Laborda et al. Financial Innovation (2024) 10:64
https://doi.org/10.1186/s40854-023-00591-2

Financial Innovation

RESEARCH Open Access

Can ETFs affect U.S. financial stability? A quantile cointegration analysis

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Abstract
This study evaluates whether exchange traded funds (ETFs) threaten financial market stability by testing two hypotheses relating the growing importance of ETFs to increased market volatility and rising equity valuations. We estimate quantile cointegration models using Standard & Poor's 500 Index (S&P 500) and Chicago Board Options Exchange volatility Index (VIX) data for 1994–2020. We found that an increase in ETFs is positively and significantly related to the long-term valuation of the S&P 500 for quantile values above the median. By contrast, ETFs have only a negative and significant effect on the VIX for quantiles around the median. Ultimately, two novel results were obtained. First, the distortion in the value of the S&P 500 relative to its fundamentals is driven by investor flow into ETFs during a bull market. Second, the impact of equity ETFs on the VIX is only affected when fundamental factors are in play, decreasing it. Therefore, ETFs contribute to forming equity bubbles and support valuation market dynamics. Both regulators and policymakers should consider these conclusions.

Keywords: Passive investment, ETFs, Volatility, Stock prices, Financial stability

JEL classification: C22, C58, G12, G18, G23

Introduction
Over the last three decades, passive investment vehicles championed by exchange-traded funds (ETFs) have gained importance in financial markets. According to the Investment Company Institute (2022), U.S. ETFs and indexed funds increased from $27 billion Assets under Management (AuM) in 1993 to more than $12 trillion by 2021. Most notably, this increase has occurred both in absolute and relative terms, as the balance of power has been shifting from active funds to passive instruments, which currently represent 43% of AuM in the U.S. Looking at these figures, it is undeniable that since their inception, these investment vehicles have started a new revolution in the asset management industry. This is explained by their innovative and cost-effective nature, which allows retail and institutional investors to diversify their portfolios while minimizing management costs.

Nonetheless, not all glitters are gold, as their widespread use is beginning to negatively affect the stability of global markets. Many voices have arisen to warn of the possible contributions of these instruments to systemic risk, from the European Systemic Risk Board (Pagano et al. 2019) to the CFA Institute (Bhattacharya and O'Hara 2020).

Different studies have analyzed the implications for financial stability through their impact on liquidity and redemption risks, market volatility, price discovery, co-movement of underlying indexes, concentration in the asset management industry, and the correlation between asset returns and liquidity (Ben-David et al. 2017; Anadu et al. 2020; Liebi 2020). The shift from active to passive investment strategies, particularly via ETF growth, has also been accompanied by innovation and complexity in some of these products -leveraged, inverse, and synthetic ETFs- raising concerns about systemic risk and its potential role in volatility (Aggarwal and Schofield 2014; Bhattacharya and O'Hara 2020). The active-to-passive shift also leads to a higher concentration in the asset management industry, which increases its exposure to idiosyncratic events (Anadu et al. 2020).

The development of ETFs, which mostly attempt to replicate the performance of a basket of assets, has encouraged index-linked investing, which can have important economic consequences (Wurgler 2011). Index inclusion effects that favor co-movement, volatility, and detachment, which can lead to episodes of bubbles and crashes, would affect economic decision-making. In this way, the share price is increasingly related to fundamentals and index membership, which affects corporate investment and financing decisions and investors' asset allocation decisions (Wurgler 2011). Recent research (Easley et al. 2021) considers a significant portion of active ETF investments, which alleviates concerns about the detrimental effects of ETFs on price formation. By contrast, other recent research (Brown et al. 2021) suggests that ETF flows contain a strong non-fundamental demand signal; thus, asset prices are distorted to the detriment of fundamentals.

Thus, the purpose of this study is twofold. On the one hand, it intends to determine the potential consequences of the downfall of active investment funds and the rise of ETFs on U.S. aggregate stock valuations over the long term, which could threaten the efficiency and soundness of the market. With the exponential increase in passive investment vehicles, investors and authors have recently begun to point out that this could lead to a new stock market bubble (Fischer 2012; Tokic 2020) compatible with a large valuation premium for firms in the S&P 500. We hypothesize that the existence of such a bubble in the equity index as a consequence of consolidation in the financial industry of ETFs should be reflected in the long-term relationship between the price of the index and its determinants so that it is affected not only by fundamental variables but also by flows oriented to these ETFs. The potential distortion that ETF-driven flows could have on price formation in the S&P 500 is especially dangerous in financial markets during financial stress and illiquidity. In such episodes, massive selloffs could intensify, fueled by the deviation between prices and fundamentals related to the upward pressure on stock prices from ETF activity. We consider the Inelastic Market Hypothesis (Gabaix and Koijen 2021) as an explanatory mechanism for the effect that a massive Flow of Funds (FoF) directed to ETFs may have on securities pricing. This hypothesis begins by exploring whether institutions own most equity in the market. However, many constitutive and regulatory directives constrain the trading activities of institutions. Therefore, the price elasticity of demand in the aggregate stock market decreased significantly. According to their simplest model, the equity market's price elasticity is 0.2, which means that a 1%

increase in demand leads to a 5% increase in equity market prices. We test the hypothesis that a higher inflow of funds into ETFs and passive funds leads to market prices increasing above the value linked to the fundamental variables.

On the other hand, it aimed to elucidate the effects of these instruments on the stock market's volatility. Some authors have found a causal relationship between ETFs and volatility (Malamud 2016; Ben David et al. 2018; Wang and Xu 2019).

Hence, this study assessed the hypothesis that passive investment threatens financial market stability. We test two sub-hypotheses that relate the increasing importance of passive investment to (1) rising long-term stock valuations and (2) increasing market volatility. We test these hypotheses by applying quantile cointegration regression analysis models (Xiao 2009) to quarterly data from the S&P 500 and the VIX from 1994 to 2020. By doing so, we allow the value of the cointegrating coefficients to vary over time as affected by shocks.

Much of the literature on the effect of ETFs (Madhavan and Sobczyk 2016; Ben David et al. 2018) using panel data or a pool does not explore whether the valuation of the stock set is increasingly disconnected from the fundamentals of the underlying firm as a consequence of increased flows into ETFs. However, those studies obtained contradictory results (Malkiel and Radisich 2001; Morck and Yang 2001). Regarding the impact of ETFs on stock market volatility, in general, most studies show that ETFs and other passive investment instruments increase the non-fundamental volatility of the underlying securities (Lin and Chiang 2005; Krause et al. 2014; Malamud 2016; Wang and Xu 2019). However, some authors have shown that such behavior is concentrated near the closing of daily trading sessions (Bogousslavsky and Murayev 2019; De Rossi and Steliaros 2022), or is due to specialized passive investment strategies such as leveraged, inverse, and synthetic ETFs (Cheng and Madhavan 2009; Tuzun 2014; Anadu et al. 2020).

To some extent, there seems to be a contradiction between studies that show a positive impact of ETFs on stock market valuation and those that find that the increase in FoFs towards ETFs increases volatility. None of these studies considered that most of the analysis period was conditional on a low-interest-rate environment. We aimed to consider this period of analysis and to close these inconsistencies.

The results suggest that the increase in FOF into equity ETFs translated into higher stock prices in the long run only for the values of quantiles above the median. This unprecedented finding is ultimately the distortion of the value of the S&P 500 relative to its fundamentals driven by investor flows into ETFs during a bull market. As a result, it can help create equity bubbles and drive certain valuation dynamics. However, the impact of equity ETF on the VIX is significant only when fundamental factors are at play. They reduce the VIX. In all other scenarios, where the market is either undervalued or overvalued, and the dynamics are not fundamentally driven, equity ETF flows have no significant impact on volatility. These results are undoubtedly more consistent with stock market dynamics and resolve the inconsistencies observed between the results of the previous research.

These results suggest that a reduction in the role of active players in the asset management industry leads to an increasing disconnect between a firm's fundamentals and its share prices. This should serve as a reflection for rethinking investment approaches and as a warning sign for policymakers who should try to limit these distorting effects, which may affect financial stability, by introducing new regulations and tighter controls on using passive investment vehicles.

The remainder of this paper is organized as follows: First, we provide an overview of global ETFs growth, detailing past, current, and future trends in this investment vehicle. Second, we review the literature on the impact of passive investments and ETFs on equity valuation and volatility levels. Third, we describe the empirical models used to test the hypothesis that ETFs threaten financial stability. Fourth, we present the database, variables used, and the empirical results obtained. Finally, the main conclusions of this study are summarized.

The growth of global ETFs: past, present and future trends

Fama (1970) argues that financial markets, owing to their efficient nature, already incorporate all the available information when pricing securities. This implied that pursuing a "buy and hold" strategy, the core idea behind passive investing would always produce more returns than a traditional active approach. Following Fama's Efficient Market Hypothesis, John C. Bogle, CEO of Vanguard Group, created the Vanguard 500 Index in 1976, an investment fund with the main purpose of mirroring the S&P's 500 performance. It was the first to offer a passive investment vehicle to retail investors and began a wave of new indexed funds. Sharpe (1991) states that, on average, a passive investor holding every security in a market will outperform an active investor for any period. This is mainly because of the higher costs associated with active investment strategies.

By combining Fama's (1970) and Sharpe's (1991) arguments, it is natural to assume that rational investors seek to allocate wealth to the cheapest and most liquid passive vehicles. Nonetheless, existing indexed funds are expensive, illiquid, and sometimes have minimum investment thresholds, making them less appealing to the general public. ETFs were created to fill this void by providing innovative and cost-effective access to diversified passive portfolios worldwide. These instruments hold a pool of securities, usually about a specific index, and trade on an exchange, similar to regular stocks. Therefore, investors who buy one share of an ETF purchase only a small percentage of the pool of underlying securities. Hence, the intraday value of the ETF in the stock market must almost, if not completely, equal the Net Asset Value (NAV) of the securities it holds.

The arbitrageur mechanism that assures this equality between ETFs' prices and its NAV occurs in both the primary and secondary markets. In the primary market, the ETF issuer or sponsor designates some Authorized Participants (AP), usually market makers or large financial institutions, who can create and redeem ETF shares in two ways: in kind, by delivering the constituting securities, or in cash. Therefore, if in the secondary market, the ETF is trading at a premium to its NAV, the authorized participants would short-sell the ETF shares and buy the underlying securities basket to redeem it for ETF shares, close the short position, and make a profit (Ferri 2009). There are three basic types of weighting for the composition of the pool of securities: market capitalization weighting, fundamental weighting, and fixed weighting (Ferri 2009).

Regarding impact, ETFs rank as one of the most important recent financial innovations (Lettau and Madhavan 2018): ETFs have made market investments much easier

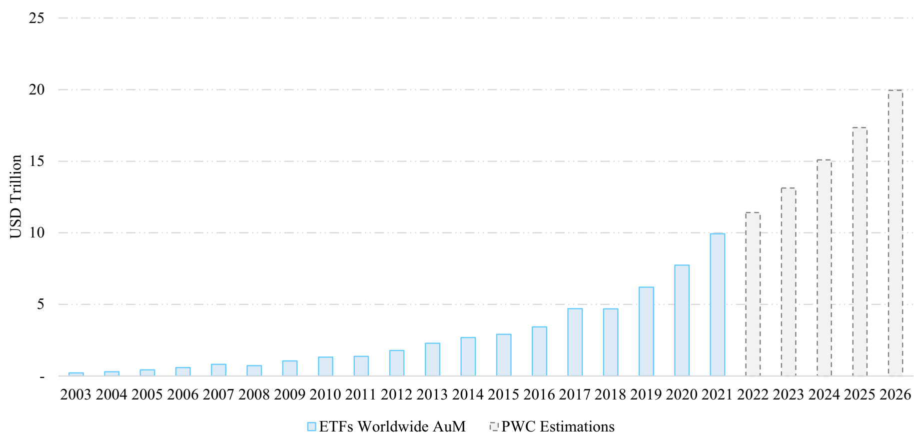

Fig. 1 Evolution of Worldwide ETFs by AuM. *Source* Own elaboration using data from Investment Company Institute (2022) & PWC (2022)

and cheaper. They have helped create better and more diversified personal portfolios by opening up new asset classes for many investors that were previously only accessible to privileged investors. To exemplify the cost-effective nature of this investment vehicle, according to Armour (2022), for 2021, an active fund would charge, on average, 0.60% as a managing fee, while an investor in a passive fund would only be charged 0.12%.

However, this boom poses a systemic risk. Bhattacharya and O'Hara (2020) point out two distinct sources of systemic risk. One set of systemic effects stems from the original passive basket structure. The long-term effects of the erosion of active investing at the asset level brought about by passive instruments such as ETFs are beginning to unfold in markets. A second set of systemic issues relates to ETFs' role in market disruptions as "Flash Crashes." Over the past few years, the frequency, weakness, and severity of such disruptions have surprised regulators and market participants.

Aggarwal and Schofield (2014) note that while original ETFs are simple and easy to understand, some recent products, such as leveraged, inverse, and synthetic ETFs, have become much more complex and introduce additional dimensions of risk. Therefore, they can play a key role on days of volatility during flash crashes. Added risk, complexity, and reduced transparency have led to increased regulatory scrutiny. Concerns include systemic risk, excessive volatility, retail suitability, lack of transparency and liquidity, securities lending, and counterparty risk. A shift towards multiple counterparties, over-collateralization, and disclosing collateral and index holdings address these concerns. Appropriate regulatory and market reforms can ensure ETFs' continued success.

Despite these risks, the high success rate of ETFs remains undeniable. Since their inception, ETFs have experienced quasi-exponential increases. As Fig. 1 shows, from 2003 to 2021, worldwide ETFs increased from $204 billion AuM to almost $10 trillion, near the 23% compound annual growth rate (CAGR). This sustained growth rate over 19 years is an astonishing figure that reflects the strength and popularization of this investment vehicle.

This growth has not occurred only at absolute levels, as investors are shifting from active to passive investment instruments (See Fig. 2). In the U.S., the weight of passive investments over the total AuM will reach 43% in 2021, which means that for every $2

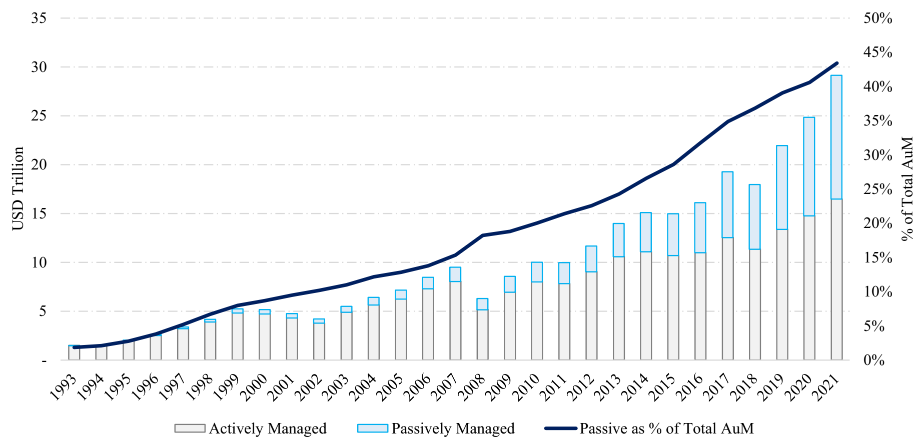

Fig. 2 Evolution of Passive Investments' Share of Total AuM in the U.S. *Source* Own elaboration using data from Investment Company Institute (2022)

invested, almost $1 will be invested in passive instruments. These numbers are especially surprising, considering that 10 years before these instruments only represented 21% of the market was represented ten years before these instruments. The shift is driven by the spectacular increase in ETFs and the continuous outflow of capital from mutual funds. From 2015 to 2020, U.S. active funds suffered negative net flows, probably due to higher costs and underperformance than passive investment instruments (Sabban and Jackson 2022).

Looking ahead, the surge in passive investment vehicles seems unstoppable, as inflows into ETFs will reach a record $1 trillion for the first time in 2021 (Wursthorn 2021). A recent report by the consulting company PwC (2022) estimated that, by 2026, the worldwide ETFs market would be worth around $20 trillion (Fig. 1). If the current trend of directing outflows from active investment funds to ETFs continues, by 2026, financial markets will be controlled by passive investment vehicles. This threatens pricing mechanisms, implying that due diligence and fundamental analysis will progressively become rare in stock markets.

Effects of ETFs on financial markets

This section provides an overview of existing literature on the effects of passive investments and ETFs on financial market stability. First, we examine prior understanding of its impact on stock valuations. Second, we summarize the effects on volatility levels.

Effect on stock valuation

Most of the literature on ETF valuation is concerned with the spread between the NAV of the pool of securities and the ETF price (Madhavan and Sobczyk 2016; Ben David et al. 2018), but these studies do not delve into whether the valuation of the pool of securities is increasingly disconnected from the fundamentals of the underlying company. Goetzmann and Massa (2003) are among the first to link passive investment with stock market bubbles. They analyzed the impact of index investing on stock prices by examining the FoF. They find that the growth experienced by the S&P 500 in the 1990s was not driven by changing economic fundamentals but by demand shocks generated by uninformed investors. Moreover, by examining the behavior of S&P 500 futures indices, they showed that these price changes were not temporary but permanent. De Simone et al. (2021) show that passive investment growth increases stock prices on the Tel Aviv Stock Exchange, disregarding firms' fundamentals.

Following Shleifer's (1986) finding that demand curves for stocks in an index are downward sloping, Morck and Yang (2001) examined Tobin's Q ratio of more than 2,000 firms from 1978 to 1997. Their results show a large valuation premium for firms in the S&P 500. They conclude that this premium, around 40%, is related to inflows into index funds, as it appears a few years after the launch of the first S&P 500 index fund. However, the conclusions of Morck and Yang (2001) contradict those of Malkiel and Radisich (2001), whose results from a regression including 258 stocks included in the S&P 500 over the period 1980–1999 show that the presence of a company in this index does not affect its share price.

Exploring this topic further, Fischer (2012) developed a model of bounded rational investors who could choose to pursue an active investment strategy (holding both risky and risk-free assets) or a passive approach (holding only risky assets). The results show two equilibrium regimes: one dominated by active investors, where stock prices equal the fundamental value of the portfolio, and the other, where all investors switch to passive strategies, leading to prices above the fundamental value of the underlying assets. Moreover, his model indicates that the bubble size created by passive investors mainly depends on the market's liquidity and the time that investors rebalance their portfolios.

Subsequently, Israeli et al. (2017) studied, from an information-based perspective, how ETF ownership could reduce the pricing efficiency of underlying stocks. Their results show that ETF ownership is associated with a decline in the number of analysts covering stock and, most importantly, a decline in the future earnings response coefficient, which measures how a firm's current stock return reflects its future earnings. Hence, a decrease in this coefficient strengthens the idea that ETFs encourage a mismatch between a firm's fundamentals and stock performance. Glosten et al. (2021) studied the Russell 1000/2000 indices from 2004 to 2013 and found that ETF activity has a positive effect on the short-term informational efficiency of the underlying stocks, mainly due to the incorporation of systematic earnings information.

Most recently, Brown et al. (2021) studied the impact of non-fundamental demand shocks produced by arbitrage procedures exercised by ETFs' market makers on asset prices. In their research, they show how being long on a low-flow ETF and short on a high-flow ETF would lead to excess returns of 1, 1–2% per month related to the "technical" adjustments on the NAV of these instruments and not to the fundamentals of the underlying assets.

Another widely explored topic the literature shows consensus about is the increased beta of a stock being added to an index. According to the existing literature, this increase in the correlation between the newly added stock's return and the returns of the other stocks conforming to the index is not driven by fundamental factors but merely by belonging to the index (Barberis et al. 2005; Greenwood and Sosner 2007).

Regarding the dangers of the exponential increase in passive investment, hedge fund manager Michael Burry, famous for predicting the 2008 mortgage crisis, warned Bloomberg about a bubble that may form in passive investing (Stevenson 2019). In his view, money inflows directed towards ETFs and other passive instruments pump large capitalization stocks while neglecting small caps, which offers active investors an opportunity to profit. He also pointed out the similarities with the subprime mortgage bubble, as in both cases, the fundamental analysis, key to the "price discovery" process, had been replaced by risk models and algorithms.

Effect on volatility

The academic community generally agrees that ETFs and other passive investment instruments increase the non-fundamental volatility of underlying securities, mainly by attracting arbitrageurs. Malamud (2016) develops a dynamic general equilibrium model of ETFs, showing how, through the arbitrageur process, ETFs increase the volatility of underlying securities. Similarly, Ben David et al. (2018) conclude that stocks with higher ETF ownership have higher volatility levels. Their study demonstrated how ETF markets attract high-frequency traders. Thus, when a liquidity shock occurs, ETFs propagate to the underlying basket of securities through arbitrage channels. Therefore, stock price volatility is not a product of a price discovery mechanism but a consequence of non-fundamental demand shocks in the ETF market.

Krause et al. (2014) examine the relationship among ETFs, liquidity, and volatility in financial markets, providing empirical evidence of spillovers from ETFs to their underlying markets. The authors found significant volatility spillovers from ETFs, which increased the volatility of the largest underlying securities. Volatility spillovers flow from ETFs to their component stocks, and the magnitude of these spillovers is positively related to ETF liquidity and the proportion of each stock in the ETF. Deviations from the NAV, fund flows, and market capitalization of the ETF also generate significant volatility spillovers from sector ETFs to their constituents. These effects are generally stronger for smaller ETF components, and the importance of each factor changes over time. These findings are relevant to market practitioners, regulators, and investors of these increasingly popular products.

Parallel conclusions were drawn from a study of emerging markets. For instance, Lin and Chiang (2005) analyzed the impact on volatility levels of introducing the first Taiwanese ETF, the Taiwan Top 50 Tracker Fund. Their findings show that 61.2% of the stocks that comprise the index suffered from higher volatility levels after the launch of the ETF. Further evidence is provided by Wang and Xu (2019), who studied 70 Chinese ETFs from 2015 to 2017 and found that flows directed towards ETFs significantly increased the volatility of the underlying securities on the next trading day.

Using higher-frequency data, De Rossi and Steliaros (2022) and Bogousslavsky and Murayev (2019) find that passive funds tend to propagate liquidity shocks to the underlying securities; thus, increasing stock volatility is concentrated near the close of daily trading sessions. They argue that this may be due to the concentration of ETF portfolio trades at that time. De Rossi and Steliaros (2022) find that among U.S. stocks, a two-standard-deviation increase in ETF ownership generates a 2.99% relative increase in volatility for the median stock near close. Bogousslavsky and Murayev (2019) show that the closing stock price is determined in a special call auction, strongly associated with ETF ownership and institutional rebalancing. Auction price deviations contribute substantially to daily volatility. Related to this research, Wu (2019) shows that market-on-close orders submitted to closing auctions are an important trading channel through which passive investing affects the underlying stocks.

Market volatility can also increase due to deviations in ETF share prices from their net asset values (Pagano et al. 2019; Pan and Zeng 2017), such that large deviations can threaten financial stability.

Anadu et al. (2020) suggest that specialist passive investment strategies, such as leveraged, inverse, and synthetic ETFs, amplify asset price volatility, which may induce a systemic source of risk. In this research line, Cheng and Madhavan (2009) and Tuzun (2014) show that leveraged and inverse ETFs are positive and negative multiples of an underlying index return, contributing to stock market volatility, especially during stress periods. Volatility-linked leverage ETFs contributed substantially to an unprecedented spike in stock return volatility, as measured by the VIX, in "Flash Crash" in February 2018, putting downward pressure on stock prices (Sushko and Turner 2018).

However, Box et al. (2021) recently strongly opposed these views. They directly address the proposition that arbitrage mechanisms in ETF markets generate noise in the prices of the underlying securities. Analyzing 423 passively managed U.S. funds between 2006 and 2015, they found no spillover effects from ETF trading and that ETF trading could help shield security baskets from demand shocks.

For further references on the effects of ETFs and other passive investment instruments on financial system stability, see Deville (2008), Liebi (2020), or Wurgler (2011).

Inelastic market hypothesis

Gabaix and Koijen (2021) introduce a new theory that serves as an explanatory mechanism for understanding the impact of a massive FoF on financial markets: the Inelastic Market Hypothesis. This hypothesis begins by exploring whether institutional investors own most equity in the market. However, many constitutive and regulatory directives constrain the trading activities of institutions. Therefore, the price elasticity of demand in the aggregate stock market decreased significantly. This hypothesis suggests that in certain situations, when there is a substantial inflow or outflow of funds into or out of a market, the market may exhibit an inelastic response, meaning that the prices of assets or securities may not fully adjust to reflect increased or decreased demand.

The underlying idea behind the Inelastic Market Hypothesis, in the context of a large FoF for equity ETFs, is that the market's capacity to absorb and efficiently process such large-scale flows is limited. When a significant FoF to an equity ETFs occurs, it can disrupt the normal stock price discovery mechanism. These inflows can lead to equity bubbles as the market may not be able to accommodate the increased demand or supply immediately. Therefore, the Inelastic Market Hypothesis has implications for passive equity investors and other participants. It highlights the challenges and risks associated with large-scale FoFs to equity ETFs. It emphasizes the importance of carefully managing and monitoring the impact of these huge inflows on equity market dynamics.

Departing from the Inelastic Market Hypothesis, De Simone et al. (2021) explored the consequences of an increased demand for Exchange Traded Notes, including ETFs, after the 2012 Tel Aviv Stock Exchange reform. Their findings imply that the growth of passive investment increases stock prices, disregarding the firm's fundamentals.

The Inelastic Market Hypothesis can help us explain what this paper aims to do, which is to assess whether equity ETFs pose a risk to financial stability by testing two hypotheses that link the growing importance of ETFs to increased market volatility and rising equity valuations.

Methodology background

This section considers the quantile cointegration model (Xiao 2009) applied to S&P 500 price data, variables related to index fundamentals, and fund flows to ETFs. By doing so, we allow the value of the cointegrating coefficients to vary over time as affected by shocks. Different situations have occurred in the sample that could justify this change in the coefficients of the long-run relationship between stock prices and explanatory variables, such as the 1973 oil crisis, the Great Recession of 2008, the COVID pandemic, or technological revolutions such as the development of the Internet.

We control for the fundamental factors that account for increases in stock prices and market volatility. First, the trailing 12 months of both earnings per share (EPS) and dividends per share (DPS) of the S&P 500 are taken as proxies for profitability and returns obtained by investors (Somoye et al. 2009; Nisa and Nishat 2011; Gill et al. 2012; Asma et al. 2014; Johnson and Lee 2014; Chen et al., 2015; Islam and Dooty 2015). The main hypothesis of the research examining the relationship between the EPS and DPS of the S&P 500 and its price is that as companies experience higher EPS and DPS, the price of their shares tends to increase. This hypothesis suggests that investors value companies with higher earnings and dividends, leading to a positive correlation between EPS, DPS, and stock prices in the S&P 500.

Second, we use the natural logarithm of the debt-to-equity ratio of the S&P 500 to monitor the financial leverage of the index (Ozdagli 2012; Johnson and Lee 2014; Gomes and Schmid 2010). This factor is considered crucial for determining the value of a stock; however, it has advantages and disadvantages. Insufficient leverage can negatively impact profitability because shareholders do not benefit from the tax advantages of debt or tax shields and need to invest more capital to achieve the same level of profits. Conversely, increasing the debt-to-equity ratio carries risks, as it raises the likelihood of default, which can result in credit rating downgrades. These downgrades diminish a company's ability to raise capital, ultimately harming its growth potential. In summary, the appropriate leverage level is a delicate balance that affects a stock's valuation.

Lastly, the U.S. Federal Funds Effective Rate is included to monitor changes in the interest rate (Somoye et al. 2009). Three hypotheses relate to the U.S. Federal Funds Effective Rate and S&P 500 prices. The first is the interest rate expectation (IRE) hypothesis. The U.S. federal fund effective rate directly impacts the cost of borrowing and influences investors' expectations of future interest rates. A decrease in the federal fund rate may stimulate economic growth and increase investor confidence, leading to higher S&P 500 prices. Conversely, if the Federal Funds Rate is expected to increase, it may dampen economic activity and investor sentiment, potentially resulting in a lower S&P 500 price. Second, the risk-return tradeoff hypothesis: The U.S. Federal Funds Effective Rate is a benchmark for the risk-free rate of return. When interest rates are low, investors may seek higher returns on riskier assets, such as stocks, including those in the S&P 500. This increased demand for equities can drive up S&P 500 prices. Conversely, when interest rates rise, investors may shift their investments towards safer assets, reducing the demand for stocks and potentially leading to lower S&P 500 prices. Third, liquidity and cost of capital hypotheses. Changes in the U.S. Federal Funds Effective Rate can influence the availability of liquidity and the cost of capital. Lower interest rates can provide easier access to credit and lower borrowing costs for companies, stimulating corporate investment and potentially boosting S&P 500 prices. Conversely, higher interest rates can restrict liquidity and increase borrowing costs, potentially dampening corporate investment and lowering the S&P 500 prices.

We also consider the effect of a massive FoF directed to ETFs on the pricing of equities, as suggested by the Inelastic Market Hypothesis, as an explanatory mechanism. We test the hypothesis that a higher inflow of funds into ETFs and passive funds leads to market prices increasing above the value linked to the fundamental variables. Our main independent variable was the net FoF to equity ETFs ratio and the nominal Gross Domestic Product (GDP). The reasons for taking this ratio are (1) to account for inflation and (2) to link the FoF to the economic situation so that inflows during recessions have a higher weight than during expansionary periods.

Let p_t, be the natural logarithm of the S&P 500 price. Consider the following model.

$$p_t = \alpha + \beta_{d,t} d_t + \beta_{EPS,t} EPS_t + \beta_{FED,t} FED_t + \beta_{Lev,t} Lev_t + \beta_{ETFFOF,t} ETFFOF_t + u_t \tag{1}$$

where d, is the logarithm over the last 12 months of dividends per share, EPS is the logarithm over the last 12 months of earnings per share, FED is the U.S. Federal Funds Effective Rate, Lev is the natural logarithm of the debt-to-equity ratio of the S&P 500, and ETF FOF is the ratio of net FoF to equity ETFs to nominal Gross domestic product (GDP).

Due to the endogeneity of the cointegration model, we decomposed u_t into a sum of the lead and lag terms of the explanatory variables and a pure innovation ε_t to eliminate the bias originating from the correlation between the explanatory variables and u_t. Model (1) can be rewritten as follows (Xiao 2009):

$$\begin{aligned} p_t =& \alpha + \beta_{d,t} d_t + \beta_{EPS,t} EPS_t + \beta_{FED,t} FED_t + \beta_{Lev,t} Lev_t \\ &+ \beta_{ETFFOF,t} ETFFOF_t + \sum_{j=-K}^{K} \pi_{d,jt} \Delta d_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{EPS,jt} \Delta EPS_{t-j} + \sum_{j=-K}^{K} \pi_{FED,jt} \Delta FED_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{Lev,jt} \Delta Lev_{t-j} + \sum_{j=-K}^{K} \pi_{ETFFOF,jt} \Delta ETFFOF_{t-j} + \varepsilon_t \end{aligned} \tag{2}$$

We allow the values of the cointegrating coefficients to be influenced by the shock received in each period and thus vary as a function of the quantiles of S&P 500 innovation. Cointegration coefficients are a function of the process ε_t, capturing additional volatility of the S&P 500 price. We denote the τ-th quantile of ε_t as $Q_\varepsilon(\tau)$, let $\mathcal{F}_t = \sigma\{x_t, \Delta x_{t-j}, \forall j\}$ the information accumulated up to time t. Then, conditional on $\mathcal{F}_t$ the above model has the following quantile domain representation (Xiao 2009):

$$\begin{aligned} Q_{p_t(\tau|\mathcal{F}_t)} =& \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t \\ &+ \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t \\ &+ \sum_{j=-K}^{K} \pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K} \pi_{EPS,jt}\Delta EPS_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K} \pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + F_{\varepsilon}^{-1}(\tau) \end{aligned} \tag{3}$$

Quantile regression estimates of the cointegrating coefficients at each quantile in Eq. (3) solve the problem.

$$\begin{aligned} &\text{Min} \sum \rho_\tau(p_t - \alpha(\tau) - \beta_d(\tau)d_t - \beta_{EPS}(\tau)EPS_t \\ &- \beta_{FED}(\tau)FED_t - \beta_{Leverage}(\tau)Leverage_t \\ &- \beta_{ETFFOF}(\tau)ETFFOF_t - \sum_{j=-K}^{K} \pi_{d,j}(\tau)\Delta d_{t-j} \\ &- \sum_{j=-K}^{K} \pi_{EPS,jt}\Delta EPS_{t-j} - \sum_{j=-K}^{K} \pi_{FED,j}(\tau)\Delta FED_{t-j} \\ &- \sum_{j=-K}^{K} \pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} \\ &- \sum_{j=-K}^{K} \pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j}) \end{aligned} \tag{4}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ with I representing an indicator function.

In this study, we analyze the effect of ETFs' FOF on the valuation of the S&P 500, as well as on equity volatility, as measured by the VIX. Therefore, we also estimate the quantile cointegration model presented above by jointly considering the natural logarithm of the VIX and the remaining variables used to explain S&P 500 prices.

Empirical results

This section introduces the database, estimation strategy, and variables used. Then, the main results and conclusions on stock valuation using quantile cointegration regression are analyzed. Finally, we make a similar assessment of the regression results on the effects of passive investment on volatility.

Database, variables, and estimation strategy

We test whether an increase in ETFs leads to an increase in stock prices and an upsurge in market volatility by analyzing the S&P 500 and VIX. Quarterly data for 1994–2020 were used, resulting in a time series of 108 data points. Most data were retrieved using Compustat. Table 1 summarizes all the variables and data sources used in the proposed models.

Table 1 Variables description

Variable	Description	Definition	Frequency	Source
Dependent variables				
SP500 Price	The Standard and Poor's 500 Index level	Ln(SP500)_t	Quarterly	Compustat
Volatility	CBOE's VIX	Ln(VIX)_t	Quarterly	CBOE
Independent variables				
ETF Flow of Funds (FoF)	Net FoF to Equity ETFs as % of Nominal GDP	$\Delta\text{(ETF FoF/Nominal GDP)}_t$	Quarterly	BoG of the U.S. Federal Reserve System
Control variables				
EPS	Earnings Per Share (TTM)	Ln(EPS)_t	Quarterly	Compustat
DPS	Dividend Per Share (TTM)	Ln(DPS)_t	Quarterly	Compustat
Leverage	Debt-to-Equity Ratio	$\text{Ln(Total Liabilities/Total Equity)}_t$	Annual	Compustat
Fed Rate	U.S. Fed Effective Rate (Annual Mean)	(FED Rate)_t	Quarterly	BoG of the U.S. Federal Reserve System

Table 2 Unit root tests

Variable	DF-GLS tau test statistic	5% critical value
S&P500	− 1.42	− 2.72
VIX	− 2.52	− 2.79
d	− 1.94	− 2.90
FED	− 1.73	− 2.07
Leverage	− 1.73	− 2.85
ETFFOF	− 2.47	− 2.77

We analyzed whether the variables in this study were $I(1)$. For this purpose, we consider the modified Dickey-Fuller t-test proposed by Elliott et al. (1996). Elliott et al. (1996) showed that this test has significantly higher power than previous versions of the augmented Dickey-Fuller test. The number of lags k was selected using the sequential Ng-Perron t-test. Table 2 shows that all variables are $I(1)$.

Results on the effect on stock valuation. Quantile cointegration results

Table 3 shows the ordinary least squares (OLS) and quantile regression estimates of the cointegrating coefficients and the respective p-values based on Model 2 using a lag of order 2 (K = 2).[1]

Evidence shows that all variables' estimated cointegrating coefficients vary over time, so they have different values for the range of quantile values considered. They bring additional volatility to asset prices in addition to market and non-market fundamentals (Xiao 2009). Failure to consider this asymmetric pattern affects the conclusions drawn from linear estimation.

[1] Results are similar for $K = 1$.

Table 3 Quantile cointegration estimates for S&P 500 model

τ	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
β_d	0.99	0.85	0.85	0.84	0.84	0.89	0.88	0.88	0.89
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.31	0.42	0.34	0.34	0.38	0.36	0.40	0.44	0.44
p-value	0.02	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00
β_{FED}	− 0.02	− 0.04	− 0.02	0.00	0.00	0.01	− 0.01	− 0.01	− 0.01
p-value	0.51	0.17	0.39	0.83	0.82	0.72	0.64	0.57	0.62
β_{Lev}	1.02	1.24	0.87	0.74	0.81	0.95	1.32	1.43	1.45
p-value	0.04	0.00	0.04	0.04	0.02	0.01	0.00	0.00	0.00
β_{ETFFOF}	0.07	0.05	0.08	0.08	0.08	0.09	0.06	0.07	0.08
p-value	0.47	0.59	0.39	0.19	0.26	0.18	0.37	0.23	0.15

τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**	**OLS**
β_d	0.76	0.71	0.71	0.66	0.62	0.58	0.64	0.63	0.72	0.58
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.47	0.47	0.42	0.43	0.45	0.42	0.45	0.46	0.46	0.48
p-value	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.07	0.00
β_{FED}	− 0.01	0.02	0.03	0.04	0.04	0.05	0.06	0.06	0.08	0.01
p-value	0.72	0.41	0.20	0.11	0.08	0.00	0.00	0.00	0.00	0.37
β_{Lev}	1.48	1.23	1.07	1.06	1.01	0.80	0.89	0.90	0.84	0.80
p-value	0.00	0.01	0.03	0.03	0.02	0.06	0.05	0.05	0.09	0.09
β_{ETFFOF}	0.10	0.11	0.13	0.12	0.13	0.14	0.14	0.14	0.14	0.10
p-value	0.05	0.02	0.02	0.04	0.01	0.00	0.01	0.01	0.05	0.05

The Table 3 shows the OLS and quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the S&P 500 price data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t + , \sum_{j=-K}^{K}\pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K}\pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K}\pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K}\pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} + \sum_{j=-K}^{K}\pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, and ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP. Quarterly data for the period 1994–2020 is used, resulting in a time series with 108 data points. Most data is retrieved from Compustat

Focusing also on the long-run relationship between the S&P 500 price and the explanatory variables, we find that the variable d_t, related to the fundamentals of the S&P 500 price, is significant for every quantile with a positive coefficient β_d that decreases as we move from the lowest to the highest quantiles. That is, the impact of the logarithm over the last 12 months on dividends per share is larger when the S&P 500 is smaller. We also find that the variable EPS_t, also related to the fundamentals of the S&P 500 price, is significant for every quantile with a positive coefficient β_d that increases as we move from the lowest to the highest quantiles. That is, the impact of the logarithm over the last 12 months in earnings per share is larger when the S&P 500 is larger. Conversely, the FED variable has estimated coefficient β_{FED} with an increasing pattern across quantiles being significant only for quantiles above 0.70. The positive impact of the Fed rate on the S&P 500 is greater when its value of the S&P 500 is higher, with the interest rate reflecting higher growth. Interestingly, the OLS specification shows no relationship between the FED rate and the S&P 500 price. The Leverage variable is also significant for every quantile with the highest estimated coefficient values, β_{LEV} for the quantiles around the median. The sign of our estimates is as expected (see the discussion above on methodology).

It is interesting to note that the variable of interest in this study, the ratio of net FoF to equity ETFs to nominal GDP, which reflects the impact of a variable unrelated to the fundamentals of the S&P 500 price, has a coefficient β_{ETFFOF} that having a positive value shows an increasing pattern across quantiles, going from values around 0.07 for low quantiles to values around 0.14 for higher quantiles. Furthermore, this variable is significant for quantiles above the median. Consequently, the impact of this variable on the long-term valuation of the S&P 500 is more relevant and the higher the value of the S&P 500. This introduces a distortion of the value of the S&P 500 relative to its fundamentals linked to investor flows to ETFs in bull markets and could favor dynamics linked to valuation bubbles. This is consistent with the initial hypothesis that passive investment contributes to stock market valuation distortion, which aligns with De Simone et al.'s (2021) findings and supports Gabaix and Koijen's (2021) Inelastic Market Hypothesis.

However, our main achievement, compared to previous research, lies in the successful application of Quantile Cointegration Regression. This analysis demonstrates that an increase in the FoF into equity ETFs translates into higher equity prices in the long term, only for the quantiles above the median. Thus, the influence of this variable on the long-term valuation of the S&P 500 becomes more significant as its value of the S&P 500. This phenomenon distorts the value of the S&P 500 relative to its fundamentals, mainly driven by investor flows into ETFs in a bull market. As a result, it may contribute to forming equity bubbles and support certain valuation market dynamics. Regulators, economic and monetary authorities, and policymakers should consider this empirical evidence.

Results on the effect on volatility. Quantile cointegration results

Extending the study on the effect of the ratio of net FoF to equity ETFs to nominal GDP on financial markets, we analyze the long-run relationship between the VIX, which we use as a proxy for equity market volatility, and the remaining explanatory variables. That is, we consider

$$\begin{aligned} VIX_t =& \alpha + \beta_{d,t} d_t + \beta_{FED,t} FED_t + \beta_{Leverage,t} Leverage_t \\ &+ \beta_{ETFFOF,t} ETFFOF_t + \sum_{j=-K}^{K} \pi_{d,jt} \Delta d_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{FED,jt} \Delta FED_{t-j} + \sum_{j=-K}^{K} \pi_{Leverage,jt} \Delta Leverage_{t-j} \\ &+ \sum_{j=-K}^{K} \pi_{ETFFOF,jt} \Delta ETFFOF_{t-j} + \varepsilon_t \end{aligned} \tag{5}$$

Table 4 shows the quantile regression estimates of the cointegrating coefficients and the respective p-values based on Model 5 using a lag of order two.

Table 4 Quantile cointegration estimates for VIX

τ	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
β_d	0.95	0.46	0.38	−0.60	−0.81	−2.14	−1.25	-1.27	0.13
p-value	0.80	0.89	0.92	0.88	0.87	0.67	0.84	0.85	0.98
β_{EPS}	2.02	1.78	−0.55	0.21	0.78	1.77	1.19	1.21	0.81
p-value	0.60	0.63	0.89	0.96	0.87	0.70	0.84	0.84	0.89
β_{FED}	−1.56	−1.57	−1.49	−1.52	−1.55	−1.57	−1.51	−1.47	−1.28
p-value	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.05
β_{Lev}	21.89	19.86	15.03	15.97	17.37	17.82	14.52	16.41	16.72
p-value	0.02	0.04	0.08	0.09	0.07	0.08	0.21	0.19	0.21
β_{ETFFOF}	−3.29	−2.95	−2.31	−2.12	−2.42	−2.49	−3.08	−3.51	−4.27
p-value	0.13	0.11	0.20	0.20	0.21	0.22	0.13	0.09	0.04
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**	**OLS**
β_d	−0.11	−1.81	−0.27	−0.71	−2.52	−9.17	−9.94	−7.61	−9.86	−0.86
p-value	0.99	0.77	0.97	0.91	0.71	0.16	0.15	0.31	0.27	0.79
β_{EPS}	1.42	3.25	2.53	2.71	2.99	6.11	6.17	6.29	5.48	1.12
p-value	0.80	0.55	0.67	0.66	0.64	0.33	0.36	0.36	0.48	0.64
β_{FED}	−1.19	−1.32	−1.23	−1.21	−1.20	−1.39	−1.25	−1.27	−1.30	−1.23
p-value	0.08	0.05	0.07	0.08	0.09	0.07	0.12	0.07	0.02	0.00
β_{Lev}	17.52	23.53	22.45	20.92	19.68	7.76	4.97	8.55	12.26	12.89
p-value	0.21	0.08	0.11	0.16	0.24	0.66	0.81	0.69	0.62	0.09
β_{ETFFOF}	−4.13	−2.98	−3.85	−4.06	−3.02	−3.38	−3.39	−4.79	−1.69	−3.21
p-value	0.05	0.06	0.07	0.09	0.24	0.21	0.21	0.16	0.61	0.14

The Table 4 shows the OLS and quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the VIX data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{VIX(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t + , \sum_{j=-K}^{K}\pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K}\pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K}\pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K}\pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} + \sum_{j=-K}^{K}\pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, and ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP. Quarterly data for the period 1994–2020 is used, resulting in a time series with 108 data points. Most data is retrieved from Compustat

In this case, the FED variable has a negative estimated coefficient β_{FED} with an increasing pattern across quantiles being significant only for all quantiles. Thus, Central Banks help reduce equity market volatility, especially in bear markets. The Leverage variable is also significant for quantiles below 30 with a positive coefficient β_{LEV}, as expected, which decreases as we move from the lowest to the highest quantiles. It is interesting to note that neither variable d nor the EPS variables are significant.

Finally, the ratio of net FoF to equity ETFs to nominal GDP has a negative coefficient β_{ETFFOF} showing the highest values in the quantiles around the median when they are significant. Therefore, this variable would not be related to the VIX for the lower or higher quantiles in the long run. It is precisely in the high quantiles that the dispersion of information can be more relevant, owing to uncertainty and the role of active players. Our results do not validate the hypothesis that ETFs' FOF amplifies volatility according to the volatility model.

These results do not support our initial hypothesis or the prior conclusions of Malamud (2016) and Ben David et al. (2018), partially confirming Box et al.'s (2021) results that suggest that ETFs contribute to reducing volatility levels. The statistical significance of the coefficient, primarily within the range of values around the median, suggests that the impact of equity ETFs on the VIX is only affected when fundamental factors are in play, decreasing it. However, in all other scenarios where the market is either undervalued or overvalued, and the dynamics are not fundamentally driven, the flow of funds through equity ETFs does not significantly affect volatility.

Robustness tests

In this section, we analyze the robustness of the results. To do so, we focus on the quantile cointegration analysis carried out on equity prices, for which we find more empirical evidence of the relationship between net FoF and equity ETFs and nominal GDP.

We develop two types of analysis.[2]

Our first analysis considers equity indices alternative to the S&P 500, such as the Russell 2000 and SVX. The Russell 2000 index is a stock market index consisting of 2000 small-cap U.S. companies. This is the main reference for measuring the performance of small caps in the United States and the benchmark to be beaten by all managers specializing in this type of company. The SVX reflects the performance of companies with low price-to-book values. In this way, we attempt to verify that the effect of the ratio of net FoF to equity ETFs to nominal GDP on stock market valuations extends to the universe of small- and small-value companies and is not limited to large caps.

Panels A and B of Table 5 show the quantile regression estimates of the cointegrating coefficients and the respective p-values based on Model 2 using a lag of order two for the Russell 2000 and SVX. In panel A, it can be observed that the ratio of net FoF to equity ETFs to nominal GDP has a coefficient β_{ETFFOF} that having a positive value shows an increasing pattern across quantiles except for quantiles above 80%. Furthermore, this variable is significant for all quantiles and not only above the median. Consequently, the impact of this variable on the long-term valuation of the Russell 2000 is even more relevant than that of the S&P 500. Panel B also shows a significant positive relationship between the ratio of net FoFs to equity ETFs to nominal GDP and the valuation of the SVX for all quantiles considered. These results again highlight the relevance of a net FoF to equity ETFs in equity valuation.

Our second analysis extends the range of state variables used in the cointegration relationship with the S&P 500 prices. To do so, following the empirical literature and according to data availability, we choose the following alternative state variables after performing the non-stationarity analysis: the long-term interest rate (Campbell 1987; Fama and French 1989), the BAA/AAA credit spread (Fama and French 1988; Fama and French 1989) and the equity share of new issues (Baker and Wurgler 2000). In our analysis, for model parsimony, we considered each variable separately.

Panels A–C of Table 6 show that none of the additional variables considered are significant, and the results previously obtained for the S&P 500 are maintained. In other words, β_{ETFFOF} has a positive value, showing an increasing pattern across the quantiles. Furthermore, this variable is significant for quantiles above the median.

[2] In the corresponding tables, the database used and its characteristics are indicated.

Table 5 Quantile cointegration estimates for Small and Value Caps models

Panel A. Quantile cointegration estimates for Small caps model

τ	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
β_d	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05
p-value	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
p-value	0.05	0.00	0.00	0.00	0.00	0.02	0.00	0.03	0.05
β_{FED}	−0.03	−0.04	−0.03	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03
p-value	0.05	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01
β_{Lev}	0.10	−0.03	−0.02	0.04	0.15	0.10	0.15	0.13	0.17
p-value	0.81	0.93	0.95	0.89	0.53	0.67	0.50	0.53	0.31
β_{ETFFOF}	0.19	0.20	0.21	0.19	0.19	0.23	0.22	0.21	0.20
p-value	0.05	0.05	0.04	0.07	0.03	0.00	0.00	0.00	0.00
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
β_d	0.05	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
p-value	0.08	0.13	0.10	0.06	0.05	0.10	0.17	0.19	0.21
β_{FED}	−0.03	−0.02	−0.02	−0.03	−0.03	−0.03	−0.01	−0.01	−0.01
p-value	0.01	0.05	0.12	0.08	0.05	0.14	0.39	0.49	0.45
β_{Lev}	0.13	0.13	0.15	0.19	0.34	0.24	−0.05	−0.13	−0.08
p-value	0.47	0.43	0.48	0.48	0.26	0.44	0.89	0.75	0.84
β_{ETFFOF}	0.23	0.23	0.25	0.26	0.27	0.31	0.22	0.20	0.19
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00

Panel B. Quantile cointegration estimates for Value caps model

τ	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
β_d	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.03
p-value	0.24	0.25	0.54	0.29	0.11	0.07	0.11	0.05	0.01
β_{EPS}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
p-value	0.20	0.23	0.08	0.15	0.08	0.01	0.06	0.15	0.27
β_{FED}	0.04	0.04	0.04	0.04	0.03	0.03	0.02	0.03	0.01
p-value	0.40	0.38	0.41	0.35	0.40	0.41	0.61	0.19	0.67
β_{Lev}	−0.29	−0.29	−0.18	−0.24	−0.23	−0.30	−0.21	−0.40	−0.21
p-value	0.66	0.62	0.77	0.64	0.65	0.55	0.66	0.34	0.57
β_{ETFFOF}	0.24	0.24	0.25	0.21	0.18	0.18	0.16	0.18	0.14
p-value	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.00	0.03
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
β_d	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03
p-value	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01
p-value	0.19	0.12	0.09	0.06	0.11	0.13	0.47	0.23	0.23
β_{FED}	0.01	0.01	0.00	0.00	0.00	0.00	−0.01	−0.01	−0.01
p-value	0.63	0.77	0.94	1.00	0.94	0.83	0.69	0.55	0.57
β_{Lev}	−0.19	−0.02	0.17	0.17	0.12	0.12	0.11	0.26	0.26
p-value	0.63	0.96	0.66	0.71	0.77	0.72	0.75	0.49	0.49
β_{ETFFOF}	0.14	0.16	0.14	0.15	0.15	0.13	0.12	0.10	0.10
p-value	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04

Table 5 (continued)

Panel A The table shows the quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the Russell 2000 price data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t +, \sum_{j=-K}^{K}\pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K}\pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K}\pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K}\pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} + \sum_{j=-K}^{K}\pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, and ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP. Quarterly data for the period 1995-2020 is used. Most data is retrieved from Bloomberg.

Panel B The table shows the OLS and quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the Value caps price data (SVX Index from Bloomberg), variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t +, \sum_{j=-K}^{K}\pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K}\pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K}\pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K}\pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} + \sum_{j=-K}^{K}\pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, and ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP. Quarterly data for the period 2004-2020 is used. Most data is retrieved from Bloomberg.

Conclusions

We provide empirical evidence that passive investing, related to a FoF in equity ETFs, could be an additional factor in the long-term valuation and volatility of the equity market, posing a problem for financial stability. Our analysis contributes to the existing literature by testing the effect of passive investment on both equity valuations and volatility, expecting a positive statistical relationship in both cases.

The SP500 models show how an increase in FoF into equity ETFs translates into higher equity prices in the long term for quantiles above the median. This conclusion aligns with our initial hypotheses and supports Gabaix and Koijen's (2021) Inelastic Market Hypothesis and De Simone et al.'s (2021) findings. This means a distortion of the value of the S&P 500 relative to its fundamentals linked to investor flows to ETFs in bull markets, which could favor dynamics linked to valuation bubbles. By contrast, passive investment has only a negative and significant effect on the long-run VIX for quantiles around the median. Therefore, this variable would not be related to the VIX for the lower or higher quantiles in the long run. Our results do not validate the hypothesis that ETFs' FOF amplifies volatility according to the volatility model.

These findings suggest that a reduction in the role of active players in the asset management industry leads to an increasing detachment between a firm's fundamentals and its stock price. This should serve as a reflection for reviewing investment approaches and as a warning sign for policymakers who should try to limit these distorting effects, which may affect financial stability, by implementing new regulations and tighter controls on using passive investment vehicles.

Given the distortion of ETFs on the long-term valuation of equity indexes, this would be a financial innovation that does not meet the criteria of contributing to the economic development process and, therefore, cannot be considered Schumpeterian (Akdere and Benli 2018).

Table 6 Quantile cointegration estimates for S&P 500 model

Panel A. 10 years

τ	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45
β_d	0.91	0.84	0.82	0.73	0.71	0.75	0.72	0.72	0.64
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.41	0.43	0.42	0.49	0.46	0.43	0.41	0.43	0.43
p-value	0.02	0.02	0.03	0.01	0.01	0.43	0.03	0.04	0.04
β_{FED}	− 0.02	− 0.01	− 0.02	0.00	0.01	0.01	0.02	0.02	0.03
p-value	0.62	0.89	0.63	0.93	0.77	0.87	0.60	0.70	0.44
β_{Lev}	1.26	1.21	1.04	1.35	1.34	1.47	1.45	1.48	1.47
p-value	0.00	0.01	0.03	0.00	0.00	0.01	0.00	0.01	0.01
β_{ETFFOF}	0.05	0.07	0.07	0.07	0.08	0.09	0.10	0.10	0.12
p-value	0.36	0.23	0.16	0.26	0.13	0.08	0.08	0.13	0.07
β_{Y10}	0.02	0.00	0.01	− 0.02	− 0.04	− 0.04	− 0.06	− 0.05	− 0.08
p-value	0.81	1.00	0.79	0.77	0.50	0.52	0.30	0.42	0.27
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
β_d	0.64	0.47	0.56	0.55	0.56	0.48	0.56	0.48	0.58
p-value	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.02	0.02
β_{EPS}	0.42	0.47	0.47	0.49	0.46	0.48	0.44	0.43	0.37
p-value	0.05	0.05	0.04	0.03	0.03	0.03	0.03	0.06	0.15
β_{FED}	0.05	0.05	0.05	0.05	0.06	0.07	0.06	0.07	0.09
p-value	0.26	0.19	0.15	0.08	0.12	0.04	0.06	0.08	0.08
β_{Lev}	1.40	1.24	1.29	1.30	1.17	1.04	0.94	0.82	0.73
p-value	0.02	0.04	0.04	0.03	0.03	0.12	0.16	0.26	0.36
β_{ETFFOF}	0.12	0.15	0.14	0.10	0.11	0.13	0.13	0.12	0.12
p-value	0.06	0.01	0.02	0.05	0.04	0.03	0.03	0.03	0.12
β_{Y10}	− 0.09	− 0.10	− 0.06	− 0.06	− 0.05	− 0.06	− 0.03	− 0.06	− 0.04
p-value	0.27	0.21	0.38	0.35	0.49	0.35	0.62	0.49	0.65

Panel B. Spread BAA/AAA

τ	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45
β_d	0.91	0.87	0.75	0.78	0.80	0.83	0.83	0.80	0.77
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.38	0.39	0.36	0.33	0.36	0.42	0.42	0.45	0.42
p-value	0.00	0.00	0.00	0.01	0.01	0.42	0.00	0.00	0.02
β_{FED}	− 0.06	− 0.04	− 0.01	0.00	0.01	0.00	0.00	− 0.01	− 0.01
p-value	0.01	0.03	0.62	1.00	0.70	0.88	0.91	0.49	0.48
β_{Lev}	1.44	1.26	0.59	0.56	0.77	0.97	1.21	1.38	1.33
p-value	0.00	0.00	0.15	0.23	0.10	0.03	0.01	0.01	0.02
β_{ETFFOF}	0.04	0.04	0.08	0.09	0.10	0.06	0.05	0.06	0.09
p-value	0.59	0.46	0.10	0.04	0.03	0.28	0.46	0.32	0.15
$\beta_{\mathrm{SpreadBAA/AAA}}$	0.00	0.06	0.22	0.12	0.07	0.04	0.09	0.02	0.02
p-value	0.99	0.70	0.28	0.49	0.68	0.84	0.61	0.91	0.91
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
β_d	0.68	0.55	0.61	0.58	0.51	0.48	0.46	0.42	0.37
p-value	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.08	0.11
β_{EPS}	0.52	0.51	0.49	0.47	0.51	0.54	0.55	0.56	0.61
p-value	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.01
β_{FED}	− 0.01	0.03	0.04	0.04	0.04	0.05	0.06	0.06	0.06
p-value	0.79	0.10	0.02	0.01	0.01	0.00	0.00	0.00	0.00
β_{Lev}	1.44	0.97	1.06	0.94	0.88	0.81	0.77	0.69	0.61
p-value	0.01	0.04	0.03	0.07	0.09	0.09	0.10	0.11	0.15
β_{ETFFOF}	0.11	0.15	0.14	0.13	0.13	0.13	0.12	0.13	0.13

Table 6 (continued)

τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
p-value	0.06	0.02	0.04	0.05	0.04	0.01	0.06	0.09	0.08
$\beta_{\text{SpreadBAA/AAA}}$	0.13	0.17	0.09	0.09	0.12	0.18	0.20	0.24	0.40
p-value	0.54	0.43	0.71	0.70	0.59	0.36	0.31	0.26	0.06

Panel C **Net equity share**

τ	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
β_d	0.85	0.72	0.87	0.69	0.87	0.82	0.79	0.77	0.78
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
β_{EPS}	0.37	0.47	0.31	0.45	0.37	0.43	0.48	0.44	0.44
p-value	0.02	0.00	0.04	0.00	0.00	0.43	0.00	0.00	0.01
β_{FED}	− 0.01	− 0.01	− 0.02	0.00	0.01	0.00	0.00	− 0.02	− 0.01
p-value	0.85	0.78	0.30	0.99	0.59	0.89	0.77	0.23	0.55
β_{Lev}	0.68	0.60	0.87	0.77	0.92	1.04	1.28	1.44	1.41
p-value	0.23	0.25	0.05	0.08	0.01	0.00	0.00	0.00	0.00
β_{ETFFOF}	0.11	0.09	0.10	0.13	0.09	0.07	0.07	0.10	0.10
p-value	0.10	0.15	0.20	0.10	0.21	0.28	0.28	0.07	0.06
$\beta_{Netequityshare}$	− 0.16	− 0.26	− 0.02	− 0.15	0.01	− 0.05	− 0.06	− 0.01	0.03
p-value	0.71	0.50	0.97	0.73	0.98	0.87	0.86	0.98	0.92
τ	**0.5**	**0.55**	**0.60**	**0.65**	**0.70**	**0.80**	**0.85**	**0.90**	**0.95**
β_d	0.74	0.66	0.65	0.55	0.50	0.47	0.45	0.50	0.44
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
β_{EPS}	0.49	0.56	0.54	0.62	0.61	0.64	0.62	0.62	0.60
p-value	0.01	0.01	0.01	0.01	0.03	0.01	0.01	0.03	0.05
β_{FED}	-0.01	0.02	0.03	0.03	0.04	0.05	0.05	0.06	0.07
p-value	0.73	0.41	0.22	0.11	0.03	0.00	0.00	0.00	0.00
β_{Lev}	1.47	1.37	1.28	1.34	1.16	1.25	1.15	1.33	0.95
p-value	0.01	0.01	0.02	0.02	0.06	0.06	0.08	0.03	0.19
β_{ETFFOF}	0.09	0.10	0.11	0.13	0.13	0.15	0.16	0.18	0.16
p-value	0.02	0.02	0.02	0.05	0.00	0.00	0.00	0.00	0.02
$\beta_{Netequityshare}$	− 0.01	− 0.12	− 0.12	− 0.21	− 0.16	− 0.20	− 0.20	− 0.24	− 0.34
p-value	0.98	0.74	0.76	0.61	0.67	0.56	0.58	0.55	0.40

Expanding the set of state variables

Panel A The table shows the quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the S&P500 price data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t + \beta_{Y10}(\tau)Y10_t$$
$$+ \sum_{j=-K}^{K} \pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K} \pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K} \pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K} \pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} \quad ,$$
$$+ \sum_{j=-K}^{K} \pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + + \sum_{j=-K}^{K} \pi_{Y10,j}(\tau)\Delta Y10_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP and Y10 is the long-term interest rate. Quarterly data for the period 1994–2020 is used. Most data is retrieved from Bloomberg.

Panel B The table shows the quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K = 2) applied to the S&P500 price data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t + \beta_{ETFFOF}(\tau)ETFFOF_t$$
$$+\beta_{\text{SpreadBAA/AAA}}(\tau)SpreadBAA/AA_t + \sum_{j=-K}^{K} \pi_{d,j}(\tau)\Delta d_{t-j} + \sum_{j=-K}^{K} \pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K} \pi_{FED,j}(\tau)\Delta FED_{t-j} \quad ,$$
$$+ \sum_{j=-K}^{K} \pi_{Leverage,j}(\tau)\Delta Leverage_{t-j} + \sum_{j=-K}^{K} \pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + + \sum_{j=-K}^{K} \pi_{\text{SpreadBAA/AAA},j}(\tau)\Delta SpreadBAA/AAA_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

Table 6 (continued)

where d, is the logarithm over the last twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP and the spread BAA/AAA. Quarterly data for the period 1994–2020 is used. Most data is retrieved from Bloomberg.

Panel C The table shows the quantile regression estimates of the cointegrating coefficients and the respective *p*-values using a lag of order 2 (K=2) applied to the S&P500 data, variables related to index fundamentals and fund flows to ETFs. The model estimated is

$$Q_{p_t(\tau|\mathcal{F}_t)} = \alpha(\tau) + \beta_d(\tau)d_t + \beta_{EPS}(\tau)EPS_t + \beta_{FED}(\tau)FED_t + \beta_{Leverage}(\tau)Leverage_t$$

$$+\beta_{ETFFOF}(\tau)ETFFOF_t + \beta_{Netequityshare}(\tau)Netequityshare + \sum_{j=-K}^{K}\pi_{d,j}(\tau)\Delta d_{t-j}$$

$$+\sum_{j=-K}^{K}\pi_{EPS,jt}\Delta EPS_{t-j} + \sum_{j=-K}^{K}\pi_{FED,j}(\tau)\Delta FED_{t-j} + \sum_{j=-K}^{K}\pi_{Leverage,j}(\tau)\Delta Leverage_{t-j}$$

, where d, is the logarithm over the last

$$+\sum_{j=-K}^{K}\pi_{ETFFOF,j}(\tau)\Delta ETFFOF_{t-j} + + \sum_{j=-K}^{K}\pi_{Netequityshare,j}(\tau)\Delta Netequityshare_{t-j} + F_{\varepsilon}^{-1}(\tau)$$

twelve months in dividend per share, EPS is the logarithm over the last twelve months in earning per share, FED is the U.S. Federal Funds Effective Rate, Lev, is the natural logarithm of the debt-to-equity ratio of the S&P 500, ETF FOF is the ratio of net FoF to equity ETFs to nominal GDP and New equity share is the share of equity issues in total new equity and debt issues Quarterly data for the period 1994–2020 is used. Most data is retrieved from Bloomberg.

Abbreviations

AP	Authorized participants
AuM	Assets under management
CAGR	Compound annual growth rate
DPS	Dividends per share
EPS	Earnings per share
ETFs	Exchange traded funds
FoF	Flow of funds
GDP	Gross domestic product
NAV	Net asset value
S&P 500	Standard & Poor's 500 index
VIX	The CBOE volatility index

Acknowledgements
Not applicable.

Author contributions
The authors collaborated in the development of all the parts of this work with similar levels of effort. All authors read and approved the final manuscript.

Funding
This work was supported by the MCIN/AEI/https://doi.org/10.13039/501100011033[PID2020-113338RB-I00]; and the Departamento de Ciencia, Universidad y Sociedad del Conocimiento del Gobierno de Aragón [S42_23R: CREVALOR].

Availability of data and materialS
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 27 March 2023 Accepted: 18 December 2023
Published online: 05 March 2024

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