The Role of Market Power and Competition in the European ETF Industry

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Abstract

Various industry studies highlight the negative effects of dominant market players and high market concentration, yet these effects on the financial market have been largely unexplored. This study is the first to provide empirical results on market dominance in the ETF market and its effect on the efficiency of financial innovation. Using monthly data on 350 European ETFs, which capture more than seventy percent of the entire ETF market, we examine the influence of market power and concentration of individual funds on financial outcomes such as expense ratio, tracking error, and premium. Our findings reveal that while higher market power of an ETF provider is associated with an increase in the total expense ratio, higher market concentration leads to a decrease in tracking error. These results underscore the trade-offs present in financial markets, where market dominance results in higher costs for investors but also greater efficiency in tracking performance. By documenting these effects, our study makes a significant contribution to the understanding of how market structure impacts financial innovation and investor outcomes in the ETF market.

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Keywords: Asset Management; ETF; Europe; Competition; Market Concentration; Market Power; Effect; Total Expense Ratio; Tracking Error; Premium

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1 Introduction

Market power, the ability of a firm or a group of firms to control prices and exclude competition, can have profound and often detrimental effects on the economy. Earlier studies [1] [2] have discussed how dominant financial institutions can manipulate market conditions to their advantage, setting higher loan rates and lower deposit rates, thereby exerting a broad economic impact. However, the 2010 Flash Crash has been analyzed in a study [3] demonstrating how the actions of large algorithmic traders contributed to rapid price declines and market instability, resulting in huge losses for investors. It has been further illustrated [4] that firms with significant market power can elevate prices above competitive levels, leading to substantial consumer welfare losses.

Innovation has emerged as a pivotal source of market power, enabling firms to disrupt established competitors and secure substantial market share. Foundational insights [5, 6] have been provided regarding how innovative enterprises can drive technological progress while potentially entrenching monopolistic practices through sustained dominance via patents and intellectual property rights. The advent of financial technology has catalyzed a surge of innovations in areas such as blockchain, algorithmic trading, and cloud computing, leading to the development of new financial products, such as Exchange Traded Funds (ETFs) [7, 8, 9]. In the latter, we notice a creation of a structure similar to an oligopoly where a few institutions are the main providers of these instruments to the market, exerting significant dominance. Such a situation relates to three main ETF providers exerting a market share of over seventy percent in the European ETF market and eighty percent in the US market. Especially, BlackRock and Vanguard alone account for a significant portion of the market, with their assets under management (AUM) totaling USD 2.3 trillion and USD 2 trillion in September 2023, respectively, indicating their strong and continuing presence.

We utilize a dataset comprising 346 ETFs with total assets amounting to EUR 162.1 billion, covering approximately seventy percent of all Europe domiciled equity and fixed-income ETF markets. We track the funds using monthly observations spanning from December 2008 to December 2018. This period includes significant market events, providing a comprehensive overview of ETF performance under varying conditions. All data have been retrieved from Bloomberg and Thomson Reuters' Datastream.

Following the financial literature, we construct the Herfindahl-Hirschman Index (HHI), a market concentration index that measures the market share of individual funds as well as the combined share of the three largest funds (CR3). This index helps us examine how market structure affects the cost and efficiency of ETF products. Higher concentration and market power could imply that a few firms hold a large share of the market, potentially resulting in a less competitive market. However, the consequences of such a market structure are not straightforward in our case. The industry studies document the disruptive effect of market power and market concentration on consumer markets, while the financial literature suggests that economies of scale and scope may benefit clients by reducing costs and increasing the efficiency of the market [10, 11, 12, 13, 14, 15].

To examine the association between market power, competition among individual ETFs, and their cost and efficiency, we employ two-way fixed effects modelling focusing on fund-specific characteristics that are observable and time-invariant. This could relate to ETF providers implementing specific strategies or policies regarding the products they offer. Additionally, we include time-variant controls to capture the time changes in the dynamics of the ETF market and fund characteristics. We also present robustness check results using cross-sectional regressions, where we additionally incorporate various qualitative fund characteristics to ensure that our findings are not influenced by specific ETF features.

Our study finds that higher market power in the ETF market tends to result in higher total expense ratios. This suggests that dominant players in the ETF market can charge higher fees, potentially due to their perceived value or lack of competition, potentially resulting in collusive behavior among market participants. However, the tracking error, which measures how closely an ETF follows its benchmark index, decreases as market concentration increases. This suggests that in a more concentrated market, ETFs tend to track their benchmarks more efficiently, possibly due to lower costs associated with rebalancing and executing trades among dominant issuers. Importantly, our results suggest that market power and concentration are more likely to have significant effects in equity ETF markets, highlighting the importance of market size for effective exertion of such power. While the results regarding ETF pricing are not consistent across all model specifications, they generally indicate that ETFs from dominant players tend to deviate from efficient pricing, often being priced at a higher premium.

Our study significantly contributes to the understanding of the role of market structure in the efficiency of innovations, as well as the impact of market power and concentration on financial markets.

The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 outlines the research methodology, Section 4 presents the findings, Section 5 discusses the results, and Section 6 concludes with policy implications and future research directions.

2 Literature Review and Hypothesis Development

The first stream of literature examines how market structure and market power affects the efficiency of financial innovation. Firms with significant market power can allocate substantial resources to research and development (RD), enabling them to create high-quality, innovative products that smaller firms may not be able to develop due to resource constraints [5, 16]. Moreover, market power allows firms to invest not only in product development but also in quality enhancement, resulting in superior products that offer greater value to consumers [10].

In the context of ETFs, the ability of funds to accurately track their benchmarks can be influenced by the market power of providers. Larger funds can spread fixed costs over a larger asset base, reducing per-unit costs and potentially improving tracking precision. Additionally, larger ETFs typically enjoy greater liquidity, which can reduce the impact of trading costs and market friction when rebalancing portfolios to track their underlying indices. Higher liquidity helps in executing trades more efficiently, thus reducing tracking errors [11, 8, 17]. Given the maturity and size of the equity ETF market compared to the fixed-income ETF market, we expect these effects to be more significant in the equity sector. Based on this discussion, we state the first hypothesis:

H1: Market structure and fund power improve the efficiency of financial innovation, with more significant effects observed in the equity ETF market.

Secondly, we explore the link between market power and the cost of financial innovation. The effect of market power on consumer prices or investors' costs has been well-documented in the literature. On one hand, industry studies highlight a negative relationship between market power and concentration, and consumer prices. For instance, it has been shown that higher market power and increased concentration often lead to higher prices for consumers due to reduced competition and potential collusive behavior among dominant firms [18, 19, 12]. An interesting previous study [22] highlights that high concentration among a few large dealers can lead to reduced liquidity, as these dealers may wield significant market-making power [20]. Moreover, the authors document that such concentration can result in wider bid-ask spreads and higher transaction costs, negatively impacting market efficiency and investor returns.

On the other hand, larger financial institutions can leverage economies of scale to reduce the per-unit cost of providing financial services. This enables them to lower transaction costs and offer competitive pricing by spreading fixed costs over a greater asset base [21, 22]. By efficiently utilizing their resources, these institutions can achieve cost savings that smaller firms may not be able to realize, ultimately benefiting consumers through lower fees and more attractive financial products. Following this discussion, we hypothesize:

H2: Dominant ETF providers offer financial products at reduced cost due to economies of scale and scope, with more significant cost reductions observed in the equity ETF market.

Finally, we add to the literature on market structure and the pricing of financial innovation. Existing literature provides ample evidence on how market power allows dominant firms to influence prices significantly [23]. In financial markets, a greater dominance of an institution may result in prices that do not accurately reflect the underlying value of assets, leading to price distortions and reduced efficiency. Dominant firms often engage in large trades that can move market prices, creating temporary price distortions [24]. These price changes can affect the overall market and lead to the mispricing of assets [25]. However, ETFs may not be influenced by such behavior due to the industry's underlying creation-redemption mechanism. To balance supply and demand, resulting in the convergence of market price and net asset value per share, ETF issuers contract several Authorized Participants who exploit potential arbitrage opportunities. Consequently, the management company does not have an influence on the level of premium. Thus, one could conclude that the magnitude of the fund mispricing is independent of the respective competition level due to issuers' inability to exercise influence. Based on this discussion, we state the third hypothesis:

H3: Dominant ETFs are priced more efficiently, reducing inefficiencies and lowering costs for investors, with more significant effects observed in the equity ETF market.

3 ETF Industry

Exchange Traded Funds (ETFs) are a popular type of open-end fund designed to track the performance of specific indices. They stand out from mutual funds due to several distinct features that enhance their appeal to investors.

First, ETFs enable investors to be exposed to an entire (equity) market, sector or region through one single transaction highly increasing its risk diversification level [26]. Second, the passive investment style, namely tracking a specific index by weighting the respective securities according to pre-defined quantitative indicators, makes ETFs a very cost-efficient investment product reflected in smaller expense ratios compared to open-ended or closed-end mutual funds as well as hedge funds. Moreover, because of the passive character, the product is considered to be highly transparent [26]. Third, due to the ETF's indirect relationship with investors and capital markets through Authorised Participants, the product can externalise transaction costs and operates tax-efficiently, in contrast to mutual funds with its direct link to the mentioned stakeholders. The nature of mutual funds requires the portfolio manager to either sell securities in case of net outflows, realizing capital gains, or buy securities in case of net inflows, incurring transaction costs covered by the fund, thus negatively affecting the fund's net asset value. Thereof a discrimination of existing investors compared with new/old investors arise, which is non-existent for ETFs [27]. Fourth, as ETFs are traded throughout the day on secondary markets, investors are provided with a significant degree of liquidity [28]. Taking into account all the aforementioned advantages of ETF investment, investors can substantially benefit from ETFs' product features and characteristics from which the above discussed advantageous over mutual funds arise.

In 2019, the ETF industry counted more than 8,000 individual ETFs with total net assets (TNA) approximately equal to 5.37 trillion USD worldwide. Since the Financial Crisis of 2008, the industry has experienced a tremendous net inflow of new funds amounting to roughly 4.7 trillion of USD, which represents almost an eight-fold increase in TNA. The predominant amount of money was invested into equities, with its share amounting to approximately 78%. The second largest asset class, fixed income, accounted for another 19% of total net assets, leaving other categories such as commodity, money market and alternative investment at the border. In Panel A of Table 1 we report the detailed numbers on the size of the worldwide ETF market along with the asset class focus and related market shares. Since the equity and fixed income ETFs account for around 97% of the worldwide ETFs in terms of TNA, we focus on these two ETF asset classes.

Regarding the geographical location, the US is the absolute hub of the ETF industry. In 2019, with approximately 3.6 trillions of USD TNA invested into equity or fixed income ETF, it accounted for around 70% of the worldwide TNA within those asset categories. This is consistent with the country's historically high importance for global financial markets and underlines the US superior role in the ETF industry. Europe, as the second-largest center for the ETF industry, lags far behind the US with TNAs of roughly 0.77 trillion USD (15% of the worldwide TNA of ETFs focused on equity and fixed income). In Panel B of Table 1 we provide the overview of equity and fixed income ETFs with respect to the country of domicile.

Based on the rapid development of the ETF market, one would expect a relatively fierce competition in this market. The ETF industry, however, remains to be highly concentrated as indicated in Table 2. We can observe in Panel A of Table 2 that the three largest management companies, Blackrock, Vanguard and State Street, manage around 68% of global equity ETF assets with Blackrock being a clear market leader (34%). The top 10 management companies control almost 83% of equity TNA, which reflects the market's strong segmentation and massive concentration. Very similar situation can be observed in fixed income ETF global market, as per Panel B of Table 2. This market is even more concentrated as the same three companies are responsible for the management of roughly 74% of global equity ETF assets (again, Blackrock dominates the market with managed funds share of 48%) and the top 10 management companies have almost 90% of fixed income TNA under their umbrella.

The concentration trend of the ETF issuers in the worldwide ETF market is driven mainly by the US ETF market, which dominates the worldwide ETF industry. The distribution of the market players in the European ETF market is a bit different as can be seen in Table 3. The three largest management companies, Blackrock, DWS and Lyxor control 62% of TNA of all EU-28 domiciled equity ETFs (Panel A of Table 3), which is a less than 68% in the equivalent global market. On the other hand, the market share of the top 10 companies amounts to 91%, as compared to 83% in the equivalent global market. Thus the European equity ETF market is more concentrated in terms of the top 10 ETF issuers in comparison to the worldwide equity ETF market, but the distribution of shares between them is more equal. Regarding the European fixed income ETF sector, it is more concentrated than the equivalent worldwide sector. Specifically, the three largest fixed income ETF issuers (Blackrock, DWS and Lyxor) control 91% of the European fixed income ETF assets and the top 10 issuers are responsible for management of around 96% of fixed income TNA (Panel B of Table 3). In both, equity and fixed income ETF markets, Blackrock again dominates in Europe with funds share under management of 40% and 60% respectively.

4 Data

4.1 Sample

In this study, we consider Exchange Traded Funds (ETFs) which are domiciled in the EU-28 region with the geographical focus on either EU-28 countries or the European/Euro region. The focus on the European ETFs allows us to consistently define the fund market, which is crucial for the main aim of our study. We collect the data on ETFs from Bloomberg. We include in our sample only equity and fixed income ETFs with information on the underlying index that the fund is tracking. As a consequence, our final sample consists of 346 ETFs (280 equity ETFs and 66 fixed-income ETFs) with total assets of around 162 billion EUR and it covers approximately 70% of all Europe-domiciled equity and fixed income ETF assets. A brief overview of the distribution of the AuM of our ETFs in relation to asset class and geographic focus is presented in Table A1 in the Online Appendix. The detailed list of all the ETFs that we consider in this research is included in Table A2 in the Online Appendix. The data has been retrieved from Bloomberg.

The ETFs dataset covers the ten-year period from December 2008 until December 2018. We use monthly data, except for the total expense ratio which is reported on an annual basis only. In this study, we consider the following characteristics of the ETFs: total Assets under Management, bid price, ask price, last/closing price (for both ETFs and its underlying index), net asset value per share, and total expense ratio. The historical data on all the variables were collected from Bloomberg, apart from the total expense ratio which we extracted from Thomson Reuters Datastream.

4.2 Definition of variables

4.2.1 Efficiency of ETF instruments

In our study, we aim to examine how the ETF fund market structure impacts the cost and the efficiency of ETF instruments. To this extent, we use three indicators: the tracking errors (TE and ATE), the expense ratio (TER), and pricing defined as a premium or discount to NAV ($PREM$).

The idea of a tracking error is to measure how far the return on the ETF fund is from the return on the index that the fund is tracking. It is an important indicator of the quality and efficiency of the ETF in replicating the performance of the index it tracks. A lower tracking error indicates that the ETF closely follows the performance of its benchmark. In line with our H1, we expect that the closer ETF is to its benchmark, the lower tracking error, and thus a higher quality of such an instrument. The existing literature provides multiple definitions of tracking error using both different frequency of data as well as measures.

For the purpose of this study, our definition of the tracking error is based on monthly returns. [29] notice that when tracking errors are based on daily or weekly data, they are artificially inflated. The reason for that is the high serial correlation of daily or weekly returns. This problem is, however, mitigated when monthly returns are used for the purpose of tracking error computation which well fits our case. For the purpose of our study, we consider two measures of tracking error which are commonly used in the literature [30, 26].

First, we measure the tracking error for ETF i in year t as the annualized average of absolute values of monthly return differences between the returns on the ETF and its underlying index:

$$ATE_{i,t} = 12 \cdot \left(\frac{1}{12} \sum_{\tau \in t} |r_{i,\tau} - r_{ind,i,\tau}| \right) \quad (1)$$

where $r_{i,\tau}$ denotes the return on ETF i in month τ and $r_{ind,i,\tau}$ is the return on the fund's i underlying index in the same month.

As an alternative definition, we use the tracking error for ETF i in year t as the annual volatility of the monthly return differences between the returns on the ETF and its underlying index:

$$TE_{i,t} = \sqrt{12} \cdot \sqrt{\frac{\sum_{\tau \in t} (r_{i,\tau} - r_{ind,i,\tau})^2}{12 - 1}} \tag{2}$$

where $r_{i,\tau}$ denotes the return on ETF i in month τ and $r_{ind,i,\tau}$ is the return on the fund's i underlying index in the same month. The expense ratio is a second determinant of the quality of ETF innovation. It is a critical measure of the cost associated with ETF investments. It represents the annual fee that all funds or ETFs charge their shareholders and is expressed as a percentage of the fund's average assets under management. In line with our hypothesis (H2), we expect that ETFs should provide access to well-diversified portfolios at favorable prices due to their cost efficiency and competitive fee structures. Lower expense ratios are typically associated with passively managed ETFs, which track a specific index and involve less frequent trading and lower operational costs [31, 32, 33].

The ETF performance is often measured using the NAV. NAV represents the per-share value of a fund's assets minus its liabilities, calculated at the end of each trading day. It provides investors with an indication of the fund's underlying value and is crucial for various fund operations, including pricing, performance measurement, and regulatory compliance [31, 17].

Due to market inefficiencies and transaction costs, the NAV and market price are distinct concepts. While NAV reflects the per-share value of the ETF's underlying assets, the market price is the price at which ETF instruments are traded on the stock exchange throughout the day. This price can fluctuate based on supply and demand dynamics and may differ from the NAV. Consequently, the NAV can be traded at a premium or discount depending on the difference between the fund's market price and net asset value (NAV) [31, 17]. Using market price rather than NAV for fund return determination would significantly inflate the return measure for investors leading to biased empirical results and distortion in the studied relations. Thus, following the literature, we use ETF NAV to measure ETF return. We define the return of ETF i over the month $t + 1$ as follows:

$$r_{i,t+1} = \ln \left(\frac{NAV_{i,t+1}}{NAV_{i,t}} \right) \tag{3}$$

where $NAV_{i,t}$ denotes the net asset value of ETF i in month t. In an equivalent way, we define the return on the index that the ETF i is tracking:

$$r_{ind,i,t+1} = \ln \left(\frac{PXL_{i,t+1}}{PXL_{i,t}} \right) \tag{4}$$

where $PXL_{i,t}$ denotes the value of the index that the ETF i is tracking in month t.

Consequently, we would observe the premium on the ETF market when the ETF's market price is higher than its NAV, while a discount occurs when the market price is lower than its NAV. Consequently, we define premium/discount as the difference between the fund's market price and its net asset value divided by the net asset value. Aggregating over annual periods, we measure the premium on ETF i in year t as follows:

$$PREM_{i,t} = \frac{1}{12} \sum_{\tau \in t} \frac{(P_{mid,i,\tau} - NAV_{i,\tau})}{NAV_{i,\tau}} \tag{5}$$

where $NAV_{i,\tau}$ denotes the Net Asset Value of ETF i in month τ and $P_{mid,i,\tau}$ is the market mid-price of ETF i in month τ, defined as the average of the fund's bid and ask prices, $P_{mid,i,t} = \frac{P_{ask,i,\tau}+P_{bid,i,\tau}}{2}$.

The proximity of an ETF's trading price to its NAV is a critical measure of its efficiency. When an ETF trades near its NAV, it signifies that the ETF's market price accurately reflects the value of its underlying assets, thereby reducing the potential for arbitrage opportunities. This alignment indicates that the ETF is efficiently managed and that the market mechanisms, such as arbitrage, are functioning effectively to keep the ETF's price in line with its NAV [7].

4.2.2 Definition of ETF market concentration variables

Market structure plays a significant role in how financial instruments are priced, determined, and their costs. A well-structured market with a high level of competition should lead to lower expense ratios as firms strive to attract investors by reducing costs [34]. Therefore, we expect that a competitive market could enhance the quality of ETFs by minimizing tracking errors, enhancing informational efficiency priced in NAV, and improving management practices, resulting in lower tracking errors.

In contrast, a market dominated by a few large players should exhibit higher expense ratios and tracking errors due to reduced competitive pressure and lower efficiency of instruments. Additionally, the presence of fewer authorized participants can lead to greater premiums or discounts to NAV, indicating inefficiencies in price alignment and arbitrage opportunities.

Extensive literature on market concentration in the banking sector [35] reveals that several approaches, ranging from structural to non-structural methods, have been applied by academic researchers to quantify competition and market power in the industry [18]. Structural approaches typically involve concentration ratios as the share of a few largest institutions or the Herfindahl-Hirschman Index (HHI), which measures the size distribution of firms within a market. Non-structural approaches, on the other hand, often involve econometric models that assess market behavior and performance.

Due to the unique characteristics of the financial sector, these methods provide valuable insights into how market structure influences competitive dynamics and the behavior of financial institutions. Structural measures help identify the level of market concentration and potential for monopolistic behavior, while non-structural methods capture the competitive conduct and efficiency of market participants. By applying these approaches, researchers can better understand the implications of market power on financial stability, efficiency, and innovation.

As a measure of fund market power, we use the market share of an individual ETF in a specific market J in a given year i. Consequently, we divide the respective fund's total assets in EUR by the sum of total assets in EUR of all ETFs belonging to the corresponding market. More specifically, we calculate these measures on a monthly basis as follows:

$$MktShare_{i,t} = \frac{1}{12}\sum_{\tau \in t}\left(\frac{TotalAssets_{i,\tau}}{\sum_{j \in J} TotalAssets_{j,\tau}}\right) \tag{6}$$

where $TotalAssets_{j,\tau}$ denotes the total assets value of ETF i in month τ and $\sum_{j \in J} TotalAssets_{j,\tau}$ is the total asset value of all the funds in market J in month τ.

In our analyses, we use two measures of fund market concentration. Firstly, we calculate the Herfindahl-Hirschman Index (HHI) for each fund i in a year t as defined:

$$HHI_t = \frac{1}{12}\sum_{\tau \in t}\sum_{i=1}^{N} MktShare_{i,\tau}^2 \tag{7}$$

where $MktShare_{i,\tau}$ denotes the market share of ETF i in month τ (in percentages) in market J and it is computed as $MktShare_{i,\tau} = TotalAssets_{i,\tau}/\sum_{j \in J} TotalAssets_{j,\tau}$ and N is the number of ETFs in the sample. The value of HHI ranges from 1 (the least concentrated, perfect competition) to 10,000 (the most concentrated, monopoly). For example, the U.S. Department of Justice[1] considers a market with the HHI of less than 1,000 to be a competitive marketplace, the HHI between 1,000 and 1,800 to be a moderately concentrated marketplace, and an HHI of 1,800 or greater to be a highly concentrated marketplace.

We also consider a concentration ratio of three largest ETFs (CR). More specifically, the n-fund concentration ratio (CRn) reflects the concentration of the top n funds with the highest market share. The most commonly used value of n is 3 so in this study we use $CR3$ concentration ratio, which for year t we define as follows:

$$CR3_t = \frac{1}{12}\sum_{\tau \in t}\sum_{i=1}^{N} \frac{MktShare_{1,\tau} + MktShare_{2,\tau} + MktShare_{3,\tau}}{3} \tag{8}$$

where $MktShare_{1,\tau}, MktShare_{2,\tau}, MktShare_{3,\tau}$ represent market shares of the top three ETFs with the largest market shares in month τ.

[1] see https://www.justice.gov/d9/2023-12/2023%20Merger%20Guidelines.pdf

In the context of our study, it becomes crucial to carefully consider a relevant definition of the market that a particular ETF is operating on and for which we define the market share within the concentration measures ($MktShare_{i,\tau} = \frac{TotalAssets_{i,\tau}}{\sum_{j \in J} TotalAssets_{j,\tau}}$).

The literature [36, 37] indicates that market shares based on locally defined markets (state-level) reflect much more accurately the prevalent competitive situation and market power of an institution in a given local region than when using country-level markets. The concept of local-level market shares can be easily adopted in the ETF industry, considering additional market segmentation by investment theme, enhancing the informative power of market shares compared to the aggregated ETF issuer-level approach. Specifically, it allows one to capture the different competitive conditions in various investment categories triggered, for example, by specialized or geographically focused ETF issuers. Consequently, one can measure more accurately the potential effects of market concentration on the fund-specific characteristics such as expense ratio, tracking error, or premium.

Thus, based on the above-mentioned considerations, we divide the universe of ETFs in our sample into various markets (with respect to which we measure market shares), taking into account the following characteristics of the funds: asset class (equity or bond), geographical focus, and industry focus. Additionally, in the case of equity ETFs, we further distinguish between large-, mid- and small-cap stocks and for the bond ETFs, we also group them by the bond issuer (corporate issuer vs public issuer). Applying the aforementioned fund features, the sample of our ETFs was screened leading to 68 distinctive markets which are listed in Table A3 in the Online Appendix.

4.2.3 Other Control Variables

In our study, we also use a set of various control variables to ensure that the observed effects on ETF characteristics are not confounded by other factors. More specifically, we control for the liquidity $Liquidity$ and volatility $Volatility$ of ETFs, which may have a significant effect on multiple characteristics of ETFs, including their performance, tracking error, and premium/discount to NAV [38, 39, 40].

As a measure of risk of ETF, we use the standard deviation of fund's returns following such studies as [41, 42, 43]. We follow this strand in the literature and measure $Volatility$ of a fund i in year t in the following way:

$$Volatility_{i,t} = \sqrt{12} \cdot \sqrt{\frac{\sum_{\tau \in t}(r_{i,\tau} - \overline{r}_{i,\tau})}{12 - 1}} \tag{9}$$

where $r_{i,\tau}$ is the return on ETF i in month τ defined in equation (3) and $\overline{r}_{i,\tau}$ is the average return over year t.

We also account for several fund-specific qualitative characteristics by constructing the following dummy variables: $SecuritiesLending$ (SEC), $AssetClass$ (AC), $InvestmentTopic$ (IT), $IncomeTreatmentError$ (ITE), and $ReplicationMethod$ (RM). More specifically, the $AssetClass$ dummy determines whether an ETF aims to track an equity benchmark index ($AC = 1$) or a fixed-income benchmark index ($AC = 0$); the $InvestmentTopic$ dummy controls whether the ETF is country-specific ($IT = 1$) or industry-specific ($IT = 0$).

With regards to $IncomeTreatmentError$, we control for the income use of an ETF and the computation method of its underlying index.

In general, an index can be calculated as a performance index with underlying securities' dividends (in the case of equity indices) and coupons (in the case of bond indices) being reinvested or as a price index where dividends and coupons are not taken into consideration. Similarly, an ETF either distributes the received dividends and coupons to the respective shareholders or reinvests the cash accordingly. Theoretically, a reinvesting ETF tracks a performance index and vice versa. However, due to various diverse reasons, some of the funds included in the final sample do not comply with the outlined concept. Therefore, the dummy variable of $IncomeTreatmentError$ is expected to control for this shortcoming. Consequently, it takes the value of 1 ($ITE = 1$) in case an ETF reinvests any income but tracks a price index or distributes any income but tracks a performance index and it takes the value of 0 ($ITE = 0$) in case an ETF reinvests any income and tracks a performance index or distributes any income and tracks a price index. $SecuritiesLending$ takes the value of ($SEC = 1$) if the lending of the securities is allowed, and zero otherwise. Finally, $ReplicationMethod$ indicates whether an ETF performs physical replication of the tracked index, that is invests directly into the securities included in the index ($RM = 0$) or it performs synthetic replication, that is through derivatives such as swaps or futures ($RM = 1$). The inclusion of these variables allows us to control for fund-specific characteristics, which potentially might influence the efficiency and pricing of ETF products [44, 45, 46, 47, 8, 48, 49].

4.3 Summary Statistics

In Table 4 and Table 5 we provide the descriptive statistics of our main variables of interest, namely total expense ratio (TER), absolute return differences (ATE), volatility of return differences (TE), and premium ($PREM$) split by asset classes and time periods.

We can observe from Table 4 economically substantial pricing differences between fixed-income and equity ETFs with a mean TER of 0.294% and 0.170%, respectively. With the overall average being equal to 0.271% in mind, the general proximity between total and equity-related numbers can be traced back to the fact that the sample consists of 280 equity ETFs and 66 fixed income funds. Furthermore, the statistics in Table 5 show a considerable decline in expenses between the periods 2009-2013 and 2014-2018 amounting to approximately 10%. Similar to the findings of a previous study [50], we observe in both tables that the distribution of TER, ATE, TE, and $PREM$ is right-skewed and leptokurtic in almost all cases, indicating fatter tails compared to a normal distribution. The distribution of premiums for equity ETFs is an exception, being skewed to the left. Our study's sample confirms the results of another relevant study [51] regarding tracking accuracy, reporting an annual underperformance of ETFs compared to their corresponding underlying benchmarks, ranging from 0.5% to 1.5%. The overall average ATE amounts to 1.510% while the mean TE equals 1.390%. Interestingly, similar to another previous study [52], fixed-income ETFs exhibit relatively higher tracking precision compared to equity ETFs. All in all, in 2,216 out of 2,912 observations an underperformance can be observed which implies economically substantial tracking inaccuracies. However, in contrast to studies such as [53] or [50], which report absolute tracking errors based on daily returns of 0.35% and 0.08% (87.5% p.a. and 20% p.a.), respectively, our sample shows substantially smaller annual imprecision, with the overall median being 0.606%. We believe this can be explained by methodological differences regarding the returns' time base and the timeliness of data. As outlined by one of the previous studies [29], tracking errors based on high-frequency data such as weekly or daily returns are substantially inflated due to autocorrelation. In addition, the timeliness of data seems to play a substantial role in the magnitude of tracking errors. Consequently, the comparison of data based on daily or weekly returns with results estimated on a monthly return base is inaccurate and explains the discrepancies. In addition, the timeliness of data seems to play a substantial role with regards to the magnitude of tracking errors. Although both previous studies [53] as well as [50], focus on the German ETF market, there is a significant difference in the reported absolute return differences. However, However, while study [53] uses data from 2003 to 2005, study [50] applies a more current dataset covering the period from 2001 to 2013.

In Table 5, we can observe that average or median values of total expense ratio TER, absolute tracking error ATE, tracking error TE, and premium $PREM$ are lower over the 2014–2018 period than over the years 2009–2013. For example, the median ATE declined from 0.846% between 2009 and 2013 to 0.444% over the 2014–2018. This trend of declining magnitude is surprisingly consistent over various measures. With the development of the industry in mind, one can conclude that the magnitude of tracking error has substantially decreased over time as a result of increasing popularity and rising demand.

Consistent with findings from a relevant study [54], the mispricing of the study's sample ETFs is economically trivial, with an overall median of 0.02%. This can be mainly attributed to the fact that the sample consists exclusively of domestic ETFs as per above definition which is why stale prices are non-existent. In general, the academic literature which has almost solely focused on US-listed ETFs comes to the conclusion that domestic funds are priced efficiently. The study's results confirm this US-specific conclusion for the European ETF market. Similar to tracking error, one can additionally observe decreasing magnitudes of the premium over time. However, the relatively high standard deviation of 2.289% indicates that by no means all ETFs are priced accurately. Moreover, fixed income ETFs seem to be priced relatively worse in comparison with equity ETFs.

Table 6 shows the correlation matrix for all explanatory variables used in our studies. The monitored correlations do not provide any indications for multicollinearity with the highest absolute correlation being equal to 0.398 observed for $MktShare$ and HHI. The descriptive statistics of the independent variables are reported in Table 7.

5 Methodology

In this section, we provide the details of the methodological approach we use in order to investigate how the ETF market structure of the European market influences the ETFs characteristics such as total expense ratio, tracking error, and ETF premium. Additionally, we also discuss the relationship between those characteristics and our other control variables in accordance with the suitable academic literature. We consider three model specifications in our analyses: with respect to all ETF instruments as well as considering equity and bond ETFs separately.

To verify H1, we examine the impact of the ETF fund market structure on a fund's tracking error TE (the most commonly used performance measure of ETF) using the following model:

$$\begin{aligned} TE_{i,t} = \theta_0 &+ \theta_1 MktConc_{i,t} \\ &+ \theta_2 ln(TotalAssets_{i,t}) + \theta_3 Volatility_{i,t} + \theta_4 Liquidity_{i,t} + \theta_5 MktShare_{i,t} \\ &+ \theta_6 TER_{i,t} + \theta_7 PREM_{i,t} + \sum_j \gamma_j X_{j,i,t} + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $TE_{i,t}$ is the tracking error of ETF i in year t (as a robustness check, we also use the absolute tracking error ATE as an alternative measure of tracking error). In line with the existing literature documenting the impact of other controls influencing the ETF tracking error, we include $TotalAssets_{i,t}$, $Volatility_{i,t}$, $Liquidity_{i,t}$, $ln(TotalAsset)$ as the size of the ETF fund expressed in the natural logarithm. As measures of market concentration $MktConc_{i,t}$, we use HHI and $CR3$ as discussed in the previous Section. As a measure of fund market power, we use $MktShare$. Additionally, we include the fund-qualitative characteristics in $X_{j,i,t}$, represented as a set of dummies: $SecuritiesLending$, $AssetClass$, $InvestmentTopic$, $IncomeTreatmentError$ and $ReplicationMethod$.

To verify the effect of ETF market structure and fund power on TER as specified in H2, we specify the following model:

$$\begin{aligned} TER_{i,t} = \theta_0 &+ \theta_1 MktConc_{i,t} \\ &+ \theta_2 ln(TotalAssets_{i,t}) + \theta_3 MktShare_{i,t} \\ &+ \sum_j \gamma_j X_{j,i,t} + \epsilon_{i,t} \end{aligned} \tag{11}$$

where $TER_{i,t}$ is the total expense ratio of ETF i in year t. Other choices of regressors in $X_{j,i,t}$ are defined as in the previous model.

Finally, we also investigate the impact of fund market structure on fund premium. To this extent, we estimate the following model:

$$
\begin{aligned}
PREM_{i,t} = \theta_0 &+ \theta_1 MktConc_{i,t} \\
&+ \theta_2 ln(TotalAssets_{i,t}) + \theta_3 Volatility_{i,t} + \theta_4 Liquidity_{i,t} + \theta_5 MktShare_{i,t} \\
&+ \sum_j \gamma_j X_{j,i,t} + \epsilon_{i,t} \qquad (12)
\end{aligned}
$$

where $PREM_{i,t}$ is the premium of ETF i in year t. Again, the regressors appearing in the model are in line with the existing literature and are defined the same as in the model specification for TE.

We estimate all equations using two-way fixed-effect models. The choice of the model has been driven by the result of the Breusch-Pagan Test and Hausman Test that are rejected at the 99% confidence level, implying the preference of the fixed-effect panel regression over pooled and random effect panel regressions.

Moreover, the fixed-effect model allows us to capture the unobservable time-invariant fund features. This might relate to specific ETF issuer strategy or investment policy. We also include time-variant controls, which allow us to capture the time changes in the dynamics of the ETF market as well as the changing regulatory environment in Europe. In our fixed-effect models, we also control for other fund characteristics which appear as time variant. However, we include the time-invariant control variables (qualitative fund characteristics) in models where some autocorrelation in the standard errors is detected. We then switch from panel regressions to cross-sectional regressions for selected sample years. In such cases, we can include in our models time-invariant characteristics which will not correlate with the fixed effect. These results might also be seen as alternative ways of testing the robustness of our panel regression results.

6 Empirical Results

For a coherent presentation and discussion of the obtained results, this Section is divided into three sub-sections. The first sub-section provides the outcomes and implications of the regression analysis related to the relationship between fund market structure and expenses given in equation (11). The second sub-section reviews the results with regard to the drivers of tracking error, provided in equation (10) and debates the respective implications. Finally, the determinants of premium, as expressed in equation (12) are reported and discussed in the last sub-section.

6.1 Fund tracking error and the ETF market structure

In this sub-section, we present the regression results verifying H1 regarding the link between the ETF market structure and the efficiency of innovation measured in the tracking error. As discussed, we use two measures of tracking error as defined in equations (2), TE, which we refer to simply as tracking error, and (ii) (1), ATE, which we refer to as absolute tracking error.

We present the regression results using the two fixed-effect models controlling for the fund unobservable features as well as time variant factors. We also split our regression results into equity and fixed-income ETF markets to capture the potential heterogeneity of the effects which might exist from the specific market type. The empirical results are reported in Table 11 and Table 12.

We can observe in Table 11 that market share has a statistically negative influence on tracking error. Specifically, the coefficients on $MkrShare$ range from -0.024 to -0.033 which implies a 0.024% to 0.033% reduction of tracking error per 1% rise of fund market share. This finding confirms our H1, suggesting that ETFs with greater market power can execute trades more efficiently, potentially at lower transactional costs, and thus more frequently rebalance their portfolios, reducing tracking error [55, 56]. Moreover, our finding is also in line with the market efficiency hypothesis, where the superior quality and knowledge of managers explain the relatively better (tracking) performance of the ETF [57, 58].

Additionally, the statistically negative relationship of market concentration variable as measured by $CR3$ and tracking error supports this conclusion. The outstanding quality of some management companies, due to greater experience, allows them to more efficiently reproduce their respective benchmark performance, which in turn increases market concentration. Interestingly, we do not observe such a relationship between the HHI and the tracking errors. This could suggest that these results are sensitive to the measure of market concentration used in the analysis.

Moreover, the results on other control variables also present interesting conclusions. In line with [52] and [59], we find that the size of the fund is found to be statistically positive with a consistent amplifying effect on ETFs' tracking error in any case irrespective of the measure of it. This result confirms the theory of diseconomies of scale, which implies that larger funds experience problems in precisely and efficiently reproducing the performance of the underlying benchmark. Consistent with [53], the premium is of statistical relevance with coefficients of around 0.26 and 0.21 for TE and ATE, respectively which is equivalent to an increase in tracking error of 0.26% and 0.21%, respectively as a result of a 1% rise in premium. However, in comparison to the median premium in our sample of ETFs equal to 0.02%, the economic importance of premium can be considered as comparably low. The result seems to suggest that less efficient ETFs are also more likely to be mispriced.

In addition, the results related to the influence of fund risk $Volatility$ on tracking error confirm the findings of earlier studies [60] or [61]. The risk of ETF is found to be a statistically significant factor with economically high coefficients of magnitude between 0.91 and 0.95, which imply that a 1% increase in fund's risk results in a 0.91%–0.95% increase in tracking error. Higher fund volatility increases the execution costs, and thus probably decreases the incentives of fund to rebalance.

The question that arises at this point is which risk layer is the trigger for tracking error since, in theory, ETFs should be only exposed to systematic risk and thereby do not differ from the corresponding underlying benchmark. In order to understand the sample funds' exposure to systematic and non-systematic risk, the CAPM approach was applied where we regress ETFs' annualized average monthly returns on the corresponding benchmark returns. We found the market beta coefficient to be statistically significant and of magnitude of 0.88, which is only slightly lower than the market beta of the market portfolio.[2] In consistency with [53], this result implies that the considered ETFs apply optimized replication strategies instead of full replication, which is why they are not only subject to systematic risk but also exposed to a certain level of diversifiable risk. Moreover, the level of unsystematic risk is further influenced by a fund's cash holdings. In summary, the statistical relevance of $Volatity$ reveals the sample funds' substantial exposure to non-systematic risk, which in turn causes the ETFs to imprecisely track the respective benchmark.

Moreover, from Table in Table 11 we notice that that TER is irrelevant for TE, in line with previous findings [62]. This can be intuitively explained by the fixed nature of expenses. Since yearly fund expenses have a stable impact on net asset value, the tracking error should not be influenced by TER. On the other hand, one recent studies [63] empirically finds expenses to have a statistically significant impact on tracking error. However, the statistically negative relationship that can be observed between TER and absolute tracking error ATE seems to be rather counter-intuitive. It could be, however, explained by the fact, that funds which decide to rebalance their portfolio more frequently tend to have higher expenses than other funds.

The results on the fund liquidity $Liquidity$ seems to be in line with the existing studies. Higher fund liquidity results in less costly rebalancing, and thus allow the ETF to track the index more carefully, reducing the tracking error [50].

In line with our H1, we expect that market structure should be more relevant for the ETF equity market than the bond market as the maturity of instruments is less relevant, and thus more frequent rebalancing mechanisms may be in place at the fund. To analyze how our effects of $MktShare$ and $MktConc$ measures might impact the efficiency of financial instruments, we run our regression results on equity ETFs and fixed-income ETFs, separately. We report them in Table 12. Since the empirical results are qualitatively similar for both market concentration measures, HHI and $CR3$, thus in order to save space, we present the results only for $CR3$, while the equivalent results for HHI are available upon request.

The estimation results in Table 12 document that our results from Table 11 are mainly driven by equity ETFs. This is not surprising given the fact that the ETF market is dominated by the equity ETFs as well as the fact that equity ETFs might be more prone to rebalancing due to the nature of securities.

Interestingly, when considering the results on market share and market concentration measures, we can observe that while market share is statistically significantly correlated with the tracking error on both markets, the market concentration, as measured by $CR3$ is statistically important terminator only for equity ETFs, but not for the fixed-income funds.

However, interestingly, we find that the market share variable coefficients exhibit opposite signs, depending on the market. Specifically, for equity ETFs funds with higher market share experience lower tracking errors, while fixed income ETFs with higher market share have higher tracking errors. The results might suggest that in deeper markets, the market power gives the advantages for market participants to exert their market power and execute transactions more efficiently, while this does not seem to be the case for less developed or smaller markets. The same conclusion

[2]The results of this estimation are available upon request.

can be derived from the results on $CR3$ where we see that higher concentration, and thus generally greater market power of a few institutions improves the operating efficiency, providing better quality of financial innovation, however, this can only be achieved when the markets are sufficiently matured to do it. The bond ETF market due to their limited scope does not allow, and thus we do not notice any statistical effect of $CR3$ measure on any tracking errors.

While the signs of other control variables do not significantly differ between equity and fixed-income ETFs, the result concerning ETF size is particularly interesting. The size of the ETF has a positive sign for tracking errors in equity ETFs but a negative sign for fixed-income ETFs. These findings suggest that in markets where more rebalancing is required, it is more difficult for larger funds to track the benchmark accurately and efficiently.

To verify H2 referring to the role of market structure on the cost of financial innovation measured by Total Expense Ratio (TER), we report the estimation results in Table 8. In order to analyse whether we can notice the same results on equity and fixed-income ETF markets, we run equivalent regressions separately for each of the two groups of ETFs.

From the table, we observe that our fund concentration measures as HHI and $CR3$ as well as market share variable $MktShare$ are highly statistically significant when considering the full sample of ETFs. More importantly, the coefficients indicate positive signs, documenting that higher concentration and market share of individual funds result in anti-competitive pricing, and thus reduces the benefits of financial innovation.

However, at the same time, we notice that larger funds have, on average, lower expense ratios, consistently with the argument of economies of scale and scope realized by financial institutions [57, 58].

Interestingly, we notice that the effect of market structure differs in relation to the type of the market. While we confirm a negative effect of market power and concentration measures on the costs of ETFs on the equity market, we do not notice such a relationship on the fixed-income market. One of the reasons could be that the equity market is deeper and the funds are more able to exert their power than on the bond market.

From an econometric perspective, we notice that our models reported in Table 8 seem to suffer from the autocorrelation problem (the values of the Durbin-Watson test statistic range from 0.63 to 0.66, indicating the rejection of the null hypothesis of no autocorrelation). While OLS estimators remain unbiased in the presence of autocorrelation, they are no longer efficient [64]. This means that the standard errors of the coefficients are underestimated, potentially leading to overly optimistic p-values and confidence intervals. These results are reported in Table 9.

To address the issue of autocorrelation and to verify the robustness of our results from Table 8, we perform cross-sectional regressions for individual years: 2009, 2013, and 2018. These years have been selected to represent equal intervals within our sample, ensuring that we capture potential structural changes and different economic conditions over time. Cross-sectional regressions allow us to examine the relationships between variables within a specific year, eliminating the temporal component that contributes to autocorrelation. Moreover, such a model specification also allows us to include additional fund-specific controls which in the fixed-effect model has been eliminated due to the collinearity with this effect. Consequently, we include the fund-specific characteristics as $ReplicationMethod$ (RC), $AssetClass$ (AC), and $InvestmentTopic$ (IT). Those results are reported in Table 9.

The results present interesting conclusions. Firstly, the results for the year 2018 confirm our previous conclusions that higher market power of individual funds and greater market concentration increase costs for investors, thereby diminishing the benefits of financial innovations in the financial market. All three measures (HHI, $CR3$, and $MktShare$) are highly statistically significant, showing a positive relationship with the TER.

However, the results are weaker for the previous years (2009 and 2013). While the $MktShare$ variable remains statistically significant across all years, the market concentration variables (HHI and $CR3$) do not show statistical significance for 2009 and 2013. One possible explanation is that the concentration of individual ETF funds has been increasing over the years, reaching its peak in 2018. This trend could also explain the Durbin-Watson statistics related to autocorrelation.

From an economic perspective, the coefficients of $MktShare$ range from 0.00077 to 0.00151 which implies an increase in the total expense ratio by 0.07–0.15 basis points per 1% increase in market share. In relation to the sample's average TER of approximately 30 basis points (0.3%), the magnitude of the estimated coefficients is economically substantial. Thus, we conclude that ETFs obtain considerable benefits from their market power as higher market shares are monetized in the form of higher expense ratios. However, the positive coefficients on $CR3$ (HHI) of 0.00100 (0.00046) for 2018 years implies higher fund expenses at the amount of roughly 0.1 (0.046) basis points per 1% increase in $CR3$ (HHI) accumulated market share. In other words, the higher the concentration of a specific market is the higher the expense ratios of the related funds are which confirms the anticipated collusive pricing behavior [65].

Regarding the fund of the size, we can still observe in Table 9 negative values of estimated coefficients which confirm the presence of economies of scale, however, the influence of fund size is not significant from a statistical perspective. This could be that the effects have been captured in our other control measures. We notice a positive and statistically significant coefficient on dummy variables $AssetClass$ (AC) and $ReplicationMethod$ (RM) , indicating higher expense ratios for equity ETFs (which confirms the patterns observed in the descriptive statistics in Table 4) and for ETFs that apply synthetic replication in tracking the underlying index, Table 4. On the other hand, country-specific ETFs have lower expense ratios than industry-specific ones as implied by the negative sign of the dummy variables $InvestmentTopic$ (IT).

The $adjusted - R^2$ coefficients range from 37% to 42% which indicates relatively high explanatory power of the model and underlines the importance of the analysed factors.

We also present the cross-sectional regression results while splitting the fund market into equity and fixed-income in line with the previous results that the $AssetClass$

might matter for the TER. The empirical results are qualitatively similar for both market concentration measures, HHI and $CR3$. To save space, we report results only for $CR3$, while equivalent results for HHI are available upon request. These results are presented in Table 9.

The estimation results for equity ETF confirm the findings from Table 9. Specifically, the positive and statistically significant coefficient on market share indicates that equity ETFs with higher market power have higher expense ratios. Moreover, equity ETFs that apply synthetic replication in tracking the underlying index and industry-specific ETFs also have higher expense ratios. Moreover, equity ETFs that apply synthetic replication in tracking the underlying index and industry-specific ETFs also have higher expense ratios. The statistically negative coefficients of fund size for the years 2018 and 2013 indicate the prevalence of lower fees for equity ETFs resulting from economies of scale, consistent with the findings of a previous study [53]. We do not find, however, any statistically significant impact of market concentration on total expense ratios for equity ETFs.

On the contrary, the empirical findings for fixed income ETFs are relatively blended and it turns out that market concentration is an important factor influencing fund expenses within fixed income ETFs, although the coefficient signs are mixed between various years which makes a valid discussion of implications relatively challenging. However, together with the statistically significant but positive coefficient of size on TER in the year 2018 could suggest that ETF funds can exert their power given the appropriate depth of the market. Market power seems to be less exercised in smaller or less developed markets. The estimated coefficients for other determinants also seem to depend on the year of estimation, and thus might correlate with the development and depth of the ETF market.

Consequently, we conclude that the empirical results provide strong evidence for the market power hypothesis. This implies higher expense ratios for ETFs with higher levels of market share, indicating that funds with greater market power can charge more. On the other hand, economies of scale are observed, with total expenses being smaller for larger funds.

Interestingly, our regression results suggest that the effect of market concentration varies with the development and depth of the ETF market. This variation implies that a sufficiently large market must exist for collusive behavior among market participants to emerge. In less developed or smaller markets, the potential for collusive behavior may be limited, whereas in more mature and larger markets, the likelihood of such behavior increases.

The estimation results related to the link between ETF market structure and fund's premium are reported in Table 13. Similarly, as in the previous sub-sections, we consider separately equity and fixed-income ETFs.

The regression results present interesting conclusions. Firstly, consistent with our previous results, the estimated model coefficients show that market power tends to matter for equity ETFs but does not significantly impact the premium of fixed-income ETFs. Again, the results might indicate that sufficient depth and size of the market might matter to exert market power.

Secondly, the results document that the market power of ETF is positively correlated with its premium, indicating less efficient pricing. The estimated coefficient on $MktShare$ is 0.018, implying an economically substantial premium increase of around 1.8 basis points per 1% rise in market share of the fund. This might suggest that more demanded ETFs may have inflated pricing [40, 43]. Interestingly, the regression results present opposite results on the concentration measures HHI and $CR3$. This seems to indicate that competition improves the efficiency of pricing of ETFs, which could be in line with studies documenting a positive effect of competition on fair valuation [66, 67]. The ETF pricing premium does depend, however, on the measure used. In particular, we find that if we use HHI in our regressions, higher levels of market concentration are associated with a lower premium. In contrast, fixed income ETFs show a similar relation with $CR3$ measure of market concentration. Interestingly, for fixed income ETFs, their market power does not seem to have an impact on the level of mispricing.

Concerning the results of other control variables, we notice a significant effect of $Volatility$ and $Liquidity$ but only on the premium of fixed-income ETFs which might suggest that these measures affect pricing in probably less efficient due to its lower maturity, markets.

Again, from an econometric perspective, we notice that the models reported in Table 13 suffer from the autocorrelation problem (the values of the Durbin-Watson test statistic range from 1.09 to 1.17, indicating the rejection of the null hypothesis of no autocorrelation). Similarly, as in the expense ratio results, we try to test the robustness of our results by performing cross-sectional regressions for the 2009, 2013, and 2018 years. These cross-sectional regressions allow us to control more specifically for greater heterogeneity in fund characteristics which previously was not possible due to collinearity with the fund fixed effect. The empirical results from those regressions are reported in Table 14.

These results cannot confirm our fixed-effect panel data results suggesting that the effect of ETF market power or market concentration on premium might be dependent on specific moments. Alternatively, this might be a result of the industry's underlying creation-redemption mechanism. In order to balance supply and demand which in turn results in the convergence of market price and net asset value per share, ETF issuers contract several Authorized Participants which exploit potential arbitrage opportunities. Consequently, the management company does not have an influence on the level of premium whereas the previously analyzed fund characteristics are influenced by the decisions of the ETF issuer. Thus, one could conclude that the magnitude of fund mispricing is independent of the respective competition level due to issuers' inability to exercise influence.

Considering the influence of qualitative fund characteristics, we observe in Table 14 that, in line with our expectations, country-specific ETFs are priced more efficiently with the coefficients on $InvestmentTopic$ (IT) implying a lower premium of 2.21%, 0.98%, and 0.57% for the years 2009, 2013, and 2018, respectively. The binary variables on $SecurityLending$ (SL) and $IncomeTreatmentError$ (ITE) do not reveal a statistically relevant relationship with fund premium as anticipated. Interestingly, the $ReplicationMethod$ (RM) seems to possess strong explanatory power. Equity ETFs that apply synthetic replication are considered to have a lower premium, while fixed income ETFs with physical replication tend to be priced more efficiently.

The relatively low explanatory power of models estimated in Table 14 could be attributed to data intervals. This study uses annualized monthly data, while the literature on ETF premium often applies daily or even intra-daily data. Nevertheless, in light of the research question, the selected interval structure fits well to investigate the effect of competition on fund premiums, although it lacks the ability to yield relevant results for variables found by previous studies to be statistically significant. However, it obviously lacks the ability to receive relevant results for variables which have been found by previous studies to be statistically significant.

7 Conclusions and Policy Implications

To conclude, the superior objective of this study was to analyse the impact of competition on the direct and implicit costs of Exchange Traded Funds. The study contributes to the existing academic literature by enhancing the understanding of the influential factors of total expense ratio, tracking error, and premium. In addition, practitioners/investors are provided with factors which might be worth considering in advance of an investment decision. To the best of our knowledge, this is the first study to introduce competition-related measures as determinants of the selected quantitative fund characteristics. The study finds some support and certain evidence-based clarification of the abstract concepts of market power and efficient structure in the European Exchange Traded Fund industry. In general, the efficiency of the European ETF market with regards to tracking error and mispricing have substantially increased in recent years. Similarly, the expense ratio has continuously decreased since 2008. However, the level of tracking error remains economically substantial. Moreover, mispricing continues to be of relevance, although the funds are priced relatively accurately on average. Regarding direct expenses, the results indicate the validity of the market power hypothesis, implying higher expense ratios with higher levels of market share. Conversely, the absence of robustness regarding market concentration makes any conclusions on possible collusive behavior by market participants questionable. Competition is also found to play a substantial role in relation to ETFs' implicit cost measured by the tracking error. On the one hand, competition measures show strong evidence for the efficient structure hypothesis in relation to the equity market which implies lower implicit costs with higher market shares. On the other hand, the market power hypothesis is valid for the fixed income market. Additionally, for equity ETFs, one can observe that premiums, total assets, and volatility have a deteriorating impact on tracking quality, while liquidity and fund expenses are considered irrelevant. These findings support the presence of diseconomies of scale and unsystematic risk exposure, attributed to issuers' inability to influence fund premium levels due to the creation-redemption mechanism. On the contrary, both existing explanatory approaches, the market power hypothesis and the efficient structure theory are not able to explain the formation of fund premium – the second layer of implicit costs. This is attributed to the issuers' inability to exercise influence on the level of fund premium as a result of the creation-redemption mechanism. Future research ought to aim to analyze the results' robustness by transferring the applied concepts and approaches to different geographic markets. Especially, the US market seems to be predestined due to its size and extraordinary high importance for the global ETF industry. Furthermore, it becomes apparent that the determination of tracking error and premium differs between equity and fixed income ETFs, necessitating further research to consistently explain various influential factors of equity and fixed income ETFs' tracking error and premium.

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8 Tables and Figures

Table 1: ETF Assets

Panel A: Global ETF Funds per Asset Class

Asset Class	**Fund Assets (bln of USD)**	**Market Share (%)**
EQUITY	4185.5	78.0%
FIXED INCOME	990.7	18.5%
COMMODITY	94	1.8%
MONEY MARKET	70.6	1.3%
MIXED ALLOCATION	16.7	0.3%
SPECIALITY	5.9	0.1%
ALTERNATIVE INVESTMENTS	4.3	0.1%
GLOBAL ETF MARKET	**5367.8**	**100%**

Panel B: Equity and Fixed Income ETF Funds per Country of Domicile

Country of Domicile	**Fund Assets (bln of USD)**	**Market Share (%)**
NORTH AMERICA	**3785.1**	**73.6%**
UNITED STATES	3660.2	71.1%
CANADA	124.8	2.4%
EUROPE	**774.7**	**15.1%**
IRELAND	468.8	9.1%
LUXEMBOURG	209.1	4.1%
GERMANY	53.6	1.0%
FRANCE	43.1	0.8%
ASIA	**371.7**	**7.2%**
JAPAN	328.1	6.4%
CHINA	43.6	0.8%
OTHER	**213.8**	**4.2%**
TOTAL EQUITY & FIXED INCOME	**5145.3**	**100%**

Table 2: Global Top 10 ETF Issuers

Management Company	**Company Location**	**Fund Assets (bln of USD)**	**Market Share (%)**
Panel A: Global Top 10 Equity ETF Issuers			
BLACKROCK (iShares)	US	1415.4	34.1%
VANGUARD	US	846.2	20.4%
STATE STREET (SPDR)	US	557.2	13.4%
INVESCO	US	162.8	3.9%
NOMURA ASSET MANAGEMENT	JPN	148.3	3.6%
CHARLES SCHWAB	US	112.2	2.7%
DWS	GER	68.4	1.6%
NIKKO ASSET MANAGEMENT	JPN	64.9	1.6%
DAIW A ASSET MANAGEMENT	JPN	64.7	1.6%
FIRST TRUST	US	54.6	1.3%
OTHER	N/A	715.4	17.2%
Global Equity		**4155.5**	**100%**
Panel B: Global Top 10 Fixed Income ETF Issuers			
BLACKROCK (iShares)	US	478.4	48.3%
VANGUARD	US	175.8	17.8%
STATE STREET (SPDR)	US	79.1	8.0%
INVESCO	US	28	2.8%
PIMCO	US/GER	26.4	2.7%
CHARLES SCHWAB	US	21	2.1%
DWS	GER	20.3	2.1%
LYXOR	FRA	17.3	1.8%
BMO	CAN	14.9	1.5%
FIRST TRUST	US	14.3	1.4%
OTHER	N/A	114.2	11.5%
Global Fixed Income		**989.8**	**100%**

Table 3: European Top 10 ETF Issuers

Management Company	Company Location	Fund Assets (bln of USD)	Market Share (%)
Panel A: Top 10 Equity ETF Issuers in Europe			
BLACKROCK (iShares)	US	230.8	40.7%
DWS	GER	67.6	11.9%
LYXOR	FRA	53.4	9.4%
AMUNDI	FRA	46.4	8.2%
UBS	CHE	41.1	7.2%
V ANGUARD	US	38.5	6.8%
ST A TE STREET (SPDR)	US	20.5	3.6%
INVESCO	US	16.6	2.9%
WISDOM TREE	US	0.9	0.2%
FIRST TRUST	US	0.7	0.1%
OTHER	N/A	51.1	9.0%
EU-38 Domiciled Equity		**567.6**	**100%**
Panel B: Top 10 Fixed Income ETF Issuers in Europe			
BLACKROCK (iShares)	US	128.6	60.2%
DWS	GER	17.5	8.2%
LYXOR	FRA	17.3	8.1%
AMUNDI	FRA	13.5	6.3%
ST A TE STREET (SPDR)	US	12	5.6%
PIMCO	US/GER	7.8	3.6%
UBS	CHE	5.6	2.6%
INVESCO	US	2.1	1.0%
V ANGUARD	US	1	0.5%
BMO	CAN	0.4	0.2%
OTHER	N/A	7.7	3.6%
EU-38 Domiciled Fixed Income		**213.6**	**100%**

Table 4: Descriptive Statistics of Dependent Variables per Asset Class

	Obs	**Mean (%)**	**Median (%)**	**Std (%)**	**Min (%)**	**Max(%)**	**Skew**	**Kurt**
Panel A: Total Expense Ration (TER)								
Equity ETFs	2193	0.294	0.300	0.099	0.050	0.740	0.588	1.356
Fixed income ETFs	497	0.170	0.150	0.068	0.070	0.500	3.286	11.809
Total	2690	0.271	0.280	0.106	0.050	0.740	0.649	0.706
Panel B: Tracking Error (ATE)								
Equity ETFs	2353	1.542	0.586	1.886	0.000	18.412	2.398	10.995
Fixed income ETFs	559	1.374	0.762	1.455	0.000	9.823	1.384	2.662
Total	2912	1.510	0.606	1.812	0.000	18.412	2.340	10.827
Panel C: Tracking Error (TE)								
Equity ETFs	2339	1.501	0.787	2.033	0.000	26.775	3.365	19.895
Fixed income ETFs	557	0.925	0.620	1.127	0.003	12.759	3.541	25.775
Total	2896	1.390	0.732	1.906	0.000	26.775	3.545	22.257
Panel D: Premium (PREM)								
Equity ETFs	2332	-0.260	0.010	2.542	-28.462	14.412	-8.203	78.108
Fixed income ETFs	557	0.085	0.044	0.168	-1.165	1.809	2.433	29.926
Total	2889	-0.194	0.020	2.289	-28.462	14.412	-9.153	97.587

Table 5: Descriptive Statistics of Dependent Variables per Time Period

	Obs	**Mean (%)**	**Median (%)**	**Std (%)**	**Min (%)**	**Max(%)**	**Skew**	**Kurt**
Panel A: Total Expense Ration (TER)								
2009-2013	1145	0.283	0.300	0.107	0.090	0.740	0.677	0.501
2014-2018	1545	0.263	0.250	0.104	0.050	0.740	0.628	0.870
2009-2018	2690	0.271	0.280	0.106	0.050	0.740	0.649	0.706
Panel B: Tracking Error (ATE)								
2009-2013	1298	1.681	0.846	1.705	0.000	9.273	0.971	0.188
2014-2018	1613	1.372	0.444	1.884	0.000	18.412	3.223	17.358
2009-2018	2912	1.510	0.606	1.812	0.000	18.412	2.340	10.827
Panel C: Tracking Error (TE)								
2009-2013	1292	1.680	1.048	2.208	0.003	26.775	3.607	21.977
2014-2018	1603	1.157	0.507	1.585	0.000	12.759	2.871	12.347
2009-2018	2896	1.390	0.732	1.906	0.000	26.775	3.545	22.257
Panel D: Premium (PREM)								
2009-2013	1284	-0.303	0.036	3.017	-28.462	14.412	-7.153	59.317
2014-2018	1605	-0.106	0.011	1.462	-24.246	2.414%	-12.449	171.966
2009-2018	2889	-0.194	0.020	2.289	-28.462	14.412	-9.153	97.587

Table 6: Correlation Matrix

	TotalAssets	**Volatility**	**Liquidity**	**MktShare**	**HHI**	**CR3**
TotalAssets	**1**	-0.083	-0.105	-0.118	0.000	0.000
Volatility		**1**	0.232	0.092	0.000	0.000
Liquidity			**1**	0.153	0.000	0.000
MktShare				**1**	0.000	0.000
HHI					**1**	0.000
CR3						**1**

Table 7: Descriptive Statistics of Explanatory Variables per Time Period

	Mean (%)	**Median (%)**	**Std (%)**	**Min (%)**	**Max(%)**
TotalAssets					
2009-2013	4.186	3.947	1.521	0.943	8.775
2014-2018	4.634	4.561	1.729	-0.589	9.071
2009-2018	4.435	4.256	1.654	-0.589	9.071
Volatility					
2009-2013	14.634	13.685	7.64	0.399	46.204
2014-2018	11.684	11.426	6.219	0.342	38.913
2009-2018	12.998	12.262	7.041	0.342	46.204
Liquidity					
2009-2013	0.937	0.384	3.027	-0.826	82.913
2014-2018	0.324	0.25	0.306	-0.35	3.317
2009-2018	0.596	0.299	2.052	-0.826	82.913
MktShare					
2009-2013	22.806	14.383	24.95	0.028	100
2014-2018	20.366	10.936	23.67	0.03	100
2009-2018	21.452	12.347	24.27	0.028	100
HHI					
2009-2013	40.308	33.412	21.9	16.779	100
2014-2018	40.57	36.804	19.25	15.411	100
2009-2018	40.453	35.424	20.47	15.411	100
CR3					
2009-2013	85.912	88.233	12.32	33.333	100
2014-2018	86.716	89.549	11.67	16.667	100
2009-2018	86.357	88.935	11.97	16.667	100

Table 8: Regression results for Total Expense Ratio (TER) using two-way fixed effect model

	All ETFs		**Equity ETFs**		**Fixed income ETFs**	
Variables:	**HHI**	**CR3**	**HHI**	**CR3**	**HHI**	**CR3**
Const	0.00288***	0.00309***	0.00317***	0.00348***	0.00175***	0.00178***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
ln(TotalAssets)	-0.000079***	-0.000095***	-0.000098***	-0.000010***	-0.000022	-0.000026
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MktShare	0.00025**	0.00033***	0.00030**	0.00040***	0.000047	0.000064
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
MktConc	0.00030**	-0.000031	0.00034**	-0.00011	0.000083	0.000030
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
SER	0.00029	0.00029	0.00032	0.00032	0.00009	0.00009
LSDV R^2	0.93405	0.93352	0.91036	0.90963	0.98496	0.98475
Within R^2	0.05493	0.04737	0.06305	0.05540	0.05676	0.05023
Durbin-Watson test	0.63069	0.62776	0.63473	0.63354	0.66477	0.65588
Obs	2688	2688	2191	2191	497	497

Table 9: Regression results for Total Expense Ratio (TER) using cross-sectional OLS for selected years

	2018		2013		2009	
Variables:	**HHI**	**CR3**	**HHI**	**CR3**	**HHI**	**CR3**
Const	0.00218***	0.00144***	0.00192***	0.00224***	0.00192***	0.00166***
	(0.0001)	(0.0005)	(0.0002)	(0.0005)	(0.0002)	(0.0005)
ln(TotalAssets)	-5.9e-05	-4.2e-05	-0.0001*	-0.0001**	-6.7e-05	-6.9e-05
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
MktShare	0.00151***	0.00141***	0.00127***	0.00150***	0.00077***	0.00083***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0002)
MktConc	0.00046*	0.00100**	0.00034	-0.0002	0.00023	0.00039
	(0.0003)	(0.0005)	(0.0004)	(0.0006)	(0.0003)	(0.0006)
RM	-4.4e-05	-3.4e-05	0.00034***	0.00034***	0.00046***	0.00046***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AC	0.00074***	0.00076***	0.00121***	0.00120***	0.00121***	0.00122***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
IT	-0.0007***	-0.0007***	-0.0004**	-0.0003*	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
SER	0.00083	0.00083	0.00083	0.00083	0.00082	0.00082
R^2	0.39135	0.39488	0.38541	0.38335	0.43516	0.43516
R^2_{adj}	0.37993	0.38352	0.37066	0.36855	0.41704	0.41704
Obs	327	327	257	257	194	194

Table 10: Regression results for Total Expense Ratio (TER) using cross-sectional OLS for selected years (per asset class)

	2018		2013		2009	
Variables:	**Equity ETFs**	**FI ETFs**	**Equity ETFs**	**FI ETFs**	**Equity ETFs**	**FI ETFs**
Const	0.00323***	0.00059*	0.00340***	0.00054	0.00296***	0.00181***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
ln(TotalAssets)	-0.0001**	0.00017**	-0.0002**	0.00011	-5.7e-05	-7.6e-05
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
MktShare	0.00197***	-0.0002	0.00168***	-2.7e-05	0.00099***	0.00046*
	(0.0004)	(0.0006)	(0.0005)	(0.0007)	(0.0003)	(0.0003)
MktConc (CR3)	5.5e-05	0.00094*	-0.0003	0.00149**	0.00044	-0.00043**
	(0.0003)	(0.0005)	(0.0005)	(0.0007)	(0.0004)	(0.0002)
RM	-6.4e-05	-9.6e-05	0.00035***	7.9e-06	0.00054***	0.00033***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
IT	-0.0006***		-0.0003		-0.0007***	
	(0.0001)		(0.0002)		(0.0002)	
SER	0.00085	0.00064	0.00087	0.00057	0.00088	0.00024
R^2	0.33554	0.25966	0.20315	0.37766	0.23666	0.50847
R^2_{adj}	0.32276	0.20678	0.18342	0.32108	0.21235	0.43285
Obs	266	61	208	49	163	31

Table 11: Regression results for Tracking Error and Absolute Tracking Error (TE and ATE) using two-way fixed effect model

	TE		ATE	
Variables:	**HHI**	**CR3**	**HHI**	**CR3**
Const	-0.1551***	-0.1149***	-0.1572***	-0.1196***
	(0.0227)	(0.0239)	(0.0239)	(0.0243)
PREM	0.25608**	0.25612**	0.20483*	0.20448*
	(0.1018)	(0.1007)	(0.1182)	(0.1172)
ln(TotalAssets)	0.00476***	0.00385***	0.00482***	0.00389**
	(0.0015)	(0.0014)	(0.0016)	(0.0015)
Volatility	0.90815***	0.90856***	0.94767***	0.94807***
	(0.1029)	(0.1027)	(0.1091)	(0.1089)
Liquidity	-0.1508	-0.1522	-0.3341***	-0.3355***
	(0.1128)	(0.1127)	(0.1255)	(0.1259)
TER	-2.5248	-2.0607	-6.2052**	-5.7135**
	(2.3390)	(2.3346)	(2.5040)	(2.4918)
MktShare	-0.0277**	-0.0242**	-0.0333***	-0.0296**
	(0.0109)	(0.0108)	(0.0122)	(0.0121)
MktConc	0.00501	-0.0409**	0.00646	-0.0373**
	(0.0090)	(0.0170)	(0.0095)	(0.0172)
SER	0.03283	0.03278	0.03491	0.03488
LSDV R^2	0.89556	0.89585	0.89174	0.89195
Within R^2	0.87956	0.8799	0.87476	0.87501
Durbin-Watson test	1.58094	1.5865	1.62133	1.62582
Wald test (p-value)	0.000	0.000	0.000	0.000
Obs	2663	2663	2669	2669

Table 12: Results of Fixed Effect Panel Regressions with Time Dummies for Tracking Error (per Asset Class)

	Equity ETFs		**Fixed income ETFs**	
Variables:	**TE**	**ATE**	**TE**	**ATE**
Const	-0.1443***	-0.1459***	0.03289	0.04015
	(0.0242)	(0.0246)	(0.0252)	(0.0262)
PREM	0.25989**	0.21006*	0.65319	-0.3135
	(0.1007)	(0.1155)	(0.7025)	(0.4523)
ln(TotalAssets)	0.00441***	0.00412**	-0.0025***	-0.0024***
	(0.0017)	(0.0018)	(0.0008)	(0.0008)
Volatility	0.92416***	0.96523***	0.13580*	0.11098
	(0.0908)	(0.0958)	(0.0699)	(0.0695)
Liquidity	-0.0760	-0.2454**	0.10978	-0.0744
	(0.1110)	(0.1212)	(0.3160)	(0.3286)
TER	-0.3416	-3.6424	-13.492**	-16.930*
	(2.4777)	(2.5883)	(5.5996)	(8.7454)
MktShare	-0.0245**	-0.0283**	0.01569**	0.01175*
	(0.0116)	(0.0131)	(0.0073)	(0.0059)
MktConc (CR3)	-0.0505***	-0.0533***	0.00528	0.01044
	(0.0172)	(0.0179)	(0.0222)	(0.0213)
SER	0.03401	0.03603	0.00674	0.00744
LSDV R^2	0.90846	0.90574	0.71804	0.78313
Within R^2	0.8947	0.89128	0.32712	0.27682
Durbin-Watson test	1.59355	1.65104	0.92943	1.10544
Wald test (p-value)	0.000	0.000	0.000	0.000
Obs	2169	2175	494	494

Table 13: Regression results for Premium (PREM) using two-way fixed effect model

	Equity ETFs		Fixed income ETFs	
Variables:	**HHI**	**CR3**	**HHI**	**CR3**
Const	0.0051	0.00022	0.00264	0.00785**
	(0.0034)	(0.0089)	(0.0017)	(0.0035)
ln(TotalAssets)	-0.0011	-0.0007	-0.0003	-0.0002
	(0.0009)	(0.0009)	(0.0002)	(0.0001)
Volatility	-0.0012	-0.0013	0.02089**	0.01850**
	(0.0026)	(0.0026)	(0.0096)	(0.0074)
Liquidity	-0.0798	-0.0796	0.10194***	0.09420***
	(0.0589)	(0.0590)	(0.0279)	(0.0272)
MktShare	0.01820***	0.01605***	0.00194	0.00091
	(0.0043)	(0.0043)	(0.0012)	(0.0008)
MktConc	-0.0061**	0.00123	-0.0026	-0.0072**
	(0.0029)	(0.0079)	(0.0020)	(0.0033)
SER	0.01213	0.01214	0.00113	0.00109
LSDV R^2	0.80132	0.801	0.60937	0.64024
Within R^2	0.07732	0.07584	0.2043	0.26719
Durbin-Watson test	1.16564	1.16322	1.09409	1.1223
Wald test (p-value)	0.000	0.000	0.000	0.000
Obs	2324	2324	555	555

Table 14: Regression results for Premium (PREM) using cross-sectional OLS for selected years (per asset class)

	2018		2013		2009	
Variables:	**Equity ETFs**	**FI ETFs**	**Equity ETFs**	**FI ETFs**	**Equity ETFs**	**FI ETFs**
Const	-0.0043	-0.0008	-0.0087	1.21e-05	-0.0166	-0.0003
	(0.0069)	(0.0007)	(0.0097)	(0.0010)	(0.0130)	(0.0036)
ln(TotalAssets)	0.00126	0.00011	0.00142	-3.9e-05	0.00381	0.00036
	(0.0010)	(0.0001)	(0.0013)	(0.0002)	(0.0026)	(0.0006)
Volatility	-0.0392	0.01346**	-0.0211	0.00262	-0.0788*	0.04533
	(0.0244)	(0.0068)	(0.0191)	(0.0097)	(0.0413)	(0.0340)
Liquidity	0.52005	0.08266	0.08255	0.22333*	0.52533***	0.26207*
	(0.4382)	(0.0657)	(0.1011)	(0.1271)	(0.1218)	(0.1368)
MktShare	-0.0035	-0.0006	0.00474	0.00152	-0.0066	0.00352
	(0.0057)	(0.0007)	(0.0108)	(0.0014)	(0.0145)	(0.0036)
MktConc (HHI)	0.00254	0.00114*	-0.0013	0.00064	0.0181	-0.0032
	(0.0104)	(0.0006)	(0.0221)	(0.0009)	(0.0251)	(0.0056)
SL	-0.0002	0.00013	0.00095	-0.0002	0.00388	-0.0001
	(0.0006)	(0.0002)	(0.0017)	(0.0004)	(0.0049)	(0.0012)
RM	0.00423*	-0.0006*	0.00696*	-0.0007*	0.01079**	-0.0028***
	(0.0024)	(0.0003)	(0.0038)	(0.0004)	(0.0048)	(0.0009)
IT	-0.0057*		-0.0098		-0.0221*	
	(0.0033)		(0.0073)		(0.0120)	
ITE	0.00156	2.99e-05	0.0038	0.00016	0.01139*	0.00013
	(0.0010)	(0.0002)	(0.0024)	(0.0004)	(0.0060)	(0.0008)
SER	0.0156	0.00071	0.02829	0.00104	0.03603	0.00358
R^2	0.05315	0.21824	0.05349	0.28202	0.24172	0.27927
R^2_{adj}	0.021	0.10851	0.01405	0.15437	0.20272	0.08708
Obs	275	66	226	54	185	39

Online Appendix

In this Online Appendix we include additional information about:

(1) the Assets under Management (AuM) of the ETFs in relation to asset class and geographic focus (Table A1),

(2) the detailed list of all ETFs that we consider in our empirical study (Table A2),

(3) the list of markets for which we compute the levels of competitiveness (Table A3)

Table A1: Fund Class Total Assets (mln of EUR)

	AT	**EASTEU**	**EU27**	**EU28**	**EMU**	**FR**	**DE**	**IT**
Equity	131.19	218.03	3897.25	41742.6	42138.2	5994.12	18628.4	671.12
CSPC	131.19	218.03	2692.2	32111	39501.6	5994.12	17771.2	671.12
COM				705.67	12.02			
COND				529.65				
CONS				566.29				
ENGY				1107.83				
FIN				2435.19	1949.29			
HELC				1184.99				
INDS				303.51				
MA TS				503.09				
REAE			1205.04	677.65				
TECH				248.53			857.16	
THEM				777.38	675.31			
UTIL				591.83				
Fixed Income	5847.36	23705.8	1864.32	2420.08				
GRAND TOTAL	131.19	218.03	3897.25	47590	65844	5994.12	20492.7	671.12

	NL	**NORDIC**	**PO**	**ES**	**GB**	**GRAND TOTAL**
Equity	555.4	1616.62	103.07	1164.46	11358.1	128218.52
CSPC	555.4	1616.62	103.07	1164.46	11358.1	113888.1
COM						717.69
COND						529.65
CONS						566.29
ENGY						1107.83
FIN						4384.48
HELC						1184.99
INDS						303.51
MA TS						503.09
REAE						1882.69
TECH						1105.69
THEM						1452.68
UTIL						591.83
Fixed Income					2420.08	33837.57
GRAND TOTAL	555.4	1616.62	103.07	1164.46	13778.2	162056.09

Table A2: List of ETFs in our sample

#	ISIN	#	ISIN	#	ISIN
1	DE000A0D8Q23	117	IE00B1YZSC51	233	LU0378437098
2	LU0659579063	118	LU0274209237	234	IE00B5MTWZ80
3	LU0392496690	119	LU1681042609	235	IE00BKWQ0K51
4	FR0010204073	120	FR0010261198	236	DE000A0H08R2
5	LU1681043755	121	LU1437015735	237	LU1834988609
6	FR0011871086	122	IE00B4K48X80	238	LU0292104030
7	IE00B910VR50	123	IE00BKWQ0Q14	239	DE0006289317
8	LU1602144575	124	IE00B60SWY32	240	LU0378437171
9	IE00B0M62T89	125	DE000ETFL284	241	IE00B5MJYB88
10	LU0147308422	126	IE00B5BD5K76	242	DE000A0H08S0
11	LU0846194776	127	LU0392494646	243	FR0010344838
12	LU1646360971	128	IE00B945VV12	244	IE00B5MJYC95
13	IE00B0M62V02	129	IE00B14X4N27	245	LU0378437254
14	DE000A0D8Q07	130	LU1681043326	246	DE000A0Q4R02
15	LU0908501058	131	DE000A2DPCP0	247	LU1834988864
16	IE00BCLWRF22	132	IE00BKX55S42	248	IE00B5MTXK03
17	IE00B3F81R35	133	LU1861137484	249	LU0292104899
18	LU0478205379	134	LU1753045415	250	LU0378437338
19	IE00B3T9LM79	135	IE00B52VJ196	251	FR0007068036
20	IE00BZ163G84	136	IE00BFMNHK08	252	IE00BKWQ0P07
21	IE00BFNM3B99	137	IE00BFNM3D14	253	FR0010688234
22	LU1792117340	138	FR0010821819	254	IE00BF20LF40
23	LU0629460675	139	DE000ETFL458	255	LU0322253732
24	FR0010754143	140	LU1681041973	256	LU1681041544
25	FR0010823385	141	IE00BYYHSM20	257	LU0392496260
26	LU1650489385	142	DE0002635299	258	DE000ETFL292
27	LU0290357333	143	LU1812092168	259	DE0005933998
28	LU0444606452	144	DE000A0Q4R28	260	IE00B60SX063
29	IE00B4WXJH41	145	FR0010344630	261	LU0322253906
30	DE000ETFL128	146	LU0378435043	262	IE00BKWQ0M75
31	LU0444605991	147	IE00B5NLX835	263	LU0392496344
32	IE00B14X4Q57	148	DE000A0F5UJ7	264	IE00BQN1K901
33	FR0010754135	149	LU1834983477	265	LU0486851024
34	LU1650487413	150	IE00B3Q19T94	266	IE00BSPLC306
35	IE00B6YX5F63	151	LU0292103651	267	LU1681042518
36	LU0290356871	152	IE00B5MTWD60	268	IE00B3LK4Z20
37	DE000ETFL136	153	FR0007068077	269	FR0007052782
38	LU0444606023	154	LU0378435399	270	LU1681046931
39	IE00B1FZS681	155	DE0006289309	271	FR0010150458
40	FR0010754168	156	LU1829219390	272	LU0322250985
41	LU1650488494	157	DE000A0F5UK5	273	LU0419740799
42	IE00BS7K8821	158	LU0292100806	274	FR0010655704
43	LU0290356954	159	LU0378435472	275	IE00BP3QZJ36
44	DE000ETFL144	160	IE00B5MTWY73	276	DE000A0D8Q31
45	LU0444606296	161	DE000A0H08E0	277	DE000ETFL219
46	IE00B4WXJG34	162	FR0010345470	278	LU0444607005
47	FR0010754176	163	LU0378435555	279	DE000ETFL185
48	LU1287023003	164	IE00B5MTY077	280	LU0468897110
49	IE00BYSZ5Y35	165	DE000A0H08F7	281	LU0721553351
50	LU0290357176	166	FR0010345504	282	DE000ETFL193
51	DE000ETFL151	167	LU0378435639	283	LU0613540854
52	LU0444606379	168	IE00B5MTY309	284	DE0006289481

Table A2 (cont.)

#	ISIN	#	ISIN	#	ISIN
53	IE00B1FZS806	169	DE000A0H08G5	285	DE000A0H08L5
54	FR0010754184	170	FR0010345363	286	DE0006289499
55	LU1287023185	171	LU0378435712	287	LU0444606965
56	IE00BYSZ5Z42	172	IE00B5MTYK77	288	LU0603933895
57	LU0290357259	173	DE000A0H08H3	289	DE0002635273
58	LU0290358224	174	LU1834985845	290	DE0005933972
59	LU1650491282	175	LU0292105359	291	DE000ETF9082
60	IE00B0M62X26	176	LU0378435803	292	DE0005933931
61	LU0444607187	177	IE00B5MTYL84	293	LU0274211480
62	FR0010754127	178	DE000A0Q4R36	294	DE000ETFL011
63	IE00B5M1WJ87	179	LU1834986900	295	LU0378438732
64	IE00B0M62S72	180	LU0292103222	296	LU0252633754
65	DE0002635281	181	LU0378435985	297	DE000ETFL060
66	DE000ETFL482	182	IE00B5MJYY16	298	LU0838782315
67	FR0010717090	183	FR0007068093	299	FR0010655712
68	LU0378434236	184	IE00BKWQ0H23	300	DE000ETF9017
69	DE000ETFL078	185	FR0010688192	301	LU0488317024
70	IE00BFTWP510	186	DE000A0H08J9	302	IE00BG143G97
71	LU1717044488	187	IE00B5MJYX09	303	DE0005933923
72	IE00BDGN9Z19	188	FR0010344887	304	DE000ETFL441
73	LU1215454460	189	LU0292106084	305	LU1033693638
74	LU1237527160	190	LU0378436017	306	DE000ETF9074
75	LU1377381717	191	IE00BKWQ0J47	307	FR0011857234
76	LU1681041627	192	FR0010688218	308	FR0010010827
77	LU1598689153	193	DE000A0H08K7	309	IE00B1XNH568
78	LU0671493277	194	FR0010344903	310	LU0274212538
79	FR0010900076	195	IE00B5MTXJ97	311	LU1681037518
80	DE000A0D8QZ7	196	LU0378436108	312	FR0010655720
81	IE00B60SWZ49	197	DE000A0H08L5	313	LU1104574725
82	DE0005933956	198	FR0010344929	314	IE00B0M62Y33
83	FR0007054358	199	LU0378436363	315	NL0009272749
84	LU0274211217	200	IE00B5MTZ488	316	NL0009272756
85	IE0008471009	201	IE00BKWQ0C77	317	LU1681044217
86	DE000ETFL029	202	FR0010688184	318	SE0001710914
87	FR0012739431	203	FR0010713735	319	IE00B9MRHC27
88	IE00B60SWX25	204	IE00BKWQ0N82	320	LU1681044647
89	LU0378434079	205	IE00BKWQ0D84	321	IE00B4M7GH52
90	IE00B4K6B022	206	FR0010688168	322	LU0459113907
91	LU0908501215	207	FR0010791137	323	PLBTETF00015
92	ES0105321030	208	IE00BKWQ0L68	324	FR0010251744
93	DE000ETF9504	209	DE000A0H08M3	325	ES0105336038
94	LU0488317297	210	LU1834988278	326	LU0592216393
95	IE00BF4R5F15	211	FR0007068085	327	FR0010655746
96	DE000ETFL466	212	LU0292101796	328	LU1104577314
97	IE0008470928	213	LU0378436447	329	IE00B1FZSB30
98	FR0010790980	214	IE00B5MTWH09	330	LU1407892592
99	DE0005933949	215	DE000A0H08N1	331	IE00B3W74078
100	DE000ETFL250	216	FR0010344978	332	IE00B42WWV65
101	LU1681047236	217	LU0378436520	333	IE0005042456
102	DE0002635307	218	IE00B5MTZ595	334	IE00B810Q511
103	LU0328475792	219	IE00B0M63284	335	LU1650492173
104	LU0908500753	220	LU0489337690	336	IE00B42TW061
105	FR0011550193	221	LU1291091228	337	LU0838780707

Table A2 (cont.)

#	ISIN	#	ISIN	#	ISIN
106	LU1681040223	222	LU1681039480	338	LU0292097234
107	IE00B60SWW18	223	LU1812091194	339	IE00B60SWT88
108	LU0378434582	224	FR0011869304	340	LU0488316216
109	DE000ETF9603	225	DE000A0H08P6	341	FR0010655761
110	IE00B66F4759	226	FR0010344986	342	IE00BKX55Q28
111	LU1681040496	227	IE00B5MTZM66	343	IE00B00FV128
112	IE00B6YX5M31	228	LU0378436876	344	LU0292097317
113	LU1109942653	229	DE000A0H08Q4	345	IE00B64PTF05
114	IE00B41RYL63	230	LU1834988518	346	IE00B60SWV01
115	IE00B3DKXQ41	231	LU0292104469		
116	DE000A2JLJC9	232	FR0007068069		

Table A3: List of ETF markets

	Market Name	Class	Focus	Industry	Theme	#	AuM (mln of EUR)
1	AUT_EQT	Equity	AT	Country-Specific	Large Cap	3	131.19
2	EASTEU_EQT	Equity	CEE	Country-Specific	Large Cap	3	218.03
3	EMUBROAD_EQT	Equity	EMU	Country-Specific	All Cap	10	9212.21
4	EMUCORB_FIC	Bond	EMU	Country-Specific	Corporate	4	8621.41
5	EMUESG_EQT	Equity	EMU	Country-Specific	ESG	3	705.84
6	EMUGOVB10-15_FIC	Bond	EMU	Country-Specific	Public	6	476.52
7	EMUGOVB1-3_FIC	Bond	EMU	Country-Specific	Public	7	3689.18
8	EMUGOVB3-5_FIC	Bond	EMU	Country-Specific	Public	7	3919.41
9	EMUGOVB5-7_FIC	Bond	EMU	Country-Specific	Public	7	1325.29
10	EMUGOVB7-10_FIC	Bond	EMU	Country-Specific	Public	7	1241.28
11	EMUGOVBINFLPT_FIC	Bond	EMU	Country-Specific	Public-Inflation Prot.	5	2375.16
12	EMUHIDVD_EQT	Equity	EMU	Country-Specific	High Dividend	7	3161.38
13	EMULOWV_EQT	Equity	EMU	Country-Specific	Low Volatility	7	1183.81
14	EMUSCAP_EQT	Equity	EMU	Country-Specific	Small-Cap	5	719.8
15	ESTXX50_EQT	Equity	EU28	Country-Specific	Euro Stoxx 50	20	27437.22
16	ESTXX600_EQT	Equity	EU28	Country-Specific	Euro Stoxx 600	8	10207.18
17	EURCORBHY_FIC	Bond	EU28	Country-Specific	Corporate	4	5864.61
18	EUROAGGB_FIC	Bond	EU28	Country-Specific	Mixed	3	2040.33
19	EUROBROAD_EQT	Equity	EU28	Country-Specific	All Cap	12	15753.88
20	EUROBROADEXUK_EQT	Equity	EU27	Country-Specific	All Cap	4	2704.23
21	EUROESG_EQT	Equity	EU28	Country-Specific	ESG	5	800.64
22	EUROEXEMU_EQT	Equity	EU28	Country-Specific	All Cap	2	205.89
23	EUROHIDVD_EQT	Equity	EU28	Country-Specific	High Dividends	4	642.48
24	EUROIDAUTO_EQT	Equity	EU28	Automotive	N/A	4	240.99
25	EUROIDAUTO_EQT	Equity	EU28	Automotive	N/A	4	240.99
26	EUROIDBANK_EQT	Equity	EU28	Banks	N/A	9	3927.16
27	EUROIDBASRES_EQT	Equity	EU28	Basic Resources	N/A	4	319.07
28	EUROIDCHEM_EQT	Equity	EU28	Chemicals	N/A	4	113.55
29	EUROIDCONRES_EQT	Equity	EU28	Consumer Resources	N/A	4	51.5
30	EUROIDFINSER_EQT	Equity	EU28	Financial Services	N/A	4	57.18
31	EUROIDFOOBEV_EQT	Equity	EU28	Food & Beverage	N/A	5	380.5
32	EUROIDHEALTH_EQT	Equity	EU28	Healthcare	N/A	8	1184.99
33	EUROIDINDUST_EQT	Equity	EU28	Industrials	N/A	7	303.51
34	EUROIDINSU_EQT	Equity	EU28	Insurance	N/A	4	400.14
35	EUROIDMEDIA_EQT	Equity	EU28	Media	N/A	4	23.97
36	EUROIDMSCICDIS_EQT	Equity	EU28	Consumer Discret.	N/A	2	101.97
37	EUROIDMSCICOM_EQT	Equity	EU28	Communication	N/A	2	44.26
38	EUROIDMSCICSTA_EQT	Equity	EU28	Consumer Staples	N/A	2	185.79
39	EUROIDMSCIMAT_EQT	Equity	EU28	Materials	N/A	2	18.96
40	EUROIDOILGAS_EQT	Equity	EU28	Oil & Gas	N/A	6	1107.83
41	EUROIDPERHOU_EQT	Equity	EU28	Personal & Households	N/A	4	116.18
42	EUROIDREALEST_EQT	Equity	EU28	Real Estate	N/A	6	1882.69
43	EUROIDRETAIL_EQT	Equity	EU28	Retail	N/A	4	29.07
44	EUROIDTECH_EQT	Equity	EU28	Technology	N/A	7	248.53
45	EUROIDTLC_EQT	Equity	EU28	Telecommunication	N/A	6	649.46
46	EUROIDTRALEI_EQT	Equity	EU28	Travel & Leisure	N/A	4	41.44
47	EUROIDUTIL_EQT	Equity	EU28	Utilities	N/A	8	591.83
48	EUROMCAP_EQT	Equity	EU28	Country-Specific	Mid Cap	7	945.51
49	EUROSCAP_EQT	Equity	EU28	Country-Specific	Small Cap	3	877.15
50	EUROVAL_EQT	Equity	EU28	Country-Specific	Value	5	1200.26
51	FRALCAP_EQT	Equity	FR	Country-Specific	Large Cap	5	5890.95
52	FRAMSCI_EQT	Equity	FR	Country-Specific	Large Cap	2	103.17
53	GERGOVB10+_FIC	Bond	DE	Country-Specific	Public	3	283.2
54	GERGOVB1-3_FIC	Bond	DE	Country-Specific	Public	3	451.72
55	GERGOVB3-5_FIC	Bond	DE	Country-Specific	Public	3	341.56
56	GERGOVB5-10_FIC	Bond	DE	Country-Specific	Public	3	787.84
57	GERHIDVD_EQT	Equity	DE	Country-Specific	High Dividend	2	582.97
58	GERIDTEC_EQT	Equity	DE	Technology	N/A	2	857.16
59	GERLCAP_EQT	Equity	DE	Country-Specific	Large Cap	11	15011.19
60	GERMCAP_EQT	Equity	DE	Country-Specific	Mid Cap	5	2177.02
61	ITALCAP_EQT	Equity	IT	Country-Specific	Large Cap	6	671.12
62	NEDLCAP_EQT	Equity	NL	Country-Specific	Large Cap	4	555.4
63	NORDIC_EQT	Equity	NORDIC	Country-Specific	All Cap	3	1616.62
64	POLLCAP_EQT	Equity	PO	Country-Specific	Large Cap	4	103.07
65	SPALCAP_EQT	Equity	ES	Country-Specific	Large Cap	5	1164.46
66	UKGOVB_FIC	Bond	GB	Country-Specific	Public	4	2420.08
67	UKLCAP_EQT	Equity	GB	Country-Specific	Large Cap	10	9707.43
68	UKMCAP_EQT	Equity	GB	Country-Specific	Mid Cap	5	1650.65

Table A4: Variable Definitions and Synonyms

	VARIABLE	SYNONYM(S)	DEFINITION
1	Absolute Return Differences	-	The annualised yearly average of monthly absolute return differences
2	CR3	-	Structural competition measure determined by the accumulated market share of the three largest market participants
3	(Market) Competition	(Market) Concentration	Determined by structural concentration measures
4	Domestic ETFs	-	ETFs which are domiciled/listed in the same time zone or country as the fund's underlying index
5	Exchange Traded Funds	Funds	-
6	ETF Return	-	Calculated as the continuous monthly NAV returns
7	Fund Risk	-	Determined by the annualised standard deviation of monthly returns
8	Fund Market Share	-	An ETF's fund total assets in EUR divided by the sum of all assets in EUR of all ETFs belonging to a corresponding market
9	Fund Total Assets	-	The total amount of a fund's assets under management in the respective fund currency
10	Herfindahl-Hirschman Index	-	Structural concentration measure calculated as the sum of squared market shares of all market participants
11	Index Return	-	Calculated as the continuous monthly returns on the base of index values
12	Industry	Sector	-
13	Liquidity	-	Defined by the percentage bid-ask spread
14	Mid-Price	-	Determined by the average of bid and ask price
15	Net Asset Value (per Share)	-	Determined by an ETFs net total assets divided by the number of shares outstanding
16	Premium	-	End-of-month difference between mid-price and net asset value
17	Total Expense Ratio	Expense Ratio	All direct expenses incurred by an ETF in % terms in relation to total assets
18	Volatility of Return Differences	-	Annual volatility of monthly return differences