Do ETFs increase the comovements of their underlying assets?
Evidence from a switch in ETF replication technique

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Abstract

We investigate the impact of Exchange-Traded Funds (ETFs) on the comovements of their constituent securities using a novel identification which exploits the switch from synthetic to physical replication of a large French ETF. After the switch, constituent stocks experience greater commonality, in both returns and liquidity. For both the full sample of ETF constituents and the least liquid ETF constituents, a larger part of the variation in individual stock returns or liquidity is explained by market-wide variations. We present evidence that ETF arbitrage is the transmission mechanism of the comovements. Moreover, we show that the comovements do not appear excessive.

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1. Introduction

Exchange Traded Funds (ETFs) have experienced exceptional growth in the last 20 years. As of July 2022, according to ETFGI[1], 9,093 ETFs were traded worldwide, totaling $9.1 trillion in Assets under Management (AuM). The success of ETFs arises from the advantages they provide in terms of diversification, transparency, tax efficiency, management fees, and liquidity (Madhavan (2016), Ben-David, Franzoni, and Moussawi (2017)).

Besides these benefits however, a growing literature has pointed out troublesome results regarding the impact of ETFs on their underlying assets. Ben-David, Franzoni, and Moussawi (2018) find that stocks with higher ETF ownership display significantly higher volatility. Dannhauser (2017) evidences reduced liquidity for high yield bonds that become eligible to ETFs. Da and Shive (2018) report excessive return comovements for ETF constituent securities while the findings by Agarwal, Hanouna, Moussawi, and Stahel (2018) indicate that ETF ownership significantly increases the liquidity commonality of ETF underlying stocks. Collectively, these results suggest that ETFs may impair the market quality of their constituent assets and give rise to increased risk premia.

Whether ETFs harm their constituent securities market is an important question. This issue is all the more relevant as the effects that have been highlighted so far are likely to gain importance in the future due to the expected development of the ETF market. In this paper, we test the effects of ETFs on their constituent stock properties using a novel identification strategy that relies on a change in the way an ETF tracks its benchmark index.

Index tracking by an ETF is achieved either by physical replication or synthetic replication. In the physical replication framework, the ETF sponsor physically holds the constituent securities, while in synthetic replication the sponsor enters into a swap contract with a counterparty (typically its parent bank) to obtain the exact performance of the benchmark index. In both structures, the link between the ETF price and the value of its constituent securities

[1]ETFGI (www.etfgi.com) is an independent research and consulting firm covering the global ETF and ETP products.

is ensured by authorized participants (APs). When the price of the ETF deviates from the value of its basket, APs perform arbitrage trades that result in the creation or redemption of ETF shares. In synthetic ETFs, ETF units are created or redeemed in exchange for cash. In contrast, in physical ETFs, the creation or redemption is made *in-kind*, i.e. in exchange for the constituent securities. An important feature of the in-kind process is that arbitrage trades by APs involve the simultaneous purchase or sale of each of the ETF benchmark constituent securities. These portfolio-wide trades are likely to be responsible for the documented increase in correlation across ETF underlying stocks (Malamud (2015)). Conversely, in synthetic ETFs, the arbitrage process does not involve any exchange of the ETF constituents between the AP and the sponsor since creation and redemption are made in cash. We thus hypothesize that the impact of synthetic ETFs on their constituent securities should be less pronounced than for physical ETFs.

We test this prediction using a sample of European ETFs whose baskets contain European stocks. We first analyze the effect of ETF ownership on stock-level daily commonality in liquidity and returns over a long period in a panel regression setting. During the period from December 2013 to January 2017, we find a positive relation between ETF ownership and securities commonality in both liquidity and returns. This result is our first piece of evidence indicating that ETFs increase the comovements of their constituent securities. However, although our analysis includes controls for observable stock characteristics and includes time fixed effects, ETF ownership might be endogenous and two mechanisms could be responsible for our findings. The first one is the *index effect*. In this view, the comovements we document may just reflect the fact that ETFs replicate existing indexes and thus own stocks that already comove as they pertain to the same index. The second possibility is the *ETF effect*. In this view, the ETF causes commonality as a result of the arbitrage activity of APs.

To disentangle the *index effect* from the *ETF effect*, we exploit a quasi-natural experiment provided by a recent ETF replication method change in Europe. On July 11, 2014, the

Lyxor CAC, the largest French ETF tracking the CAC 40 index, switched from synthetic to physical replication. After the switch, ETF APs have to deliver all the constituent securities as part of the creation/redemption process, including the least liquid constituent securities. Therefore, we would expect an increase in stock comovements after the ETF switched from synthetic to physical replication. Our approach is to compare the comovements around the switch between stocks subject to this event and a control group of stocks unrelated to the switched ETF. We find that, relative to the control group, stocks included in the Lyxor CAC experience a statistically significant increase by 8% of a standard deviation in return commonality and a statistically significant increase by 27% in liquidity commonality. Moreover, the least liquid stocks also exhibit greater commonality, consistent with the fact that we expect these stocks to be more impacted by the trading activity related to APs' arbitrage trades. Next, we investigate the transmission mechanism by studying whether the arbitrage activity of ETF APs is responsible for the increased comovements we document. We find that constituent stocks exhibit stronger commonality on days with ETF arbitrage activity compared to those without.

Finally, we investigate whether the increase in comovements is excessive. Looking at price reversals, we find no evidence of a change in the autocorrelation of constituent stock successive daily returns after the switch. Turning to variance ratios, we find that the switch is followed by a significant 7% decrease in the weekly–to–5-day variance ratio of constituent stock returns. Collectively, besides showing that ETF-induced comovements are not excessive, our results rather suggest that ETFs improve the link between market fundamentals and stock prices.

There is a rapidly growing literature on the effect of ETFs on the comovements of their constituent stocks. Da and Shive (2018) find that ETFs increase return commonality. Our study is also closely related to Agarwal, Hanouna, Moussawi, and Stahel (2018) analysis of the effect of ETFs on stock commonality in liquidity in U.S markets. They show that ETFs significantly increase stock liquidity commonality. Our main contribution is to resolve endogeneity concerns via a different quasi-natural experiment. In a theoretical model, Cespa and Foucault (2014) show that the liquidity across markets can be influenced by cross-market arbitrageurs, whose activity may lead to liquidity spillovers. Our findings that the commonality is stronger on the days with arbitrage support this theoretical prediction.

Another strand of the literature focuses on the effect of ETFs on the price efficiency of their constituent stocks. The results have mostly shown a beneficial effect of ETFs on the price efficiency of their components. Glosten, Nallareddy, and Zou (2021) find that ETF ownership is linked to better incorporation of earnings information. Similarly, Huang, O'Hara, and Zhong (Forthcoming) show that by facilitating hedge funds' long-short strategies (long stock-short industry ETF), ETFs have reduced the post-earnings-announcement-drift of industry ETF components. More generally, Easley, Michayluk, O'Hara, and Putnins (2018) show that the amount of stock-specific information in prices is stable through time, although ETF ownership has been growing rapidly. In contrast with these studies, Israeli, Lee, and Sridharan (2017) find that stocks whose ETF ownership increases experience a decline in their pricing efficiency. In particular, they evidence that greater ownership is associated with larger stock return synchronicity across ETF constituents and a decline in future earnings response coefficients. Bhattacharya and O'Hara (2016) document possible herding and propagation of shocks in the extreme case of U.S.-traded Greek ETFs and stocks when Greek markets were closed, amidst the downturn of August 2015. Using microstructure measures of price efficiency, our results support the view that ETFs increase the price efficiency of their stocks.

Finally, our paper adds to the vast literature on commonality. Pindyck and Rotemberg (1993), Chordia, Roll, and Subrahmanyam (2000), Hartford and Kaul (2005), Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) all document commonality in returns and liquidity across stocks. Lee, Shleifer, and Thaler (1991), Barberis and Shleifer (2003), Barberis, Shleifer, and Wurgler (2005), and Kumar and Lee (2006) provide behavioral explanations to the commonality issue. Andrade, Chang, and Seasholes (2008), Greenwood and Thesmar (2011), and Antón and Polk (2014) investigate financial friction-based explanations of commonality. Koch, Ruenzi, and Starks (2016) establish a demand-side explanation of commonality. Finally, Boulatov, Hendershott, and Livdan (2013) and Pasquariello and Vega (2015) analyze the extent to which return comovements are caused by informed order flow. We contribute in showing that although ETFs do increase the comovements of their constituents, they also increase their price efficiency.

The remainder of the paper is as follows: Section 2 presents our hypotheses development. Section 3 describes the data. Section 4 analyzes the relations between ETF ownership and commonality in a panel setting, and through a quasi-natural experiment. Section 5 and Section 6 make further use of the quasi-natural experiment to investigate if the comovements we document are excessive and their transmission mechanism. Section 7 presents several robustness tests. Section 8 concludes.

2. Institutional background and hypotheses development

2.1. Physical and Synthetic ETFs institutional details

ETFs are exchange-traded products which seek to replicate an underlying index. There are two ways for an ETF to reproduce its index. In this section, we detail both replication methods and their evolution.

For an ETF that uses physical replication, the assets of the fund are a basket of securities that aims to replicate the index. The market capitalization of these assets determines the Net Asset Value (NAV) of the ETF. In the simple structure of a physical ETF, the ETF investors hold all the liabilities of the fund in the form of ETF shares. The ETF portfolio managers' objective is to minimize the difference between the evolution of the NAV and the index. However, physical replication can be costly for ETFs that track indexes that include a large number of - or illiquid securities.[2]

By contrast, the use of a total return swap by synthetic ETFs theoretically avoids both tracking error risk and the cost of trading constituent securities. In a synthetic ETF, the ETF enters into a total return swap with a financial intermediary (often its parent bank) which provides the return of the index to the ETF. The swap involves two steps. In the first step, the ETF transfers the cash from the investors in ETF shares to the swap counterparty in exchange for a basket of collateral assets. Since the primary purpose of the collateral is to protect the ETF from a default of the swap counterparty,[3] the collateral assets of a synthetic ETF can differ vastly from the index it tracks. For example, as reported in Table 1, several of the main securities collateralized for an ETF tracking French stocks were not French. In the second step, the total return of the collateral basket is exchanged for the index return. While in the U.S. the Investment Company Act of 1940 limits the use of synthetic ETFs in the profit of physical ETFs, in Europe the UCITS regulations permit synthetic ETFs, and issuers launched predominantly synthetic ETFs.

Even in Europe, synthetic ETFs gradually are becoming unpopular for two reasons. First, in a context of stricter capital requirement imposed by Basel III, the swap is increasingly using the capital of the financial intermediaries that provide the swaps to the ETFs.[4] Second, synthetic ETFs are criticized for their complexity and their potential counterparty risk compared with physical ETFs.[5] Due to the above considerations, from 2014 onward there

[2] For example, the Russell 3000, the MSCI World, and several bond indexes include over a thousand securities. Illiquid securities such as emerging market stocks or bonds imply higher transactions costs. To mitigate costs, ETF portfolio managers can choose to replicate the index with only a subset of its constituents (see for example Koont, Ma, Pastor, and Zeng (2022)). Yet, these sampling strategies can result in large tracking errors.

[3] See Hurlin, Iseli, Pérignon, and Yeung (2019) for a detailed analysis of the counterparty risk of physical and synthetic ETFs.

[4] Even though swaps can reduce the capital requirements of the banks (Shan, Tang, and Yan (2017)), in the case of a synthetic ETF the swap counterparty is still prompted to post capital for the swap. Physical ETFs are a superior structure in that regard: a physical ETF is a separate entity entirely funded by the investors holding ETF shares, which therefore consumes no capital for its issuer.

[5] For instance, Larry Fink from Blackrock (which owns iShares, the lead issuer of physical ETFs in the U.S.) wrote in December 2011 "If you buy a Lyxor product, you're an unsecured creditor of SocGen" (French bank Société Générale, also known as SocGen, is Lyxor's parent company, and provides the swap that guarantees the index returns to Lyxor ETFs).

has been an institutional change: large European ETFs have switched from synthetic to physical replication. As a result, a 2017 FED report shows that physical ETFs account for 98% of the AuM of ETFs across the world.[6]

2.2. Liquidity provision and ETF structure

APs provide liquidity to ETFs during the trading day. The arbitrage operations they perform ensure that the price of ETFs in the secondary market stays in line with the value of their constituent securities. However, the arbitrage process takes a different form depending on the ETF structure.

For a physical ETF with full replication (such as the main large cap equity ETFs), APs who participate to an ETF creation or redemption trade *all* the constituent securities. For instance, if the ETF is trading at a premium, APs will sell the ETF and proceed to the creation of ETF shares. During the trading day, to hedge themselves, APs will buy *all* the constituent securities. At the end of the day, through the ETF primary market, APs will cover their short ETF position by receiving the newly created ETF shares from the issuer,[7] and unwind their constituent securities position by delivering *all* the constituent securities to the issuer.

In contrast, for a synthetic ETF, APs trade any relevant security as a hedge (a futures contract, another ETF, or a selected basket of liquid securities). For example, APs can sell an ETF trading at a premium and buy futures contract as a hedge. If they proceed to the creation of ETF shares to cover their short ETF position, APs will unwind their futures position at the time of the ETF creation. Since the ETF creation of a synthetic ETF takes place in cash, APs will receive the ETF shares in exchange for cash without exchanging the constituent securities.

[6] "Synthetic ETF net assets remained steady around $75 billion, which represents about 2% of all global ETFs." (Aramonte, Caglio and Tuzun, 2017). "Synthetic ETFs" FED Notes, Washington (Board of Governors of the Federal Reserve System, August 10, 2017).

[7] Following a creation, the ETF balance sheet grows: its assets with the constituent securities and its liabilities with the newly created ETF shares.

In summary, for the ETF primary market, APs of physical ETFs trade all the constituent securities while APs of synthetic ETFs do not. This difference between synthetic and physical ETFs fosters our hypothesis that the comovements generated by ETFs should depend on the ETF structure.

2.3. Testable implications

Malamud (2015) argues that ETFs increase the comovements of their components because of the arbitrage activity of APs. To create physical ETF shares, APs have to deliver all the components of the index. Hence, if ETFs increase the comovements of their components because of arbitrage, stocks held by physical ETFs should exhibit greater comovements than those of synthetic ETFs. Thus, we formulate our main testable hypothesis :

Hypothesis 1 *For physical ETFs, ETF ownership increases the comovements of the underlying stocks.*

Since they are costly to trade, it is unlikely that the illiquid constituent securities would be used for the arbitrage by APs in the case of a synthetic ETF, or used as collateral for the swap by the parent bank. In contrast, for physical ETFs, APs must exchange with the fund even the least liquid components of the index. Therefore, the impact of physical ETFs should be stronger for the least liquid index constituents. This motivates the following testable hypothesis:

Corollary 1 *The least liquid stocks included in an ETF co-move more with the market after the ETF switches to physical replication.*

Following Malamud (2015) and Shim (2019), the transmission channel should be the arbitrage process by the APs. Hence, physical ETFs should impact their components via the ETF primary market. This latter consideration leads to our second corollary:

Corollary 2 *For physical ETFs, the comovements should be stronger on days with arbitrage.*

3. Data

3.1. ETF sample

Our sample period goes from December 2013 to January 2017. We first identify from their main issuer websites and from the ETFdb website[8] European ETFs replicating the major European indexes (Eurostoxx 50, STOXX 50, IBEX, STOXX 600, CAC 40, DAX MSCI Europe, and MSCI EMU) as well as U.S. ETFs with an exposure to European, EMU and World developed indexes. The reason for including the latter is that major U.S. ETFs replicating these indexes own a non trivial fraction of European stocks. Since we focus on the effect of ETF ownership, we consider only ETFs physically holding their index constituent stocks over the whole sample period, or synthetic ETFs that eventually switched to physical replication before January 2017. To avoid any potential bias, the physical ETFs we include in our sample are those that reproduce their indexes without sampling.[9] Finally, to avoid potential representativeness issues, we further restrict our sample to ETFs holding a minimum of 1 billion euro of assets under management. This procedure yields a sample of 11 ETFs.

3.2. Variable definitions

3.2.1. ETF ownership per stock

We retrieve the composition of our set of indexes either from Refinitif-Eikon or from the index providers. To avoid currency fluctuations, we only include European firms whose stock is trading in euro. The procedure yields 853 stocks. For the CAC 40 and the DAX, the index composition is available but the Refinitiv database does not report the index weights. We thus use the information on the free float to obtain the stock weights in the index.

[8] https://etfdb.com

[9] For large indexes with multiple thousand components, the composition and the assets of the ETF can differ slightly from the index. In this instance, fund managers use a sampling strategy. Those ETFs are excluded from this study as the main country large-cap indexes such as the S&P 500, the CAC and the DAX are replicated fully without sampling.

We compute ETF ownership for stock i on day t as in Ben-David, Franzoni, and Moussawi (2018) and Dannhauser (2017) :

$$\mathrm{ETFown_{i,t}} = \frac{\sum_{j=1}^{J} \mathrm{holdings_{i,j,t}}}{\mathrm{MarketCap_{i,t}}} \tag{1}$$

where $\mathrm{holdings_{i,j,t}}$ is the holding (in euro), of stock i by ETF j on day t, and $\mathrm{MarketCap_{i,t}}$ is the market capitalization (in euro) of stock i on day t. For European ETFs, we compute $\mathrm{holdings_{i,j,t}}$ as the product the stock's weight in the ETF and the ETF market capitalization.[10] For U.S. ETFs, we first retrieve ETF quarterly holdings from the CRSP mutual fund database. We then compute $\mathrm{holdings_{i,j,t}}$ as the product of the quarterly weight of stock i in ETF j (keeping the weight constant on a given quarter) and the daily ETF market capitalization. Finally, we use the daily EURUSD exchange rate to convert the U.S. holdings into euro.

3.2.2. Comovement variables

The potential comovements arising from ETF ownership are analyzed first by looking at *return* comovements across ETF consituents. Second, we analyze whether ETFs are responsible for increased comovements in the *liquidity* of their underlying assets. Following Koch, Ruenzi, and Starks (2016) and Agarwal, Hanouna, Moussawi, and Stahel (2018) we measure liquidity using the Amihud (2002) illiquidity ratio. We compute the ratio as the absolute value of daily return over euro volume in millions so that we measure the price impact in basis point for a 1 million euro trade. We use Amihud (2002) in two ways. First, as the measurement of commonality in liquidity requires a metric that captures changes in stock liquidity levels, we use the first difference in daily log Amihud (2002) value.[11] Second, for

[10] We can compute the holding of a stock as per (1) since the ETFs we consider use full replication without sampling. Therefore, the weight of stock i in ETF j is the same as the weight of stock i in the underlying index that is replicated by ETF j.

[11] We have tested that our results on liquidity comovements are materially unchanged when using the following alternative measures of liquidity: (i) Corwin and Schultz (2012)'s transaction cost measure based on daily high and low prices, and (ii) euro volume. The results are available upon request.

additional robustness tests, the daily Amihud (2002) value also enters our regressions as a control variable that accounts for the potential effect of stock liquidity levels.

Table 2b presents summary statistics for the daily stock-level sample of our main explanatory variables before standardization. The ETF average ownership per stock is 1.6%. It is lower than in Ben-David, Franzoni, and Moussawi (2018), who document an average ETF ownership of 2.6% for S&P 500 stocks and 2.8% for Russell 3000 stocks over the period 2000-2015. Although our sample period runs from 2013 to 2017, the 1.6% average we find is close to their 2006 estimate of ETF ownership for the U.S. market. This gap reflects the later development of ETFs in Europe. The firms in our sample display an average Amihud ratio of 37 basis points and an average market value of 7.68 billion euro. Our sample thus contains firms whose liquidity and size are in between those of S&P 500 and Russell 3000 firms according to Ben-David, Franzoni, and Moussawi (2018)'s findings. Collectively, our estimates are consistent with the fact that, by selecting stocks that pertain to major European indexes, our sample contains large and actively-traded stocks. We further describe our variables in later sections and provide definitions in Table 2a. In the rest of the analyses, all variables are standardized to facilitate interpretation, and daily returns and Amihud ratios are winsorized at their 1% and 99% percentiles to mitigate the impact of outliers.

4. Liquidity and return commonality

4.1. Empirical approach

We investigate the relation between ETF ownership and daily comovements using panel regressions. Specifically, we run the following regression, for each stock i in our full sample of European stocks, and for day t in our sample period (December, 2013 to January, 2017):

$$\begin{aligned}\Delta \mathrm{y}_{\mathrm{i,t}} \;=\;& \alpha_i + \lambda_t + \theta_1 \cdot (\mathrm{ETFown}_{\mathrm{i,t\text{-}1}} \times \Delta\, \mathrm{y}_{\mathrm{market,t}}) + \;\theta_2 \cdot \Delta\, \mathrm{ETFown}_{\mathrm{i,t\text{-}1}} \\ &+ \beta' \cdot X_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{2}$$

where ETF ownership captures the physical ETF ownership of a stock by both European and American ETFs.

For the commonality in liquidity analysis, $\Delta \mathrm{y_{i,t}}$ is the daily change of the Amihud ratio, $\Delta\, \mathrm{y_{market,t}}$ is the value-weighted mean of the daily change of the Amihud ratio from all stocks in the sample. Analog to Chordia, Roll, and Subrahmanyam (2000), $X_{i,t}$ includes as controls the lead and lagged dependent variable to capture lagged adjustment in commonality. As in Ben-David, Franzoni, and Moussawi (2018), $X_{i,t}$ also includes the inverse of the price and the market capitalization as time-varying stock controls to account for the potential effect of stock price and firm size. To account for time-invariant stock heterogeneity, we include stock fixed effect α_i. Finally, we include daily time fixed effects λ_t to control for common time trend in ETF ownership and liquidity comovements. Since variable $\Delta\, \mathrm{y_{market,t}}$ is subsumed by the fixed effects, it is not included in regression (2).

We proceed analogously for the commonality in returns. We run regression (2) where $\Delta \mathrm{y_{i,t}}$ now denotes the daily stock return of stock i, and $\Delta\, \mathrm{y_{market,t}}$ denotes the value-weighted mean return for all stocks in the sample.

Coefficient θ_1 on the interaction term ($\mathrm{ETFown_{i,t\text{-}1}} \times \Delta\, \mathrm{y_{market,t}}$) captures the impact of ETF ownership on the sensitivity of a stock's movements (either in prices or in liquidity) to the movements of the market. As such, it measures the contribution of ETF ownership to stocks' commonality. Since our main hypothesis states that securities with a high level of ETF ownership should exhibit greater comovements than those with a low level of ETF ownership, we expect a positive estimate for θ_1. A potential issue however, is that ETF ownership might impact returns and changes in liquidity *directly* rather than through increased comovements. To rule out this possibility and get a better identification of the effect of ETF ownership on commonality, we also include variable $\mathrm{ETFown_{i,t\text{-}1}}$ without interaction in regression (2).

4.2. Results

The estimates of regression (2) are reported in columns 1 and 2 of Table 3. Coefficient θ_1 is positive and significant at the 1% level: stocks with a larger value of lagged ETF ownership display a higher sensitivity to market returns (column 1) and to market liquidity (column 2). This finding supports our hypothesis that comovements increase with ETF ownership.

To account for a potential non-linear impact of ETF ownership on comovements, we also report in columns 3 and 4 of Table 3 the coefficients of regression (2) where we replace lagged ETF ownership by the lagged value of HighETFown, a dummy variable equal to one for stocks that are in the top quartile of ETF ownership and zero otherwise. For high ETF ownership stocks, a one-standard-deviation increase (decrease) in market return is related to a 11.4% standard deviation increase (decrease) in stock return relative to other stocks. The economic magnitude is large: since the standard deviation is 1.97% for stock returns and 1.14% for market returns, a 1% increase (decrease) in market return implies a 19.7 basis points increase (decrease) in high ETF ownership stock returns relative to other stocks. Differently stated, the sensitivity of high ETF ownership stocks to market movements is around 2% higher compared with other stocks. Similarly, a one-standard-deviation increase (decrease) in the market liquidity is associated with a 7.7% standard deviation increase (decrease) of the stock's liquidity for the stocks in the top quartile of ETF ownership relative to other stocks.

This positive link we document between ETF ownership and commonality in returns and liquidity provides our first piece of evidence in support of the hypothesis of a positive effect of ETFs on the comovements of their stocks.[12]

[12]In the internet appendix, we show that results are robust to quarterly comovements using a two-stage process as Koch, Ruenzi, and Starks (2016) and Agarwal, Hanouna, Moussawi, and Stahel (2018).

4.3. Quasi-natural experiment: switch in replication technique

4.3.1. Identification methodology

In this section, we further investigate the causal relation between ETF and the comovements of stocks. ETFs could self-select stocks that tend to comove more. In line with this idea, the comovements could result from an *index effect* rather than an *ETF effect*.

To investigate the causal impact of ETFs, we use a novel identification strategy which exploits the Lyxor CAC switch in replication method that occurred on July 11, 2014. The switch from synthetic to physical replication provides us with the opportunity to test the causal impact of physical ETF for several reasons. First, once the switch has occurred, the ETF fund has to hold all constituent stocks. This change entails a positive exogenous shock in CAC constituents' ETF ownership. Second, beside the variation in ownership, after the change APs must trade all ETF constituents when performing arbitrage trades and proceeding to creation/redemption. Third, although ETF ownership increases and the way arbitrage trades are conducted is different, the index and its constituents stay the same during both the pre and post period. Collectively, these features allow us to distinguish the *index effect* from the physical *ETF effect*.

We select the Lyxor CAC for three main reasons. First, it is the first large ETF switch with assets under management of 4.4 billion euros at the time of the switch.[13] Second, no other large ETF changed its replication technique during the Lyxor CAC event window. Third, as the Lyxor CAC replicates the major French CAC 40 index, it has trading activity, in the form of both turnover and creation/redemption intensity, above the average of large European ETFs. These characteristics of the Lyxor CAC entail a sustained level of activity from the APs, which is key for identifying their contribution to comovements.

We adopt a difference-in-differences approach to identify the physical ETF causal impact

[13]French ETF assets amount to 63.3 billion euros in 2016 according to the AMF (the French market authority). As with every other ETF market, the French ETF market is heavily concentrated. For instance, even though the French ETF market is composed of hundreds of ETFs, the Lyxor CAC ETF exceeds 10% of the total assets (the Lyxor CAC accounted for 7 billion euros in 2016). The CAC ETF tracks the French blue chips stocks index.

on the commonality in liquidity and returns of its underlying stocks. We compare stocks included in the lyxor CAC ETF (treated stocks) to a group of non-treated stocks that are otherwise as similar as possible. Following Dannhauser (2017), our data set is constructed using a 6-month window around the switch event. To avoid the potential noise arising from the rebalancing of the ETF before the event, we exclude the month preceding the switch.

We define the treated stocks as stocks included in the CAC 40 index for the full sample period. Control stocks are selected among all European stocks in our sample which are neither in a physical ETF nor in an ETF whose replication method has switched during the sample period. To select control stocks as similar as possible to our treated stocks, we use Propensity Score Matching (PSM).[14] Since the CAC 40 index selects stocks based on their size, we use market capitalization as the main variable to select control stocks. To further enhance the quality of the matching procedure, we include also dummy variables on the 11 GICS sectors.

We compute PSM by running first the following logistic regression over the 6-month estimation window preceding the switch, for all stock i in our sample of 853 stocks:

$$\mathbb{1}_{\mathrm{Treated_i}} = \frac{1}{1 + e^{-(\alpha + \gamma \cdot \mathrm{MV_i} + \varphi' \cdot \mathrm{Sector} + \ \varepsilon_i)}} \tag{3}$$

where $\mathbb{1}_{\mathrm{Treated_i}}$ takes on the value 1 for CAC 40 stocks and 0 otherwise; $\mathrm{MV_i}$ denotes stock i's average market capitalization over the estimation window; Sector is a 853×11 matrix where each row represents a sample stock and each column represents one of the 11 GICS sector. Cell (i, j) of matrix Sector equals 1 if stock i's GICS sector is equal to j and 0 otherwise. We next use the estimated PSM values to match each CAC 40 stock with its minimum distance control stock imposing a one-to-one match.

[14] In the robustness section, we test the sensitivity of our findings to alternative choices to select control stocks. We show that the main results hold when we select the control stocks (i) by using only a market capitalization filter instead of PSM and (ii) using PSM with different selection criteria

We then estimate the following regression for each stock i, and day t:

$$\begin{aligned} \mathrm{y_{i,t}} \;=\;& \alpha_i + \lambda_t + \;\theta_1 \cdot (\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_i}}) + \;\theta_2 \cdot (\mathbb{1}_{\mathrm{Treatment_i}} \times \mathrm{y_{market_t}}) \\ &+ \theta_3 \cdot (\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_i}} \times \mathrm{y_{market_t}}) \\ &+ \beta' \cdot X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

In the liquidity commonality analysis, $\mathrm{y_{i,t}}$ is the daily change in the Amihud ratio, and $\mathrm{y_{market_t}}$ is the daily change in the value-weighted Amihud ratio of the portfolio of treated and control stocks. In the return commonality analysis, $\mathrm{y_{i,t}}$ is the stock return, and $\mathrm{y_{market_t}}$ is the daily value-weighted return of the portfolio of treated and control stocks.[15] In both analyses, $\mathbb{1}_{\mathrm{Post_t}}$ is a dummy variable that takes on the value 1 after the switch date and 0 before; $\mathbb{1}_{\mathrm{Treatment}_i}$ is a dummy variable that takes on the value 1 for CAC 40 stocks and 0 for control stocks.

Consistent with our previous regression, $X_{i,t}$ controls for daily market capitalization and the inverse of the lagged stock price. Day time fixed effects, λ_t, control for common shocks and trends. To account for time-invariant stock heterogeneity, stock fixed effects α_i are included. As variables $\mathrm{y_{market_t}}$, $\mathbb{1}_{\mathrm{Post_t}}$, $\mathbb{1}_{\mathrm{Treatment_i}}$ and the interaction term $(\mathbb{1}_{\mathrm{Post_t}} \times \mathrm{y_{market_t}})$ are subsumed by the fixed effects, we do not include them in regression (4).

Our coefficient of interest is θ_3, which captures the differential impact of the switch on stocks' commonality between CAC 40 constituents and control stocks. Since our main hypothesis states that the switch to physical replication should result in stronger comovements across constituent stocks, we expect θ_3 to be positive.

4.3.2. Quasi-natural experiment results

The results in Table 4 show that treated stock commonality in both liquidity and returns increases following the Lyxor CAC switch to physical replication. The coefficient on the triple interaction term $(\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_i}} \times \mathrm{y_{market_t}})$ is positive and statistically significant

[15] The results are qualitatively unchanged when computing market return and market liquidity using equal-weighting instead of value-weighting.

at the 1% level. Relative to control stocks, the switch leads to an increase in comovements for CAC 40 stocks of 8% of a standard deviation for returns and 27% of a standard deviation for liquidity. The magnitude of the increase appears to be quite large considering that the average change in CAC 40 stock ownership caused by the switch is around 0.3 percentage point.

To test our hypothesis that the effect of the switch should be particularly significant for the least liquid stocks, we split the previous sample in two. We define illiquid treated stocks as those whose liquidity level is below their group liquidity median. Similarly, the illiquid control stocks are those whose liquidity level is below their group liquidity median. We rerun regression (4) on the sub-sample that now contains the illiquid control stocks and the illiquid treated stocks. For both return and liquidity comovements, the impact of the switch on treated stocks is positive and statistically significant at the 1% level. Relative to the least liquid control stocks, the return comovements of the CAC 40 least liquid stocks increase by 13% of a standard deviation, compared to 8% for the whole sample. After the switch the relative increase in liquidity comovements of CAC 40 least liquid stock is equal to 30% of a standard deviation, compared to 27% for the whole sample. Collectively, these findings support our hypothesis that ETFs induce comovements, especially for the least liquid stocks.

5. Transmission mechanism

In this section, we investigate the transmission mechanism driving our results. We test the hypothesis that ETFs impact the comovements of their stocks through ETF arbitrage activity. To capture ETF arbitrage, we use the absolute value of the Lyxor CAC primary market activity per day, where primary market activity is defined as the change in the number of ETF shares. We investigate how the comovements evolve after the switch in the replication method for both the days with primary market activity and for the days without by running regression (4) separately on both types of days. Since arbitrage can take more than one day, we include both the day of the creation/redemption and the following day in our sub-sample of days with ETF arbitrage. Our sub-sample of days without ETF arbitrage includes the rest of the days.

Table 5 presents the results of the main difference-in-differences framework for both sub-samples. Results in column 1 show that the commonality in returns increases for treated stocks on days with ETF arbitrage. In contrast, results in column 3 indicate that there is no increase in return comovements on days without ETF arbitrage. This result validates our hypothesis that the arbitrage activity of the ETF APs increases return commonality.

Next we turn to the liquidity commonality. Consistent with our previous findings, we find that the liquidity commonality of the treated stocks increases for the sub-sample of days with ETF arbitrage, as the coefficient on the interaction term ($\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_i}} \times \mathrm{y}_{\mathrm{market_t}}$) is positive and significant at the 1% level. Turning to the sub-sample of days without ETF arbitrage, the estimates drop from 0.45 to 0.12 and are only significantly different from zero at the 10% level, even though the sample size is twice as large. These results are consistent with the view that it is the ETF arbitrage activity that drives the effect of ETFs on their stock commonality in liquidity.

In summary, following the ETF switch to physical replication, the comovements of the underlying stocks are greater on the days with ETF arbitrage activity. These findings suggest that ETF arbitrage by APs is the mechanism that is responsible for the increase in comovements.

6. Pricing efficiency

We have shown in section 4.2 that stocks whose ETF ownership is higher exhibit a greater sensitivity in both returns and liquidity to market movements. Whether this stronger response to market fluctuations reflects excessive comovements or is the outcome of a better incorporation of market-wide information into stock prices is an important question. We address this issue using two alternative approaches. The first one relies on price reversals, whereas the second one analyzes the behavior of variance ratios.

6.1. Price reversals

To test if comovements are excessive, we first follow Da and Shive (2018) and investigate price reversals. If ETFs cause stock prices to deviate from a random walk, then ETFs should make returns more negatively autocorrelated. Using our difference-in-differences setting, we regress stock returns on their lagged returns. This specification allows us to test if there is a change in the magnitude of price reversals for stocks whose ETF switched to physical replication. Specifically, we estimate the following regression for each stock i, and day t:

$$\begin{aligned}\mathrm{R_{i,t}} \;=\;& \alpha_i + \lambda_t + \theta_1 \cdot \mathrm{R_{i,t\text{-}1}} + \theta_2 \cdot (\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_i}}) \\ &+ \theta_3 \cdot (\mathbb{1}_{\mathrm{Post_t}} \times \mathrm{R_{i,t\text{-}1}}) + \theta_4 \cdot (\mathbb{1}_{\mathrm{Treatment_i}} \times \mathrm{R_{i,t\text{-}1}}) \\ &+ \theta_5 \cdot (\mathbb{1}_{\mathrm{Post_t}} \times \mathbb{1}_{\mathrm{Treatment_t}} \times \mathrm{R_{i,t\text{-}1}}) \\ &+ \beta' \cdot X_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where $\mathrm{R_{i,t}}$ denotes the return of stock i on day t.

Our coefficient of interest is θ_5, which measures the impact of the switch on the autocorrelation of returns for CAC 40 (treated) stocks relative to control stocks. Our estimates are reported in Table 6. We find no evidence of a significant change in the magnitude of price reversals after the switch. We repeat our analysis for a subsample composed of illiquid stocks and find similar results. Therefore, our results do not support the claim that comovements are excessive and thus differ from earlier findings by Da and Shive (2018).

6.2. Variance Ratio

To further test if the comovements are excessive, we next follow Lo and MacKinlay (1988) and compute variance ratios. Similar to Ben-David, Franzoni, and Moussawi (2018) we compute variance ratios as:

$$\text{VarianceRatio}_{\text{i,m}} = \left| \frac{\text{Var}_{\text{m}}(\text{R}_{\text{i,w}})}{5 \times \text{Var}_{\text{m}}(\text{R}_{\text{i,t}})} - 1 \right| \tag{6}$$

where the variance ratios are computed for every stock i and month m. $\text{R}_{\text{i,w}}$ is the non-overlapping weekly return, and $\text{R}_{\text{i,t}}$ is day t return. Again, we use our difference-in-differences setting to test if the variance ratios increase for the stocks in the CAC 40 after its ETF switched to physical replication. We estimate the following regression for each stock i, and month m:

$$\begin{aligned} \text{VarianceRatio}_{\text{i,m}} \quad &= \quad \alpha_i + \lambda_m + \theta_1 \cdot (\mathbb{1}_{\text{Post}_{\text{m}}} \times \mathbb{1}_{\text{Treatment}_{\text{i}}}) \\ &\quad + \beta' \cdot X_{i,m} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

Our difference-in-differences analysis of variance ratios is reported in Table 7. Consistent with the previous analysis using price reversals, the results from variances ratios do not indicate a decrease in price efficiency. We even find that, relative to control stocks, the variance ratios of the treated stocks decrease after the switch at the 1% level. We show that this finding is present for the full sample of stocks but not for the subsample composed only of the least liquid stocks. Based on variance ratios, ETFs seem to increase pricing efficiency of the most liquid stocks. Overall the results from both variance ratios and price reversals suggest that the comovements are not excessive.

7. Robustness

7.1. Panel regressions robustness

To account for non-linearity, we reproduce our analysis by sorting stocks into sizes quartiles. Indeed, our results could potentially be driven by a few large stocks. To test that our results are consistent across multiple stock sizes, we aggregate stocks in quartiles based on their market value on the last day of 2017, where quartile 1 (4) contains the stocks with the lowest (highest) market capitalizations. We run our specification separately for each quartile. Table 8 and Table 9 report the results. We find supporting evidence of a positive association between comovements and ETF ownership. The estimates in column 2 to 4 show that for the quartiles including stocks with higher ETF ownership, the coefficient on our commonality measure is positive and significant. In contrast, for the bottom quartile (stocks with low market capitalization but also low ETF ownership), the coefficient is insignificant.

7.2. *Quasi-natural experiment: placebo test*

To mitigate concerns about model mis-specification and endogeneity, we conduct a falsification test. We rerun regression (4) where $\mathbb{1}_{\mathrm{Post_t}}$ is now a dummy variable equal to 1 one year before the actual switch date. We use a six-month window period around this "phantom" event. Apart from this sample period modification, we reproduce our main difference-in-differences framework and use of treated and control stock groups.

Table 10 presents the results for the placebo test. In support of our identification strategy, advancing the switch date by one year results in an insignificant θ_3 coefficient. The placebo test therefore confirms that it is only *after* the ETF switches to physical replication that its stock comovements increase. In addition, the results of the placebo test validate both the parallel trend assumption and our selection process for control stocks.

7.3. *Quasi-natural experiment: robustness*

To test the robustness of our main results, we use three alternative specifications.

First, to test if the main results are corroborated when using an alternative method for the selection of control stocks, we select the control stocks without using a propensity score matching procedure. Indeed, the choice of the selection criteria of the propensity score matching is potentially a source of bias due to researchers' discretion regarding the selection of the matching criteria. In this alternative specification, to remove penny stocks and stocks that barely trade, we simply filter out the control stocks so that their trading volume and liquidity is above the minimum of the treated stocks. We obtain 722 control stocks instead of 40 after the PSM. We show in Table 11 that the results of the quasi-natural experiment are materially unchanged compared with those obtained using propensity score matching.

Second, we use alternative measures of liquidity. We test that the results for liquidity comovements are reproduced using both the change in Corwin and Schultz (2012)'s transaction cost and also the change in dollar volume instead of Amihud (2002). The main results (available upon request) are qualitatively unchanged.

Finally, we verify that the results are robust when using an alternative measure of comovements. Following Morck, Yeung, and Yu (2000), we consider a comovement measure based on the R^2 from regressions of individual stock returns (liquidity) on market returns (market liquidity). We proceed in two steps. As a first step, analog to Malceniece, Malcenieks, and Putniņš (2019), for each stock i in each month m, we estimate the following regression using daily observations t to obtain its R^2:

$$\mathrm{y_{i,t}} = \alpha_i + \beta_1 \cdot \mathrm{y_{market_{t\text{-}1}}} + \beta_2 \cdot \mathrm{y_{market_t}} + \beta_3 \cdot \mathrm{y_{market_{t+1}}} + \varepsilon_{i,t} \tag{8}$$

As in our main specification, for the liquidity commonality analysis, $\mathrm{y_{i,t}}$ is the daily change in the Amihud ratio, and $\mathrm{y_{market_t}}$ is the daily change in the value-weighted Amihud ratio of the portfolio of treated and control stocks. Similarly, in the return commonality analysis, $\mathrm{y_{i,t}}$ is the stock return, and $\mathrm{y_{market_t}}$ is the daily value-weighted return of the portfolio of treated and control stocks. In addition, to control for day-of-the-week effects in liquidity following Karolyi, Lee, and van Dijk (2012) and Malceniece, Malcenieks, and Putniņš (2019), we also include day of the week dummies in the liquidity commonality analysis. Consistent with this literature, we also proceed to the logit transformation of the regression R^2 to make it into an unbounded variable. Next, for the second step, in line with the difference-in-differences approach of Section 4, we then estimate the following regression for each stock i, and month

m:

$$\begin{aligned} log(R^2_{i,m}) &= \alpha_i + \lambda_m + \ \theta_1 \cdot (\mathbb{1}_{\mathrm{Post_m}} \times \mathbb{1}_{\mathrm{Treatment_i}}) \\ &\quad + \beta' \cdot X_{i,m} + \varepsilon_{i,m} \end{aligned} \tag{9}$$

The results in Table 12 show a higher R^2 for the stocks belonging to the ETF switching to physical replication after the switch (relative to the stocks in the control group). These results confirm our baseline results and indicate a higher degree of comovement for stocks in physical ETFs. Following the switch, an increasing part of the variation in the individual stock returns or liquidity of stocks in the treatment group is explained by market-wide variations.

8. Conclusion

In this study, we investigate the effect of equity ETFs on the comovements of their stocks. Using first panel regressions, we show that a stock's liquidity and return comovements are positively linked to ETF ownership. We then exploit the exogenous switch of the Lyxor CAC ETF from synthetic to physical replication to establish the causal impact of an ETF on its stock comovements. We show that this switch is responsible for a significant increase in both return and liquidity comovements of CAC 40 stocks and that the effect is particularly significant for the least liquid stocks. Finally, analyzing the transmission mechanism, we find that the comovements are driven by the ETF arbitrage activity.

Prior literature finds a positive causal relation between ETFs and the commonality of their stocks returns (Da and Shive (2018)) and liquidity (Agarwal, Hanouna, Moussawi, and Stahel (2018)). Our main contribution is that we corroborate these works by using a quasi-natural experiment that disentangles the *ETF effect* from the *index effect*. Our second contribution is to show that contrary to earlier findings, the comovements do not appear excessive. We leave for future research to determine if the comovements contribute to the information efficiency by incorporating systematic source of risk to stock prices (Glosten, Nallareddy, and Zou (2021)).

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Table 1 – Synthetic ETF collateral composition
Extract of the audited Lyxor CAC synthetic ETF in December 2009. The table displays part of the composition of the assets in the ETF collateral of the swap. Several stocks in the ETF collateral are non-French stocks and are not constituents of the French CAC 40 index.

ISIN	Name	Weight %
DE000SG0VLWF	SOCGEN CT CAC40 OPEN	9.97
FR0000120271	TOTAL	9.58
IT0003132476	ENI SPA	7.88
IT0000072618	UNICREDIT SPA	7.40
FR0000130809	SOCIETE GENERALE	3.23
ES01132111835	BANCO BILBAO	3.01
DE000ENAG999	E.ON AG	2.72
DE00007236101	SIEMENS AG_NOM	2.14

Table 2 – Summary statistics

Panel A details the variables of interests at the stock-day level for stocks composing European ETFs. Panel B presents the summary statistics. The sample ranges from December 2013 to January 2017 and includes 853 stocks. Variables are winsorized at the 1% and 99% levels. Return is the daily return in %. Amihud is the price impact in % for a trade of 1 million euro. ETF Own is the share of stocks' market value held by European and U.S. ETFs, expressed in %. Liquidity is the daily log difference of the Amihud ratio. Market Return is the volume-weighted average return across all stocks in the sample. Market Liquidity is similarly constructed. MV is the market capitalization in billion euros.

Panel A: Variable description

Variable	Description	Source
Return	The daily discrete return net of dividends.	Refinitiv
Amihud	The absolute daily return over the dollar volume.	Refinitiv
Liquidity	The daily change in the Amihud ratio.	Refinitiv
prcinv	Inverse of the nominal share price.	Refinitiv
RefinitivIndex composition	Index weight per stock per month or quarter.	Refinitiv, CRSP
Primary market activity	The daily change in the number of ETF shares outstanding.	Refinitiv
Switch date	Date of the index replication method switch.	ETF Issuer

Panel B: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
ETF Own	601,619	1.77	2.26	0.00	0.18	1.20	2.65	16.90
Return	601,619	0.04	1.97	−5.50	−1.03	0.02	1.07	6.02
Market Return	601,149	0.04	1.14	−4.26	−0.61	0.09	0.67	4.02
Liquidity	601,619	−0.00	1.41	−3.65	−0.87	−0.00	0.86	3.66
Market Liquidity	601,149	−0.00	0.50	−1.58	−0.32	−0.02	0.32	1.65
Amihud	601,619	0.36	1.23	0.00	0.00	0.02	0.16	9.56
MV	601,619	7.68	1.63	1.79	6.41	7.55	8.84	12.20

Table 3 – Commonality in Return and Liquidity panel regressions
This table presents the results of regression (2) where individual stock returns and changes in liquidity are regressed against market returns (MarketReturn) and liquidity variation (MarketLiquidity) interacted with lagged ETF ownership (lagETFown). The sample ranges from December, 2013, to January, 2017 and includes 853 European stocks. Columns 1 and 2 report the coefficients of the baseline specification. To account for potential non-linear effects, columns 3 and 4 report the coefficients of the same regression where lagged ETF ownership is replaced by HighETFown, a dummy variable equal to one for stocks that are in the top quartile of ETF ownership. Liquidity is measured as the log difference in the Amihud ratio across successive trading days. Controls include the lagged log market value (l_MV), the lagged inverse of the price (l_prcinv), the lagged Amihud ratio (l_Amihud), and the lead and lag of the dependent variable. Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return	Liquidity	Return	Liquidity
MarketReturn×lagETFown	0.042***			
	(0.008)			
MarketLiquidity×lagETFown		0.022***		
		(0.005)		
MarketReturn×lagHighETFown			0.114***	
			(0.012)	
MarketLiquidity×lagHighETFown				0.077***
				(0.006)
lagETFown	0.048***	−0.008*		
	(0.012)	(0.004)		
l_HighETFown			−0.017*	−0.001
			(0.009)	(0.005)
l_MV	−0.094***	−0.073***	−0.096***	−0.073***
	(0.018)	(0.012)	(0.018)	(0.012)
l_prcinv	0.006***	−0.006***	0.007***	−0.006***
	(0.002)	(0.001)	(0.002)	(0.001)
l_Amihud	−0.011***	−0.163***	−0.012***	−0.163***
	(0.003)	(0.007)	(0.003)	(0.007)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Observations	599,443	599,443	599,443	599,443
R^2	0.253	0.506	0.253	0.507

Table 4 – Quasi-natural experiment regressions

This table reports the results of difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch on the comovements of its constituents. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. Treated stocks are the CAC 40 index constituents, and the CAC 40 is the index whose ETF switches to physical replication. Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Liquidity is measured as the log difference in the Amihud ratio across successive trading days. MarketReturn is the return of the value-weighted portfolio of treated and control stocks. MarketLiquidity is the value-weighted Liquidity of the portfolio of treated and control stocks. We run the regressions on the full sample of stocks and on a sub-sample composed of illiquid stocks (those below the group liquidity median). Controls include the lagged log market value (l_MV) and the lagged inverse of the price (l_prcinv). Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Robust standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return	Liquidity	Return	Liquidity
Post×Treatment×MarketReturn	0.08**		0.13***	
	(0.03)		(0.04)	
Post×Treatment×MarketLiquidity		0.27***		0.30***
		(0.05)		(0.07)
Post×Treatment	−0.003	0.03	0.01	0.02
	(0.03)	(0.02)	(0.03)	(0.03)
Treatment×MarketReturn	−0.04		−0.09	
	(0.04)		(0.06)	
Treatment×MarketLiquidity		−0.12***		−0.17***
		(0.05)		(0.06)
l_MV	0.21	−0.10	−0.06	0.16
	(0.22)	(0.11)	(0.20)	(0.18)
l_prcinv	0.08***	0.004	0.06***	0.02
	(0.01)	(0.01)	(0.02)	(0.02)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Sample	Full	Full	Illiquid	Illiquid
Observations	19,504	19,403	9,516	9,462
R^2	0.43	0.12	0.53	0.17

Table 5 – Quasi-natural experiment: Transmission mechanism

This table reports the results of difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch on its underlying stocks' commonality. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Liquidity is measured as the log difference in the Amihud ratio across successive trading days. MarketReturn is the return of the value-weighted portfolio of treated and control stocks. MarketLiquidity is the value-weighted Liquidity of the portfolio of treated and control stocks. We run the regressions on the sub sample of days with ETF arbitrage and the sub-sample of days without. Controls include the lagged log market value (l_MV) and the lagged inverse of the price (l_prcinv). Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Robust standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	With arbitrage		Without Arbitrage	
	Return	Liquidity	Return	Liquidity
Post×Treatment×MarketReturn	0.18***		0.02	
	(0.05)		(0.04)	
Post×Treatment×MarketLiquidity		0.45***		0.12*
		(0.07)		(0.07)
Post×Treatment	0.06	0.07	−0.002	−0.02
	(0.06)	(0.05)	(0.03)	(0.04)
Treatment×MarketReturn	−0.08		0.005	
	(0.05)		(0.04)	
Treatment×MarketLiquidity		−0.17***		−0.05
		(0.05)		(0.06)
l_MV	0.23	−0.28	0.36	0.03
	(0.19)	(0.19)	(0.26)	(0.16)
l_prcinv	0.10***	−0.01	0.08***	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Observations	6,758	6,708	12,667	12,616
R^2	0.43	0.15	0.44	0.10

Table 6 – Quasi-natural experiment: Price reversals

This table reports the results of the difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch to physical replication on the price reversals of its underlying stocks. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. Price reversals are measured by regressing the stock return on its lagged return. We run the regressions on the full sample of stocks and on a sub-sample composed of illiquid stocks (those below the group liquidity median). Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Controls include the lagged log market value (l_MV) and the lagged inverse of the price (l_prcinv). Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Robust standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return	
Post×Treatment×lagged Return	−0.044	0.010
	(0.032)	(0.038)
Treatment×lagged Return	0.031	−0.003
	(0.020)	(0.026)
Post×Treatment	0.00001	0.0001
	(0.0004)	(0.001)
Post×lagged Return	0.001	−0.021
	(0.030)	(0.031)
lagged Return	−0.007	0.017
	(0.016)	(0.019)
l_MV	0.003	−0.001
	(0.003)	(0.003)
l_prcinv	0.001***	0.001***
	(0.0002)	(0.0002)
Stock FE	Yes	Yes
Time FE	Day	Day
Sample	Full	Illiquid
Observations	19,504	9,516
R^2	0.433	0.529

Table 7 – Quasi-natural experiment: Variance Ratio

This table reports the results of difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch on the variance ratio of its constituents. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. Variance ratio is computed as the absolute value of five times the daily variance over weekly variance minus one. The frequency of the data is monthly at the stock level. We run the regressions on the full sample of stocks and on a sub sample composed of illiquid stocks (those below the group liquidity median). Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Controls include the log market value (MV) and the inverse of the price (prcinv). Stock and month fixed effects are included. Robust standard errors clustered at the month and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	VarianceRatio	
Post×Treatment	-0.07^{***}	0.01
	(0.02)	(0.05)
MV	-0.08	-0.04
	(0.23)	(0.43)
prcinv	-0.01	-0.01
	(0.02)	(0.03)
Stock FE	Yes	Yes
Time FE	Month	Month
Sample	Full	Illiquid
Observations	1,040	507
R^2	0.26	0.29

Table 8 – Quartile regressions Commonality in Return

This table presents the results of the regression of individual stock returns against market returns (MarketReturn) interacted with lagged HighETFown, a dummy variable equal to one for stocks that are in the top quartile of ETF ownership and 0 otherwise. The sample ranges from December, 2013, to January, 2017 and includes 853 European stocks. We split stocks into quartiles based on their market value for the last day of 2017, with quartile 1 being the lowest (column 1) and quintile 4 the highest (column 4). We report for each quartile the median ETF ownership (ETFown) for the last day of 2017. Controls include the lagged log market value (l_MV), the lagged inverse of the price (l_prcinv) and the lead and lag of the dependent variable. Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return			
	(1)	(2)	(3)	(4)
MarketReturn×lagHighETFown	0.03	0.07***	0.06***	0.07***
	(0.03)	(0.03)	(0.02)	(0.02)
lagHighETFown	−0.02	−0.03*	−0.04***	0.003
	(0.03)	(0.02)	(0.01)	(0.01)
l_MV	−0.10***	−0.12***	−0.07**	0.05
	(0.02)	(0.03)	(0.04)	(0.03)
l_prcinv	0.01***	1.92	6.21**	8.10***
	(0.002)	(1.95)	(2.81)	(2.76)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Observations	141,423	137,864	151,711	167,167
R^2	0.17	0.22	0.29	0.43
ETFown	0.59%	1.49%	1.74%	3.11%

Table 9 – Quartile regressions Commonality in Liquidity

This table presents the results of the regression of individual stock liquidity changes against market liquidity changes (MarketLiquidity) interacted with lagged HighETFown, a dummy variable equal to one for stocks that are in the top quartile of ETF ownership and 0 otherwise. The sample ranges from December, 2013, to January, 2017 and includes 853 European stocks. We split stocks into quartiles based on their market value for the last day of 2017, with quartile 1 being the lowest (column 1) and quintile 4 the highest (column 4). We report for each quartile the median ETF ownership (ETFown) for the last day of 2017. Controls include the lagged log market value (l_MV), the lagged inverse of the price (l_prcinv) and the lead and lag of the dependent variable. Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquidity			
	(1)	(2)	(3)	(4)
MarketLiquidity×lagHighETFown	0.002	0.02***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
lagHighETFown	0.003	0.002	0.02***	−0.0001
	(0.01)	(0.01)	(0.01)	(0.01)
l_MV	0.004	0.005	0.001	−0.02
	(0.004)	(0.01)	(0.01)	(0.02)
l_prcinv	−0.01***	−0.11	−0.47	−1.06
	(0.0004)	(0.18)	(0.69)	(0.79)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Observations	141,423	137,864	151,711	167,167
R^2	0.47	0.48	0.51	0.54
ETFown	0.59%	1.49%	1.74%	3.11%

Table 10 – Placebo Test

This table reports the results of difference-in-differences regressions where Post is a dummy variable that takes on the value zero before the pseudo switch (1 year before tha actual switch date) and 1 after. The sample period is adjusted accordingly. Treated stocks are the CAC 40 index constituents, and the CAC 40 is the index whose ETF switches to physical replication. Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Liquidity is measured as the log difference in the Amihud ratio across successive trading days. MarketReturn is the return of the value-weighted portfolio of treated and control stocks. MarketLiquidity is the value-weighted Liquidity of the portfolio of treated and control stocks. Controls include the lagged log market value (l_MV) and the lagged inverse of the price (l_prcinv). Variables have been winsorized at the 1% and 99% percentiles and standardized. Stock and day fixed effects are included. Robust standard errors clustered at the day and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return	Liquidity
Post×Treatment×MarketReturn	−0.04	
	(0.03)	
Post×Treatment×MarketLiquidity		0.03
		(0.10)
Post×Treatment	0.02	−0.02
	(0.03)	(0.03)
Treatment×MarketReturn	0.09**	
	(0.04)	
Treatment×MarketLiquidity		0.03
		(0.09)
l_MV	0.08	0.04
	(0.11)	(0.08)
l_prcinv	0.09***	0.02
	(0.01)	(0.01)
Stock FE	Yes	Yes
Time FE	Day	Day
Sample	Full	Full
Observations	19,723	19,723
R^2	0.34	0.08

Table 11 – Quasi-natural experiment-Robustness without PSM

This table reports the results of difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch on its underlying stocks' commonality. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. Treated stocks are the CAC 40 index constituents, and the CAC 40 is the index whose ETF switches to physical replication. Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Liquidity is measured as the log difference in the Amihud ratio across successive trading days. MarketReturn is the return of the value-weighted portfolio of treated and control stocks. MarketLiquidity is the value-weighted Liquidity of the portfolio of treated and control stocks. We run the regressions on the full sample of stocks and on a sub sample composed of illiquid stocks (those below the group liquidity median). Controls include the lagged log of the market capitalization (l_MV) and the lagged inverse of the price (l_prcinv). Stock and day fixed effects are included. Variables are winsorized and standardized. Robust standard errors clustered at the day and stock levels are presented in parentheses and . ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return	Liquidity	Return	Liquidity
Post×Treatment×MarketReturn	0.089***		0.136***	
	(0.022)		(0.026)	
Post×Treatment×MarketLiquidity		0.159***		0.198***
		(0.032)		(0.040)
Post×Treatment	0.044***	0.013	0.034***	0.020
	(0.011)	(0.017)	(0.013)	(0.018)
Treatment×MarketReturn	0.060**		−0.019	
	(0.028)		(0.041)	
Treatment×MarketLiquidity		0.121***		0.043
		(0.022)		(0.033)
l_MV	0.846	−1.919	1.325	−0.530
	(2.582)	(2.118)	(3.053)	(1.519)
l_prcinv	0.001***	−0.0002***	0.162	−0.008
	(0.0001)	(0.00003)	(0.101)	(0.015)
Stock FE	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day
Sample	Full	Full	Illiquid	Illiquid
Observations	174,341	171,048	79,529	79,325
R^2	0.206	0.032	0.292	0.052

Table 12 – Quasi-natural experiment: Robustness test using R^2.

This table reports the results of difference-in-differences regressions to estimate the effect of the Lyxor CAC ETF switch on the comovements of its constituents. The sample ranges from a 6-month window around the switch event that occurred on July 11, 2014 to 6 months after, and the month before the switch is excluded. We measure comovement in returns (liquidity) using the R^2 from regressions of individual stock returns (liquidity) on market returns (market liquidity). The frequency of the data is monthly at the stock level. Treated stocks are the CAC 40 index constituents, and the CAC 40 is the index whose ETF switches to physical replication. Treatment is a dummy variable that takes on the value 1 for treated (CAC 40) stocks and 0 for control stocks. Post is a dummy variable that takes on the value zero before the switch and 1 after. Controls include the lagged log of the market capitalization (l_MV) and the lagged inverse of the price (l_prcinv). Stock and month fixed effects are included. Robust standard errors clustered at month and stock levels are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Return R^2	Liquidity R^2
Post×Treatment	0.46^{**}	0.53^{**}
	(0.20)	(0.22)
l_MV	−0.21	−1.12
	(1.56)	(1.15)
l_prcinv	−0.14	−0.10
	(0.11)	(0.10)
Stock FE	Yes	Yes
Time FE	Month	Month
Sample	Full	Full
Observations	1,034	888
R^2	0.63	0.44