara, 2020). Thus, we aim to shed some light on this relation besides serving as a control variable.

To calculate the HHI for each stock, we first take the percentage of each 100 ETFs on the total ETF AuM and then sum the squares of such percentages.

Similar to Ben-David et al. (2014), to account for the effect of size, we include market capitalization as a control variable to consider the possible link between the firm size and risk (Perez-Quiros & Timmermann, 2000). The influence of a firm's size on the volatility of stock portfolio returns is also documented by, among others, Chelley-Steeley and Steeley (1995).

## IV. Results

### *A. Fixed-Effects Model Results*

Table 1 outlines the findings from the fixed-effect model regression, utilizing beta as the primary dependent variable, aligning with the initial hypothesis in this empirical investigation.

All the regressions presented show a positive coefficient for the ETF ownership variable. Its magnitude oscillates between 0.80 and 1.11, indicating that every ten-percentage point increase in ETF ownership corresponds to an increase in the beta of between 0.08 and 1.1 points, corresponding to 7.3% and 10.0% of the median beta (1.1). Note that the effect is maintained regardless of whether control variables are included and when some are dropped. Therefore, our results are not only statistically robust, but also economically relevant.

**Table 1: Impact on Systematic Risk.**

Note: *p-value<0.05; **p-value<0.01; ***p-value<0.001. Robust standard deviations inside parentheses. All the regressions presented in the table include stock and time-fixed effects. Regressions that include the PBV ratio as a control variable have fewer observations due to the negative values being excluded. The time sample is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency and based on the S&P constituents during this period.

| **Variables** | **β** | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| **Constant** | 1.063948*** (0.024215) | 1.098431*** (0.019145) | 1.054540*** (0.023739) | 1.064077*** (0.024031) | 1.080370*** (0.023859) | 1.121008*** (0.017431) |
| **ETF Ownership** | 0.971700** (0.428624) | 0.928566** (0.428281) | 1.116235*** (0.421233) | 0.971359** (0.428540) | 0.800946* (0.426581) | 0.821177** (0.417657) |
| **Market Capitalization** | 0.000481*** (0.000123) | 0.000478** (0.000123) | 0.000420*** (0.000121) | 0.000484*** (0.000108) | | |
| **Stock Price** | 2.93E-06 (6.72E-05) | 6.16E-06 (6.72E-05) | 7.81E-05 (6.43E-05) | | 0.000129** (5.90E-05) | |
| **PBV Ratio** | 0.000275* (0.000163) | 0.000286* (0.000163) | | 0.000275* (0.000163) | 0.000292* (0.000163) | |
| **Herfindahl-Hirschman** | 2.43E-05** (1.04E-05) | | 2.34E-05** (1.02E-05) | 2.43E-05** (1.04E-05) | 2.39E-05** (1.04E-05) | |
| **Observations** | 16832 | 16832 | 17377 | 16832 | 16832 | 17377 |
| **Adj. R-Squared** | 0.587 | 0.587 | 0.588 | 0.587 | 0.587 | 0.588 |
| **Time FE** | YES | YES | YES | YES | YES | YES |
| **Stock FE** | YES | YES | YES | YES | YES | YES |

Overall, the results strongly favor the confirmation of the first hypothesis. All six tests find a positive and significant relation between ETF ownership and beta. The loading was the highest for regression (3), where the price-to-book value is excluded. In addition, the ETF ownership variable is significant at a 5% level in all regressions, except for regression (5), where the level of significance is 10%. Moreover, all tests show a considerable explanatory power with an Adj. R-squared consistently over 0.58.

As for the control variables, we note that market capitalization is estimated to be statistically significant at a 1% level for all combinations and consistently has a positive loading. However, this was not in line with our expectations since companies with high market capitalization are usually more stable and predictable businesses, whereas smaller firms tend to be more volatile (Perez-Quiros & Timmermann, 2000).

The HHI variable is positively related to beta and its significance is pertinent at a 5% level for all regressions. These results align with Bhattacharya and O'Hara (2020) proposal, which argued that issuer concentration could be a source of volatility.

Contrary to the previous variables, the stock price and price-to-book value ratio proved non-statistically significant in this regression, except for regression (5), in which the stock price is statistically significant for a 5% confidence level. In turn, the PBV ratio variable is significant at a level of significance of 10 per cent.

Next, an overview of the results for the second hypothesis is displayed in Table 2, where price volatility is used as the dependent variable, applying the same set of controls.

**Table 2: Impact on Volatility.**

Note: **p*-value<0.05; ***p*-value<0.01; ****p*-value<0.001. Robust standard deviations inside parentheses. All the regressions presented in the table include stock and time-fixed effects. Regressions that include the PBV ratio as a control variable have fewer observations due to the negative values being excluded. The time sample is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency and based on the S&P constituents during this period.

| Variables | Volatility | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Constant** | 0.016745*** (0.000271) | 0.016602*** (0.000214) | 0.016759*** (0.000270) | 0.016447*** (0.000270) | 0.016580*** (0.000267) | 0.015676*** (0.000199) |
| **ETF Ownership** | 0.011604** (0.004804) | 0.011788** (0.004799) | 0.010658** (0.004784) | 0.012392** (0.004814) | 0.013320*** (0.004780) | 0.016805*** (0.016805) |
| **Market Capitalization** | -4.84E-06*** (1.38E-06) | -4.82E-06*** (1.38E-06) | -5.42E-06*** (1.37E-06) | -1.08E-05*** (1.21E-06) | | |
| **Stock Price** | -6.74E-06*** (7.53E-07) | -6.75E-06*** (7.53E-07) | -6.19E-06*** (7.30E-07) | | -8.01E-06*** (6.61E-07) | |
| **PBV Ratio** | -1.37E-07 (1.83E-06) | -1.83E-07 (1.83E-06) | | -5.50E-07 (1.84E-06) | -3.10E-07 (1.83E-06) | |
| **Herfindahl-Hirschman** | -1.01E-07 (1.17E-07) | | -8.80E-08 (1.16E-07) | -1.23E-07 (1.17E-07) | -9.70E-08 (1.17E-07) | |
| **Observations** | 16852 | 16852 | 17398 | 16852 | 16852 | 17398 |
| **Adj. R-Squared** | 0.729 | 0.729 | 0.728 | 0.727 | 0.729 | 0.725 |
| **Time FE** | YES | YES | YES | YES | YES | YES |
| **Stock FE** | YES | YES | YES | YES | YES | YES |

According to the results, ETF ownership is a determinant of stock volatility. First, all six combinations resulted in a positive coefficient for the relation between volatility and ETF ownership. Also, when the controls are fully implemented, an increase of 1% in ETF ownership means a rise of 1.6% in stock return volatility, demonstrating a significant economic meaning.

Furthermore, the main independent variable is consistently significant for a 5% confidence level; particularly, in regressions (5) and (6), it is even significant for a 1% level. The estimation also shows a high level of variance explanation power, with an R-squared superior to 0.7 in all combinations. This value is considerably higher than previous research that focused on different styles of ETFs (Ben-David et al., 2014; Hansson & Perers, 2018). Also, we note that the highest R-squared is found on regression (1) when all controls are included, which indicates that all the variables introduced served to increase the explanatory power of our model.

In this hypothesis, we find that market capitalization and stock price were statistically significant for all combinations at a 1% level. The coefficient for market capitalization is now negative, which is more in line with our initial expectations.

Intuitively, a higher stock price should result in fewer investors being able to trade the security, leading to lower liquidity. On the other hand, lower prices mean that trading is available to a broader range of investors, which means these securities tend to have higher liquidity and trade at a higher frequency. Hence, lower prices should relate to higher volatility since they attract noise traders to a greater extent, which aligns with our estimations. To strengthen this idea, Atkins and Dyl (1997) show evidence that stocks with low transaction costs are more volatile.

Finally, the price-to-book value ratio and the HHI show low statistical significance levels. For the PBV ratio, the loadings were also not in line with the initial intuitive proposal. We had expected a higher ratio to be positively related to volatility since growth companies tend to be more volatile. As for the HHI, the negative loading is not aligned with the effect described by Bhattacharya and O'Hara (2020).

## B. Robustness and other additional tests

This section is dedicated to implementing several robustness checks and other additional tests to complement our results.

### B.1. ETF AuM test

First, we applied the same regressions with a different independent variable by replacing ETF ownership with ETF AuM. This change accounts for the company's market capitalization, which can influence ETF ownership. By using ETF AuM, we can assess if the results remain consistent for an absolute measure of popularity. The results of this regression are in Table 3.

**Table 3: Results of the ETF AuM test.**

Note: *$p$-value<0.05; **$p$-value<0.01; ***$p$-value<0.001. Robust standard deviations inside parentheses. All the regressions presented in the table include stock and time-fixed effects. Regressions that include the PBV ratio as a control variable have fewer observations due to the negative values being excluded. The time sample is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency and based on the S&P constituents during this period.

| Variables | β | Volatility |
|---|---|---|
| | (1) | (2) |
| Constant | 1.116200***<br>(0.015373) | 0.017378***<br>(0.000172) |
| ETF Ownership | 0.024340***<br>(0.004736) | 0.000312***<br>(5.31E-05) |
| Market Capitalization | -0.001014***<br>(0.000311) | -2.39E-05***<br>(3.48E-06) |
| Stock Price | 6.82E-05<br>(6.84E-05) | -5.90E-06***<br>(7.67E-07) |
| PBV Ratio | 0.000276*<br>(0.000163) | -1.30E-07<br>(1.83E-06) |
| Herfindahl-Hirschman | 2.51E-05**<br>(1.04E-05) | -8.96E-08<br>(1.17E-07) |
| Observations | 16832 | 16852 |
| Adj. R-Squared | 0.587 | 0.730 |
| Time FE | YES | YES |
| Stock FE | YES | YES |

The results indicate that, generally, there were no significant hidden effects from fluctuations in market capitalization that influenced the economic meaning related to the previous results. This is because when using ETF AuM instead of ETF ownership, the estimation once again reports a positive coefficient that is statistically significant for a 1% confidence level. Also, the remaining control variables evidenced a similar relation to the main results, except for the market capitalization variable in equation (1). In this case, the sign was reversed compared to Table 1. This is due to the high Pearson correlation between the ETF AuM and Market Capitalization variables (0.67). The results remain the same if the regression does not include Market Capitalization [equation (2)].

### *B.2. Random sample test*

As an additional robustness test for the previous conclusions, we implement the same methodology on a sample of 50 randomly picked stocks. The results are not reported but are available upon request. They indicate that the relationship between the main independent and dependent variables was maintained in both regressions, indicating that the previous results appeared robust.

**Table 4: Results of the random sample Test.**

Note: **p*-value<0.05; ***p*-value<0.01; ****p*-value<0.001. Robust standard deviations inside parentheses. All the regressions presented in the table include stock and time-fixed effects. Regressions that include the PBV ratio as a control variable have fewer observations due to the negative values being excluded. The time sample is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency and based on the S&P constituents during this period.

| **Variables** | **β** | **Volatility** |
|---|---|---|
| | **(1)** | **(2)** |
| **Constant** | 0.756471***<br>(0.065455) | 0.015721***<br>(0.001183) |
| **ETF Ownership** | 3.363349***<br>(1.023662) | 0.027675<br>(0.018521) |
| **Market Capitalization** | 0.000857*<br>(0.000857) | -3.00E-05***<br>(8.69E-06) |
| **Stock Price** | 0.000568*<br>(0.000321) | 4.27E-06<br>(5.81E-06) |
| **PBV Ratio** | 0.011597***<br>(0.002010) | 0.000103***<br>(3.64E-05) |
| **Herfindahl-Hirschman** | 7.21E-05**<br>(3.60E-05) | -5.01E-07<br>(6.51E-07) |
| **Observations** | 1107 | 1108 |
| **Adj. R-Squared** | 0.779 | 0.726 |
| **Time FE** | YES | YES |
| **Stock FE** | YES | YES |

### *B.3. Disentangling systematic risk from volatility*

Next, we address the suggestion from Hansson and Perers (2018) that systematic risk could be the driving force behind the rise in price volatility, the results of which can be found in Table 5.

The results show that beta is a determinant of volatility with a high level of statistical significance at a 1% level. The economic significance is, however, up for debate, as an increase in 0.01 points in beta leads to a small rise of 0.000707% in price volatility.

**Table 5: Results of the random sample Test.**

Note: *$p$-value<0.05; **$p$-value<0.01; ***$p$-value<0.001. Robust standard deviations inside parentheses. All the regressions presented in the table include stock and time-fixed effects. Regressions that include the PBV ratio as a control variable have fewer observations due to the negative values being excluded. The time sample is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency and based on the S&P constituents during this period.

| Variables | Volatility |
|---|---|
| | (1) |
| **Constant** | 0.015950*** (0.000287) |
| **ETF Ownership** | 0.011947** (0.004797) |
| **Market Capitalization** | -5.17E-06*** (1.38E-06) |
| **Stock Price** | -6.72E-06*** (7.52E-07) |
| **PBV Ratio** | -3.41E-07 (1.83E-06) |
| **Herfindahl-Hirschman** | -1.25E-07 (1.17E-07) |
| **Beta** | 0.000707*** (8.78E-05) |
| **Observations** | 16832 |
| **Adj. R-Squared** | 0.731 |
| **Time FE** | YES |
| **Stock FE** | YES |

More importantly, ETF Ownership remained statistically significant with the introduction of beta in the model and even had a higher loading than the first regression, indicating that the relation between ETF Ownership and price volatility is evident even when disentangling it from the effect explained by systematic risk. This estimation strengthens the idea that noise trading activity is, in fact, the main contributor to the positive relation between passive ETF Ownership and volatility. Also, it is important to mention that the regression had high explanatory power, with an Adjusted R squared of 0.731.

### *B.4. Other considerations*

In this subsection, we explore the potential endogeneity in the results—whether ETF ownership could directly influence the volatility and beta of underlying securities? Instead, it may be the case that ETFs inherently opt for stocks with higher beta or greater risk, raising some questions about the findings. However, the methodology employed offers inherent protection against this risk due to the passive nature of the sample. The sample exclusively comprises indexing-style ETFs, eliminating the active selection of securities within these indexes.

Moreover, unlike most indexes that use market capitalization rules for stock weighting, this empirical study utilizes the S&P 500 index as a filtering tool to select analyzed stocks. Consequently, there is no bias favoring higher market capitalization stocks, as all stocks are treated as equivalent sample observations.

Additionally, to address concerns regarding a potentially spurious link between stock market capitalization and volatility/beta, a market capitalization control variable was introduced in all the regressions executed.

Lastly, using fixed effects mitigates potential time effects arising from COVID-19 and the sovereign debt crisis. However, it is important to recognize that these possible effects may exist and that both circumstances warrant independent studies beyond this research's scope.

## V. Conclusions

Many researchers have argued that the mass migration to an indexing investing style may increase asset pair correlation and higher systematic risk in the underlying securities, lowering the benefits of asset diversification. Recently, this issue has become a focal point for several market regulators.

This paper, analyzing the S&P 500 index constituents from 2010 to 2020, contributes to this debate, providing evidence that passive ETF ownership catalyzes market instability by raising stock price volatility and beta. The paper's results align with Ben-David et al. (2014) and Hansson and Perers (2018). Furthermore, they are also consistent with Da and Shive (2018) and Sullivan and Xiong (2012), which concluded that the rise in popularity in ETFs is related to an increase in asset pair correlation and a rise in aggregate and individual beta within US equities.

Systemic risk combines several factors, such as the firm's market capitalization, the sensitivity of its equity returns to market shocks, and financial leverage (Engle et al., 2015). This empirical research confirms that ETFs have led to a new layer of systematic risk that can have systemic implications. This work contributes to the growing evidence that emphasizes the urgent need for an active approach from regulators to act and implement measures that minimize the issues this paper presents.

Some limitation factors limited the extension of this research. The number of ETFs considered for each stock for technical reasons was limited, excluding a relatively small amount of data. Further research on this topic might give a complete overview of other geographies besides the market, which the current literature lacks. Also, while we deepen the equity market analysis, the same detrimental effects are, in theory, applicable to other asset classes, which would be an interesting complement to this work.

In sum, ETFs offer retail investors simplified access to diversified portfolios. However, their benefits come with added costs to the overall stability of the equity market, suggesting the necessity of an active regulatory approach to mitigate such instability and safeguard investor interests.

**Funding:** This research was financed by the European Union and Portuguese public funds through the Science and Technology Foundation *(Fundação para a Ciência e a Tecnologia, I.P.)* and the European Social Funds (*Operational Program Norte 2020*) under project number UIDB/04105/2020 (CEF.UP).

**Conflicts of Interest:** The authors declare no conflict of interest.

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## APPENDIX

**Table A1: Individual variable summary statistics.**

| Variable | Description | Source |
|---|---|---|
| Beta | $Beta_{it}$ is the systematic risk of share i on date t, calculated according to the CAPM, each quarter, calculated over a 5-year moving period. | Thomson Reuters Datastream |
| Volatility | $Volatility_{it}$ is the standard deviation of the daily returns on share i recorded in the quarter ending on date t. | Thomson Reuters Datastream |
| ETF AuM | ETF $AuM_{it}$ is the sum of the amount held in stock i, on date t, by the ETFs with the largest positions in that stock, the number of ETFs in each stock being limited to a maximum of 100. | Thomson Reuters Datastream |
| ETF Ownership | ETF $Ownership_{it}$ is the percentage of the stock i held by ETFs, i.e. the ratio between ETF AuMit and the market capitalization of the stock i on date t. | Thomson Reuters Datastream |
| Market Capitalization | The Market $Capitalisation_{it}$ is the product between the share price of share i on date t and the number of shares listed on the same date. | Thomson Reuters Datastream |
| Stock Price | The stock $price_{it}$ is the market price of the stock i on date t. | Thomson Reuters Datastream |
| PBV Ratio | $PBV_{it}$ is the ratio between the market capitalization and the equity book value of stock i on date t. | Thomson Reuters Datastream |
| Herfindahl-Hirschman | $Herfindahl\text{-}Hirschman_{it}$ is the sum of the squares of the percentage (values from 0 to 100) of each ETF on the total ETFs AuM of the stock i on date t. | Thomson Reuters Datastream |

**Table A2: Individual variable summary statistics.**

| Variables | Mean | Median | Max | Min | Std Dev | Obs |
|---|---|---|---|---|---|---|
| Volatility | 0.02 | 0.01 | 0.11 | 0.00 | 0.01 | 17398 |
| Beta | 1.15 | 1.10 | 2.09 | 0.39 | 0,47 | 17377 |
| ETF Ownership | 0.04 | 0.04 | 0.22 | 0.00 | 0.02 | 17398 |
| ETF AuM | 1654 | 766 | 83324 | 0.34 | 3294 | 17398 |
| Herfindahl-Hirschman | 1350 | 1227 | 9490 | 483 | 643 | 17398 |
| Market Capitalization | 39287 | 17349 | 1392759 | 1211 | 68864 | 17398 |
| PBV Ratio | 3.82 | 2.67 | 13.27 | 0.86 | 3.22 | 16852 |
| Stock Price | 80.45 | 53.58 | 3983.60 | 1.67 | 125.51 | 17398 |

**Table A3: Correlation matrix.**

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| Volatility | (1) | 1.00 | 0.27 | -0.03 | -0.06 | -0.19 | -0.02 | -0.02 | 0.04 |
| Beta | (2) | 0.27 | 1.00 | -0.17 | -0.12 | -0.20 | -0.03 | -0.03 | 0.13 |
| ETF Ownership | (3) | -0.03 | -0.17 | 1.00 | 0.19 | 0.11 | 0.02 | 0.02 | -0.59 |
| ETF AuM | (4) | -0.06 | -0.12 | 0.19 | 1.00 | 0.67 | 0.05 | 0.05 | -0.16 |
| Market Capitalization | (5) | -0.19 | -0.20 | 0.11 | 0.67 | 1.00 | 0.08 | 0.08 | -0.06 |
| Stock Price | (6) | 0.01 | -0.05 | 0.12 | 0.26 | 0.25 | 1.00 | 0.07 | -0.12 |
| PBV Ratio | (7) | -0.02 | -0.03 | 0.02 | 0.05 | 0.08 | 0.07 | 1.00 | -0.02 |
| Herfindahl-Hirschman | (8) | 0.04 | 0.13 | -0.59 | -0.16 | -0.06 | -0.12 | -0.02 | 1.00 |