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Keywords: ETFs, Subsidization, Banks, Shadow Banking, Distress.
JEL Codes: G2

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Abstract

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Keywords: ETFs, Subsidization, Banks, Shadow Banking, Distress.
JEL Codes: G20

"*The speed and breadth of financial innovation in the ETF market has been remarkable…, and has brought new elements of complexity and opacity into this standardized market*."

-- Financial Stability Board [1]

Introduction

Over the last decade, the market has witnessed the rise of exchange-traded funds (ETFs). According to the Financial Stability Board (FSB), the global ETF industry experienced an astonishing 40% annual growth rate over the ten-year period from 2001 to 2010, compared with the 5% annual growth rate in global mutual funds and equity markets over the same period. The press has extolled the benefits of ETFs as cheap alternatives to traditional open-end mutual funds (OEFs) and even to index funds because they combine high diversification (i.e., tracking of broad benchmarks and the absence of active management risk) with low cost (i.e., no load fees and extremely limited management fees). In short, ETFs have been heralded as the harbingers of a new era of low cost/low risk investment opportunities that are available to the general public.

However, this brief narrative does not tell the entire story. Indeed, to be able to charge low fees, ETF sponsors may seek alternative investment techniques, such as, among others, synthetic replication with affiliated banks, the lending of shares in the market, and active divergence from the benchmark (e.g., Ramaswamy, 2011). These techniques create a direct "investment link" between the ETFs and their affiliated financial conglomerate. To illustrate this point, consider a Nikkei index ETF that receives $100 of investment. Instead of investing this money as required by the index, the ETF can invest the entire $100 in a different type of risky equity portfolio and at the same time enter a total return swap with its affiliated bank, whereby it swaps the total return on the invested portfolio with the return on the index. In this way, although the ETF is able to track the benchmark at low cost, the actual portfolio allocation will

[1] Financial Stability Board: "Potential financial stability issues arising from recent trends in Exchange-Traded Funds (ETFs)", issued in April 12, 2011.

deviate from the benchmark. Because ETF investors only require the index return, the benefits of the ETF's deviation may be reaped by those entities affiliated with the ETF. If the swap counterparty defaults on the promised delivery of the index return, however, ETF investors may face unexpected exposure. In other words, ETF investors may not fully enjoy the upside of the actual portfolio investment, although they may be exposed to additional risk.

These features have raised regulators' concerns regarding potential conflicts of interest. For example, the Financial Services Authority has stated that it is "extremely important" for ETF providers to properly highlight the difference between a straightforward ETF and "more complex investment strategies" that may involve derivatives and that one of the major concerns is the potential for conflicts of interest.[2] Practitioners have voiced similar concerns. BlackRock stated that "it believes that potential conflicts of interest arise when a synthetic ETF provider enters into a derivative agreement with its investment banking parent because the costs it pays for the swap could be uncompetitive and beneficial to the bank".[3]

In this paper, we investigate whether the data support such concerns by addressing both the positive and negative effects of ETF affiliation with financial conglomerates. We argue that the positive effects may arise from what can be hypothesized as an *information channel* in which affiliation with a financial conglomerate provides ETFs with bank-loan related information as it does for affiliated OEFs (e.g., Irvine, Lipson and Puckett, 2007; Ritter and Zhang, 2007; Massa and Rehman, 2008). This information channel allows ETFs to deviate from their benchmarks in a profitable way – e.g., by overweighting good stocks that the affiliated bank has more information. ETFs may pass on the benefits to their own investors via lower fees, they may swap the benefits to their affiliated entities, or they may do both.

In addition, ETFs may also benefit from a *securities lending channel* by lending out the stocks in their portfolios. Lending securities generates additional income for the ETFs, which may (again) be passed on

[2] Article entitled "UK Regulator Declares ETF Concerns", published in the *Financial Times* on April 2, 2012.
[3] Article entitled "BlackRock Calls for Action on Conflicts of Interest in ETFs" by Reuters published on March 31, 2012.

to investors or to affiliated entities.[4] The difference between the information and securities lending channel is that ETFs do not need to deviate from their benchmarks to benefit from lending their securities. Instead, ETFs have incentives to stay with their benchmarks as much as they can – and thus minimize tracking-error-related risk – if they are able to generate significant income from securities-lending.

The negative effects of affiliation can be related to the need to provide "services" to affiliated entities. This *subsidization channel* can take the form of holding the stock of the affiliated bank to support its price (particularly when the bank is lagging in terms of profitability or credit ratings) or acting as counterparty in cross-trades to help affiliated OEFs. These motives may also induce ETFs to deviate from the benchmark investment. However, in contrast to the information and securities lending channels, subsidization-induced deviations may expose ETF investors to additional risk. Although the negative impact faced by ETF investors might be mitigated by the affiliated bank's guarantee to deliver the index return, the value of the promise largely depends on the distress risk of the bank (i.e., counterparty risk). The higher the distress risk, the lower the value of the promise. Because banks with higher distress risk need more help, the negative impact will be further amplified as enhanced tracking errors and credit risk intertwine.

Although it is highly complex (if not impossible) to quantify the risk enhancement effect of each off-benchmark operation, we can utilize a unique feature of the ETF industry to gauge the impact of off-benchmark operations on investor demand. Unlike OEFs, ETF flows are typically associated with sophisticated investors.[5] We can therefore hypothesize that sophisticated investors would penalize pure subsidization (resulting from additional risk/lower performance) by reducing their demand.

We explore these channels and their implications using the universe of worldwide equity ETFs and OEFs during the 2001–2009 period. We use international data because the global markets present a much

[4] In either case, ETFs would be exposed to additional risk (e.g., "rehypothecation risk"). ETFs typically manage this risk by asking for more than 100% collaterals.

[5] Retail investors of Vanguard's S&P 500 Index Fund (an OEF), for instance, face a minimum investment request of $3,000 USD, whereas the prospectus of the Vanguard S&P 500 ETF indicates that shares "can be redeemed with the issuing Fund at NAV … only in large blocks known as Creation Units, which would cost millions of dollars to assemble". ETF flows are often regarded as a built-in arbitrage mechanism to ensure that ETF market prices do not deviate substantially from NAVs.

larger cross-sectional variation in benchmarks and thus provide a stronger basis upon which to analyze the ETF industry. We begin by documenting three stylized facts about ETFs. First, unlike OEFs, ETFs are more likely to be affiliated with bank conglomerates (as opposed to specialized asset management companies). More than 75% of ETFs (and 80% of their net assets) were affiliated with bank conglomerates during the late 2000s compared with 40% for OEFs (and 30% of their net assets). Therefore, ETFs can hardly be considered as stand-alone investment products.

Second, not only do ETFs hold stocks in proportions that do not reflect the indices they track, but such deviations in holdings – which we will label "*Divergence*" – are persistent. Moreover, the deviation between the holding-based return and the gross-of-fee reported return of the ETFs (referred to herein as the "*Swapped Transfer*") is also persistent. Because ETF investors are not entitled to receive the performance above the benchmark, a positive *Swapped Transfer* implies a net cash flow transfer from an ETF to its affiliated bank. Persistency suggests that ETFs may *systematically* deviate from their benchmarks and generate cash flows that are not passed on to the ETF investors.[6]

Third, and most importantly, such deviation is not random but related to an ETF's affiliation with a financial conglomerate and, in particular, to its affiliation with a bank. More specifically, affiliation with the same bank increases the degree of commonality in *Divergence* among ETFs by 9.1% and that between ETFs and OEFs by 8.7%. These observations suggest that affiliation with (bank) conglomerates may systematically affect ETF investment strategies.

Given these stylized facts, we seek to explore the drivers that might incentivize ETFs to deviate from their benchmarks. We consider four drivers based on our previous hypotheses that relate to information, securities lending, and subsidization: the ownership of stocks that borrow loans from the affiliated bank, the level of securities-lending fees, the ownership of the stock of the affiliated bank itself, and the performance of affiliated OEFs. We document a strong correlation between these drivers and alternative

[6] In additional to *Swapped Transfer*, the performance generated by *Divergence* can also be passed on to investors through the channel of reduced ETF fees. Here we focus on the part that is not transferred to investors to reveal the complexity of the ETF industry—we will examine both *Swapped Transfer* and fees shortly.

proxies for deviation, including not only *Divergence* but also *Tracking Error*, which is a commonly used measure for assessing the ability of funds to replicate their benchmarks. In particular, stocks of firms to which the affiliated banks provide bank-loan services display a *Divergence* (*Tracking Error*) with respect to the benchmark that is 11.8% (9.4 bps) higher, which suggests that ETFs tend to diverge more in stocks on which they may have more information. By contrast, lending fees that are higher by one standard deviation reduce *Divergence* (*Tracking Error*) by 0.35% (2 bps), which confirms that securities lending reduces the need to diverge from the benchmark. Furthermore, the stocks of affiliated banks display a *Divergence* (*Tracking Error*) that is higher by 18.9% (30.6 bps). Finally, a one-standard-deviation worse (benchmark-adjusted) performance of the affiliated OEFs increases *Divergence* (*Tracking Error*) by 4.1% (31.5 bps). The latter two patterns are consistent with the idea that ETFs may have incentives to overweight the stocks of affiliated banks and to help their affiliated and underperforming OEFs.

Next, we ask how the cash flows generated by *Divergence* are shared among ETF investors and affiliated entities. In general, any benefit can be passed on either to the fund investors through reduced ETF fees (referred to as *Fees*) or to the affiliated bank through the *Swapped Transfer* (in which case a positive value implies a transfer from an ETF to its sponsor, i.e., to its affiliated bank). We find that the information channel is positively related to *Swapped Transfer*, whereas *Fees* are unaffected. Thus, the use of affiliated bank loan information primarily helps affiliated banks. By contrast, high stock-lending fees translate into lower *Fees* but not into higher *Swapped Transfer*, which suggests that participation in the stock-lending market directly benefits ETF investors. Excess ownership of affiliated bank stock affects neither *Swapped Transfer* nor *Fees*, whereas the need to help underperforming OEFs increases both *Fees* and *Swapped Transfer*, suggesting that the OEF subsidization channel imposes certain direct costs to investors.

These findings suggest that the global ETF industry is much more complicated than a simple offering of index trackers might otherwise indicate. Moreover, there indeed seems to be some reason to worry about conflicts of interest (except with respect to the securities lending channel, whose impact is straightforward). The next step, therefore, is to investigate whether these documented effects are spurious or whether they provide evidence of direct "assistance" links between the ETFs and their affiliated financial conglomerates. To achieve this goal, we conduct additional analyses to further investigate the information and subsidization channels.

Regarding the information channel, we further confirm its usefulness by showing that changes in bank loan-related ETF ownership can predict out-of-sample stock returns. Each 1% increase in bank-lending related abnormal stock ownership of ETFs translates into a 12 bps higher Daniel, Grinblatt, Titman and Wermers (1997, or DGTW)-adjusted abnormal return or an 11 bps higher raw return per year. In a "Placebo" test, we find that changes in abnormal ETF ownership of stocks that are unrelated to affiliated bank loans do not predict abnormal return. Thus, despite the common view that ETFs are passive index funds, ETF divergence can actually concentrate in very promising stocks that deliver higher performance. In other words, our additional analyses demonstrate that ETFs have a surprising "selection ability" through the affiliated information channel.

We then explore how ETFs can be used to help affiliated entities in the two subsidization channels. We first document that ETF ownership of affiliated bank stocks helps reduce the sensitivity of that affiliated bank's market-to-book ratio with respect to its profitability. By reducing this sensitivity, ETF ownership effectively protects the stock price of the bank when the bank reports low profitability. Moreover, ETF ownership of affiliated bank stocks in excess of benchmark holdings seems to boost the affiliated bank's market-to-book ratio regardless of its profitability.

With respect to the OEF subsidization channel, we find that stocks held in common by the ETFs and the OEFs in excess of their benchmarks (henceforth, *ETF/OEF Common Divergence*) demonstrate more cross-trading between ETFs and affiliated OEFs. These ETF/OEF cross-trades, in turn, promote OEF returns and flow. A one-standard-deviation increase in the ETF/OEF cross-trades due to (instrumented on) *ETF/OEF Common Divergence* leads to an annualized 5.9% higher return and 13.84% higher inflows for the affiliated OEFs.

Finally, we explore how sophisticated investors react to the existence of these information and subsidization channels. We find that positive *Swapped Transfer* and high *Fees* are typically associated with higher ETF outflows. A one-standard-deviation increase in *Swapped Transfer* (*Fees*) is associated with an annual outflow of 2.1% (5.24%). Moreover, ETF investors also withdraw capital when the affiliated bank's rating or return on assets (ROA) drops. A deterioration in bank rating of one standard deviation translates into 9.59% lower flows per year. More importantly, the outflow sensitivity with respective to *Swapped Transfer* increases with worsening ratings/ROAs of the affiliated bank. These patterns suggest that investors do not appreciate the links between ETFs and affiliated banks when the latter become risky.

These findings are the first – to the best of our knowledge – to provide evidence in support of recent regulatory concerns that the growth in ETFs (particularly synthetic ETFs) might have a serious impact on the market (FSB, 2011; IMF, 2011; Ramaswamy, 2011). Indeed, the popularity of ETFs among investors and their "deviant" allocation strategies may pose a risk to financial stability. For instance, the very stability of the financial market may be jeopardized in the event that affiliated banks become distressed because a crisis that should be limited to the banking sector might spread to the equity market as a whole (e.g., FSB, 2011; IMF, 2011; Ramaswamy, 2011).

Our analysis also contributes to the literature on delegated asset management, particularly on passive benchmarking. There have been only a few attempts to address the issue of the relationship between ETFs and affiliated banks, despite their normative implications for both consumer protection and financial stability. Retail investors have been perceived as not fully aware or capable of understanding their exposure to distress risk. Our results on flows of ETFs should help alleviate such concerns.

Our findings also relate to the economics of mutual fund families. Research on the constraints and benefits that family affiliation imposes on funds has identified how family strategies condition fund performance, risk taking, and investment (Mamaysky and Spiegel, 2001; Massa, 2003; Nanda, Wang and

Zheng, 2004; Gaspar, Massa and Matos, 2006). We broaden the focus to ETFs and their relationships with affiliated OEFs and banks.

II. The Industry, the Data and the Main Variables

In this section, we describe our data and how we construct the main variables we will use in the analysis.

A. Data Sources

Our data are drawn from different sources. The ETF and OEF holdings data are from the Factset/Lionshares database.[7] The Factset/Lionshares holdings data on international funds are sparse before 2001, so our sample is restricted to the 2001–2009 period.[8] We match the database to the Morningstar mutual fund database, which reports monthly total returns for global mutual funds. We use Morningstar classifications to identify ETFs ("Exchange-Traded Funds Universe" in Morningstar), index funds ("Index Funds" from "Open End Funds Universe"), and OEFs (the rest of the "Open End Funds Universe"). From Morningstar, we obtain additional variables such as fund net asset value (NAV), fund total net assets (TNA), fund age, management expenses, market price, volatility of fund returns, and the benchmark tracked by ETFs and index OEFs ("Primary Prospectus Benchmark"). We focus on funds that have "Equity" as the Morningstar "Broad Category Group".

Monthly stock return data and annual stock characteristics, such as market capitalization, net income, sales and total assets, are obtained from Datastream/Worldscope for international stocks, with all the

[7] A detailed description of the dataset can be found in Ferreira and Matos (2008). We find that approximately 40% of investment vehicles in the Factset/Lionshares database report quarterly portfolio holdings and approximately 50% report semi-annual holdings, the remaining 10% report either monthly or yearly holdings. We address the issue of different reporting frequencies by institution from different countries by using the latest available holdings updates at quarter-end.
[8] In 2009, the so-called "funded swap model" was introduced in Europe. In this model, the counterparty posts collateral assets in a segregated account with a third-party custodian. The account can be held either in the name of the *fund* (in the case of a transfer of title) or in the name of the *counterparty* and pledged in favor of the fund (in the case of a pledge arrangement). The first case might dilute the validity of holding information for our tests. Thus, we restrict our testing sample to 2009. Interested readers may refer to the 2012 Morningstar report, "Synthetic ETFs Under the Microscope: A Global Study", for institutional details.

variables quoted in USD. The short-sale data come from DataExplorers. For our tests involving securities lending, we consider the period from 2002 to 2009, for which short-selling data are available.[9]

Data on banks come from BvD BankScope. This dataset contains annual financial data of banks, including total assets, ROA, equity/liabilities ratio, loan loss reserve/gross loans ratio, net interest margin, cost/income ratio, and net loans/total assets ratio. The characteristics of the loan contracts and the identities of the borrowers and lenders are taken from Thomson Reuters LPC DealScan. The monthly S&P long-term issuer credit ratings come from Compustat. Because bank variables are observed only on an annual basis, we adopt annual frequency in our main tests. Using quarterly frequency based on available quarterly variables leads to similar conclusions.

B. The ETF Industry

Exchange Traded Funds, or ETFs, are index-tracking investment vehicles that allow investors to replicate an index cheaply. They represent a fixed combination of assets held as a function of their representation in the index they track, such as the S&P 500. Unlike Index Funds, investors can either invest the money in the fund/redeem its shares (for large orders) or buy/sell certificates representing ownership of ETFs. We will focus on ETFs that replicate equity indices and exclude leveraged or inverse ETFs.

Table 1 provides a snapshot of the ETF industry. For each year, we tabulate the number and TNA (in billions of USD) of the ETFs in the first two columns of Panel A. As of 2009, for instance, the ETF sample contains 921 ETFs with TNA of USD 760 billion. By contrast, there are only 109 ETFs and 61 billion TNA as of year 2001, which confirms the astonishing rate of growth in the industry. Among the 921 ETFs existing in 2009, 480 are from the U.S., and 357 are from Europe, compared with 85 and 16, respectively, in the year 2001. Thus, the importance of ETFs has increased even more outside the U.S..

In the U.S., ETFs tend to physically replicate the underlying index, which seems to be driven by regulatory rules. For example, the Investment Act of 1940 requires ETFs to hold 80% of their assets in

[9] DataExplorers has monthly short-selling information since 2002, weekly information since 2005, and daily information since July 2006. We report the tests based on the longest possible period.

securities matching the fund's name. By contrast, more than 50% of the ETFs in Europe use synthetic structures. UCITS-compliant ETFs that are synthetically replicated tend to be registered in Luxemburg to reduce haircuts on the collateral assets posted.[10]

In the next few columns of Table 1, Panel A, we report the three replication methods as reported by Morningstar: full replication, optimized sampling, and synthetic replication. Table 1 shows that only 30% of the ETFs in the world use "full replication". In our view, only full replication can prevent the ETF from deviating from its benchmark. The holdings for other types of ETFs might deviate from their benchmarks that are affected by various information and subsidization motivations.

The next few columns of Panel A report the fraction of ETFs that are affiliated with bank conglomerates and the analogous statistics of OEFs reported on an annual basis. We define "bank conglomerates" as the financial groups in which either the ultimate parent of the ETF is a bank or a bank belongs to the same group. A bank is defined as a "Bank Management Division" or "Broker/Investment Bank Asset Management" in Factset.[11] We cross-check bank identities using bank-loan data from BvD Bankscope. Ultimately, we identify 33 bank conglomerates with available banking data, approximately half (17) of which are domiciled in Europe.

Appendix B tabulates the list of ETF sponsors, including both bank and non-bank conglomerates in 2009, and Appendix C reports the top three ETF sponsors for each year. In 2009, for instance, three major ETF providers (out of 42) – Barclays (later Blackrock),[12] State Street, and Vanguard – controlled 79% of the global market, with $600 billion in assets. In Europe, Societe Generale, Credit Suisse, and Deutsche Bank had $45 billion in assets and controlled approximately 6% of the market. These statistics suggest

[10] Indeed, the UCITS regulation permits exchange-traded and OTC derivatives to be held in the fund to meet investment objectives. Under UCITS regulations, the daily NAV of the collateral basket, which can include cash or equities and bonds of OECD countries, should cover at least 90% of the ETF NAV, limiting the swap counterparty risk to a maximum of 10% of the ETF market value (Ramaswamy, 2011).
[11] For instance, "EasyETF DJ Euro Stoxx" is an ETF managed by the fund family named "BNP Paribas Asset Management (France) SAS". Classified as "Bank Management Division" in Factset, the fund family is owned by "BNP Paribas SA".
[12] In December 2009, Barclays sold its Barclays Global Investors, including the iShares ETFs, to BlackRock in exchange for a 19.6% share of BlackRock, which it recently made plans to sell (e.g., Bloomberg: Barclays to Sell Entire $6.1 Billion BlackRock Investment, May 22, 2012). Nonetheless, Barclays was a top ETF sponsor during our sample period.

that ETFs can be roughly classified into those run by pure asset managers (e.g., Vanguard) and those affiliated with "bank conglomerates" (e.g., Barclays).

Returning to Panel A of Table 1, the year-by-year statistics illustrate that the involvement of banks in the ETF industry is impressive: in any year, more than 70% of ETFs and more than 80% of the TNA of the industry are affiliated with banks. By contrast, less than 30% of OEF total net assets are typically affiliated with banks. This stylized observation is the first that we want to stress. It is notable that this affiliation pattern primarily prevails in Europe, whereas in the U.S., some of the largest ETF providers, such as Vanguard, are not part of bank conglomerates. This difference suggests that the potential conflicts of interest are more significant in Europe.

The last two columns of Panel A report the fraction of ETFs for which we are able to construct the index portfolios that they should follow.[13] Our sample typically covers between 45% and 55% of ETFs in terms of numbers and from 67% to 90% of the TNA of the industry. The final sample contains 420 ETFs, among which 107 are domiciled in the U.S. and 261 in Europe. Altogether, 16,365 stocks are held by ETFs, of which 8,809 are listed in the U.S. and 3,431 are listed in Europe.[14]

C. Main Variables

The most straightforward approach to understand ETFs' strategies, and the one adopted in this paper, is to examine how ETF holdings deviate from their benchmarks. Any systematic holdings difference may involve a transfer between the ETF and its sponsor. This sort of provides a "pool of capital" to the affiliated financial conglomerate, which, in principle, can be invested in anything. Synthetic operations, such as swaps, allow the conglomerate to deliver the committed return of the benchmark to the ETF investors and – in return – to receive whatever performance can be generated by the actual holdings of the

[13] For each ETF, we proxy for the benchmark portfolio it should hold by using the average holdings of the open-end index funds that follow the same index. If there are no index OEF funds tracking the benchmark, we use the average holdings of ETFs using full replication to proxy for the index holding.

[14] Table 1 includes benchmarks that are only followed by one ETF, which occurs, for instance, with approximately 244 indices in the year 2009. Our main regressions further exclude those one-ETF indices that are not followed by index OEF funds. Our main results are robust if we exclude all indices that are not followed by index OEFs, or if we use the average of all index OEF and full replicating ETF holdings to proxy for index holdings.

ETF. To implement this concept, we define a variable, *Divergence*, that captures the overall holding deviations of an ETF from its benchmark as follows:

$$Divergence_{f,t} = \sum_{i \in f} DivStock_{i,f,t} = \sum_{i \in f} \left| w_{i,f,t} - \widehat{w}_{i,f,t} \right| / 2, \tag{1}$$

where $w_{i,f,t}$ is the investment weight of stock i in fund f in year t, $\widehat{w}_{i,f,t}$ is the benchmark investment weight, and $DivStock_{i,f,t} = \left| w_{i,f,t} - \widehat{w}_{i,f,t} \right| / 2$ refers to the stock-level divergence of stock i in fund f. We first compute stock-level divergence in each quarter and then average it over the year.[15]

The construction of *Divergence* relies on the literature describing the "activeness" of OEFs (e.g., the "active share" of Cremers and Petajisto, 2009). However, in the context of the ETF industry, its meaning is different. Indeed, ETFs are typically regarded as passive index funds and, unlike active OEFs, are not required to have "active shares" to enhance their performance in the first place. Second, the value creation generated by deviating from the benchmark does not necessarily accrue to the ETF investors. These two differences suggest that the incentives for ETFs to diverge may not be the same as those that induce OEFs to pursue active shares. We therefore label this measure differently to capture this intuition.

Another way to understand ETF activities is to focus on return-based divergence, which is known as the fund *Tracking Error*. From Morningstar, we obtain the fund's total return (net of fees) in U.S. dollars, we add back the fees, and we refer to the resulting gross-of-fee return as the *NAV-based Return*.[16] And we define *Tracking Error* as the standard deviation of the difference between the monthly ETF gross-of-fee NAV-based return and its gross-of-fee benchmark return during a particular year. *Tracking Error* is a standard measure used by the market to assess the ability of the fund to replicate the benchmark.

Because any deviation from the index may produce additional cash flows by bearing more risk, the most important implications for ETF investors lie in the difference between what these investors actually

[15] Alternatively, we have also used $\sum_{i \in f} (w_{i,f,t} - \widehat{w}_{i,f,t}) \times I\{w_{i,f,t} > 0\}$, where $I\{\cdot\}$ is an indicator function, to capture the deviations of ETF investments by focusing on the stocks that are actually invested in by ETFs. The difference between this measure and previous definitions of *Divergence* is found in the stocks that should be invested in according to the indices but that are not actually included in the real ETF portfolios. The main conclusions remain the same.

[16] When a portfolio has multiple share classes, we compute its total return as the lagged total net asset (TNA)-weighted return of all the share classes of the portfolio. Similarly, we construct the gross-of-fee benchmark return by using the index funds that track the same benchmark.

receive and what they would have received based on the overall ETF investment. To understand the difference, we begin with the *Holding-based Return*, which is defined as the investment value-weighted average of the returns of the stocks in the portfolio. It represents the return the ETF would have earned based on the stocks in its portfolio. We then compute the difference between *Holding-based Return* and gross-of-fee *NAV-based Return*, and we label this difference *Swapped Transfer*.

Swapped Transfer is related to the "output gap" concept in macroeconomics, which represents how much the output might have grown had all the factors of production been properly employed, and to the "return gap" for OEFs (Kacperczyk, Sialm and Zheng, 2008). Unlike OEFs where the return gap implies better performance that accrues to investors because of the dynamic trading strategies adopted by active OEFs, however, ETFs are not expected to engage in dynamic trading strategies at all. In this case, the difference between holding- and NAV-based returns has a very different implication in the ETF industry. Indeed, ETFs "swap" their holding-based return with their affiliated banks in exchange for a return that equals the benchmark that can be passed on to investors. A positive difference implies that affiliated banks receive more cash flows from the ETFs than the benchmark return delivered back to investors. We thus use the "*Swapped Transfer*" label to highlight the spirit of such cash flow exchange from the bank's perspective.

Swapped Transfer alone, however, does not exhaust all the possible ways in which ETFs can distribute the additional cash flows that are potentially generated from *Divergence* or *Tracking Errors*. Because ETFs are only required to deliver gross-of-fee returns as high as index returns, the additional benefits may also be passed on to investors as reduced fees. Therefore, we must consider ETF *Fees* jointly with *Swapped Transfer* to derive an overall picture of the distribution of *Divergence*-related cash flows in the ETF industry. A side-by-side examination of the two values (*Fees* and *Swapped Transfer*) allows us to separate the benefits passed on to ETF investors (i.e., reduced *Fees*) from those swapped with affiliated banks (i.e., *Swapped Transfer*).

To capture the main factors affecting the decision of ETFs to deviate from their benchmarks, we consider four channels: the information ETFs derive from their affiliated banks, the benefits ETFs derive from lending their shares, the need to support the stock prices of their affiliated banks, and the need to help their affiliated OEFs.

First, to capture the information benefits accruing from the affiliation with the bank conglomerate, we use the LPC DealScan data and define a dummy variable, $InformationDummy_{i,f,t}$, that equals one if, with respect to ETF f, its affiliated bank provides bank-loan services to firm i in year t and zero otherwise. This dummy variable proxies for the divergence motivated by information that ETFs may obtain from their affiliated banks based on such banks' processing of corporate loans.

Second, to capture the benefits derived from lending shares, we define a variable $StockLendingFee_{i,t}$, which is the average lending fee of stock i in year t (as weighted by the market value of stock-lending contracts). This variable can help us pin down whether the benefits of engaging in the short selling market help incentivize ETFs to not deviate from their benchmarks.

Third, to capture the potential need of ETFs to support the price of their affiliated banks, we define a dummy variable $BankStockDummy_{i,f,t}$ that equals one if ETF f holds the stock of its affiliated bank i in year t and zero otherwise.

Finally, to proxy for the need to engage in cross-trades with affiliated OEFs, we define a variable $OEF\ BmkAdjReturn_{f,t}$ that equals the lagged TNA-weighted average benchmark-adjusted return of all the other OEFs affiliated with the ETF, where the benchmark-adjusted OEF return is computed as the OEF returns minus the average return of OEFs tracking the same benchmark. Given that the need to help affiliated OEFs concentrates in periods when they underperform, this variable can be used to detect the incentives for ETFs to deviate from their benchmarks to subsidize their affiliated OEFs when the latter have experienced poor performance.

D. Other Variables

Although ETF investors typically exit by selling the ETF in the market as opposed to redeeming the shares, as explained in footnote 5, sophisticated investors can nonetheless create inflows and outflows at the fund level. This unique feature allows us to use ETF flows to proxy for fund demand from sophisticated investors. We compute monthly ETF flows as $Flow_{f,m} = \left[TNA_{f,m} - TNA_{f,m-1} \times \left(1 + R_{f,m}\right)\right]/TNA_{f,m-1}$, where $TNA_{f,m}$ refers to the total net asset of fund f in month m, and $R_{f,m}$ refers to fund total return in the same month. Annual ETF flows are computed as the average of monthly flows within a year. In additional robustness checks, we also compute the flows using annual frequency. The results do not change.

To define stock performance, we use the Daniel, Grinblatt, Titman and Wermers (1997, DGTW) methodology. That is, we first create stock styles by double-sorting all the stocks into 25 independent book-to-market and size portfolios within each country. We then adjust the return of a given stock by its style average to compute its DGTW-adjusted return. Finally, we obtain portfolio-level DGTW-adjusted returns as the investment value-weighted average of stock-level DGTW-adjusted returns for all the stocks in the portfolio.

Similarly, OEF performance is proxied by benchmark-adjusted fund returns or DGTW-adjusted holding-based returns. As an additional robustness check, we also construct performance as alpha net of the risk factors posited by the international CAPM model and the international Fama-French-Carhart model. The latter model extends the standard factor-based risk corrections used in the domestic literature to account for the international dimension. It includes four international factors as the value-weighted average of the four domestic factors (market, size, book-to-market, and momentum).[17] The construction of these international factors is in the spirit of Griffin (2002). We extend these international factors to

[17] For a given country, we download all the (active and defunct) stocks from Thomson Datastream and complement them with necessary accounting data from the Worldscope database. Then, for each country, we construct market (RMF), size (SMB), value (HML), and momentum (MOM) factors, closely following the original methodology of Fama and French (1993) and Carhart (1997). The four international factors are the value-weighted average of the four domestic factors in all countries.

include the momentum factor because of its importance in the mutual fund literature. Further details regarding the construction of the factors are available in Appendix A.[18]

We use bank ratings to proxy for distress risk. Following Avramov, Chordia, Jostova and Philipov (2009), our bank rating score transforms the S&P ratings into ascending numbers as follows: AAA = 1, AA+ = 2, AA = 3, AA– = 4, A+ = 5, A = 6, A– = 7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, D = 22. In addition, we use ROA to proxy for the financial conditions of the affiliated bank.

Finally, we also control for lagged fund, stock, and bank characteristics. Fund characteristics include the following: *Log(Stock Size in Fund)*, defined as the logarithm of the investment value-weighted average market value of stocks invested in by the fund; *Log(Fund TNA)*, defined as the logarithm of fund TNA; *Log(Fund Age)*, defined as the logarithm of the number of operational months since inception; *Expense Ratio*, defined as the annual expense ratio; *Fund Return*, defined as the annual return of the fund; and *Fund Flow*, defined as the annual fractional flow received by the fund. Stock characteristics include the following: *Log(Stock Size)*, defined as the logarithm of the market value of the stock; *Turnover*, defined as the annual turnover ratio of the stock; *Log(Stock Illiquidity)*, defined as the logarithm of the Amihud (2002) stock illiquidity; *Log(Net Income)*, defined as the logarithm of its net income; *Log(Sales)*, defined as the logarithm of its sales; and *Log(Total Assets)*, defined as the logarithm of its total assets. Bank characteristics include the following: *Log(Bank Total Assets)*, defined as the logarithm of bank total assets; *Equity/Liabilities*, defined as the ratio of equity to liabilities; *Loan Loss Reserve/Gross Loans*, defined as the ratio of loan loss reserve to total loans; *Net Interest Margin*, defined as the ratio of net interest revenue to total earnings assets; *Cost/Income*, defined as the ratio of the overhead or costs of running the bank to income generated before provisions; and *Net Loans/Total Assets*, defined as the ratio of net loans to total assets. Appendix A provides a detailed definition for each variable.

[18] We use these three to be conservative. Indeed, the benchmark-adjusted return allows us to control for the benchmark and is closer in spirit to the performance that investors observe. The international Fama-French-Carhart four-factor model employs the broadest set of factors and has been used to estimate mutual fund performance (e.g., Carhart 1997; Bollen and Busse, 2005; Avramov and Wermers, 2006; Mamaysky, Spiegel and Zhang, 2007, 2008).

Panel B of Table 1 reports the descriptive statistics of the variables, including the mean, median, standard deviation, and quantile distribution of monthly ETF and OEF returns, ETF swapped transfers, and major characteristics (in annual frequency) of the funds. Panel C reports similar statistics related to monthly stock returns, quarterly bank market-to-book ratios, ETF ownership, and other annual bank and stock characteristics. It is notable that the ETF *Holding-based Return* and gross-of-fee *NAV-based Return* have different distributions, which provides some initial evidence of the existence of synthetic operations in the ETF industry.

Additionally, the DGTW-adjusted return for ETF holdings has a wide distribution. At the 75% quantile level, for example, the DGTW holding-based abnormal return is 23 bps per month. The economic magnitude involved is quite large, which suggests that ETFs invest in very good stocks. It is also notable that the characteristics of affiliated members of ETFs, such as banks and OEFs, also exhibit wide distributions. In the next section, we conduct more formal tests to explore how ETFs' deviations from their benchmarks may help transfer value to affiliated parties.

III. Preliminary Evidence

A. Stylized Patterns of ETF Deviation

We begin by describing a few patterns that show how ETFs deviate from their benchmarks. Panel A1 of Table 2 reports the distribution of *Divergence*, *Swapped Transfer*, and the *Number of Stocks* held by ETFs and the indices they track and shows that ETF holdings may be quite different from their benchmarks. On average, the ETFs diverge by 27.7% in terms of *Divergence*. At the 75% quantile, these ETFs have more than 38.2% of their portfolios invested in stocks that are different from their benchmarks, which translates into a *Swapped Transfer* equivalent to 54 bps per year on average that spikes to 266.4 bps per year for the 75% quantile.

Panels A2 and A3 split the sample and report the distribution of the variables described above for synthetic and optimized sampling ETFs. Synthetic ETFs with a *Divergence* above the median have their entire portfolio invested in stocks that differ from their benchmark. However, the deviation is not limited to synthetic ETFs. ETFs using the sampling replicating methodology also exhibit large deviations. At the 75% quantile value, these ETFs may have more than 38% of their portfolios invested in stocks that differ from their benchmarks. Furthermore, synthetic ETFs typically invest in fewer stocks than their benchmarks, which leads to a high portfolio concentration. This effect is less obvious for sampling ETFs when the number of stocks in the benchmark is relatively small. However, when there are many stocks in the benchmark, even sampling ETFs concentrate in fewer stocks.

Panels B1 and B2 tabulate the distributions of ETFs by domicile regions and show that there is a substantial difference in terms of *Divergence* between European ETFs and U.S. ETFs. European ETFs deviate more from their benchmarks than U.S. ETFs. For instance, at its 75% quantile value, *Divergence* is approximately 33.9% for U.S. ETFs and 79.9% for European ETFs. Similar variations occur with *Swapped Transfer*. The average European ETF displays a *Swapped Transfer* corresponding to 62.4 bps compared with 31.2 bps for the average U.S. ETFs per year. At its 75% quantile value, the number is approximately 75.6 bps for U.S. ETFs and 218.4 bps for European ETFs. If we consider the same quantile level, a U.S. ETF invests in approximately 966 stocks out of the 1063, as required by its index, whereas a European ETF invests in approximately 102 stocks out of the 324 requested by its index. Overall, the differences confirm that U.S. ETFs are more likely to use the full replication methodology than their European counterparties, leaving the European ETF market more vulnerable to potential conflicts of interest, as we will explore later.

Next, we assess whether there is evidence that such deviations ─ *Divergence* and *Swapped Transfer* ─ are persistent over time. In the interest of brevity, we report the results in Table IN1 in the Internet Appendix but discuss our main findings here. We find a strong positive autocorrelation for *Divergence* and *Swapped Transfer* over time, which holds across the different specifications. Funds with *Divergence* (*Swapped Transfer*) that is one standard deviation higher in one year display a 20.63% (133.7 bps) higher

Divergence (*Swapped Transfer*) the following year. These results offer evidence that ETF investment strategies are different from pure benchmark tracking and persist over time.

Next, we investigate whether there is evidence of a "common behavior" of all the ETFs affiliated with the same group and of the ETFs with affiliated OEFs. We again report the results in the Internet Appendix (Table IN2) and only discuss our main findings here. In brief, we find strong evidence that affiliated ETFs and OEFs tend to deviate from their benchmarks in a similar manner. More specifically, affiliation with the same bank increases the degree of commonality among the benchmark-adjusted holdings of ETFs by 9.1% and between those of ETFs and OEFs by 8.7%. Such commonality is highly economically significant and holds across alternative specifications and different models.

Together, these stylized facts suggest that some ETFs *systematically* deviate from their benchmarks, which might be motivated by their affiliation with a (bank-based) financial conglomerate. Therefore, as a next step, we explore whether and how such deviations form part of a conglomerate-wide strategy.

B. Drivers of ETF Deviation

We now investigate the link between ETFs' deviation from their benchmarks and the four hypothesized channels. We directly relate stock-level ETF holding deviation to the main channels defined at the stock level and a set of control variables. We estimate the annual panel regression as follows:

$$Dev_{i,t} = \alpha + \beta \times Channel_{i,t-1} + \gamma \times M_{i,t-1} + e_{i,t}, \tag{2}$$

where $Dev_{i,t}$ proxies for our measures of divergence (*Divergence*, *Tracking Error*) and $Channel_{i,t-1}$ is the vector that contains our four channels of impact (i.e., *InformationDummy*, *StockLendingFee*, *BankStockDummy*, and *OEF BmkAdjReturn*) that were previously defined. When applicable, the stock-level measures involving fund characteristics are computed as the investment value-weighted average of fund characteristics for all funds that invest in the stock. The vector *M* stacks all other stock and fund control variables, including *Log(Stock Size), Stock Return, Turnover, Log(Net Income), Log(Sales),* *Log(Total Assets), Log(Fund TNA), Log(Fund Age), Expense Ratio,* and *Fund Flow*. We estimate a panel specification with year and stock fixed effects and clustering at the stock level.

The results are reported in Table 3, Panel A, for *Divergence*, and Panel B for *Tracking Error*. In Models 1 to 4, we separately report the four channels, whereas we consider a specification with all the channels in Model 5. Model 6 reports similar regression parameters in joint models when we replace stock *Turnover* with *Log(Stock Illiquidity)* as an alternative control for the Amihud illiquidity of stocks. The results show a strong correlation between our main channels and our alternative proxies for deviation. In particular, across the different specifications, we find a strong positive relationship between *InformationDummy* and *Divergence* and a similar pattern between *InformationDummy* and *Tracking Error*. ETFs that own stock in firms that receive corporate loan services from the bank affiliated with the applicable ETF present a higher *Divergence* (*Tracking Error*) of 11.8% (9.4 bps), which is consistent with the idea that ETFs tend to diverge more in stocks on which they presumably have more information. The next section will confirm that this portfolio tilt is informative.

Additionally, stock-lending fees are negatively correlated with both *Divergence* and *Tracking Error*. This effect is also economically relevant: a one-standard-deviation higher level of fees reduces *Divergence* (*Tracking Error*) by 0.35% (2 bps), which suggests that the benefits accruing from stock-lending allow the ETF to diverge less. Thus, the fact that the ETF can generate performance by simply holding the benchmark and lending the shares reduces the need to diverge from the benchmark.

Next, we find that both *Divergence* and *Tracking Error* are related to the need to help the affiliated bank and OEFs. In particular, the stocks of affiliated banks display a *Divergence* (*Tracking Error*) that is higher by 18.9% (30.6 bps). Thus, ETFs deviate more from their benchmarks by holding the stocks of their affiliated banks. In an (unreported) analysis, we further consider the signed difference between what the ETF holds and what it should hold according to the benchmark, and we find that the ETFs overweigh the stocks of the affiliated banks. These patterns confirm that ETFs have an incentive to over-invest in the stocks of their affiliated banks, and later sections will further confirm that such actions help stabilize the price of bank stocks.

Similarly, there is a negative relationship between deviation and the performance of the affiliated OEFs – i.e., *OEF BmkAdjReturn*. A performance of the affiliated OEFs that is worse by one standard deviation raises *Divergence* (*Tracking Error*) by 4.06% (31.5 bps). This negative sign implies that when affiliated OEFs underperform their benchmarks – and are therefore more exposed to investor withdrawals – ETFs tend to deviate more from their indices. Our later sections will further explore how assistance is transferred to OEFs.

C. Consequences of ETF Deviation

We now investigate the implications of such channels in terms of *Swapped Transfer* and *Fees*. We begin with *Swapped Transfer* and report the results in Panel A of Table 4. The layout of the columns is the same as that of Table 3. We find that the information channel is positively related to *Swapped Transfer.* This result is expected as higher quality information derived from bank loans can be used to generate performance that can be transferred back to affiliated banks. By contrast, there is no link between *Swapped Transfer* and either *StockLendingFee* or *BankStockDummy*. The latter case is expected because propping up the stock price of the affiliated bank is not necessarily linked directly to cash flow changes between ETFs and affiliated banks. In the case of the lending fee, the lack of relation may instead be caused by the ETF using the benefits accruing from lending shares to reduce the fees charged to its investors. Finally, affiliated OEF performance is negatively related to *Swapped Transfer*. This correlation might arise when ETFs also indirectly subsidize affiliated OEFs through affiliated banks.

We then investigate the annual ETF expense ratio in Panel B. Here, the dependent variable reflects *Fees* charged by the ETF. *StockLendingFee* is negatively related to ETF *Fees*. In particular, a one-standard-deviation increase in lending fees translates into 0.6 bps lower *Fees* that the ETF charges its investors. By contrast, the benefit of the information channel does not accrue to ETF investors, i.e., the *InformationDummy* is uncorrelated with *Fees*. Additionally, there is no direct link between *Fees* and excess investment in the stock of affiliated banks. Finally, there is a strong negative relationship between *Fees* and *OEF BmkAdjReturn*: a one-standard-deviation worse performance of the affiliated OEFs translates to 12.8 bps higher *Fees*.

Overall, these results confirm our working hypotheses that ETFs actively diverge from their benchmarks via the information, stock-lending and subsidization channels. The information channel seems to directly benefit affiliated banks (but does not harm investors), whereas ETF investors enjoy direct benefits from the securities lending channel.

These results also raise new issues. First, although the source of income for the securities lending channel is relatively straightforward, we have not provided direct evidence that the information channel enables ETFs to generate additional income to benefit affiliated banks. Second, our findings that investing in affiliated bank stocks does not directly affect cash flows but that OEF subsidization imposes certain direct costs to the investors also raises the question of how benefits are transferred to affiliated entities. Third, we may also require additional evidence to address the potential concern that our previous conclusion may be spuriously related to, for instance, the estimation errors of our main variables (e.g., *Divergence* and *Swapped Transfer*). We will address these issues in the following section.

IV. Zooming in on the Drivers of Divergence

We now separately investigate both the information channel and each of the two subsidization channels.

A. Divergence and Bank-related Information

We begin with the information channel. In the previous analysis, we verified that one reason ETFs deviate from their benchmark holdings is information from the affiliated bank. Now, we are testing whether this (bank loan-related) deviation has any stock return predictability – only very informed deviations could predict out-of-sample stock returns. We define bank loan-related abnormal ownership for all ETFs as:

$$BkLn\ Ownership_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times I\{BankLoan_{i,f,t}\},$$

where $h_{i,f,t}$ and $\hat{h}_{i,f,t}$ refer to the real and benchmark-implied ownership of ETF f in stock i, respectively, and the indicator function takes a value of one if the affiliated bank of ETF f offers bank loan services to stock i (and zero otherwise). If lending-related divergence is indeed motivated by information, a positive change in abnormal ownership should predict higher stock returns. We then estimate the annual panel regression:

$$Perf_{i,t} = \alpha + \beta \times \Delta BkLn\ Ownership_{i,t-1} + \gamma M_{i,t-1} + e_{i,t}, \quad (3)$$

where $Perf_{i,t}$ is the average monthly DGTW adjusted return or raw return of a stock in year t, and $\Delta BkLn\ Ownership_{i,t-1}$ refers to changes in abnormal ETF ownership of stock i in year t related to bank loan information. The vector *M* stacks all the other stock and fund control variables as defined previously. We use year and stock fixed effects and cluster the errors at the stock level.

We report the results in Table 5. Models 1 through 4 report the DGTW adjusted return, whereas we use the raw return in Models 5 through 8. The results document that bank loan-related abnormal ownership of ETFs can generate significant performance out of sample: in Model 2 (Model 6), for instance, each 1% increase in bank loan-related abnormal ownership of ETFs can be transferred to a 12 bps (11 bps) higher DGTW adjusted (raw) return per year.[19]

As a "Placebo" test, we also construct abnormal ownership for all ETFs that is unrelated to bank loans as $BkLnUnrelated\ Ownership_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times I\{NoBankLoan_{i,f,t}\}$, in which the indicator function takes a value of one if the affiliated bank of ETF f does not offer bank loan services to stock i. The results reported in Models 3, 4, 7 and 8 demonstrate that abnormal ETF ownership changes unrelated to bank loans do not predict stock return. These results are consistent with our working hypothesis that the link with affiliated banks allows ETFs to select superior stocks.

Next, in Panel B, we break down the analysis into different subsamples. In Models 1, 2, 5 and 6, we consider the synthetic and sampling ETFs, whereas in Models 3, 4, 7 and 8, we consider U.S. and

[19] The dependent variable is reported as a percentage of monthly abnormal return. Thus, the impact of a 1% increase in $\Delta BkLn\ Ownership$ can be estimated for Model 2, for instance, as $1.014\% \times 12 \times 1\% = 12.17$ bps.

European ETFs. We see that lending-related abnormal ownership changes for both synthetic and sampling ETFs as well as European ETFs forecast stock performance. In contrast, U.S. ETFs do not seem to be affected. Additional (unreported) robustness checks indicate that including bank characteristics aggregated at the stock level leads to similar results.

Jointly, these results indicate that ETFs deviate from their benchmarks in stocks that have a lending relationship with affiliated banks and that such deviations result in higher performance because ETFs can overweight/underweight stocks that are somehow confirmed to be good/bad via the affiliate banks' corporate loan services. Because the holding-based return is swapped back to the financial conglomerate, our results suggest that ETFs provide additional funding or a pool of capital for the conglomerate to leverage its (bank loan-related) informational advantages. Thus, the additional tests fit well into the picture provided by our previous tests.

B. The Bank-Subsidization Channel

We now test the subsidizing role of the ETFs, beginning with the support of the affiliated banks. We directly relate the price (market-to-book ratio) of the bank's affiliated stock to the role of the ETF. More specifically, we estimate the following panel specification:

$$BankMB_{b,q} = \alpha + \beta_1 ETF\_IO_{b,q-1} + \beta_2 ROA_{b,q-1} + \beta_3 ETF\_IO_{b,q-1} \times ROA_{b,q-1} + \gamma M_{b,q-1} + e_{b,q}, \quad (4)$$

where $BankMB_{b,q}$ is the market-to-book ratio of bank *b* in quarter q, and $ETF\_IO_{b,q-1}$ refers to a list of alternative proxies of the ETF ownership of the stock of bank *b* in quarter $q-1$. They are: *ETF Dummy*, which takes a value of one if the ETF holds shares of the affiliated bank; *ETF Ownership*, which is defined as the percentage bank ownership of the affiliated ETF; and *Benchmark-Adjusted ETF Dummy* and *Benchmark-Adjusted ETF Ownership*, in which we consider the ownership in the affiliated bank net of the benchmark-implied ownership. $ROA_{b,q-1}$ is the ROA of the bank, and the vector *M* stacks all bank-specific control variables, including *Log(Bank Total Assets)*, *Equity/Liabilities*, *Loan Loss Reserve/Gross*

Loans, *Net Interest Margin*, *Cost/Income*, and *Net Loans/Total Assets*. We add quarter and bank fixed effects, and cluster the errors at the bank (or quarter) level.

We report the results in Table 6, Models 1 and 2 for *ETF Dummy*, Models 3 and 4 for *ETF Ownership*, and Models 5 through 8 for benchmark-adjusted ownership. The results show a strong negative correlation between the market-to-book value of the bank and the interaction between the bank's profitability and ETF ownership. The worse the profitability of the bank is, the higher the positive impact of ETF ownership on the affiliated bank's stock price. Thus, ETF ownership protects the market price of the bank when it reports low profitability, which somehow hedges the potential negative impacts that can be generated by price drops.[20] Similar (unreported) results hold if we consider the affiliated bank's Tobin's Q.

Overall, these results confirm the interpretation that the portfolio deviation of the ETF is related to the desire to prop up the price of the affiliated bank.

In Table IN3 in the Internet Appendix, we also explore the possibility that ETFs might directly subsidize affiliated banks when the latter perform poorly. We find that ETF *Swapped Transfer* and bank ROA are negatively correlated, in general. The negative correlation suggests that ETFs may also directly transfer cash flows when bank performance is negative. Although this evidence is more indirect, it does add to the concern that ETF capital may be used to benefit affiliated banks.

C. The OEF-Subsidization Channel

ETFs may also be used to help OEFs in the same group, which might be accomplished, for example, by cross-trading. In this case, we expect a direct link between the stocks held in common in excess of their benchmarks by the ETFs and the OEFs and the cross-trades between ETFs and OEFs, i.e., a positive

[20] Note that hedging against price drops may benefit banks, because a drop in stock price may adversely affect the cost of capital and/or the availability of capitals. To interpret the economic magnitude, in (unreported) tests we replace bank ROA with a dummy variable that takes a value of one when the bank ROA is below the median in that quarter. The slope coefficient for the interaction term of ETF Dummy × Dummy (Low Bank ROA) is 0.294 (t-value = 1.96), and the slope coefficient for the interaction term of BMK-adjusted ETF Dummy × Dummy (Low Bank ROA) is 0.885 (t-value = 3.49). Thus, for banks with profitability below the median, positive ETF ownership is related to a 0.294 (0.885) higher market-to-book value for the affiliated bank in the case of the ETF Dummy (BMK-adjusted ETF Dummy), which accounts for 18% (54%) of the average market-to-book value in the sample.

relation between the ETF/OEF-related divergence and the ETF/OEF cross-trades. We test this hypothesis by considering how common ownership between ETFs and OEFs in excess of the benchmark – *ETF/OEF Common Divergence* – is related to cross-trades between the affiliated entities and how this relationship affects the performance and volatility of the affiliated OEFs. We rely on the following two-stage regression to test the effect at the OEF level (i.e., the regression is conducted at the OEF level):

$$\text{First stage: } CrossTra_{f,t} = \alpha + \beta \times ETF/OEF\_CommonDivergence_{f,t} + \gamma M_{f,t} + e_{f,t}, \qquad (5)$$

$$\text{Second stage: } Fund\_Char_{f,t+1} = \alpha + \beta \times CrossTra_{f,t} + \gamma M_{f,t} + e_{f,t+1}, \qquad (6)$$

where $CrossTra_{f,t}$ is the average level of cross-trades of OEF f with its affiliated ETF(s) in year t (Appendix A provides the mathematical definition, following Gaspar, Massa and Matos, 2006); $ETF/OEF\_CommonDivergence_{f,t}$ is the common holding divergence between an OEF f and its affiliated ETF(s), which is defined as $\sum_{i \in \{f \cap ETF\}} DivStock_{i,f,t}$ for all stock i that is held by both OEF f and its affiliated ETF(s); and $Fund\_Char_{f,t+1}$ refers to the OEF characteristics, including average monthly flow, benchmark-adjusted return volatility (using the standard deviation of the monthly fund after netting out that of the benchmark in a given year), monthly return, and risk-adjusted return. More specifically, OEF returns are adjusted by subtracting the benchmark return, the DGTW portfolio return, the international CAPM, and the international Fama-French-Carhart (FFC) model. The vector *M* stacks all other control variables for OEFs.

We report the results in Table 7. Panel A reports the regression parameters and their t-statistics clustered at the fund level after controlling for the year and fund fixed effects. In the first stage regression, we find that common deviations between affiliated ETFs and OEFs facilitate more cross-trades between the two and that, in the second stage regression, ETF/OEF cross-trades promote the returns and flows for OEFs.[21] A one-standard-deviation increase in ETF/OEF cross-trades instrumented using *ETF/OEF Common Divergence* leads to an annualized 5.9% higher return and 13.84% higher inflow. Notably, the

[21] (Unreported) analysis suggests that OEF return and lagged ETF return are negatively correlated with a correlation of −0.33 (p-value < 1%), which confirms that ETFs are used to subsidize the affiliated OEFs.

enhanced return and flow are achieved at the cost of higher benchmark-adjusted return volatility, whereas net-of-risk performance remains mostly unchanged.

Panel B reports similar statistics at the ETF level. Unlike the case of ETF/OEF cross-trades, ETF/ETF cross-trades are much weaker and have no effect on either flow or performance. Therefore, cross-trades help OEFs but not ETFs. Overall, this result suggests another channel through which ETFs help the financial group they are affiliated with, i.e., enhancing OEFs' returns and thus helping affiliated OEFs to attract more inflows. Together with the negative correlation between the bank's market-to-book value and the interaction between the bank's profitability and ETF ownership, this finding supports our working hypotheses that ETFs are also used to subsidize affiliated parties in the financial conglomerate but do not require superior information.

Cross-trades may also explain the higher ETF fees documented in our previous tests. Indeed, the need to implement cross-trades may subject ETFs to higher trading costs. The trading cost imposes an additional expense on ETF investors, which is consistent with the negative correlation between affiliated OEF returns and ETF *Fees*.

Next, as a robustness check, we split the sample by type of ETF and report the results in Table 8. Panel A reports subsample results for ETF/OEF cross-trades with synthetic ETFs (Models 1 to 4) and optimized sampling ETFs (Models 5 to 8), and Panel B shows similar subsample results for U.S. ETFs (Models 1 to 4) and European ETFs (Models 5 to 8). We find that the ETF-OEF channel is not significant for synthetic ETFs but that optimized sampling ETFs are. U.S. ETFs are not subject to this problem; instead, the problem is concentrated in European ETFs.

V. Investors' Reaction

Our findings suggest that ETFs deviate from the benchmark to leverage their bank loan-related information advantage, to benefit from stock lending fees, and to help other members of their financial conglomerate. Although the information-motivated divergence and the participation of stock lending may boost performance, subsidization channels might lead to inferior performance during those very periods in which the affiliated bank or OEFs are most in need of subsidization. The existence of the swap with the affiliated bank is designed to protect ETF investors from such risks, but the potential distress of the bank at a time when the performance of the ETF portfolio is particularly poor may nonetheless expose ETF investors to risk. A key question, therefore, is whether this behavior is perceived by sophisticated ETF investors as detrimental.

To answer this question, we relate the ETF flows – a proxy for the sophisticated ETF investor demand – to the characteristics of affiliated banks or ETFs in the following regression with year fixed effects and clustering at the fund level:

$$Flow_{f,t} = \alpha + \beta_1 ETF\_Char_{f,t} + \beta_2 Rating_{f,t} + \beta_3 ETF\_Char_{f,t} \times Rating_{f,t} + \gamma M_{f,t-1} + e_{f,t}, \qquad (7)$$

where $Flow_{f,t}$ refers to the average monthly flows of ETF f in year t; $ETF\_Char_{f,t}$ refers to ETF characteristics that investors may regard as detrimental (*Divergence*, *Tracking Error*, *Swapped Transfer*, and *Fees*); $Rating_{f,t}$ refers to the S&P long-term domestic issuer credit rating of its affiliated bank (we also use bank ROA to replace bank rating in a few specifications); and vector *M* stacks control variables. As a robustness check, we also estimate a Fama-MacBeth specification with Newey-West adjustment. The (unreported) results are similar to the reported results.

Table 9 presents the results. Models 1 to 5 illustrate that ETF flows are uncorrelated with *Divergence* or *Tracking Error* but are negatively related to both *Swapped Transfer* and *Fees*. It is reasonable that investors are not particularly worried about *Divergence per se* because investment deviations may be related to both positive and negative effects, as we have discussed above. However, positive *Swapped Transfer* and higher *Fees* signal net negative effects, and investors respond to such net negative effects by withdrawing capital. An increase in the *Swapped Transfer* (*Fees*) of one standard deviation is associated with a lower annual flow of 2.1% (5.24%). These results suggest that investors consider these negative effects to be detrimental.

In addition, Model 6 reports a negative relationship between flows and bank rating (recall that a higher numerical value means a lower rating). A one-standard-deviation deterioration in bank rating translates to 9.59% lower flows per year. The fact that ETF investors withdraw capital when affiliated banks have poor ratings suggests that investors view the affiliation with a bad bank as detrimental. This result is not surprising because both the incentive for subsidization and the risk (for the affiliated bank) to default on the promised index return are concentrated in poor ratings. Meanwhile, if deteriorating bank ratings appear detrimental to investors, then deterioration in bank performance should also appear detrimental to investors. Model 7 verifies this equivalence by replacing bank rating with ROA. We observe that negative ROA is associated with outflows, which is a pattern that is consistent with what we observe with bank rating.[22]

More importantly, from the perspective of investors, the detrimental impact of *Swapped Transfer* should be more significant when the affiliated banks are riskier. Models 8 to 11 test this intuition by interacting *Swapped Transfer* with bank rating or ROA. Indeed, we observe that the outflow sensitivity with respect to *Swapped Transfer* increases in the poor ratings/ROAs of affiliated banks. Thus, investors do not seem to appreciate the links between ETFs and affiliated banks – particularly when *Swapped Transfer* signals potential conflicts of interest and when the banks become riskier.

Models 12 to 14 further include the four explicit drivers of ETF investment divergence into the regression. The goal is two-fold. First, we want to verify that the above results – and particularly the outflow responses to *Swapped Transfer* and bank rating – are robust even when we explicitly control for the drivers. Second, we want to examine whether any of the drivers have their own flow impact above and beyond what *Swapped Transfer*, *Fees*, and affiliated bank ratings can capture.

Perhaps unsurprisingly, the results demonstrate that the outflow responses to *Swapped Transfer*, *Fees*, and bank rating are robust to these additional variables. The interesting observation is that the

[22] To validate the interpretation of ROA, we created a dummy variable that takes a value of one when bank ROA is below the median. Unreported results show that below-median bank ROA significantly discourages monthly flows by 4.43% in the affiliated ETFs.

BankStockDummy has a significant impact on flows above and beyond *Swapped Transfer* and bank rating across all specifications. Thus, when ETFs overinvest in the stock of their affiliated banks to boost the price of that stock, investors respond by withdrawing capital even in the absence of a direct cash flow transfer from ETFs to the banks. This response suggests that investors understand that such an overinvestment benefits banks rather than the ETFs – the outflow might reflect their general concern that this arrangement may involve some risk related to conflicts of interest.

Overall, these findings show that the market is aware of the potential implications of the link between ETFs and their affiliated financial conglomerates. It appears that investors' concerns, which are expressed in lower flows, are consistent with regulatory concerns (FSB, 2011; IMF, 2011; Ramaswamy, 2011).

Conclusion

The global ETF industry provides more than simply low-cost index trackers for investors. We find that ETFs provide a cheap source of capital for their affiliated entities and for their affiliated banks and OEFs, in particular. We test and confirm the hypothesis that ETF capitals can be used to leverage informational advantages through synthetic operations. More specifically, ETFs exploit the information gathered by the affiliated bank through its lending activities and transfer the ensuing performance back to the bank. In addition, ETFs may benefit from engaging in securities lending in the short selling market. Finally, we find that ETFs are a source of subsidies within the financial conglomerate even without superior information and are notably used to support the stock price of affiliated banks and to promote the flows of affiliated OEFs. These operations reveal the conflicts of interest involved in ETFs. The market awareness of these conflicts of interest is reflected in lower demand.

These findings have important normative implications in terms of both consumer protection and financial market stability and suggest that the very stability of financial markets can be jeopardized when the affiliated banks experience distress. Indeed, non-full replicating ETFs may help propagate a crisis in the equity market as a whole that should have been limited within the banking sector. Our paper, therefore, calls for increased attention to and further research on ETFs and on the potential involvement of financial intermediaries as part of the shadow banking system.

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Appendix A: Variable Definitions

Variables	Definitions
A. ETF Performance Measures (in %)	
Holding-based Return	The investment-value weighted average of stock returns of a fund's most recently reported holding portfolio.
Gross-of-Fee NAV-based Return	Monthly fund total returns as reported by Morningstar plus one-twelfth of the annualized Expense Ratio. When a portfolio has multiple share classes, its total return is computed as the share class TNA-weighted return of all share classes, in which the TNA values are one-month lagged.
Swapped Transfer	Holding-based return minus gross-of-fee NAV-based return.
Holding-based ETF DGTW adjusted Return	The investment-value weighted average of stock-level DGTW adjusted returns, according to a fund's most recently reported holding information. More specifically, stock returns are adjusted by the style average, where stock styles are created by double-sorting remaining stocks into 25 independent book-to-market and size portfolios within each country, following Daniel, Grinblatt, Titman and Wermers (1997).
Fund Return	Monthly affiliated ETF total returns as reported by Morningstar. When a portfolio has multiple share classes, its total return is computed as the share class TNA-weighted return of all share classes, where the TNA values are one-month lagged.
Benchmark adjusted Return	ETF return minus the return of index funds tracking the same benchmark.
International Fama-French-Carhart adjusted Return	Realized fund returns minus the productions between a fund's four-factor betas multiplied by the realized four factor returns in a given month. The four international factors are the value weighted average of four domestic Fama-French-Carhart factors (market, size, book-to-market, and momentum). The betas of the fund are estimated as the exposures of the fund to the relevant risk factors in its entire sample period.
B. Holding Divergence Measures	
Divergence	Divergence in a given year t is computed as follows: $Divergence_{f,t} = \sum_{i \in f} DivStock_{i,f,t} = \sum_{i \in f} \lvert w_{i,f,t} - \widehat{w}_{i,f,t} \rvert / 2$, where $DivStock_{i,f,t}$ refers to the stock-level divergence of stock i in fund f in year t, $w_{i,f,t}$ is the investment weight of stock i by fund f in year t, and $\widehat{w}_{i,f,t}$ is the benchmark investment weight. When quarterly or semi-annual holdings are available, stock-level divergence is computed first at the quarterly or semi-annual level and then averaged over the year.
C. Other ETF Characteristics	
Tracking Error (in %)	Tracking error in a given year t is computed as the standard deviation of the difference between monthly ETF gross-of-fee NAV-based return and its gross-of-fee benchmark index return.
Fund Flow (in %)	Fund flow in a given month m is computed as follows: $Flow_{f,m} = \left[TNA_{f,m} - TNA_{f,m-1} \times \left(1 + R_{f,m}\right)\right] / TNA_{f,m-1}$, where $TNA_{f,m}$ refers to the total net asset of fund f in month m, and $R_{f,m}$ refers to fund total return in the same month. The annual ETF flow is the average of monthly flows within a year.
ETF/ETF Cross-Trades (in %)	Cross trades between ETF i and affiliated ETF j in a given quarter q is computed as follows: $CrossTra_{ij,t} = \left[\left(\sum_{s \in S_1 \cap S_2} N_{s,i,q} P_{s,q} + N_{s,j,q} P_{s,q}\right) \times I\{\Delta N_{s,i,q} \times \Delta N_{s,j,q} < 0\}\right] / \left(\sum_{s \in S_1} N_{s,i,q} P_{s,q} + \sum_{s \in S_2} N_{s,j,q} P_{s,q}\right)$, where S_1 and S_2 represent the set of companies held by fund i and j, $P_{s,q}$ is the price of company s at quarter q, $N_{s,i,q}$ and $N_{s,j,q}$ are the number of shares of company s held by fund i and j, respectively, and $I\{\cdot\}$ is an indicator function that equals one if $N_{s,i,q}$ and $N_{s,j,q}$ change in opposite directions and zero otherwise, following Gaspar, Massa and Matos (2006). Annual cross trades is the average of quarterly cross trades within a year.
Log (Stock Size in Fund)	The logarithm of the value weighted average of market capitalization, in millions, of stocks in a fund's most recently reported holding portfolio.
Log (Fund TNA)	The logarithm of total net asset as reported in Morningstar.
Log (Fund Age)	The logarithm of the number of operational months since inception.
Expense Ratio (in %)	The annualized Expense Ratio as reported in Morningstar.
D. Affiliated Bank Characteristics	
Market-to-Book Ratio	The market-to-book ratio in a given quarter q is computed as follows: $BankMB_{b,q} = ME_{b,q} / BE_{b,q}$, where $ME_{b,q}$ refers to the market value of bank b in quarter q, and $BE_{b,q}$ refers to the book value of equity in the same quarter, computed as the summation of stockholders' equity and deferred taxes, minus preferred stock.
ETF Ownership (in %)	ETF ownership in a given quarter q is computed as follows: $ETF\_IO_{b,q} = \sum_f SHR_{b,f,q} / SHROUT_{b,q} \times 100$, where $SHR_{b,f,q}$ refers to the number of shares of bank b held by its affiliated ETF f in quarter q, and $SHROUT_{b,q}$ refers to the concurrently outstanding shares.
ROA (in %)	The annual return on average assets as reported in BankScope.
Bank Rating	The monthly S&P long-term domestic issuer credit rating of the affiliated bank as reported in Compustat. We transform the S&P ratings into ascending numerical scores, where AAA = 1, AA+ = 2, AA = 3, AA– = 4, A+ = 5, A = 6, A– = 7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, and D = 22, following Avramov, Chordia, Jostova and Philipov (2009).
Log (Bank Total Assets)	The logarithm of total assets, in millions, as reported in BankScope.

Equity/Liabilities (in %)	The ratio of equity to liabilities, as reported in BankScope.
Loan Loss Reserve / Gross Loans (in %)	The ratio of loan loss reserve to total loans, as reported in BankScope.
Net Interest Margin (in %)	The ratio of net interest revenue to total earning assets, as reported in BankScope.
Cost/Income (in %)	The ratio of overhead or costs of running the bank to income generated before provisions as reported in BankScope.
Net Loans /Total Assets (in %)	The ratio of net loans to total assets, as reported in BankScope.
E. Affiliated OEF Characteristics	
ETF/OEF Cross-Trades (in %)	Cross trades between ETF i and affiliated OEF j in a given quarter q is computed as follows: $CrossTra_{ij,t} = \left[\left(\sum_{s\in S_1\cap S_2} N_{s,i,q}P_{s,q} + N_{s,j,q}P_{s,q}\right) \times I\{\Delta N_{s,i,q} \times \Delta N_{s,j,q} < 0\}\right] / \left(\sum_{s\in S_1} N_{s,i,q}P_{s,q} + \sum_{s\in S_2} N_{s,j,q}P_{s,q}\right)$, where all variables are defined the same as in ETF/ETF Cross Trades. Annual cross trades is the average of quarterly cross trades over a year.
OEF Return (in %)	Monthly affiliated OEF total returns as reported by Morningstar. When a portfolio has multiple share classes, its total return is computed as the share class TNA-weighted return of all share classes, where the TNA values are one-month lagged.
Benchmark adjusted OEF Return (in %)	OEF returns minus the average return of the open-end funds tracking the same benchmark.
F. Stock Characteristics	
Stock Lending Fee	The loan value weighted average short selling lending fee, as reported in DataExplorers.
Bank Loan-related Abnormal Ownership ($BkLn\ Ownership$)	Bank Loan-related Abnormal Ownership in a given year t is computed as follows: $BkLn\ Ownership_{i,t} = \sum_f (h_{i,f,t} - \hat{h}_{i,f,t}) \times I\{BankLoan_{i,f,t}\}$, where $h_{i,f,t}$ and $\hat{h}_{i,f,t}$ refer to the real and benchmark-implied ownership of ETF f in stock i in year t, respectively, and $I\{BankLoan_{i,f,t}\}$ is an indicator function that takes the value of one if the affiliated bank of ETF f offers bank loan services to firm i in the same year and zero otherwise. When quarterly or semi-annual holdings are available, ETF ownership is computed first at the quarterly or semi-annual level and then averaged over the year.
Abnormal Ownership Unrelated to Bank Loans ($BkLnUnrelated\ Ownership$)	Abnormal Ownership Unrelated to Bank Loans in a given year t is computed as follows: $BkLnUnrelated\ Ownership_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times I\{NoBankLoan_{i,f,t}\}$, where $I\{NoBankLoan_{i,f,t}\}$ is an indicator function that takes the value of one if the affiliated bank of ETF f does not offer bank loan services to firm i in year t and zero otherwise. All other variables are defined the same as in Bank Loan-related Abnormal Ownership.
Stock Return (in %)	The monthly stock return as reported in Datastream Worldscope.
Stock DGTW adjusted Return (in %)	Stock return minus the average return of stocks in the same style, where stock styles are created by double-sorting stocks into 25 independent size and book-to-market portfolios within each country, following Daniel, Grinblatt, Titman and Wermers (1997).
Log (Stock Size)	The logarithm of market capitalization of stocks, in millions, as reported in Datastream Worldscope.
Turnover	The monthly stock trading volume scaled by shares outstanding, as reported in Datastream Worldscope.
Log (Stock Illiquidity)	The logarithm of annual stock illiquidity. The stock illiquidity measure in a given month m is computed as follows: $ILLIQ_{i,m} = \left(\sum_{d\in m} \lvert R_{i,d,m}\rvert / VOLD_{i,d,m}\right) / D_{i,m} \times 10^6$, where $R_{i,d,m}$ refers to the percentage return of stock i in day d of month m, $VOLD_{i,d,m}$ refers to the dollar trading volume at the same time, and $D_{i,m}$ is the number of trading days for stock i in month m, following Amihud (2002). The annual stock illiquidity is the average of the monthly stock illiquidity within a year.
Log (Net Income)	The logarithm of absolute net income, in millions, as reported in Datastream Worldscope, times 1 (–1) if net income is positive (negative).
Log (Sales)	The logarithm of sales, in millions, as reported in Datastream Worldscope.
Log (Total Assets)	The logarithm of total assets, in millions, as reported in Datastream Worldscope.

Appendix B: List of ETF Sponsors (Year 2009)

Rank	Conglomerate Name for ETF Sponsors	Domicile	Bank Dummy	TNA (in millions)	Market Share (in %)
1	Barclays Plc	United Kingdom	1	354751.15	46.68
2	State Street Corp.	United States	1	165888.96	21.83
3	Vanguard Group, Inc.	United States	0	79649.11	10.48
4	Société Générale SA	France	1	32391.69	4.26
5	INVESCO Ltd.	United States	0	29107.02	3.83
6	Nomura Holdings, Inc.	Japan	1	12653.94	1.67
7	American International Group, Inc.	United States	1	11363.42	1.50
8	MidCap SPDR Trust Services	United States	0	8484.97	1.12
9	Credit Suisse Group	Switzerland	1	7296.41	0.96
10	DekaBank Deutsche Girozentrale	Germany	1	5679.00	0.75
11	Sumitomo Trust & Banking Co. Ltd.	Japan	1	5577.27	0.73
12	Bank of New York Mellon Corp.	United States	1	5065.86	0.67
13	Daiwa Securities Group Co. Ltd.	Japan	1	4889.99	0.64
14	HSBC Holdings Plc	United Kingdom	1	4695.56	0.62
15	CITIC Securities Co. Ltd.	China	1	4283.76	0.56
16	Commerzbank AG	Germany	1	4080.14	0.54
17	UBS AG	Switzerland	1	3610.78	0.48
18	Guggenheim Capital LLC	United States	1	3530.26	0.46
19	The Security Benefit Group of Cos.	United States	1	2724.24	0.36
20	BNP Paribas SA	France	1	2403.26	0.32
21	First Trust Advisors LP	United States	0	1974.46	0.26
22	Polaris Securities Co. Ltd.	Taiwan	0	1939.38	0.26
23	NASDAQ OMX Group, Inc.	United States	1	1579.42	0.21
24	Svenska Handelsbanken AB	Sweden	1	1437.14	0.19
25	Banco Bilbao Vizcaya Argentaria SA	Spain	1	1157.12	0.15
26	BOCI-Prudential Asset Management Ltd.	Hong Kong	1	881.97	0.12
27	AXA SA	France	0	793.13	0.10
28	Rue de la Boetie SAS	France	1	713.58	0.09
29	Crédit Agricole SA	France	1	404.67	0.05
30	DnB NOR ASA	Norway	1	246.25	0.03
31	Fubon Financial Holding Co. Ltd.	Taiwan	1	160.98	0.02
32	RFS Holdings BV	Netherlands	1	150.96	0.02
33	Geode Capital Management LLC	United States	0	134.09	0.02
34	Alpha Bank SA	Greece	1	96.67	0.01
35	DBS Group Holdings Ltd.	Singapore	1	32.08	0.00
36	Bank of Ireland	Ireland	1	31.01	0.00
37	Esposito Partners LLC	United States	0	24.03	0.00
38	The Capital Group Cos., Inc.	United States	1	10.21	0.00
39	Global X Management Co. LLC	United States	0	7.18	0.00
40	Medvesek Pusnik DZU	Slovenia	1	6.77	0.00
41	TMB Bank Public Co. Ltd.	Thailand	1	6.34	0.00
42	ICICI Prudential Asset Management Co. Ltd.	India	1	0.20	0.00

Appendix C: Top 3 ETF Sponsors Over Time

Year	Rank	Conglomerate Name for ETF Sponsors	Domicile	TNA (in millions)	Market Share (in %)
2001	1	State Street Corp.	United States	33894.65	55.46
2001	2	Barclays Plc	United Kingdom	17593.23	28.79
2001	3	Nomura Holdings, Inc.	Japan	5297.33	8.67
2002	1	State Street Corp.	United States	48344.80	39.00
2002	2	Barclays Plc	United Kingdom	26933.96	21.73
2002	3	INVESCO Ltd.	United States	17034.31	13.74
2003	1	State Street Corp.	United States	58615.59	31.67
2003	2	Barclays Plc	United Kingdom	53765.70	29.05
2003	3	INVESCO Ltd.	United States	25689.52	13.88
2004	1	Barclays Plc	United Kingdom	105739.02	39.87
2004	2	State Street Corp.	United States	75839.27	28.60
2004	3	INVESCO Ltd.	United States	22610.88	8.53
2005	1	Barclays Plc	United Kingdom	175199.32	49.09
2005	2	State Street Corp.	United States	82445.74	23.10
2005	3	INVESCO Ltd.	United States	23200.80	6.50
2006	1	Barclays Plc	United Kingdom	263631.41	53.74
2006	2	State Street Corp.	United States	94356.45	19.23
2006	3	INVESCO Ltd.	United States	26077.16	5.32
2007	1	Barclays Plc	United Kingdom	340059.47	50.71
2007	2	State Street Corp.	United States	149426.53	22.28
2007	3	Vanguard Group, Inc.	United States	40350.88	6.02
2008	1	Barclays Plc	United Kingdom	243692.34	45.29
2008	2	State Street Corp.	United States	145673.55	27.08
2008	3	Vanguard Group, Inc.	United States	40609.81	7.55
2009	1	Barclays Plc	United Kingdom	354751.15	46.68
2009	2	State Street Corp.	United States	165888.96	21.83
2009	3	Vanguard Group, Inc.	United States	79649.11	10.48

Table 1: Summary Statistics

This table presents the summary statistics for the data used in the paper during the 2001–2009 period. Panel A reports the number and total net asset (TNA) of ETFs, the percentage number and percentage TNA of three ETF replication methods, the percentage number and percentage TNA of ETFs and OEFs that are affiliated with bank conglomerates on a year-by-year basis. Panel B reports the mean, median, standard deviation, and the quantile distribution of monthly ETF, OEF return, ETF swapped transfer, and other annual fund characteristics. Panel C reports similar statistics for monthly stock return, quarterly bank market-to-book ratio, ETF ownership, and other annual bank and stock characteristics. Appendix A provides detailed definitions of each variable.

Panel A: Snapshots of the ETF industry

Year	All ETFs		ETF Replication Methods						Sponsors affiliated with Bank Conglomerates				With Valid Benchmark	
			Full Replication		Sampling		Synthetic		ETFs		OEFs			
	Number	TNA (in billions)	%Number	%TNA	%Number	%TNA	%Number	%TNA	%Number	%TNA	%Number	%TNA	%Number	%TNA
2001	109	61.12	18.35	67.30	77.06	31.08	4.59	1.62	98.17	98.03	36.10	23.50	52.29	93.06
2002	147	123.96	23.13	72.27	67.35	25.74	9.52	2.00	91.84	80.95	36.23	23.19	55.10	91.18
2003	166	185.08	22.29	62.42	65.66	34.76	12.05	2.83	87.95	79.87	40.05	24.50	55.42	86.18
2004	205	265.18	29.27	50.57	60.00	46.30	10.73	3.13	80.49	85.29	42.43	25.90	55.12	82.79
2005	315	356.93	38.10	45.73	52.38	50.90	9.52	3.38	77.78	87.14	44.80	39.98	56.19	78.72
2006	493	490.56	31.64	39.69	55.58	56.09	12.78	4.22	78.50	87.71	44.94	30.57	48.48	74.83
2007	687	670.64	29.99	38.97	52.98	55.87	17.03	5.16	76.13	86.53	44.00	30.93	45.71	72.96
2008	886	538.02	30.70	41.96	47.63	51.37	21.67	6.67	79.35	86.89	43.45	29.05	45.71	75.00
2009	921	759.91	30.62	35.51	48.43	55.87	20.96	8.62	79.59	83.93	43.01	29.19	45.39	67.52

Table 1—Continued

Panel B: Quantile Distribution of ETF and OEF Characteristics							
	Mean	Std.Dev.	Quantile Distribution				
			10%	25%	Median	75%	90%
Panel B1: ETF Return (monthly, in %)							
Holding-based Return	0.450	5.512	-7.580	-2.525	1.013	3.886	6.960
DGTW adjusted	-0.182	0.856	-1.180	-0.585	-0.135	0.232	0.639
Gross-of-Fee NAV-based Return	0.405	5.380	-6.922	-2.468	1.163	3.766	6.763
Swapped Transfer	0.045	0.453	-0.331	-0.128	0.056	0.222	0.458
Fund Return	0.374	5.380	-6.957	-2.497	1.132	3.740	6.730
Benchmark adjusted	0.047	0.651	-0.441	-0.109	-0.002	0.108	0.516
CAPM adjusted	0.127	0.946	-0.966	-0.471	0.032	0.741	1.424
FFC adjusted	-0.013	0.667	-0.794	-0.420	-0.006	0.367	0.816
Panel B2: ETF Characteristics							
Divergence	0.277	0.307	0.021	0.050	0.130	0.382	0.824
Tracking Error (in %)	0.515	1.001	0.021	0.039	0.105	0.618	1.391
ETF Premium (in %)	0.035	0.187	-0.080	-0.031	0.004	0.056	0.229
Log (Stock Size in Fund)	10.145	1.539	7.395	9.151	10.760	11.256	11.557
Log (Fund TNA)	19.598	2.065	16.908	18.118	19.475	21.233	22.282
Log (Fund Age)	3.751	0.776	2.639	3.258	3.892	4.382	4.625
Expense Ratio (annual, in %)	0.370	0.130	0.246	0.273	0.318	0.505	0.581
Fund Flow (monthly, in %)	2.631	8.168	-4.182	-0.312	0.008	4.597	12.611
Panel B3: OEF Return (monthly, in %)							
Holding-based DGTW adjusted Return	-0.084	0.856	-1.020	-0.500	-0.089	0.287	0.808
OEF Return	0.264	2.416	-3.801	-0.696	1.013	1.914	2.469
Benchmark adjusted	-0.014	0.903	-0.678	-0.259	0.000	0.246	0.758
CAPM adjusted	0.180	1.258	-1.117	-0.487	0.053	0.864	1.760
FFC adjusted	-0.027	0.850	-0.975	-0.467	-0.026	0.423	0.955
Panel B4: OEF Characteristics							
Log (Stock Size in Fund)	10.396	1.089	8.776	10.193	10.676	11.040	11.409
Log (Fund TNA)	18.862	1.736	16.490	17.636	19.117	20.186	20.495
Log (Fund Age)	4.431	0.835	3.296	3.951	4.522	4.956	5.366
Expense Ratio (annual, in %)	1.940	0.670	1.260	1.740	1.899	2.279	2.490
Fund Flow (monthly, in %)	1.521	5.271	-3.116	-1.415	-0.032	3.058	9.720
Panel B5: Cross Trades Measures (quarterly, in %)							
ETF/OEF Cross Trades	11.621	10.591	0.000	1.590	9.448	18.852	28.706
ETF/ETF Cross Trades	9.251	11.766	0.577	1.780	4.711	11.784	24.252

Panel C: Quantile Distribution of Bank and Stock Characteristics							
	Mean	Std.Dev.	Quantile Distribution				
			10%	25%	Median	75%	90%
Panel C1: Bank Characteristics							
Market-to-Book Ratio	1.640	0.821	0.661	1.124	1.495	2.100	2.782
ETF Ownership (in %)	1.240	3.750	0.000	0.000	0.000	0.000	5.300
Bank ROA (annual, in %)	1.719	6.464	-1.008	-0.175	0.398	0.554	4.329
Bank Rating	3.823	1.330	2.000	2.250	4.000	5.000	6.000
Log (Bank Total Assets)	11.203	1.211	10.396	10.467	10.972	11.380	13.347
Equity/Liabilities (in %)	31.191	26.646	5.910	23.573	30.534	33.604	34.212
Loan Loss Reserve/Gross Loans (in %)	13.326	44.811	4.428	11.779	19.738	24.177	30.643
Net Interest Margin (in %)	2.838	1.237	0.825	2.110	3.419	3.566	3.728
Cost/Income (in %)	67.040	21.015	59.684	60.602	63.809	66.598	73.625
Net Loans/Total Assets (in %)	49.468	14.263	27.070	43.185	56.005	58.144	58.792
Panel C2: Stock Characteristics							
Stock Return (monthly, in %)	1.161	5.418	-4.975	-1.367	0.950	3.741	7.530
DGTW adjusted	-0.024	4.126	-4.507	-2.125	-0.117	2.043	4.690
Information Dummy	0.019	0.136	0.000	0.000	0.000	0.000	0.000
Stock Lending Fee	0.607	1.166	0.110	0.139	0.191	0.421	1.553
Bank Stock Dummy	0.001	0.038	0.000	0.000	0.000	0.000	0.000
Log (Stock Size)	5.041	2.147	2.451	3.642	4.980	6.432	7.835
Turnover	0.096	0.137	0.003	0.012	0.050	0.102	0.245
Log (Stock Illiquidity)	3.768	3.038	-1.732	4.957	5.223	5.488	5.652
Log (Net Income)	1.534	3.308	-3.017	-0.222	2.345	4.121	4.543
Log (Sales)	5.706	2.055	3.127	4.333	5.834	7.028	8.017
Log (Total Assets)	6.340	2.239	3.549	4.679	6.186	8.120	8.599

Table 2: ETF Holding Divergence and Swapped Transfer

This table reports the mean, median, standard deviation, and quantile distribution of quarterly holding divergence, monthly swapped transfer, and number of stocks held by ETFs and the indices they track, in the full sample and in the subsamples of synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs. Appendix A provides detailed definitions for each variable.

Holding Divergence and Swapped Transfer							
			Quantile Distribution				
	Mean	Std.Dev.	10%	25%	Median	75%	90%
Panel A1: Full Sample							
Divergence	0.277	0.307	0.021	0.050	0.130	0.382	0.824
Swapped Transfer (monthly, in %)	0.045	0.453	-0.331	-0.128	0.056	0.222	0.458
Number of Stocks in ETF	431	680	27	50	159	500	1054
Number of Stocks in Benchmark	560	824	30	86	240	644	1364
Panel A2: Synthetic Replication ETF							
Divergence	0.890	0.193	0.658	0.814	1.000	1.000	1.000
Swapped Transfer (monthly, in %)	0.091	0.699	-0.811	-0.318	0.078	0.564	0.967
Number of Stocks in ETF	46	49	24	25	31	50	58
Number of Stocks in Benchmark	313	381	31	42	115	542	825
Panel A3: Optimized Sampling ETF							
Divergence	0.248	0.270	0.013	0.040	0.124	0.380	0.697
Swapped Transfer (monthly, in %)	0.029	0.089	-0.067	-0.019	0.017	0.062	0.142
Number of Stocks in ETF	758	845	100	226	436	966	1930
Number of Stocks in Benchmark	897	1029	100	226	472	1063	2740
Panel B1: U.S. ETF							
Divergence	0.222	0.259	0.013	0.037	0.093	0.339	0.666
Swapped Transfer (monthly, in %)	0.026	0.088	-0.063	-0.019	0.012	0.063	0.135
Number of Stocks in ETF	743	846	99	216	404	966	1930
Number of Stocks in Benchmark	875	1026	100	219	429	1063	2734
Panel B2: European ETF							
Divergence	0.385	0.381	0.036	0.068	0.187	0.799	1.000
Swapped Transfer (monthly, in %)	0.052	0.503	-0.494	-0.105	0.028	0.182	0.795
Number of Stocks in ETF	126	186	24	29	50	102	397
Number of Stocks in Benchmark	268	372	25	40	116	324	775

Table 3: The Determinants of ETF Holding Divergence and Tracking Error (Stock Level)

Panel A presents the results of the following annual panel regressions with year and stock fixed effects and their corresponding t-statistics with standard errors clustered at the stock level,

$$Divergence_{i,t} = \alpha + \beta Channel_{i,t-1} + \gamma M_{i,t-1} + e_{i,t},$$

where $Divergence_{i,t}$ is the average quarterly holding Divergence of stock i in year t, $Channel_{i,t-1}$ refers to four channels of impact: Information Dummy (a dummy variable taking a value of one if it is a lending-related stock), Stock Lending Fee (the average short selling lending fee), Bank Stock Dummy (a dummy variable taking a value of one if the ETF invests in its affiliated bank), and BMK-adjusted OEF Return (the benchmark-adjusted return of other affiliated OEFs). The Stock-level Information Dummy, Divergence, and Bank Stock Dummy (BMK-adjusted OEF Return) are computed as the investment value-weighted average of the ETF-stock-level (ETF-level) proxies across all funds holding a stock. Vector M stacks all other stock and fund control variables, including Log(Stock Size), Stock Return, Turnover, Log(Net Income), Log(Sales), Log(Total Assets), Log(Fund TNA), Log(Fund Age), Expense Ratio, and Fund Flow. Panel B reports similar regression parameters when the dependent variable is $TE_{i,t}$, which refers to the investment value-weighted average of the ETF-level Tracking Error (only the main variables are tabulated for brevity). Appendix A provides detailed definitions for each variable. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Table 3—Continued

Panel A: Out-of-sample Holding Divergence Regressed on Stock and ETF Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-0.120***	-0.139***	-0.140***	-0.149***	-0.126***	0.023
	(-4.99)	(-5.48)	(-5.51)	(-5.82)	(-5.23)	(0.81)
Information Dummy	0.118***				0.117***	0.111***
	(7.65)				(7.61)	(7.37)
Stock Lending Fee		-0.003***			-0.003***	-0.003***
		(-6.38)			(-5.83)	(-5.68)
Bank Stock Dummy			0.189***		0.180***	0.171***
			(4.13)		(4.05)	(3.76)
OEF BmkAdjReturn				-0.045***	-0.045***	-0.045***
				(-4.73)	(-4.81)	(-4.71)
Log (Stock Size)	0.007***	0.008***	0.008***	0.008***	0.007***	0.004***
	(5.48)	(5.58)	(5.81)	(5.63)	(5.04)	(3.37)
Stock Return	0.000**	0.000*	0.000*	0.000**	0.000**	0.000***
	(1.98)	(1.88)	(1.79)	(2.06)	(2.28)	(3.24)
Turnover	0.003	0.006	0.006	0.006	0.004	
	(0.73)	(1.30)	(1.22)	(1.36)	(0.95)	
Log (Stock Illiquidity)						-0.029***
						(-7.95)
Log (Net Income)	0.001**	0.000	0.000	0.000	0.001**	0.000
	(2.07)	(1.45)	(1.54)	(1.58)	(1.98)	(1.48)
Log (Sales)	-0.004**	-0.005***	-0.005***	-0.005***	-0.005**	-0.005***
	(-2.49)	(-2.83)	(-2.90)	(-2.84)	(-2.52)	(-2.71)
Log (Total Assets)	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.75)	(-0.47)	(-0.38)	(-0.40)	(-0.66)	(-0.56)
Log (Fund TNA)	0.008***	0.009***	0.009***	0.009***	0.007***	0.006***
	(7.47)	(7.98)	(7.97)	(7.75)	(7.10)	(5.59)
Log (Fund Age)	-0.021***	-0.024***	-0.024***	-0.025***	-0.021***	-0.017***
	(-10.77)	(-11.22)	(-11.31)	(-11.59)	(-10.83)	(-9.29)
Expense Ratio	0.028***	0.029***	0.028***	0.031***	0.031***	0.039***
	(4.21)	(4.38)	(4.29)	(4.64)	(4.69)	(5.90)
Fund Flow	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(8.22)	(8.09)	(8.09)	(8.00)	(8.06)	(7.24)
R-squared	0.088	0.071	0.072	0.072	0.091	0.099
Obs	46,526	46,526	46,526	46,526	46,526	46,526

Panel B: Out-of-sample Tracking Error (in %) Regressed on Stock and ETF Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-0.842***	-0.849***	-0.857***	-0.922***	-0.895***	-0.674***
	(-10.76)	(-10.76)	(-10.85)	(-11.61)	(-11.40)	(-7.30)
Information Dummy	0.094***				0.092***	0.080***
	(4.34)				(4.26)	(3.69)
Stock Lending Fee		-0.016***			-0.016***	-0.017***
		(-7.91)			(-7.78)	(-8.00)
Bank Stock Dummy			0.306***		0.290***	0.275***
			(6.81)		(5.95)	(5.93)
OEF BmkAdjReturn				-0.349***	-0.350***	-0.352***
				(-11.85)	(-11.88)	(-11.97)
Stock and Fund Controls	Y	Y	Y	Y	Y	Y
R-squared	0.378	0.378	0.378	0.382	0.384	0.383
Obs	46,526	46,526	46,526	46,526	46,526	46,526

Table 4: Impacts on ETF Swapped Transfer and Fees (Stock Level)

Panel A presents the results of the following annual panel regressions with year and stock fixed effects and their corresponding t-statistics with standard errors clustered at the stock level,

$$Swap_{i,t} = \alpha + \beta Channel_{i,t-1} + \gamma M_{i,t-1} + e_{i,t},$$

where $Swap_{i,t}$ is the average monthly Swapped Transfer of stock i in year t, and all other specifications are those described in Table 3. Panel B reports similar regression parameters when the dependent variable is $Fee_{i,t}$, which refers to the investment value-weighted average of the ETF-level annualized percentage Fee (expense ratio) across all funds holding a stock. Only the main variables are tabulated for brevity. Appendix A provides detailed definitions for each variable. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Out-of-sample Swapped Transfer (in %) Regressed on Stock and ETF Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.287***	0.284***	0.283***	0.263***	0.267***	0.174***
	(6.60)	(6.53)	(6.52)	(6.08)	(6.17)	(3.93)
Information Dummy	0.021***				0.021***	0.026***
	(2.62)				(2.67)	(3.17)
Stock Lending Fee		-0.000			-0.000	-0.000
		(-0.34)			(-0.38)	(-0.35)
Bank Stock Dummy			-0.011		-0.015	-0.009
			(-0.34)		(-0.45)	(-0.27)
OEF BmkAdjReturn				-0.113***	-0.113***	-0.113***
				(-7.21)	(-7.22)	(-7.21)
Stock and Fund Controls	Y	Y	Y	Y	Y	Y
R-squared	0.093	0.093	0.093	0.096	0.096	0.097
Obs	46,526	46,526	46,526	46,526	46,526	46,526

Panel B: Out-of-sample Fees (in %) Regressed on Stock and ETF Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.583***	0.587***	0.583***	0.571***	0.576***	0.631***
	(33.80)	(33.96)	(33.69)	(33.54)	(33.92)	(30.33)
Information Dummy	0.000				0.000	-0.002
	(0.05)				(0.02)	(-0.30)
Stock Lending Fee		-0.005***			-0.005***	-0.005***
		(-5.66)			(-5.79)	(-5.75)
Bank Stock Dummy			0.026		0.022	0.019
			(0.75)		(0.74)	(0.64)
OEF BmkAdjReturn				-0.142***	-0.142***	-0.142***
				(-21.81)	(-21.83)	(-21.74)
Stock and Fund Controls	Y	Y	Y	Y	Y	Y
R-squared	0.354	0.355	0.354	0.368	0.369	0.370
Obs	46,526	46,526	46,526	46,526	46,526	46,526

Table 5: ETF Stock Selection Based on Bank Lending (Stock Level)

Panel A presents the results of the following annual panel regressions with year and stock fixed effects and their corresponding t-statistics with standard errors clustered at the stock level,

$$Perf_{i,t} = \alpha + \beta_1 \Delta BkLn\ Ownership_{i,t-1} + \beta_2 \Delta BkLnUnrelated\ Ownership_{i,t-1} + \gamma M_{i,t-1} + e_{i,t},$$

where $Perf_{i,t}$ is the average monthly DGTW adjusted return or raw return of a stock in year t, $\Delta BkLn\ Ownership_{i,t-1}$ is the change in bank loan–related abnormal ETF ownership of stock i in year $t-1$, and $\Delta BkLnUnrelated\ Ownership_{i,t-1}$ is the change in abnormal ETF ownership unrelated to bank loans. Vector M stacks all other stock and fund control variables, including Log(Stock Size), Turnover, Log(Net Income), Log(Sales), Log(Total Assets), Log(Fund TNA), Log(Fund Age), Expense Ratio, Fund Return and Fund Flow. Appendix A provides detailed definitions of each variable. Panel B applies Models 4 and 8 in Panel A to subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs (only the main variables are tabulated for brevity). Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Out-of-sample Stock Return (in %) Regressed on ΔAbnormal ETF Ownership

	DGTW adjusted Return				Return			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	21.944***	20.789***	21.945***	20.806***	24.335***	27.890***	24.337***	27.889***
	(38.99)	(20.06)	(39.00)	(20.07)	(49.47)	(28.74)	(49.47)	(28.74)
ΔBkLn Ownership	0.976**	1.014**	0.967**	1.008**	1.466***	0.945*	1.473***	0.949*
	(2.12)	(2.19)	(2.11)	(2.19)	(2.76)	(1.93)	(2.77)	(1.93)
ΔBkLnUnrelated Ownership			-0.076	-0.043			0.145	0.095
			(-0.93)	(-0.53)			(1.47)	(0.96)
Log (Stock Size)	-3.088***	-3.084***	-3.087***	-3.083***	-3.374***	-3.333***	-3.375***	-3.333***
	(-38.85)	(-38.79)	(-38.81)	(-38.75)	(-44.60)	(-44.33)	(-44.60)	(-44.32)
Turnover	-1.398***	-1.322***	-1.396***	-1.321***	-2.397***	-2.261***	-2.399***	-2.263***
	(-5.08)	(-4.79)	(-5.07)	(-4.79)	(-8.94)	(-8.44)	(-8.95)	(-8.45)
Log (Net Income)	0.077***	0.078***	0.077***	0.078***	0.095***	0.096***	0.096***	0.096***
	(7.95)	(8.11)	(7.95)	(8.11)	(9.92)	(10.03)	(9.92)	(10.03)
Log (Sales)	0.170*	0.171**	0.170*	0.171**	0.156*	0.163*	0.156*	0.163*
	(1.96)	(1.97)	(1.96)	(1.97)	(1.69)	(1.78)	(1.69)	(1.77)
Log (Total Assets)	-0.113	-0.136	-0.114	-0.136	-0.107	-0.138	-0.107	-0.138
	(-1.26)	(-1.52)	(-1.27)	(-1.53)	(-1.18)	(-1.52)	(-1.17)	(-1.51)
Log (Fund TNA)		-0.067		-0.068		-0.144***		-0.143***
		(-1.62)		(-1.62)		(-3.48)		(-3.46)
Log (Fund Age)		0.220*		0.217*		-0.181		-0.183
		(1.74)		(1.72)		(-1.59)		(-1.61)
Expense Ratio		0.417		0.414		-1.206***		-1.206***
		(1.64)		(1.63)		(-3.56)		(-3.56)
Fund Return		-0.140***		-0.140***		-0.502***		-0.502***
		(-3.59)		(-3.59)		(-12.43)		(-12.43)
Fund Flow		-0.012**		-0.012**		-0.029***		-0.029***
		(-1.99)		(-1.99)		(-8.19)		(-8.19)
R-squared	0.168	0.170	0.168	0.170	0.446	0.452	0.446	0.452
Obs	46,198	46,198	46,198	46,198	46,198	46,198	46,198	46,198

Panel B: Out-of-sample Stock Return (in %) Regressed on ΔAbnormal ETF Ownership (Subsample)

	DGTW adjusted Return				Return			
	Synthetic	Sampling	U.S.	European	Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ΔBkLn Ownership	0.360*	1.105**	-1.746	0.593**	0.593***	0.901**	-15.212	0.528**
	(1.72)	(2.37)	(-0.14)	(2.46)	(2.68)	(2.02)	(-1.28)	(2.11)
ΔBkLnUnrelated Ownership	-0.111	-0.192**	-0.027	0.115	0.086	0.150	-0.194**	0.132
	(-1.63)	(-2.03)	(-0.33)	(1.53)	(1.22)	(1.65)	(-2.25)	(1.44)
Stock and Fund Controls	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.162	0.162	0.160	0.163	0.450	0.447	0.447	0.448
Obs	46,198	46,198	46,198	46,198	46,198	46,198	46,198	46,198

Table 6: ETF Ownership and Cash Flow Sensitivity of the Affiliated Bank (Bank Level)

This table presents the results of the following quarterly panel regressions with quarter and bank fixed effects and their corresponding t-statistics clustered at the bank (or quarter) level,

$$BankMB_{b,q} = \alpha + \beta_1 ETF\_IO_{b,q-1} + \beta_2 ROA_{b,q-1} + \beta_3 ETF\_IO_{b,q-1} \times ROA_{b,q-1} + \gamma M_{b,q-1} + e_{b,q},$$

where $BankMB_{b,q}$ is the market-to-book ratio of bank b in quarter q, $ETF\_IO_{b,q-1}$ refers to a list of ETF ownership of bank b in quarter $q-1$. Specifically, Models 1 and 2 apply *ETF Dummy*, which takes a value of one if the bank is held by its affiliated ETF, Models 3 and 4 apply *ETF Ownership*, defined as the percentage bank ownership of the affiliated ETF, and Models 5 to 8 further net out the benchmark-implied ownership. $ROA_{b,q-1}$ is the ROA, and vector M stacks all bank specific control variables, including Log(Bank Total Assets), Equity/Liabilities, Loan Loss Reserve/Gross Loans, Net Interest Margin, Cost/Income and Net Loans/Total Assets. Appendix A provides detailed definitions of each variable. Numbers with “*”, “**” and “***” are significant at the 10%, 5% and 1% levels, respectively.

	Out-of-sample Bank Market-to-Book Ratio Regressed on ETF Ownership and Bank ROA							
	ETF_IO = ETF Dummy		ETF_IO = ETF Ownership		ETF_IO = BMK-adjusted ETF Dummy		ETF_IO = BMK-adjusted ETF Ownership	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	5.395***	5.112***	5.369***	4.826***	5.570***	5.075***	5.203***	4.399***
	(3.15)	(4.54)	(3.25)	(4.50)	(3.63)	(4.90)	(3.34)	(4.16)
ETF_IO	-0.108	-0.108*	-0.001	-0.001	0.229	0.229***	0.065**	0.065***
	(-0.71)	(-1.80)	(-0.05)	(-0.12)	(1.00)	(4.33)	(2.60)	(4.21)
Bank ROA	0.100***	0.100***	0.088***	0.088***	0.098***	0.098***	0.079***	0.079***
	(3.46)	(4.64)	(3.09)	(4.25)	(3.49)	(4.49)	(2.99)	(4.15)
ETF_IO × Bank ROA	-0.096***	-0.096***	-0.007**	-0.007***	-0.095***	-0.095***	-0.029***	-0.029***
	(-3.60)	(-4.40)	(-2.70)	(-3.39)	(-3.47)	(-3.91)	(-4.46)	(-3.87)
Log (Bank Total Assets)	-0.260**	-0.260***	-0.259**	-0.259***	-0.276**	-0.276***	-0.241**	-0.241***
	(-2.08)	(-3.28)	(-2.20)	(-3.37)	(-2.59)	(-3.64)	(-2.24)	(-3.21)
Equity/Liabilities	-0.004***	-0.004***	-0.003***	-0.003***	-0.004***	-0.004***	-0.003**	-0.003**
	(-3.39)	(-2.98)	(-3.01)	(-2.84)	(-3.47)	(-2.83)	(-2.64)	(-2.56)
Loan Loss Reserve/Gross Loans	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.69)	(-0.94)	(-0.67)	(-0.90)	(-0.73)	(-0.98)	(-0.66)	(-0.87)
Net Interest Margin	-0.136***	-0.136***	-0.123**	-0.123***	-0.123**	-0.123***	-0.112*	-0.112***
	(-2.86)	(-3.50)	(-2.33)	(-3.09)	(-2.46)	(-3.32)	(-1.97)	(-2.84)
Cost/Income	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.79)	(0.87)	(0.66)	(0.79)	(0.76)	(0.88)	(0.55)	(0.70)
Net Loans /Total Assets	-0.008	-0.008	-0.008	-0.008	-0.009	-0.009	-0.010	-0.010
	(-1.12)	(-1.22)	(-1.33)	(-1.36)	(-1.48)	(-1.50)	(-1.71)	(-1.60)
R-squared	0.439	0.798	0.428	0.794	0.433	0.796	0.427	0.794
Obs	704	704	704	704	704	704	704	704
Clustering	Bank	Quarter	Bank	Quarter	Bank	Quarter	Bank	Quarter

Table 7: ETF, OEF Cross-Trades

Panel A presents the results of the following two-stage panel regressions at the OEF level and their corresponding t-statistics clustered by fund after controlling for the year and fund fixed effects,

First stage: $CrossTra_{f,t} = \alpha + \beta ETF/OEF\_CommonDivergence_{f,t} + \gamma M_{f,t} + e_{f,t}$,

Second stage: $OEF\_Char_{f,t+1} = \alpha + \beta CrossTra_{f,t} + \gamma M_{f,t} + e_{f,t+1}$,

where $CrossTra_{f,t}$ is the average quarterly cross-trades of fund f with other affiliated ETF(s) in year t, $ETF/OEF\_CommonDivergence_{f,t}$ is the ETF/OEF Common Divergence, $OEF\_Char_{f,t+1}$ refers to the OEF characteristics including average monthly flow, benchmark-adjusted return volatility (by netting out the benchmark average of return volatility, defined as the standard deviation of monthly return), monthly return, and risk-adjusted OEF return, and vector M stacks all other control variables, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Expense Ratio, OEF Return, and Fund Flow. OEF returns are adjusted by subtracting the benchmark return, the DGTW portfolio return, the CAPM, and the international Fama-French-Carhart (FFC) model. Panel B reports similar statistics of the following two-stage regressions at the ETF level,

First stage: $CrossTra_{f,t} = \alpha + \beta ETF/ETF\_CommonDivergence_{f,t} + \gamma M_{f,t} + e_{f,t}$,

Second stage: $ETF\_Char_{f,t+1} = \alpha + \beta CrossTra_{f,t} + \gamma M_{f,t} + e_{f,t+1}$,

where $ETF/ETF\_CommonDivergence_{f,t}$ is the ETF/ETF Common Divergence, $ETF\_Char_{f,t+1}$ refers to the ETF characteristics including average monthly flow, benchmark-adjusted return volatility, monthly return, and risk-adjusted ETF return, as defined above. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Table 7—Continued

Panel A: Two-stage OEF Flow (in %) and Performance (in %) Regression (OEF-Level)								
	First Stage				Second Stage			
	ETF/OEF Cross-Trades	Fund Flow	BMK-adjusted Volatility	Return	BMK-adjusted	DGTW	CAPM	FFC
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-16.781**	41.685***	5.015***	-0.097	0.253	0.274	-0.266	-1.162***
	(-2.47)	(8.57)	(5.81)	(-0.06)	(0.60)	(0.58)	(-0.51)	(-3.13)
ETF/OEF Common Divergence	11.380***							
	(11.24)							
ETF/OEF Cross-Trades		0.251***	0.036**	0.107***	0.008	-0.014**	0.010	0.000
		(3.58)	(2.37)	(4.24)	(0.92)	(-2.13)	(1.12)	(0.06)
Log (Stock Size in Fund)	1.452***	-1.142***	-0.325***	-0.501***	-0.081***	-0.073**	-0.142***	0.003
	(4.69)	(-4.73)	(-5.45)	(-5.48)	(-2.73)	(-2.40)	(-4.09)	(0.10)
Log (Fund TNA)	0.278	-1.619***	-0.129***	0.124**	0.010	0.009	0.047**	0.047***
	(1.12)	(-7.73)	(-3.65)	(2.05)	(0.56)	(0.48)	(2.16)	(3.29)
Log (Fund Age)	-0.483	0.415	0.100	0.174	0.047	0.026	0.057	-0.053
	(-0.78)	(1.14)	(1.61)	(1.28)	(1.08)	(0.66)	(1.11)	(-1.63)
Expense Ratio	3.656***	-1.760***	-0.071	0.078	0.035	0.097**	0.255***	0.216***
	(6.67)	(-4.84)	(-1.15)	(0.57)	(0.94)	(2.57)	(5.33)	(6.56)
OEF Return	-0.350***	0.079	-0.087***	-0.524***	-0.033**	0.022**	-0.015	0.059***
	(-2.68)	(0.83)	(-4.13)	(-16.39)	(-2.24)	(2.02)	(-1.02)	(6.37)
Fund Flow	-0.144***	0.281***	0.022***	0.048***	0.007**	-0.001	0.008**	0.001
	(-4.18)	(6.52)	(3.18)	(5.14)	(1.97)	(-0.23)	(2.06)	(0.30)
Obs	1,959	1,959	1,653	1,959	1,653	1,959	1,959	1,959

Panel B: Two-stage ETF Flow (in %) and Performance (in %) Regression (ETF-Level)								
	First Stage				Second Stage			
	ETF/ETF Cross-Trades	Fund Flow	BMK-adjusted Volatility	Return	BMK-adjusted	DGTW	CAPM	FFC
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.576	12.003***	2.581***	6.032***	0.506	0.357	0.395	-0.100
	(0.25)	(3.91)	(3.66)	(3.48)	(0.84)	(0.45)	(0.59)	(-0.20)
ETF/ETF Common Divergence	4.189*							
	(1.67)							
ETF/ETF Cross-Trades		0.350	0.028	0.055	-0.031	-0.084	0.050	0.058
		(1.25)	(0.47)	(0.31)	(-0.37)	(-1.21)	(0.71)	(1.05)
Log (Stock Size in Fund)	1.827***	-0.507	0.004	-0.272	0.046	0.099	-0.165	-0.071
	(8.97)	(-0.95)	(0.03)	(-0.84)	(0.29)	(0.73)	(-1.24)	(-0.66)
Log (Fund TNA)	-1.119***	0.108	-0.075	0.078	-0.050	-0.077	0.079	0.061
	(-4.57)	(0.33)	(-1.14)	(0.41)	(-0.56)	(-0.99)	(1.02)	(1.05)
Log (Fund Age)	2.354*	-2.589***	-0.424**	-1.157**	0.079	0.217	-0.243	-0.276*
	(1.90)	(-2.90)	(-2.54)	(-2.13)	(0.39)	(1.06)	(-1.22)	(-1.93)
Expense Ratio	3.595	-1.965	-0.041	-1.280	0.368	0.277	0.518	-0.208
	(1.33)	(-1.46)	(-0.14)	(-1.58)	(1.10)	(0.83)	(1.57)	(-0.83)
Fund Return	-0.254	0.099	0.037	-0.561***	0.057**	0.048*	0.080***	0.094***
	(-1.28)	(0.80)	(1.34)	(-9.20)	(2.04)	(1.71)	(2.93)	(4.36)
Fund Flow	-0.026	-0.052	-0.009	0.021	-0.005	-0.013	-0.013	-0.008
	(-0.15)	(-0.59)	(-0.75)	(0.74)	(-0.44)	(-0.76)	(-1.38)	(-0.79)
Obs	561	561	561	561	561	561	561	561

Table 8: Robustness Checks on ETF, OEF Cross-Trades

This table presents the results of the following two-stage panel regressions at the OEF level and their corresponding t-statistics clustered by fund after controlling for the year and fund fixed effects,

First stage: $CrossTra_{f,t} = \alpha + \beta ETF/OEF\_CommonDivergence_{f,t} + \gamma M_{f,t} + e_{f,t}$,

Second stage: $OEF\_Char_{f,t+1} = \alpha + \beta CrossTra_{f,t} + \gamma M_{f,t} + e_{f,t+1}$,

where $CrossTra_{f,t}$ is the average quarterly cross-trades of fund f with other affiliated ETF(s) in year t, $ETF/OEF\_CommonDivergence_{f,t}$ is the ETF/OEF Common Divergence, $OEF\_Char_{f,t+1}$ refers to the OEF characteristics including average monthly flow, monthly return and risk-adjusted OEF return (by subtracting the DGTW portfolio return), and vector M stacks all other control variables, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Expense Ratio, OEF Return and Fund Flow. Panel A reports subsample results for cross trades with Synthetic ETFs (Models 1 to 4) and Optimized Sampling ETFs (Models 5 to 8), and Panel B reports similar subsample results for U.S. ETFs (Models 1 to 4) and European ETFs (Models 5 to 8). Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Two-stage OEF Flow (in %) and Performance (in %) Regression (Replication Method)

	Synthetic Replication ETF				Optimized Sampling ETF			
	First Stage	Second Stage			First Stage	Second Stage		
	ETF/OEF Cross-Trades	Fund Flow	Return	DGTW	ETF/OEF Cross-Trades	Fund Flow	Return	DGTW
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	6.168	9.444***	-11.496***	0.041	-29.490***	21.142***	-3.905**	0.070
	(0.78)	(2.80)	(-2.98)	(0.03)	(-3.91)	(7.46)	(-2.20)	(0.13)
ETF/OEF Common Divergence	18.492***				19.563***			
	(11.52)				(17.32)			
ETF/OEF Cross-Trades		0.038	0.085**	0.019*		0.050**	0.068***	0.008
		(1.24)	(2.05)	(1.77)		(2.25)	(2.78)	(1.10)
Log (Stock Size in Fund)	0.536	-0.466**	-0.249	-0.100	1.241***	-0.685***	-0.289***	-0.083**
	(1.24)	(-2.56)	(-1.07)	(-1.23)	(3.14)	(-4.68)	(-2.91)	(-2.23)
Log (Fund TNA)	-0.429	-0.518***	0.420***	0.024	0.615**	-0.683***	0.290***	0.013
	(-1.22)	(-3.79)	(3.32)	(0.58)	(2.15)	(-5.91)	(4.33)	(0.59)
Log (Fund Age)	0.401	0.638**	0.149	-0.029	0.271	0.031	-0.046	0.029
	(0.61)	(2.55)	(0.56)	(-0.41)	(0.50)	(0.15)	(-0.27)	(0.52)
Expense Ratio	0.299	0.472	1.277**	0.039	4.327***	-0.945***	-0.160	0.047
	(0.36)	(1.25)	(2.24)	(0.46)	(6.62)	(-4.35)	(-0.96)	(1.18)
OEF Return	0.099	-0.306***	-0.805***	-0.027*	-0.289*	-0.095*	-0.657***	0.055***
	(0.55)	(-4.74)	(-11.06)	(-1.72)	(-1.81)	(-1.71)	(-17.03)	(4.46)
Fund Flow	-0.157**	0.168***	0.085*	0.026***	-0.162***	0.178***	0.061***	0.000
	(-2.54)	(5.54)	(1.83)	(2.71)	(-2.71)	(5.43)	(3.18)	(0.02)
Obs	634	634	634	634	1,233	1,233	1,233	1,233

Panel B: Two-stage OEF Flow (in %) and Performance (in %) Regression (Domicile Country)

	U.S. ETF				European ETF			
	First Stage	Second Stage			First Stage	Second Stage		
	ETF/OEF Cross-Trades	Fund Flow	Return	DGTW	ETF/OEF Cross-Trades	Fund Flow	Return	DGTW
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	15.930*	32.032***	-3.037	0.381	-31.060***	23.596***	3.362	1.633**
	(1.72)	(4.10)	(-1.49)	(0.60)	(-3.27)	(3.77)	(1.25)	(2.50)
ETF/OEF Common Divergence	11.442***				11.853***			
	(8.29)				(8.50)			
ETF/OEF Cross-Trades		0.005	0.017	-0.015		0.196***	0.135***	-0.007
		(0.04)	(0.47)	(-1.28)		(2.61)	(4.09)	(-0.97)
Log (Stock Size in Fund)	0.767	-0.779**	-0.104	-0.036	2.072***	-0.421	-0.794***	-0.163***
	(1.50)	(-2.37)	(-1.09)	(-0.80)	(4.52)	(-1.40)	(-5.07)	(-3.83)
Log (Fund TNA)	-0.699**	-1.245***	0.145*	-0.023	0.946**	-1.267***	-0.156	-0.026
	(-2.29)	(-4.04)	(1.94)	(-0.88)	(2.43)	(-4.49)	(-1.49)	(-1.00)
Log (Fund Age)	-1.508*	0.511	0.175	0.082	-0.118	0.571	0.249	0.037
	(-1.74)	(0.66)	(0.79)	(0.85)	(-0.14)	(1.63)	(1.35)	(0.86)
Expense Ratio	-0.106	0.093	0.106	0.117**	1.060	-0.327	1.829***	0.121***
	(-0.11)	(0.15)	(0.62)	(2.25)	(1.02)	(-0.46)	(7.81)	(2.58)
OEF Return	-0.365*	-0.475***	-0.512***	0.144***	-0.301*	0.150	-0.556***	-0.016
	(-1.95)	(-2.83)	(-11.21)	(6.79)	(-1.66)	(1.48)	(-11.51)	(-1.42)
Fund Flow	-0.009	0.278***	0.027*	-0.004	-0.181***	0.236***	0.055***	0.011***
	(-0.11)	(3.28)	(1.87)	(-0.51)	(-3.31)	(4.03)	(3.46)	(2.80)
Obs	557	557	557	557	1,251	1,251	1,251	1,251

Table 9: ETF Flows (ETF Level)

This table presents the results of the following regressions with year fixed effects and their corresponding t-statistics clustered at the fund level,

$$Flow_{f,t} = \alpha + \beta_1 ETF\_Char_{f,t} + \beta_2 Rating_{f,t} + \beta_3 ETF\_Char_{f,t} \times Rating_{f,t} + \gamma M_{f,t-1} + e_{f,t},$$

where $Flow_{f,t}$ refers to the average monthly flow of fund f in year t, $ETF\_Char_{f,t}$ refers to a list of ETF characteristics, including the average quarterly Divergence in ETF holdings, Tracking Error, average monthly Swapped Transfer, and annualized percentage Fee (expense ratio), Information Dummy (a dummy variable taking the value of one when the ETF holds a lending-related stock), Stock Lending Fee at the portfolio level (computed as the investment value-weighted average of stock-level short selling lending across all the stocks held by a portfolio), Bank Stock Dummy (a dummy variable taking the value of one if the ETF invests in its affiliated bank), and BMK-adjusted OEF Return (the benchmark-adjusted return of other affiliated OEFs). $Rating_{f,t}$ refers to the S&P long-term domestic issuer credit rating of its affiliated bank (the numeric rating ascending in credit risk, i.e., AAA = 1, …, D = 22) and annual bank performance measured by ROA in a few specifications. Vector M stacks all other control variables, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Fund Return, and Fund Flow. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Table 9—Continued

ETF Flow (in %) Regressed on ETF and Affiliated Bank Characteristics														
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Intercept	1.512	1.468	1.978	4.068	5.517	4.636*	6.255**	5.929**	6.528**	8.364**	10.636***	5.710	7.575**	11.862***
	(0.51)	(0.46)	(0.67)	(1.35)	(1.55)	(1.66)	(2.39)	(2.13)	(2.61)	(2.48)	(3.38)	(1.53)	(2.12)	(3.60)
Divergence	-0.392				-0.069					-0.293	0.012	-0.153	-0.047	-0.288
	(-1.05)				(-0.18)					(-0.74)	(0.03)	(-0.37)	(-0.11)	(-0.66)
Tracking Error		0.117			-0.579					-0.604	-0.828*	-0.614	-0.616	-0.962*
		(0.24)			(-1.00)					(-1.08)	(-1.76)	(-0.97)	(-0.95)	(-1.91)
Swapped Transfer			-0.387**		-0.403**			0.646	-0.992**	0.627	-1.106***	-0.376**	0.559	-1.108**
			(-2.27)		(-2.36)			(1.26)	(-2.36)	(1.23)	(-2.62)	(-2.25)	(1.10)	(-2.59)
Fees				-3.362***	-3.885***					-2.678**	-3.205***	-5.175***	-3.594**	-4.668***
				(-2.88)	(-3.01)					(-2.03)	(-2.81)	(-3.71)	(-2.46)	(-3.77)
Bank Rating						-0.601***		-0.781***		-0.746***			-0.691***	
						(-4.10)		(-5.11)		(-4.66)			(-4.33)	
Bank ROA							2.159***		1.891***		1.655**			1.468**
							(3.02)		(2.74)		(2.34)			(2.19)
Swapped Transfer × Bank Rating								-0.216**		-0.211**			-0.196*	
								(-2.11)		(-2.06)			(-1.92)	
Swapped Transfer × Bank ROA									0.622**		0.655**			0.639**
									(2.19)		(2.34)			(2.31)
Information Dummy												1.082	0.272	1.722**
												(1.38)	(0.33)	(2.20)
Stock Lending Fee												1.585***	1.245**	0.925
												(3.08)	(2.40)	(1.57)
Bank Stock Dummy												-2.314***	-2.254***	-1.015*
												(-3.80)	(-3.52)	(-1.70)
OEF BmkAdjReturn												1.532	0.251	1.839
												(1.17)	(0.21)	(1.36)
Log (Stock Size in Fund)	0.203	0.179	0.161	0.267*	0.238	0.107	0.234*	0.081	0.189	0.144	0.196	0.335*	0.253	0.227
	(1.22)	(1.05)	(1.00)	(1.66)	(1.31)	(0.73)	(1.81)	(0.55)	(1.46)	(0.83)	(1.38)	(1.84)	(1.40)	(1.55)
Log (Fund TNA)	0.489***	0.490***	0.489***	0.413***	0.389***	0.537***	0.343***	0.562***	0.305**	0.486***	0.194	0.348**	0.477***	0.140
	(3.68)	(3.65)	(3.72)	(3.30)	(2.97)	(4.46)	(2.68)	(4.66)	(2.42)	(3.81)	(1.59)	(2.49)	(3.45)	(1.17)
Log (Fund Age)	-2.296***	-2.243***	-2.336***	-2.487***	-2.599***	-2.465***	-3.692***	-2.661***	-3.452***	-2.848***	-3.551***	-2.584***	-2.879***	-3.464***
	(-5.30)	(-5.31)	(-5.54)	(-5.85)	(-5.94)	(-5.82)	(-5.83)	(-6.07)	(-5.15)	(-6.16)	(-5.43)	(-5.91)	(-6.21)	(-5.28)
Fund Return	-0.423***	-0.430***	-0.402***	-0.414***	-0.381***	-0.422***	-0.469**	-0.346**	-0.326	-0.330**	-0.298	-0.338**	-0.311**	-0.255
	(-2.85)	(-2.91)	(-2.74)	(-2.82)	(-2.60)	(-2.96)	(-2.22)	(-2.44)	(-1.56)	(-2.33)	(-1.43)	(-2.40)	(-2.25)	(-1.21)
Fund Flow	0.002	0.002	0.004	0.002	0.004	-0.002	0.008	-0.004	0.013	-0.004	0.010	0.001	-0.006	0.008
	(0.18)	(0.16)	(0.36)	(0.19)	(0.37)	(-0.15)	(0.15)	(-0.37)	(0.26)	(-0.35)	(0.21)	(0.06)	(-0.60)	(0.15)
R-squared	0.093	0.092	0.100	0.102	0.112	0.119	0.212	0.141	0.227	0.149	0.238	0.141	0.169	0.255
Obs	704	704	704	704	704	704	704	704	704	704	704	704	704	704

Internet Appendix

The Dark Side of ETF Investing: A World-Wide Analysis

In this Internet Appendix, we first assess whether there is evidence that such deviations ─ *Divergence* and *Swapped Transfer* ─ are persistent over time. We then provide evidence regarding the role of affiliation in affecting the commonality in ETF *Divergence*. Finally, we explore the relationship between ETF *Swapped Transfer* and bank ROA.

We first estimate the degree of autocorrelation in our deviation measures by estimating the following pooled OLS regressions with year fixed effects:

$$Dev_{f,t} = \alpha + \beta Dev_{f,t-1} + \gamma M_{f,t-1} + e_{f,t}, \tag{A1}$$

where $Dev_{f,t}$ is the average quarterly (or monthly) measure of deviation of fund f in year t; and the vector *M* stacks all other control variables, including *Log(Stock Size in Fund)*, *Log(Fund TNA), Log(Fund Age)*, *Expense Ratio*, *Fund Return*, and *Fund Flow*.

We report the results in Table IN1. Models 1 and 2 report the full sample result, and Models 3, 4, 5, and 6 consider subsamples that include only synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs, respectively. The results document the existence of a strong positive autocorrelation of both *Divergence* and *Swapped Transfer* over time, which holds across the different specifications. Funds with one standard deviation higher *Divergence* (*Swapped Transfer*) over one year display a 20.63% (133.7 bps) higher *Divergence* (*Swapped Transfer*) the following year. These results offer evidence that ETF investment strategies are different from pure benchmark tracking and persist over time.

Next, we investigate whether there is evidence of a common "behavior" for all the ETFs affiliated with the same group and for the ETFs with affiliated OEFs. More specifically, we seek to determine whether there is evidence that affiliation with the same group increases commonality in ownership between ETFs and other affiliated ETFs/OEFs. To illustrate this point, we perform our analysis at a pairwise level by estimating the following panel specification:

$$Diff_{ij,t} = \alpha + \beta AFL_{ij,t-1} + \gamma_1 M_{i,t-1} + \gamma_2 M_{j,t-1} + e_{ij,t}, \tag{A2}$$

where $Diff_{ij,t}$ is either the pairwise difference in holding divergence, computed as the average absolute quarterly difference in *Divergence* between fund i and fund j (i.e., another ETF or an OEF that is affiliated with the ETF industry) in year t ($|\Delta Divergence_{ij,t}|$), or the average quarterly correlation in investment weights of common holdings between fund i and fund j (i.e., another ETF or an OEF) in year t ($HoldSimilarity_{ij,t}$). $AFL_{ij,t-1}$ refers to the affiliation dummy variables, which take a value of one if both i and j are affiliated with the same conglomerate (*Same Affiliation Dummy*) or the same bank (*Same Bank Affiliation Dummy*). Vector *M* stacks *Benchmark Dummy* (a dummy variable taking a value of one if funds i and j track the same benchmark) and all other control variables for both funds, including *Log(Stock Size in Fund)*, *Log(Fund TNA)*, *Log(Fund Age)*, *Expense Ratio*, *Fund Return*, and *Fund Flow*. We include both year and fund fixed effects.

We report the results in Table IN2 in the Internet Appendix. Models 1 and 2 report results when the pairwise differences are computed from pairs of ETFs, and Models 3 and 4 report similar regression parameters when the pairwise differences are computed from pairs of ETFs and OEFs. Models 5 to 8 replace the pairwise divergence difference by holding similarity, $HoldSimilarity_{ij,t}$, which is computed as the average quarterly correlation in investment weights of common holdings between fund i and fund j (i.e., another ETF or an OEF) in year t. Panels B and C regress divergence difference and holding similarity, respectively, on the *Same Bank Affiliation Dummy* for subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs and European ETFs (only the main variable is tabulated for brevity).

The results show a strong correlation between the holdings of the ETFs with other ETFs and the holdings of ETFs with OEFs when these are part of ("affiliated with") the same group. This effect remains when the group is a banking group. More specifically, we observe a strong positive correlation between two funds affiliated with the same bank and the commonality of their holdings (in excess of the benchmark), which holds across alternative specifications and different models. Thus, bank affiliation increases the commonality of holdings among ETFs and among ETFs and OEFs, and the effect is highly economically significant. Affiliation with the same bank increases the degree of commonality among ETFs by 9.1% and between ETFs and OEFs by 8.7%.

Together, these stylized facts suggest that some ETFs systematically deviate from their benchmarks, which might be motivated by their affiliation with a (bank-based) financial conglomerate.

Next, we provide more evidence regarding the subsidizing (non-information related) role of ETFs. We directly relate the *Swapped Transfer* to the profitability of the affiliated bank. If, as argued in our text, the affiliated ETFs are used to help the affiliated bank, we would expect to see a negative relation between bank profitability and the *Swapped Transfer*. We therefore relate the divergence of the ETFs to the profitability of the affiliated bank. We estimate the following pooled specification, clustered at the fund or bank level, with fixed year and fund effects,

$$Swap_{f,t} = \alpha_0 + \beta_1 Bank\_Char_{f,t} + cM_{f,t-1} + e_{f,t}, \tag{A3}$$

where $Swap_{f,t}$ is the average monthly *Swapped Transfer* of fund f in year t; $Bank\_Char_{f,t}$ refers to the characteristics of affiliated banks, including the S&P long-term domestic issuer credit rating of its affiliated bank (the numeric rating ascending in credit risk, i.e., AAA = 1, …, D = 22) and annual bank performance measured by ROA and ROE; and the vector *M* stacks all other fund-level control variables.

We report the results in Table IN3, Panel A. We find a strong negative correlation between *Swapped Transfer* and proxies for the quality of the affiliated bank. In particular, a one-standard-deviation negative shock in ROA (ROE) is related to a 2.26% (0.86%) higher swapped transfer per month. Additionally, a one notch higher (worse) rating is related to a monthly 0.15% higher *Swapped Transfer*.

The effort to help the affiliated bank may also induce volatility in the ETF performance, which may occur more often in the case of poor bank performance. More specifically, when the affiliated bank is in worse financial condition, the ETFs will "desperately" try to help it more by investing in more volatile stocks, which will generate volatility in their *Swapped Transfer*. To test this point, in Panel B, we estimate the following panel regression with fixed year and fund effects,

$$SRV_{f,t} = \alpha_0 + \beta_1 Bank\_Char_{f,t} + cM_{f,t-1} + e_{f,t}, \tag{A4}$$

where $SRV_{f,t}$ is the standard deviation of monthly *Swapped Transfer* (the difference between ETF holding-based return and gross-of-fee NAV-based return) of fund f in year t.

The results are tabulated in Panel B of Table IN3. We find that lower quality of the affiliated bank is related to higher volatility of *Swapped Transfer*. A one-standard-deviation lower ROA (ROE) is related to a 2.17% (1.96%) higher volatility in *Swapped Transfer*. A one notch higher (worse) rating is related to a 0.52% higher volatility of *Swapped Transfer*.

Table IN1: The Existence and Persistence of ETF Divergence and Swapped Transfer

This table presents the results of the following annual pooled OLS regressions with year fixed effects and their corresponding t-statistics clustered at the fund level,

$$Dev_{f,t} = \alpha + \beta Dev_{f,t-1} + \gamma M_{f,t-1} + e_{f,t},$$

where $Dev_{f,t}$ refers to two deviation proxies of fund f in year t, and vector M stacks all other control variables, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Expense Ratio, Fund Return, and Fund Flow. Models 1 and 2 report the full sample result, and Models 3 to 6 consider subsamples that only include synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs, respectively. In Panel A, $Dev_{f,t}$ refers to $Divergence_{f,t}$ (the average quarterly holding Divergence of fund f in year t), and in Panel B, $Dev_{f,t}$ refers to $Swap_{f,t}$ (the average monthly Swapped Transfer of fund f in year t). Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Out-of-sample Holding Divergence Regressed on Lagged Holding Divergence

	Full Sample		Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.091**	-0.059	0.198	0.164	0.212	-0.683
	(2.21)	(-0.14)	(0.58)	(0.63)	(0.80)	(-0.95)
Holding Divergence	0.672***	0.681***	0.520***	0.768***	0.769***	0.607***
	(6.18)	(6.98)	(4.29)	(10.73)	(11.57)	(4.01)
Log (Stock Size in Fund)		0.022	0.024	-0.009	-0.017	0.060
		(0.60)	(1.63)	(-0.39)	(-0.74)	(1.05)
Log (Fund TNA)		0.003	0.007	0.007	0.004	0.007
		(0.26)	(0.47)	(1.18)	(0.62)	(0.40)
Log (Fund Age)		-0.012	-0.061	-0.035***	-0.017*	0.018
		(-0.93)	(-1.64)	(-2.82)	(-1.68)	(0.68)
Expense Ratio		-0.095**	0.113	-0.002	0.033	0.033
		(-2.26)	(1.41)	(-0.07)	(0.96)	(0.52)
Fund Return		0.001	-0.003	-0.002	-0.004	0.000
		(0.33)	(-0.53)	(-0.29)	(-0.54)	(0.09)
Fund Flow		-0.000	-0.000*	-0.000*	-0.000**	-0.000
		(-1.13)	(-1.71)	(-1.74)	(-2.09)	(-0.19)
R-squared	0.354	0.366	0.665	0.498	0.510	0.331
Obs	1,204	1,204	119	604	633	525

Panel B: Out-of-sample Swapped Transfer (in %) Regressed on Lagged Swapped Transfer

	Full Sample		Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.078	-0.283	3.748*	-0.455*	-0.072	-2.580*
	(0.96)	(-1.56)	(1.88)	(-1.95)	(-0.57)	(-1.68)
Swapped Transfer	0.246***	0.255***	0.260**	0.191**	0.054	0.293***
	(3.18)	(3.46)	(2.09)	(2.24)	(0.76)	(2.83)
Log (Stock Size in Fund)		0.013*	-0.228	0.011	0.006	0.027
		(1.93)	(-1.58)	(1.53)	(1.11)	(1.06)
Log (Fund TNA)		0.002	-0.050	0.015*	0.010**	-0.025
		(0.21)	(-1.17)	(1.94)	(2.11)	(-1.35)
Log (Fund Age)		-0.032	-0.254**	-0.063	-0.006	-0.069
		(-0.80)	(-2.50)	(-1.27)	(-0.23)	(-1.03)
Expense Ratio		-0.045	-0.501	0.004	0.056	6.075
		(-0.47)	(-0.80)	(0.05)	(0.67)	(1.60)
Fund Return		0.096***	0.161*	0.100***	0.091***	0.087*
		(4.30)	(1.86)	(3.43)	(4.57)	(1.89)
Fund Flow		0.003**	0.001	0.004***	0.004*	0.003
		(2.22)	(0.48)	(2.64)	(1.84)	(1.31)
R-squared	0.080	0.199	0.352	0.268	0.250	0.244
Obs	1,204	1,204	119	604	633	525

Table IN2: Similarity in Pairwise Divergence due to Bank Affiliation

Panel A presents the results of the following annual panel regressions with year and fund fixed effects and their corresponding t-statistics clustered at the fund-pair level, $|\Delta Divergence_{ij,t}| = \alpha + \beta AFL_{ij,t-1} + \gamma_1 M_{i,t-1} + \gamma_2 M_{j,t-1} + e_{ij,t}$, where $|\Delta Divergence_{ij,t}|$ is the pairwise difference in holding divergence, which is computed as the average absolute quarterly difference in *Divergence* between fund i and fund j (i.e., another ETF or an OEF that is affiliated with the ETF industry) in year t, $AFL_{ij,t-1}$ refers to the affiliation dummy variables, taking a value of one if both i and j are affiliated with the same conglomerate (*Same Affiliation Dummy*) or the same bank (*Same Bank Affiliation Dummy*), respectively, and the vector M stacks *Benchmark Dummy* (a dummy variable taking a value of one if fund i and j track the same benchmark), and all other control variables for both funds, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Expense Ratio, Fund Return and Fund Flow. Models 1 and 2 report results when the pairwise differences are computed from pairs of ETFs. Models 3 and 4 report similar regression parameters when the pairwise differences are computed from pairs between ETFs and OEFs. Models 5 to 8 replace the pairwise divergence difference by holding similarity, $HoldSimilarity_{ij,t}$, which is computed as the average quarterly correlation in investment weights of common holdings between fund i and fund j (i.e., another ETF or an OEF) in year t. Panels B and C regress divergence difference and holding similarity, respectively, on the *Same Bank Affiliation Dummy* for subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs (only the main variable is tabulated for brevity). Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Out-of-sample Pairwise Divergence Similarity Regressed on Affiliation Dummies

	Divergence Difference				Holding Similarity			
	ETF(i)-ETF(j) Pairs		ETF(i)-OEF(j) Pairs		ETF(i)-ETF(j) Pairs		ETF(i)-OEF(j) Pairs	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.254	0.145	1.052***	1.050***	0.889**	1.101***	-0.445*	-0.445*
	(0.91)	(0.51)	(9.10)	(9.10)	(2.23)	(2.84)	(-1.78)	(-1.77)
Same Affiliation Dummy	-0.114***		-0.048***		0.108***		0.082***	
	(-4.23)		(-2.92)		(3.44)		(3.40)	
Same Bank Affiliation Dummy		-0.089***		-0.055***		0.091***		0.087***
		(-3.32)		(-3.19)		(2.76)		(3.38)
Benchmark Dummy	-0.139***	-0.138***	0.004	0.004	0.178***	0.178***	0.178***	0.178***
	(-3.22)	(-3.16)	(0.15)	(0.14)	(2.89)	(2.89)	(6.21)	(6.22)
Log (Stock Size in Fund)$_i$	-0.015	-0.015	0.000	0.000	0.023	0.022	0.016	0.016
	(-0.95)	(-0.96)	(0.02)	(0.02)	(0.89)	(0.88)	(1.19)	(1.20)
Log (Stock Size in Fund)$_j$	-0.007	-0.008	-0.033***	-0.033***	0.004	0.004	0.064***	0.064***
	(-1.09)	(-1.10)	(-5.12)	(-5.11)	(0.28)	(0.28)	(4.88)	(4.86)
Log (Fund TNA)$_i$	-0.001	-0.001	-0.003	-0.003	-0.017**	-0.017**	-0.003	-0.003
	(-0.14)	(-0.14)	(-1.49)	(-1.50)	(-2.20)	(-2.24)	(-0.43)	(-0.41)
Log (Fund TNA)$_j$	-0.000	-0.000	-0.019***	-0.019***	-0.008	-0.007	-0.001	-0.001
	(-0.06)	(-0.06)	(-5.51)	(-5.50)	(-0.85)	(-0.84)	(-0.12)	(-0.12)
Log (Fund Age)$_i$	-0.051***	-0.050***	-0.006	-0.006	0.059*	0.059*	0.044**	0.044**
	(-2.94)	(-2.89)	(-1.27)	(-1.26)	(1.78)	(1.76)	(1.99)	(2.00)
Log (Fund Age)$_j$	-0.000	-0.000	-0.001	-0.001	0.042***	0.043***	0.006	0.006
	(-0.03)	(-0.05)	(-0.29)	(-0.30)	(2.59)	(2.62)	(0.76)	(0.76)
Expense Ratio$_i$	0.088*	0.088*	0.063***	0.063***	-0.027	-0.025	0.007	0.006
	(1.83)	(1.83)	(3.75)	(3.75)	(-0.34)	(-0.33)	(0.17)	(0.16)
Expense Ratio$_j$	-0.008	-0.009	-0.002	-0.001	0.043	0.041	-0.073***	-0.074***
	(-0.25)	(-0.29)	(-0.22)	(-0.19)	(0.51)	(0.48)	(-4.76)	(-4.83)
Fund Return$_i$	-0.004	-0.004	-0.000	-0.000	0.004	0.004	-0.003	-0.003
	(-0.67)	(-0.68)	(-0.00)	(-0.01)	(0.64)	(0.63)	(-0.77)	(-0.79)
Fund Return$_j$	0.000	0.000	-0.003	-0.003	-0.000	-0.000	0.002	0.002
	(0.05)	(0.03)	(-1.63)	(-1.61)	(-0.07)	(-0.07)	(0.38)	(0.38)
Fund Flow$_i$	-0.001	-0.001	-0.000	-0.000	0.001	0.001	0.001	0.001
	(-1.61)	(-1.64)	(-1.28)	(-1.28)	(0.93)	(0.91)	(1.35)	(1.44)
Fund Flow$_j$	-0.000	-0.000	0.000	0.000	0.000	0.000	0.002***	0.002***
	(-1.16)	(-1.18)	(1.19)	(1.18)	(1.41)	(1.46)	(4.58)	(4.75)
R-squared	0.48	0.474	0.078	0.078	0.523	0.521	0.152	0.152
Obs	46,257	46,257	434,057	434,057	20,925	20,925	101,905	101,905

Panel B: Out-of-sample Pairwise Divergence Difference Regressed on Affiliation Dummies (Subsample)

	ETF(i)-ETF(j) Pairs				ETF(i)-OEF(j) Pairs			
	Synthetic	Sampling	U.S.	European	Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Same Bank Affiliation Dummy	-0.236***	-0.141***	-0.088**	-0.101***	-0.044***	-0.059***	-0.072***	-0.036**
	(-5.71)	(-3.67)	(-2.09)	(-3.23)	(-2.72)	(-3.49)	(-4.31)	(-2.49)
Fund Controls	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.463	0.545	0.538	0.452	0.069	0.122	0.126	0.058
Obs	1,707	8,193	8,455	13,357	64,548	187,558	191,859	224,374

Panel C: Out-of-sample Pairwise Holding Similarity Regressed on Affiliation Dummies (Subsample)

	ETF(i)-ETF(j) Pairs				ETF(i)-OEF(j) Pairs			
	Synthetic	Sampling	U.S.	European	Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Same Bank Affiliation Dummy	0.566***	0.012	-0.001	0.242***	-0.028	0.115***	0.112***	0.031***
	(5.46)	(0.47)	(-0.06)	(5.88)	(-0.64)	(8.77)	(8.25)	(3.11)
Fund Controls	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.621	0.531	0.528	0.533	0.184	0.129	0.133	0.181
Obs	1,767	5,936	6,619	8,374	6,451	63,194	67,672	32,884

Table IN3: ETF Swapped Transfer and Its Volatility Related to Affiliated Bank (ETF Level)

Panel A presents the results of the following panel regressions with year and fund fixed effects, as well as their corresponding t-statistics clustered at the fund or bank level,

$$Swap_{f,t} = \alpha_0 + \beta_1 Bank\_Char_{f,t} + cM_{f,t-1} + e_{f,t},$$

where $Swap_{f,t}$ is the average monthly Swapped Transfer of fund f in year t; $Bank\_Char_{f,t}$ refers to the characteristics of affiliated banks, including the S&P long-term domestic issuer credit rating of its affiliated bank (the numeric rating ascending in credit risk, i.e., AAA = 1, …, D = 22) and annual bank performance measured by ROA and ROE; and the vector M stacks all other control variables, including Log(Stock Size in Fund), Log(Fund TNA), Log(Fund Age), Expense Ratio Fund Return and Fund Flow. Panel B presents similar regression parameters of the following regressions,

$$SRV_{f,t} = \alpha_0 + \beta_1 Bank\_Char_{f,t} + cM_{f,t-1} + e_{f,t},$$

where $SRV_{f,t}$ is the standard deviation of monthly Swapped Transfer (the difference between ETF holding-based return and gross-of-fee NAV-based return) of fund f in year t. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% levels, respectively.

Panel A: Swapped Transfer (in %) Regressed on ETF and Bank Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.773	1.943**	1.632**	0.773	1.943*	1.632
	(1.06)	(2.44)	(2.06)	(0.84)	(2.04)	(1.36)
Bank Rating	0.147***			0.147***		
	(4.11)			(4.56)		
Bank ROA		-0.349***			-0.349***	
		(-3.67)			(-4.07)	
Bank ROE			-0.033***			-0.033***
			(-5.31)			(-8.54)
Log (Stock Size in Fund)	-0.045	-0.086	-0.077	-0.045	-0.086***	-0.077**
	(-0.62)	(-1.26)	(-1.14)	(-0.92)	(-4.36)	(-2.94)
Log (Fund TNA)	-0.070**	-0.056	-0.057*	-0.070**	-0.056	-0.057
	(-2.07)	(-1.59)	(-1.66)	(-2.71)	(-1.65)	(-1.68)
Log (Fund Age)	0.109	0.130	0.132*	0.109**	0.130**	0.132**
	(1.41)	(1.63)	(1.67)	(3.56)	(2.80)	(2.83)
Expense Ratio	-0.950***	-0.840***	-0.936***	-0.950	-0.840	-0.936
	(-3.08)	(-2.79)	(-3.08)	(-1.89)	(-1.52)	(-1.91)
Fund Return	0.100**	0.086**	0.072	0.100**	0.086*	0.072
	(2.30)	(1.98)	(1.62)	(3.27)	(2.10)	(1.32)
Fund Flow	0.006*	0.005*	0.005*	0.006***	0.005***	0.005***
	(1.97)	(1.77)	(1.71)	(5.34)	(4.19)	(3.95)
R-squared	0.233	0.228	0.242	0.233	0.228	0.242
Obs	704	704	704	704	704	704
Clustering	Fund	Fund	Fund	Bank	Bank	Bank

Panel B: Standard Deviation of Swapped Transfer (in %) Regressed on ETF and Bank Characteristics						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	4.981	5.848	5.803	4.981	5.848	5.803
	(0.64)	(0.84)	(0.85)	(0.44)	(0.65)	(0.64)
Bank Rating	0.517*			0.517*		
	(1.89)			(2.15)		
Bank ROA		-0.336**			-0.336**	
		(-2.35)			(-2.94)	
Bank ROE			-0.075***			-0.075***
			(-2.69)			(-4.11)
Log (Stock Size in Fund)	-0.339	-0.288	-0.258	-0.339	-0.288	-0.258
	(-1.13)	(-0.93)	(-0.82)	(-1.05)	(-0.69)	(-0.63)
Log (Fund TNA)	-0.053	0.037	0.022	-0.053	0.037	0.022
	(-0.30)	(0.19)	(0.12)	(-0.59)	(0.57)	(0.35)
Log (Fund Age)	0.052	-0.021	-0.025	0.052	-0.021	-0.025
	(0.05)	(-0.02)	(-0.03)	(0.04)	(-0.02)	(-0.02)
Expense Ratio	-3.506**	-3.116*	-3.898*	-3.506*	-3.116*	-3.898**
	(-1.99)	(-1.75)	(-1.91)	(-2.11)	(-2.01)	(-3.42)
Fund Return	-0.332**	0.087	0.064	-0.332**	0.087	0.064
	(-2.48)	(0.94)	(0.68)	(-3.12)	(1.51)	(1.67)
Fund Flow	0.014**	0.007	0.007	0.014***	0.007	0.007*
	(1.99)	(1.02)	(1.09)	(4.07)	(1.85)	(2.31)
R-squared	0.328	0.299	0.307	0.328	0.299	0.307
Obs	704	704	704	704	704	704
Clustering	Fund	Fund	Fund	Bank	Bank	Bank