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

**Diogo Alexandre Guimarães Nunes**

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**Carlos Francisco Pereira Alves, PhD**

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# Abstract

Exchange-traded funds (ETFs) are recognized as a remarkable product of financial engineering, combining a simple and low-cost alternative for owning a diversified portfolio while allowing for high-frequency trading. Nevertheless, the massive growth that the ETF market has experienced has raised concerns among investors and regulators.

Due to their high liquidity and passive nature, indexed ETFs could act as a catalyst for a co-movement of stock prices and noise trading, ultimately impacting the underlying securities through the arbitrage channel.

To investigate this topic further, we explore whether an increase in ownership of passive exchange-traded funds affects US stocks through a decline in market stability. Using the S&P 500 index constituents, this study shows, theoretically and empirically, that passive ETF ownership is a key determinant of price volatility and systematic risk. Also, we find evidence that issuer concentration could act as an additional source of systematic risk.

As the ETF market growth is showing no signs of decelerating worldwide, mostly due to its attractiveness as an investment vehicle, this evidence conveys that market regulators are faced with a new challenge to prevent this modern financial instrument from negatively impacting stock market stability at the systemic level on the years to come.


**Keywords:** Exchange-Traded Funds, Passive Investing, Volatility, Systematic Risk

# Resumo

*Exchange-traded funds* (ETFs) são reconhecidos como o resultado de inovação financeira, combinando uma alternativa de baixo custo para adquirir um portfólio diversificado, com a possibilidade de negociação do instrumento a uma frequência elevada. No entanto, o elevado crescimento que este mercado tem registado, tem levantado preocupações em investidores e reguladores de mercado.

Devido à sua elevada liquidez e natureza passiva, os ETFs indexados têm potencial para serem catalisadores de co-movimentos em preços de ativos e de *noise trading*, o que poderá afetar os ativos subjacentes através do mecanismo de arbitragem.

Para investigar mais profundamente este tópico, colocamos a questão de se um aumento na percentagem de capital na posse de ETFs passivos está relacionado com um decréscimo na estabilidade de mercado. Usando os constituintes do índice S&P 500 como referência, os resultados mostram uma evidência sólida de que a percentagem de capital na posse de ETFs indexados é um fator determinante da volatilidade de preços e risco sistemático. Adicionalmente, encontramos indícios de que a concentração de emissores pode ser uma fonte adicional de risco sistemático.

Sendo expectável que o mercado de ETFs continue a sua trajetória ascendente, muito devido às suas características atrativas para os investidores, estas conclusões reforçam que os reguladores do mercado financeiro estão face a um novo desafio para impedir que este instrumento financeiro tenha impacto negativo na estabilidade do mercado acionista ao nível sistémico.

**Palavras-chave:** *Exchange-Traded Funds*, Investimento Passivo, Volatilidade, Risco Sistemático

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# 1. Introduction

*For the past five decades, a radical idea has been eating away at the soul of the global asset management industry: What if you can't beat the market? At least, not consistently. Then all the time, energy and — most important — money spent trying to do so is wasted. You'd be better off buying a so-called passive fund that holds all the stocks in an index like the S&P 500. This idea became an $11 trillion tidal wave of cash, bringing with it concerns about whether passive portfolios are distorting financial markets. What's unclear is whether this will improve investment tools or re-create the inefficiencies of the past.*

Bloomberg. November 24, 2021.

Passive investing is arguably one of the most impactful financial innovations of the last decades. Exchange-traded funds (ETFs) account for over 30% of all trading on the US stock market (Wigglesworth, 2017).

As a unique investment vehicle, it is easy to understand why ETFs highly appeal to investors. ETFs combine the diversification and simplicity benefits 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. Among these investors, noise traders or uninformed traders have a detrimental impact on 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. This mechanism is further detailed in the literature review section.

Simultaneously, there has been an extensive debate on whether the passive nature of this instrument is beneficial for the market, which the increasing herding tendency has accentuated in the ETF 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 and O'Hara, 2018). By promoting index investing, passive ETFs could catalyse a rise in asset pair correlation among index constituents and lead 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 until 2026, ETFs assets under management (AuM) probably will double and reach a total of 20 trillion dollars in the 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 (Pagano et al., 2019; McNulty, 2017; Winestock, 2017; Bhattacharya and O'Hara, 2020).

The currently available literature on ETFs is still in its early days, considering that the most significant share of the upswing in the ETF market has occurred during the last two decades. Nevertheless, this analysis is mainly related to the research from Ben-David et al. (2014) and Hansson and Perers (2018), which investigated the impact of ETF ownership on individual stock volatility in the US equity market. However, the conclusions from these authors were opposite to another empirical research from Heinen (2019), applied to European stocks, which provided evidence that ETF ownership was negatively related to stock volatility.

Also, Da and Shive (2018) and Sullivan et al. (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 empirical research, 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 choose to study the US perspective due to having the most saturated ETF market and, therefore, being the most appropriate market to access and quantify any potential detrimental effects, reaching conclusions that are relevant to markets worldwide as they are expected to follow the herding tendency in the upcoming years (Investment Company Institute, 2021; PwC, 2021). We use the S&P 500 index constituents and the passive plain-vanilla ETFs that hold these stocks, from 2010 to 2020, as the primary sample.

To our knowledge, this segment has not been further explored in the previous research. Thus, it complements the current evidence on this topic, which has included 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 thesis is as follows. Section 2 presents the relevant literature on this topic, starting by laying the foundations that led to the rise of ETFs as a form of fund investing. Then, we bring up the evidence on the active versus passive investing discussion as an investment style choice. Following this, an extensive review of ETFs' unique characteristics and the trading mechanism is provided, followed by a discussion of the current empirical research on the effects of ETFs on the financial markets. Finally, we describe some important events related to this topic and discuss the main tools available to market regulators to face such circumstances.

To start our empirical analysis, section 3 develops the hypotheses that this thesis aims to explore and their foundation in the current literature. Then, section 4 is where the data and methodology used are described, section 5 presents the empirical results, and section 6 closes the research by considering the main implications for the relevant findings.

# 2. Literature Review

## 2.1. The Rise of Passing Investing

Vanguard's founder, Jack Boggle, introduced the world to the first index fund available to retail investors. Fast-forwarding to today, this financial invention 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 exchange-traded funds, which track a specific index by either replicating fully the index, known as full replication or by holding a sample of the stocks that include it, referred to as partial replication (Watkins, 2022).

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 important market tracking indexes, such as the Nasdaq Composite (1971) and the S&P 500 (1957) in the US, the FTSE 100 (1984) in the United Kingdom, the STOXX 600 (1998) in Europe, among many others.

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 in the market they focused on, putting into question the managers' ability to effectively choose winners in an industry heavily reliant on substantial management fees.

Following these findings, Jack Boggle, considered by many the father of passive investing, introduced to the world in 1976 a new product of financial engineering with the creation of the Vanguard 500 fund, which tracked the S&P 500 index, marking the creation of the first retail index fund, which 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.

## 2.2. Institutional Funds

Institutional funds invest on behalf of other investors through vehicles such as mutual funds, ETFs, and close-ended funds. This segment has played a growing role in the US financial system, illustrating that institutional investors more and more dominate the US market.

According to the ICI report (Investment Company Institute, 2021), while in 2000, assets under management of these funds represented $7,2 trillion, at the end of 2020, US funds managed around $30 trillion in assets and invested on behalf of more than 105 million US retail investors. While already 23% of assets within US households are invested in funds in 2020, compared to only 3% in 2000, this share is expected to keep increasing, partly explained by the aging of the US population and the reliance on individual retirement accounts (IRAs) and defined contribution plans (DCs) in these funds.

Indexed funds, including mutual funds and ETFs, are on the frontline of this trend and, in the US, has grown into a $9.9 trillion industry in 2020 (Investment Company Institute, 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 overthrown active US-equity funds assets under management, standing in 2021 at 54% of the total equity mutual fund market in the US (Bloomberg Intelligence, 2021).

In their research, Sullivan et al. (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 active funds share, 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.

## 2.3. Passive versus Active Debate

The ongoing debate between the pros and cons of active versus passive investing has intensified over recent years.

Two simple ideas stand behind these investment strategies. Firstly, 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 that is superior to the management fee. On the opposite end, passive investors simply want to take part in the market returns by buying and holding an index fund, which has considerably lower fees due to its passive nature.

The overwhelming evidence is based on the rising popularity of passive investing. At its core, passive investment vehicles benefit from supporting a substantial share of the academic literature. This is because they have important 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 French (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 in a consistent basis (Stambaugh, 2014).

To further strengthen this argument, the data on stock market returns available also supports the passive investing thesis. A French (2008) study concluded that a passive investor would, on average and under reasonable assumptions, achieve a return higher by 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, in which 85% of active managers underperformed its correspondent small-cap index. In the same research, when extended to 15 years, around 90% of active managers underperformed the market benchmark in three geographies: the US, the international, and the 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 that it is 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 preposition that, under conditions of market efficiency, all stocks have implicit in their price all available information at any given time, and no single 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 amount of fees charged. In practice, this idea was aligned 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.

Alves (2005) developed an extensive literature review on this topic. One of the most relevant findings presented was the one from Treynor and Mazuy (1966), concluding that only 1 in a 57-fund sample demonstrated significant timing abilities. Furthermore, similar results were also reached, using different funds and time samples, in Cumby and Glen (1990), Henriksson and Merton (1981), Connor and Korajczyk (1991), and Fabozzi and Francis (1979), 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. Alves (2014) provides evidence of seasonality of European equity funds performance. Finally, additional evidence was provided by Carhart (1997) that did not support the existence of stock-picking skills from mutual funds portfolio managers.

However, not all findings hurt active investors' prospects. A recent study concluded that active funds managed to outperform the market if one included only the bearish periods between 2005 and 2020 (Molander and van Loo, 2020). This conclusion supports the idea that there is possibly an added benefit for active investing in bear markets 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.

Evidence gives a clear edge to passive investing under normal market conditions but highlights potential benefits for fund managers' expertise during market throughs. This seems to be in favour of a hybrid approach in which investors change their capital allocation mix of active versus passive, according to the individual investor profile and changes in macroeconomic conditions (Hunt, 2022).

A final consideration for ESG investing (Environmental, Social, and Governance) is also a point in favour of active investors. Even if ESG-themed indexes have been increasing in popularity, most of the capital in passive investing is still concentrated in broad-based indexes such as the S&P 500. This could delay the transition to ethical investing due to the nature of indexes, which will inevitably bring additional funds to institutions that would otherwise suffer from some reluctance from investors due to the nature of their business (Potter, 2021).

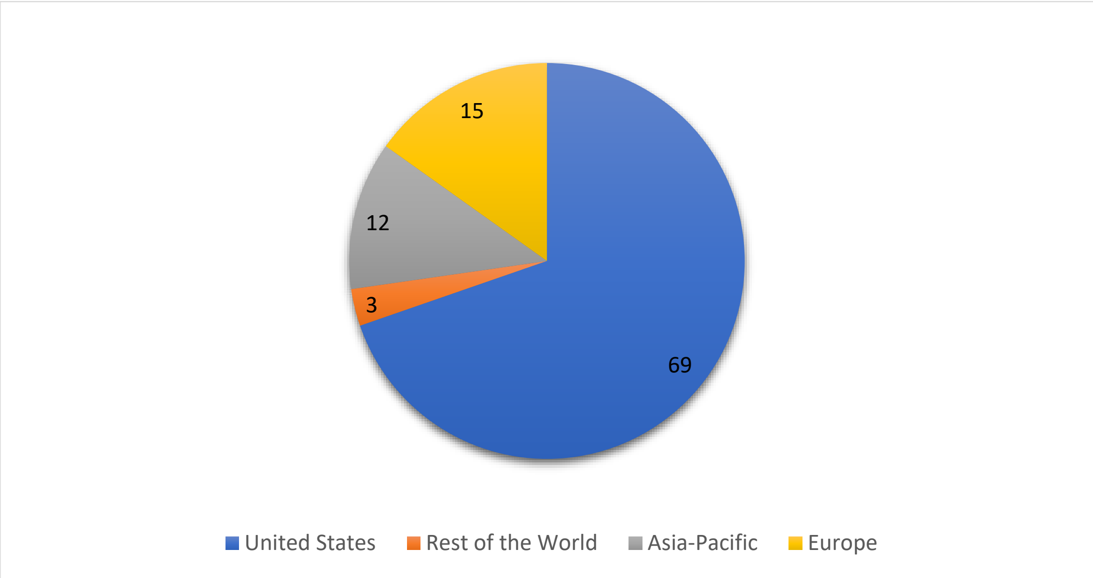
While passive investing inflows do not seem to be slowing down anytime soon, its increasing importance within the financial industry has raised concerns related to the consequences that this new reality might imply on the well-functioning and stability of the financial markets.

## 2.4. Background on Exchange-Traded Funds

Exchange-traded funds have led to the rise in passive investing. While mutual funds introduced the idea of indexing, exchange-traded funds quickly surged as the most popular passive investment vehicle in the US and are set to overthrow mutual funds on a global scale (Johnson, 2021).

In 1993, the S&P Depository Receipt (SPDR), known as Spider, marked the creation of 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). To illustrate this, according to ICI, since 2000, total assets under ETFs in the US increased from $66 billion to $5,4 trillion in 2020, with the number of ETFs going from 80 to 2296 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 (Investment Company Institute, 2021).

*Figure 1:Percentage of Total Net ETF Assets 2020*




*Source: Own elaboration through data retrieved from The Investment Company Institute and ETFGI.*

By definition, exchange-traded funds are an investment vehicle used to hold a specific basket of financial securities, including equities, bonds, commodities, currencies, or even hybrids (Kolchin, 2018). 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 is focused on the detrimental effects of indexing, we will refer to the term ETFs as solely indexed ETFs during the remaining of this empirical research, which considers over 95% of the ETF market (Marquit, 2022).

In particular, passive ETFs, like indexed mutual funds, attempt to replicate the performance of a particular index. Nevertheless, the main differentiating factor that makes ETFs such an attractive financial instrument for investors is the way they trade. Whereas mutual funds trade outside of a stock exchange and all orders are executed once a day at the same price, ETFs trade intraday on a regular 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, 2012).[1]

To illustrate this idea, 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 it is the case of the popular Vanguard S&P 500 ETF, VOO (Picker, 2021).

Even though ETFs are traded on a regular exchange, only authorized participants (APs), usually large-broker dealers (Hill et al., 2015), can participate in the primary market, where the ETF manager issues a share and the AP delivers the basket 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. In their research, Israeli et al. (2017) explain that if an ETF trades above its NAV, APs will choose to deliver the basket

[1] Redeeming in kind, means that, instead of using cash, some investors can acquire ETF shares by exchanging them for the underlying securities.

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 price (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). Following this process, 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, which are chosen 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.

Exchange-traded funds 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 and O'Hara, 2020).

## 2.5. Exchange-Traded Funds and Market Instability

Even though exchange-traded funds were thought to be an ideal financial vehicle for long-term buy-and-hold investors, the evidence shows significant deviance from this initial idea (Ben-David et al., 2014). In fact, ETF trading now accounts for over one-third of all trading volume in the US market, attracting substantial short-term high-frequency investors. To further illustrate this tendency, the most active funds often end up trading daily at a volume higher than their market capitalization (Petajisto, 2017). As ETFs' popularity rises and their liquidity increases, this financial instrument gains more and more attention from noise traders.

Israeli et al. (2017) describe noise or uninformed traders as investors who would be better off not trading since they tend to negotiate for non-fundamental motives. The reason why noise traders exist is a widely discussed theme within financial academics. For example, Black (1986) argues that the reasons behind noise trading could revolve around a false sense of information or even that noise traders get utility from trading, or in other words, they enjoy trading.

A study by Ben-David et al. (2014) determined that, on average, ETFs trade at a bid-ask spread lower by 20 basis points compared to the equivalent portfolio of underlying stocks. Petajisto (2017) argues that this phenomenon is partly explained by the fact that market makers include a larger spread on individual stocks to account for adverse selection issues.[2] Intuitively, in an ETF, this individual stock information is less impactful in the valuation and, therefore, does not require such adjustments in the spread.

Broman (2016) and Krause et al. (2014) show evidence that suggests that these characteristics attract short-horizon noise traders since they benefit from shifting to imposing their views on the market through ETFs instead of on their underlying securities, to benefit from lower transaction costs and higher liquidity. However, over time, this migration from the underlying securities to ETFs can cause a drop in liquidity on the underlying stocks, creating a disincentive for informed traders to expend resources on researching individual securities, leading to lower price efficiency (Israeli et al., 2017). Additionally, Bradley (2010) shows that ETFs undermine the traditional price discovery process on the underlying securities and can be a damaging source of systemic risk.

In addition, when ETF prices differ from the net asset value (NAV), it can create a significant price pressure that is transferred to the underlying securities through the arbitrage mechanism, through the action of the APs[3], leading to an increase in trading for non-informational motives. Ben-David et al. (2014) argue that ETFs whose prices deviate from the NAV sooner or later tend to revert to fundamentals when other sources of liquidity materialize, causing price instability throughout the process.

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[2] Adverse selection refers to the fact that some investors possess confidential information that is not available to the market, which puts the regular investor at a disadvantage.

[3] This mechanism is explained more in detail in the previous subsection.

Petajisto (2017) empirically confirms that ETF prices can deviate significantly from their NAV. In fact, the author found that this difference fluctuated by about 200 basis points, despite the arbitrage activity that takes place in the market. The author also adds that transaction costs imposed on the arbitrageurs can be detrimental to the price efficiency since they can deter the authorized participants from attempting to profit from the mispricing.

According to Ben-David et al. (2014), this arbitrage trading activity accounts for over 50% of the daily volume of the S&P 500 SPDR ETF. It is the most impactful channel of noise propagation from the ETFs to the underlying securities. In his empirical research, Malamud (2015) proves that the creation/redemption of ETF shares through the arbitrage channel serves as a shock propagation channel that can cause persistent price dislocations. This idea is in accordance with Stein (1987), which alerted to the consequences of speculators in price inefficiency and welfare reduction.

Furthermore, Israeli et al. (2017) adds that as ETF ownership increases, the correspondent securities will have more and more shares that are in possession of the APs and, therefore, even though they can be traded in a basket through ETFs, they are no longer available for trading at an individual level, resulting in a drop in stock level liquidity.

Bhattacharya and O'Hara (2018) argue that the indexing nature of ETFs could create market fragility and raise the systemic risk. The intuition for this can be understood as follows. Whereas a stock price represents the value of a single company and hence, incorporates more distinctively any information that relates to that asset, in passive ETFs, this process has a higher level of complexity since an index includes several securities. In practice, idiosyncratic shocks pertinent to one asset can affect the price of another non-correlated asset through the ETF pricing channel, leading to an upswing in correlation among assets that can generate market instability through increases in systematic risk.

In the long term, Grossman and Stiglitz (1976) debate that the market is a self-correcting mechanism and defend that this could be simply a cyclical issue. Their view is that if passive investing rises to a point where prices are not incorporating information efficiently, active investors will rise as the benefits for additional research increase, creating a natural cycle between inflows to active and passive investment strategies.

A comprehensive study on the impact of ETFs on the liquidity of underlying securities is provided by Israeli et al. (2017). In this research, the authors concluded that, in the period 2000 to 2014, ETF ownership was positively related to higher trading costs, lower benefits from information acquisition, lower response coefficient in future earnings, and a decline in the number of analysts covering the firm. These results, at first sight, contradict the conclusions of Glosten et al. (2015), which reported in their study an increase in information efficiency as ETF ownership increased. However, the differentiating factor resides in that Israeli et al. (2017) focused on the future impact of ETF ownership on the underlying security. In contrast, Glosten et al. (2015) studied the contemporary effects of a shift in ETF ownership.

In the same research, Glosten et al. (2015) documented that, in a market with a weak information environment, ETF activity resulted in higher information efficiency, which did not occur in markets that are widely covered. This suggests that ETFs might have informational benefits in markets that are hard to access and lack research coverage. In contrast, this positive effect might be negligible in well-developed financial markets, as in the US market case.

Ben-David et al. (2014) concluded that ETF ownership in the US market was a positive determinant of the underlying securities volatility from 2000 to 2012. Furthermore, in the same research, the author found evidence that the increase in volatility was accompanied by a decrease in price efficiency, measured by a lower variance ratio and a higher mean-reversion tendency of prices. This addressed a hypothesis raised by Andrei and Hasler (2015), which suggested that a symptom of efficient markets was the increase in price volatility due to a stronger unison reaction from investors to new information.

Hansson and Perers (2018) built upon the paper of Ben-David et al. (2014) by applying the same methodology to different samples of securities in the US equity market and, ultimately, were able to replicate their findings. In addition, the authors further analyzed whether this effect varied across different industry-type ETFs and concluded that, while industry and other type ETFs were related to higher volatility, core-type ETFs were associated with lowering stock price volatility.

Later, Heinen (2020) extended the research by using a different methodology applied to the European stock market. The author reached the opposite conclusion, indicating that ETF ownership was negatively related to stock volatility. These findings were partly explained by the relatively small presence of the ETF market in Europe compared to the US market. Additionally, Ivanov and Lenkey (2017) focused on leveraged ETFs, as opposed to plain-vanilla ETFs, and indicated that ETF ownership was an insignificant variable in explaining price volatility.

Several studies, such as the ones by Da and Shive (2018) and Sullivan et al. (2012), confirmed the tendency for potential harmful effects of the increase of ETF investing in a well-functioning financial market. Da and Shive (2018) concluded that increased ETF ownership led to more co-movement between individual asset pairs and pairwise correlation. This effect was stronger in small and illiquid stocks. Sullivan et al. (2012) showed evidence that ETF ownership had significant explanatory power in the historical convergence in individual stock betas and the rise of systematic risk in the equity market.

On the opposite side, Sassuoni (2017) found that the relation between ETF ownership and pairwise stock correlation was negative when applied to S&P 500 index constituents.

## 2.6. Notable Events and Regulatory Response

Bhattacharya and O'Hara (2020) write an extensive review on the main tools that market regulators have in their arsenal to respond to issues that the previous section highlights, which this section is based on. The authors also describe several events in which ETFs were shown to amplify the adverse effects felt on the markets during periods of extreme instability.

One notable event took place on August 24, 2015, when the US market experienced a surge of tremendous volatility. Notably, this surge in instability was increasingly evident in many of the largest ETFs in the US market. This event triggered significant price changes in these ETFs, many of which triggered trading halts, meaning that investors could temporarily not trade these securities. The reasoning behind this measure is that disallowing investors to trade these securities in unstable environments incentivizes serenity in the trading activity. However, the evidence on the effectiveness of this measure is conflicting as it has proved to exacerbate volatility in these situations (Bhattacharya and O'Hara, 2020; Bradley and Litan, 2010).

A different approach by Bhattacharya and O'Hara (2020) suggests focusing on the quality of the underlying assets since, as the authors explain, the quality in ETF trading reflects the issues in quality in their underlying securities. This is because the lack of quality in the underlying securities can difficult the rebalancing process from the arbitrage channel. Several empirical analyses have strengthened this idea by showing that illiquid assets tend to experience higher detrimental effects from ETF ownership (Da and Shive, 2018). Following this logic, the US Security Exchange Commission (SEC) recently disallowed the creation of ETFs based on cryptocurrency, arguing for the lack of maturity in this market.

Bradley and Litan (2010) show evidence that many small illiquid companies choose not to go public through an initial public offering partly because these companies do not wish to be included in indexed securities. The author argues that ETFs can effectively set the price of these low market capitalization companies. Besides emphasizing the importance of transparency and liquidity within the underlying securities, Bradley and Litan (2020) advocate for mitigating this issue by either enforcing a minimum liquidity threshold in securities included in ETFs or implementing a consent rule that ETFs need to obtain from these companies to have them in an ETF.

# 3. Hypothesis Development

This empirical research is focused on the US stock market, from the start of 2010 to the beginning of 2020, particularly on stocks that constituted the S&P 500 index throughout the time sample. Considering the literature review presented in the previous sections, we believe sufficient empirical and theoretical foundations support testing the following two hypotheses.

*H1: Passive ETFs increase systematic risk at the stock level in the S&P 500 index.*

Bhattacharya and O'Hara (2018) argue that passive ETFs is a propeller for inducing systemic risk since they incentivize 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 for an event to have a snowball effect with systemic implications.

The evidence indicates that an increase in the equity market free float concentration in passive ETFs should lead to higher systematic risk, measured by the stock's correlation to the market or beta, which would be in line with Sullivan et al. (2012).

*H2: Passive ETFs increase stock price volatility at the stock level in the S&P 500 index.*

This aspires to complement the research paper by Ben-David et al. (2014), which concluded that ETF ownership was positively related to individual stock volatility between 2000 and 2012, considering all US-based equity ETFs. On the other hand, if the hypothesis is confirmed, it would clash with the results from Heinen (2020), applied to the STOXX 600 in the European stock market. It is important to state that the previously mentioned authors considered both active and passive ETFs, which differs from this methodology.

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 bigger share of the equity market free float, we expect that this should have a destabilizing effect on the underlying securities, leading to an increase in individual stock volatility.

# 4. Data and Methodology

The period and frequency analyzed consist of a 10-year time spawn from the first quarter of 2010 to the first quarter of 2020, on a quarterly frequency. To ensure congruency among the different variables, all the data collected for this research was retrieved from the Thomson Reuters DataStream.

The time period is not being extended to the most recent data available because we do not wish to consider the effect that the Covid-19 pandemic had on the US equity market. However, future research might choose to make this period a focus. Despite this, while this period is not considered for the main regressions, we include an extension to the last quarter of 2021, when the last full set of quarterly data was available at the time of writing this thesis.[4]

In this empirical research, we use panel data, as opposed to time-series or cross-sectional data, since this research aims to analyze the evolution of different variables related to individual stocks throughout the time, which comprise the entity and time variable for the regression, respectively.

To analyse a panel dataset, there were three main alternatives to choose from, pooled ordinary least square (POLS), fixed effects model (FEM), and random effects model (REM). However, at a starting point, it was already clear that the POLS model would not be adequate since it is a model fit only for data sets where all entities behave similarly, which does not hold for stocks from a broad index, such as the S&P 500. Nonetheless, we run the Breusch-Pagan test through our data to confirm this, asserting the following hypotheses.

*H0: POLS is more appropriate than FEM and REM*

*H1: POLS is not more appropriate than FEM and REM.*

As expected, the test returns a p-value of 0, which means that the null hypothesis is rejected, and we must choose between FEM and REM for this data set. Finally, by testing the hypotheses below, we implement the Hausman test to assess whether REM is the most appropriate model to use in this case.

*H0: REM is more appropriate than FEM.*

*H1: REM is not more appropriate than FEM.*

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[4] The results can be found in section 5.2.

The result from the Hausman test is once again a p-value of 0, meaning that the null hypothesis is, once again, rejected and, hence, a fixed-effects model is the most adequate to use for this data set.

The first step in the data collection process was to define the filtering criteria from which the stocks analyzed would be retrieved. An alternative method, chosen by Ben-David et al. (2014), would be to limit the ETFs to those originating from the US instead of constraining the stocks' origin. However, to fulfil the goals of this research, it is more adequate to consider ETFs as a whole, 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 by using the S&P 500 index constituents, whereas ETF origin is not restrained.

Besides 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 sampling the stocks that belong to this index.

By choosing to focus on the S&P 500 index constituents, we mostly move past issues such as including low liquidity and low ETF coverage stocks as a substantial amount of our sample, which could dilute the unfavourable 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 larger broad indexes that include significantly more securities (Hansson and 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 period chosen.

## 4.1. Passive ETF Ownership

We had two choices for the main independent variable, representing the increased popularity of ETFs. The first option, as selected by previous research (Heinen, 2020; Ben-David et al., 2014), was to use the percentage of total assets under management of all ETFs on a specific stock, which is referred to as ETF ownership. However, the drawback of this method is that this measure can artificially inflate the ETF market growth in the case of a decrease in total free float, which increases the ETF ownership measure without any absolute increase in popularity of the ETF market.

The alternative method is to directly use the total assets under the management of ETFs under a certain stock. While the previous issue is no longer a concern under this approach, it is possible that the impact of an increase in total ETF AuM could have its effect diluted, at the stock level, if it is accompanied by a substantial increase in total equity-free float, which this method would not capture.

For this reason, while our main conclusions are based on passive ETF ownership as the main independent variable, we include the regression using passive ETF AuM, as the independent variable, in Section 5.2, to ensure that the conclusions are robust for both a relative and absolute surge in passive ETF assets holding a certain stock.

First, through the Thomson Reuters data stream, 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.

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 (Investment Company Institute, 2021). Furthermore, stocks with the lowest Herfindahl-Hirschman Index (HHI)[5], a market concentration index, 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

[5] More details on this variable are available on section 4.4.

for the more susceptible bottom three stocks, we leave out around 1%. From this, we can infer that, on average, during the whole period analyzed, we expect to have left out below 1% 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.

Following this, 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 the Thomson Reuters data stream and discard any actively managed ETFs. In theory, we expect that this alteration from the previous research should yield more robust results since actively managed ETFs do not share some 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 ETFs AuM for stock i at time t, we add the assets for the top 100 ETFs in 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.

## 4.2. Volatility

To obtain stock volatility, we first collected the daily closing prices for each stock for the 10-year period through the Thomson Reuters data stream. Following this process, we calculate the daily returns using the following equation: n and n-1 stand for the consecutive trading days.

*Equation 3: Return*

$$Return_{i,n} = \left(\frac{Price_{i,n}}{Price_{i,n-1}}\right) - 1$$

Using those returns, we then compute quarterly volatility using the regular standard deviation formula, which includes all the N returns available for the trading days in period t, which are on a quarterly frequency, in this research. In the equation, N represents the total number of returns during the trading days available for a specific quarter.

*Equation 4: Volatility*

$$Volatility_{i,t} = \sqrt{\frac{(\sum Return_{i,n} - \overline{Return_{i,t}})}{N}}$$

## 4.3. Beta

Systematic risk is quantified as the correlation of an asset with the market, which is commonly measured through its beta value, used in the capital asset pricing model (CAPM).

The beta was retrieved each quarter using the Thomson Reuters data stream for each stock. In particular, the available beta is a historical beta calculated with a rolling 5-year period of monthly frequency logarithmic changes, updated quarterly.

## 4.4. Control Variables

Following the calculation of the main dependent and independent variables for this research, we then introduce several control variables to isolate the effect that we seek 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 the Thomson Reuters data stream.

The link between liquidity and volatility is widely documented in the literature (Atkins and Dyl, 1997). Intuitively, a highly liquid stock should attract noise traders to a higher degree (Hansson and Perers, 2018). A common way to address this link is by using stock price as a control variable since, 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 relation between industry and price instability. Growth companies tend to be more volatile than established ones (Perez-Quiros and Timmermann, 2000). In this research, this relation is considered by introducing the price-to-book value, which is calculated using book value and market capitalization data. To assure that every variable value has a relevant economic meaning, we eliminate the values for this variable in which the ratio is negative.[6]

*Equation 5: Price to Book Value*

$$Price\ to\ Book\ Value_{i,t} = \frac{Market\ Capitalization_{i,t}}{Book\ Value_{i,t}}$$

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 important issuers that often depend on only a few authorized participants, which could act as an additional source of risk. However, intuitively, we argue theoretically that the opposite effect could also be in 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 both these effects, we introduce to the model the Herfindahl-Hirschman index (HHI) 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 and O'Hara, 2020). Thus, besides serving as a control variable, we also aim to shed some light on this relation.

To calculate the HHI for each stock, we first take the percentage of each 100 ETFs on the total ETFs AuM. In the equation below, n stands for the top 100 ETFs by holdings on the stock i, and S denotes the percentages, expressed as a whole number, calculated as explained before for each 100 ETFs.

*Equation 6: HHI*

$$HHI_{i,t} = S_1^2 + S_2^2 + \dots S_n^2$$

[6] The results were similar in economic meaning and statistical significance when including negative PBV values.

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 stock size and risk (Perez-Quiros and Timmermann, 2000).

In addition, Hansson and Perers (2018) theorize that the increase in volatility could result in an increase in systematic risk, as opposed to a separate effect. To further analyze this, we include the variable beta in the second hypothesis as an additional control variable, whose results are synthetized in section 5.2. The goal is to differentiate the impact on stock price volatility related to noise traders from the one attributed to systematic risk.

## 4.5. Data Summary

The sample analyzed in this empirical research goes from the beginning of 2010 to the first quarter of 2020, resulting in ten years at a quarterly frequency. In theory, this would result in a total of 20500 observations, corresponding to the 41 different periods for the 500 companies that take part in the S&P 500 index during the ten years. However, some companies that belong to the S&P 500 index have different share classes, which causes the S&P 500 to range from a minimum of 500 stocks to a maximum of 505 stocks during this period, resulting in a sample of 20602 total observations.

Nonetheless, the Thomson Reuters data stream does not include data for companies that, within this period, were, at some point, either acquired, merged, or got delisted. Afterward, we end up with a total sample of 17398 effective observations. We also compute the average data for the main dependent and independent variables using a time-series data set.

The tables with the individual and aggregate summary statistics can be found below.

*Table 1: Individual Variable Summary Statistics*

| Variables | Mean | Median | Max | Min | Std Dev | Obs |
|---|---|---|---|---|---|---|
| **Volatility** | 0.016367 | 0.014141 | 0.108097 | 0.004067 | 0.008639 | 17398 |
| **Beta** | 1.154766 | 1.104000 | 34.98350 | 9.626800 | 0.617812 | 17377 |
| **ETF Ownership** | 0.041093 | 0.039124 | 0.215167 | 2.56E-05 | 0.022525 | 17398 |
| **ETF AuM** | 1653.630 | 765.7320 | 83323.68 | 0.343811 | 3293.704 | 17398 |
| **Herfindahl-Hirschman** | 1349.782 | 1226.543 | 9490.449 | 483.4530 | 642.9067 | 17398 |
| **Market Capitalization** | 39287.18 | 17349.24 | 1392759. | 1211.460 | 68864.01 | 17398 |
| **PBV Ratio** | 5.527151 | 2.673232 | 802.1855 | 0.165310 | 23.70413 | 16852 |
| **Stock Price** | 80.45295 | 53.57500 | 3983.600 | 1.671900 | 125.5147 | 17398 |

*Table 2: Correlation Matrix*

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| **Volatility** | **(1)** | 1.00 | 0.27 | -0.03 | -0.06 | -0.09 | 0.01 | -0.02 | 0.04 |
| **Beta** | **(2)** | 0.27 | 1.00 | -0.17 | -0.12 | -0.12 | -0.05 | -0.03 | 0.13 |
| **ETF Ownership** | **(3)** | -0.03 | -0.17 | 1.00 | 0.19 | 0.02 | 0.12 | 0.02 | -0.59 |
| **ETF AuM** | **(4)** | -0.06 | -0.12 | 0.19 | 1.00 | 0.94 | 0.26 | 0.05 | -0.16 |
| **Market Capitalization** | **(5)** | -0.09 | -0.12 | 0.02 | 0.94 | 1.00 | 0.25 | 0.05 | -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 | 0.05 | 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 |

*Table 3: Aggregate Variable Summary Statistics*

| Variables | Mean | Median | Max | Min | Std Dev | Obs |
|---|---|---|---|---|---|---|
| **Average Volatility** | 0.016310 | 0.015100 | 0.046400 | 0.011000 | 0.005864 | 41 |
| **Average Beta** | 1.159027 | 1.148900 | 1.293300 | 1.079100 | 0.052108 | 41 |
| **Average ETF Ownership** | 0.039727 | 0.037100 | 0.067200 | 0.019400 | 0.014690 | 41 |
| **Average ETF AuM** | 1574.069 | 1488.140 | 3510.980 | 458.3500 | 867.0601 | 41 |

# 5. Results

## 5.1. Fixed-Effects Model Results

The results for the main hypotheses are presented in this subsection. To assess the impact of introducing each control variable, we present the results in a cascade form, including each control variable at one time first and the results from excluding all control variables. The first value for each variable represents the loadings followed by the robust standard deviations, which are stated in parentheses. In table 1, the results from the fixed-effect model regression, using beta as the main dependent variable, are reported, corresponding to the first hypothesis of this empirical research.

*Table 4: Results for the First Hypothesis*

| **Variables (Beta)** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| **Constant** | 1.063948*** | 1.098431*** | 1.054540*** | 1.064077*** | 1.080370*** | 1.121008*** |
| | (0.024215) | (0.019145) | (0.023739) | (0.024031) | (0.023859) | (0.017431) |
| **ETF Ownership** | 0.971700** | 0.928566** | 1.116235*** | 0.971359** | 0.800946* | 0.821177** |
| | (0.428624) | (0.428281) | (0.421233) | (0.428540) | (0.426581) | (0.417657) |
| **Market Capitalization** | 0.000481*** | 0.000478*** | 0.000420*** | 0.000484*** | | |
| | (0.000123) | (0.000123) | (0.000121) | (0.000108) | | |
| **Stock Price** | 2.93E-06 | 6.16E-06 | 7.81E-05 | | 0.000129** | |
| | (6.72E-05) | (6.72E-05) | (6.43E-05) | | (5.90E-05) | |
| **PBV Ratio** | 0.000275* | 0.000286* | | 0.000275* | 0.000292* | |
| | (0.000163) | (0.000163) | | (0.000163) | (0.000163) | |
| **Herfindahl-** | 2.43E-05** | | 2.34E-05** | 2.43E-05** | 2.39E-05** | |
| **Hirschman** | (1.04E-05) | | (1.02E-05) | (1.04E-05) | (1.04E-05) | |
| **Observations** | 16832 | 16832 | 17377 | 16832 | 16832 | 17377 |
| **R-Squared** | 0.601301 | 0.601168 | 0.602413 | 0.601301 | 0.600926 | 0.601752 |
| **Time FE** | YES | YES | YES | YES | YES | YES |
| **Stock FE** | YES | YES | YES | YES | YES | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include 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.

Overall, the results are strongly favouring the confirmation of the first hypothesis. We find a positive and significant relation between ETF ownership and beta in all six tests. Also, this relation is of economic relevance, with an increase of 0.009717 in beta for every 1% increase in ETF ownership. The loading was the highest for regression (3), where the price-to-book value is excluded. In addition, the beta variable is significant at a 5% level in all regressions, except for regression (5), in which ETF ownership is only statistically significant at a 10% level when excluding market capitalization. Moreover, all tests show a considerable explanation power with an R-squared consistently over 0.6.

As for the control variables, we note that market capitalization is estimated to be statistically significant at a 1% level for all combinations and has a positive loading consistently. However, this was against our expectations since high market capitalization companies are usually more stable and predictable businesses, whereas smaller businesses tend to be more volatile (Perez-Quiros and Timmermann, 2000).

We find that 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's (2020) proposition, which argued that issuer concentration could act as a source of instability.

Contrary to the previous variables, the stock price and price-to-book value ratio both proved to be non-statistically significant in this regression, except for regression (5), in which the stock price is statistically significant for a 5% confidence level. This could be due to the relationship that these two variables share since a higher stock price generally leads to a higher market capitalization when the number of shares available is unchanged.

Next, an overview of the results for the second hypothesis is displayed in Table 5, where price volatility is used as the dependent variable, applying the same set of controls.

*Table 5: Results for the Second Hypothesis*

| Variables (Volatility) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Constant** | 0.016745*** | 0.016602*** | 0.016759*** | 0.016447*** | 0.016580*** | 0.015676*** |
| | (0.000271) | (0.000214) | (0.000270) | (0.000270) | (0.000267) | (0.000199) |
| **ETF Ownership** | 0.011604** | 0.011788** | 0.010658** | 0.012392** | 0.013320*** | 0.016805*** |
| | (0.004804) | (0.004799) | (0.004784) | (0.004814) | (0.004780) | (0.016805) |
| **Market Capitalization** | -4.84E-06*** | -4.82E-06*** | -5.42E-06*** | -1.08E-05*** | | |
| | (1.38E-06) | (1.38E-06) | (1.37E-06) | (1.21E-06) | | |
| **Stock Price** | -6.74E-06*** | -6.75E-06*** | -6.19E-06*** | | -8.01E-06*** | |
| | (7.53E-07) | (7.53E-07) | (7.30E-07) | | (6.61E-07) | |
| **PBV Ratio** | -1.37E-07 | -1.83E-07 | | -5.50E-07 | -3.10E-07 | |
| | (1.83E-06) | (1.83E-06) | | (1.84E-06) | (1.83E-06) | |
| **Herfindahl-Hirschman** | -1.01E-07 | | -8.80E-08 | -1.23E-07 | -9.70E-08 | |
| | (1.17E-07) | | (1.16E-07) | (1.17E-07) | (1.17E-07) | |
| **Observations** | 16852 | 16852 | 17398 | 16852 | 16852 | 17398 |
| **R-Squared** | 0.738588 | 0.738576 | 0.736968 | 0.737303 | 0.738391 | 0.734561 |
| **Time FE** | YES | YES | YES | YES | YES | YES |
| **Stock FE** | YES | YES | YES | YES | YES | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include PBV Ratio as a control variable have fewer observations due to the negative values being excluded. The time sample included is from the first quarter of 2010 to the first quarter of 2020, at a quarterly frequency, and is based on the S&P 500 index constituents during this period.

According to the results, ETF ownership is clearly 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 in 1% of 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 regression (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 and 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 wider 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 is in line with our estimations. To strengthen this idea, Atkins and Dyl (1997) show evidence that stocks with low transaction costs tend to be 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 against the initial intuition. 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 goes against the effect described by Bhattacharya and O'Hara (2020).

## 5.2. Robustness and Other Additional Tests

Following the testing of the hypotheses, this section is dedicated to implementing several robustness checks and other additional tests to complement our results.

### 5.2.1. ETF AuM Test

First, we applied the same regressions with a different independent variable by replacing ETF ownership with ETF AuM. This change aims to account for the fact that the company's market capitalization can influence ETF ownership. By using ETF AuM, we can assess if the results remain consistent for an absolute measure of popularity.

In Table 6, the results for this regression are presented.

*Table 6: Results of the ETF AuM Test*

| Variables | Beta | 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 |
| **R-Squared** | 0.601822 | 0.739046 |
| **Time FE** | YES | YES |
| **Stock FE** | YES | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include 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.

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 statistically significant for a 1% confidence level. Also, the remaining control variables evidenced a similar relation as in the main results.

### 5.2.2. Random Sample Test

As an additional robustness test for the previous conclusions, we implement the same methodology to a sample of 50 randomly picked stocks, whose results can be found in Table 7.

*Table 7: Results of the Random Sample Test*

| Variables | Beta | 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 |
| **R-Squared** | 0.779086 | 0.726202 |
| **Time FE** | YES | YES |
| **Stock FE** | YES | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include 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.

In both regressions, the relationship between the main independent and dependent variables was maintained, indicating that the previous results appeared robust. However, while the regression using beta was statistically significant for a 1% level, the regression using volatility is not as significant as in the previous results using the full sample, being only significant for a 15% confidence level.

### 5.2.3. Disentangling Systematic Risk from Volatility

Next, we address the suggestion from Hansson and Perers (2018) for the possibility of systematic risk being the driving force for the rise in price volatility, whose results can be found in Table 8.

*Table 8: Results for Disentangling Systematic Risk from Volatility*

| 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 |
| **R-Squared** | 0.739990 |
| **Time FE** | YES |
| **Stock FE** | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include 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.

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.

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 R squared of 0.73.

### 5.2.4. Time-Sample Extension Test

In table 9, we compare the results from applying the methodology to the period before the beginning of the impact of the Covid-19 pandemic to the remaining time up until the end of 2021.

*Table 9: Results for Time-Sample Extension Test*

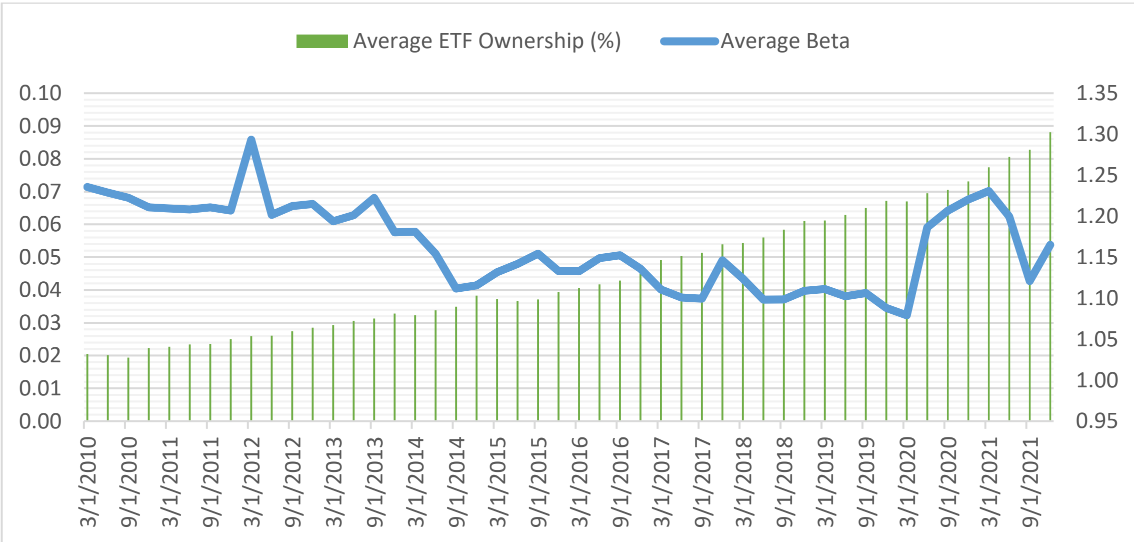
| Variables (Vol) | Beta | | Volatility | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Constant** | 1.063948*** (0.024215) | 1.244571*** (0.025227) | 0.016745*** (0.000271) | 0.019998*** (0.019998) |
| **ETF Ownership** | 0.971700** (0.428624) | -0.938296*** (0.239956) | 0.011604** (0.004804) | 0.012713 (0.016799) |
| **Market Capitalization** | 0.000481*** (0.000123) | -1.84E-05 (3.96E-05) | -4.84E-06*** (1.38E-06) | 1.02E-05*** (2.77E-06) |
| **Stock Price** | 2.93E-06 (6.72E-05) | 0.000105*** (2.06E-05) | -6.74E-06*** (7.53E-07) | 1.68E-06 (1.44E-06) |
| **PBV Ratio** | 0.000275* (0.000163) | 9.99E-05 (0.000102) | -1.37E-07 (1.83E-06) | -4.99E-06 (7.14E-06) |
| **Herfindahl-Hirschman** | 2.43E-05** (1.04E-05) | 1.05E-05 (2.28E-05) | -1.01E-07 (1.17E-07) | -3.13E-06* (1.60E-06) |
| **Observations** | 16832 | 3299 | 16852 | 3301 |
| **R-Squared** | 0.601301 | 0.988977 | 0.738588 | 0.807297 |
| **Time FE** | YES | YES | YES | YES |
| **Stock FE** | YES | YES | YES | YES |

Note: *p-value<0.1; **p-value<0.05; ***p-value<0.01. All the regressions presented in the table include stock and time-fixed effects. Regressions that include PBV Ratio as a control variable have fewer observations due to the negative values being excluded. The time sample for the regression (1) and (3) is from the first quarter of 2010 to the first quarter of 2020 at a quarterly frequency, whereas regressions (2) and (4) relate to the period between the second quarter of 2020 to the last quarter of 2021. The estimations are based on the S&P constituents during this period.

From the regression (4) estimations, we realize that ETF ownership is no longer statistically significant for the volatility regression. One possible reason for this could be the general instability that characterized this period, which this model does not account for.

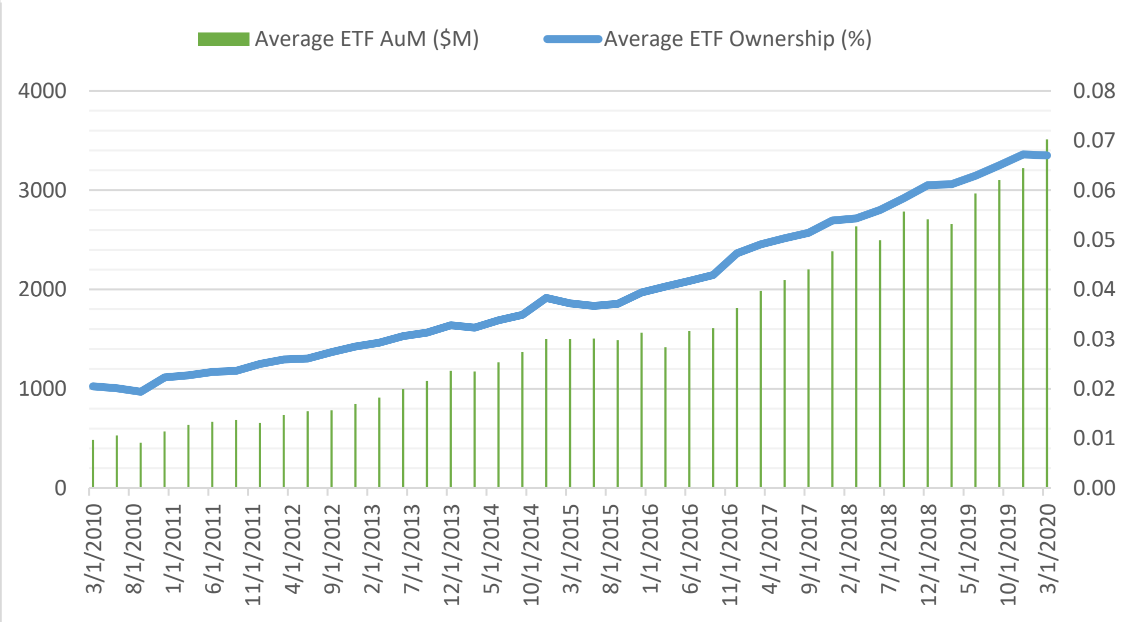
Interestingly, for regression (2), while beta remains statistically significant, it now shows a negative loading. Figure 2 shows a graphic representation of the evolution of average ETF ownership and average beta. The main difference between the period pre and during the impact of the Covid-19 pandemic is that while the beta was showing a decreasing tendency pre covid, it rapidly increased when the Covid-19 pandemic impacted the US economy, which partly explains the results from the estimations. Despite this, ETF ownership kept its steady growth before and during the pandemic.

*Figure 2: Evolution of Average ETF Ownership and Average Beta*




*Source: Own elaboration through data retrieved from the Thomson Reuters Data Stream.*

*Figure 3: Evolution of passive ETF Ownership and ETF AuM*




Source: *Own elaboration through data retrieved from the Thomson Reuters Data Stream.*

### 5.2.5. Other Considerations

In this subsection, we address the possibility of endogeneity in the results or, in other words, whether there could not be ETF ownership impacting the volatility and or beta of the underlying securities, but, instead, that ETFs may choose inherently to hold stocks that have a higher beta or that are riskier, which would undermine the results. However, this methodology is somewhat protected from this risk inherently from the passive nature of the sample. The ETFs included in the sample exclusively consist of indexing-style ETFs, which means that there is no active picking of the securities that have these indexes.

Furthermore, while most indexes use a market capitalization rule to define the weighting of each stock within the index, in this empirical research, we simply used the S&P 500 index as a filtering tool, where we chose the stocks that were analyzed. This means that, in practice, we do not give higher relevance to higher market capitalization stocks since all stocks were analyzed as similar sample observations.

Finally, we introduced a market capitalization control variable in all the regressions executed, which account for concerns related to a potential spurious hidden link between the market capitalization of a stock and its volatility and or beta.

# 6. Conclusion

Financial academics have emphasized the importance of diversifying in constructing an effective portfolio. Furthermore, a new wave of criticism has intensified related to the value inherent to the asset management profession. Many have questioned the real added value to investors worldwide and whether it justifies the considerable management fees that the industry heavily relies on.

Index investing surged as the natural alternative to the traditional active investing style, particularly through the creation and rise in popularity of exchange-traded funds, making it simple for retail investors to hold a diversified portfolio. In addition, some of the most notable equity indexes have delivered remarkable returns, consistently superior, in the long term, to the performance of the aggregate active fund managers while avoiding management fees that dilute investors' real returns.

Due to these attractive characteristics, it is no surprise that the ETF market in the US has experienced exponential growth and has risen to over five trillion dollars in assets at the end of 2020 (ICI, 2021). Even though the instrument was initially thought of as most adequate for long-term buy and hold investors, it soon caught the attention of noise traders, leading to concerns related to an accentuation of price instability through their irrational trading activity.

Moreover, many researchers have argued that the mass migration to an indexing investing style may increase asset pair correlation and lead to higher systematic risk in the underlying securities, lowering the benefits of asset diversification. In recent years, this issue has become a focal point of several market regulators, such as the US SEC and the European Systemic Risk Board, that have come out to warn investors of such dangers.

The results from this empirical research are significant. First, they show strong evidence that passive ETF ownership is a catalyst for market instability by raising stock price volatility and beta, considering the S&P 500 index constituents from 2010 to 2020.

Considering previous research on this topic, the results related to stock price volatility are in line with Ben-David et al. (2014) and Hansson and Perers (2018), applied to the US market, but opposite to Julia (2019), that considered only European stocks. Furthermore, the evidence is again consistent with Da and Shive (2018) and Sullivan et al. (2012), which concluded that the rise in popularity of ETFs was related to an increase in asset pair correlation and a rise in aggregate and individual beta within US equities.

Additional tests confirm that the same conclusions apply when replacing passive ETF ownership with an absolute measure of total assets held by indexed ETFs. In addition, the results remained robust, although less significant, when applied to a randomly picked sample. Moreover, we find that the methodology used did not fit with the period after the onset of the Covid-19 pandemic in the US, which was under the initial expectations due to the economic recession.

In this research, we also explore suggestions made by Bhattacharya and O'Hara (2020) and Hansson and Perers (2018), which led to insightful results. First, the estimations indicate that ETF issuer concentration relates to higher systematic risk, whereas evidence for the relation with stock price volatility is not conclusive. Second, we show that ETF ownership remains a significant determinant of price volatility, even when controlling for the relationship between systematic risk and price volatility, which strongly advocates for attributing this effect to the destabilizing activity of noise traders, as supported by Ben-David et al. (2014).

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

Systemic risk is a combination of several factors, such as the firm's market capitalization, the sensitivity of its equity returns to market shocks, and financial leverage (Engle et al., 2012). This empirical research confirms that ETFs have led to a new layer of systematic risk that can have systemic implications. This work contributes to a growing amount of evidence that emphasizes the urgent need for an active approach from regulators to act and implement measures that minimize the issues this thesis displays.

ETFs have undeniably benefitted retail investors, allowing them to purchase a diversified portfolio with remarkable simplicity. We show in this thesis that these benefits came with some costs for the overall stability of the US equity market. For investors, these conclusions indicate that an additional risk premium should be required to compensate for the new layer of instability that seems to be generated from ETF investing.

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