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JEL Classification: G20

Keywords: ETFs, Subsidization, banks, shadow banking, Distress

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The Unexpected Activeness of Passive Investors: A World-Wide Analysis of ETFs

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The Unexpected Activeness of Passive Investors:
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The global ETF industry provides more complicated investment vehicles than low-cost index trackers. Instead, we find that the real investments of ETFs deviates from their benchmarks to leverage informational advantages (which leads to a surprising stock-selection ability), and to help affiliated OEFs through cross-trading. These effects are more prevalent in ETFs domiciled in Europe. Market awareness of such additional risk is reflected in ETF outflows. These results have important normative implications for consumer protection and financial stability.

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"*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 open-end mutual funds (OEFs) and equity markets over the same period. The press has extolled the benefits of ETFs as cheap alternatives to traditional 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, many ETF sponsors start to seek alternative investment techniques, such as synthetic replication with affiliated banks, security lending, and active divergence from the benchmark (e.g., Ramaswamy (2011)). These techniques may 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 a lower cost, the actual portfolio allocation will deviate from the benchmark. Because ETF investors only require the index return, ETF

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

investors may not fully enjoy the upside of the actual portfolio investment, although they may be exposed to additional risk if the swap counterparty defaults on the promised delivery of the index return.

These features have raised the concerns of regulators on the incentives of ETFs. For example, the Financial Services Authority has identified the potential for conflicts of interest as one of the major concerns and suggested 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.[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 the incentives of ETFs by focusing on the universe of worldwide equity ETFs and OEFs during the 2001–2009 period.[4] We use international data because it is more common for ETFs to use alternative replication strategies in the global ETF industry.

We start by documenting a surprising selection ability of ETFs, even though these funds in public views are largely passive index trackers. More explicitly, we find strong evidence that ETFs deviate from their benchmarks in stocks that have a lending relationship with their affiliated banks ("bank loan channel"). Moreover, such deviations are highly informative: for stocks receiving corporate-loan services from banks, each 1% increase in benchmark-adjusted ownership of ETFs affiliated with these banks (hereafter, bank loan-related abnormal ownership of ETFs) is related to a 12 bps higher DGTW-adjusted return per year. By contrast, for a same stock, the abnormal ownership of ETFs unaffiliated with the banks providing loan services conveys no such information. The difference between the informativeness of ownership changes of affiliated ETFs and that of unaffiliated ETFs

[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.
[4] 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.

strongly suggests that ETFs can overweight (underweight) stocks that are somehow confirmed to be good (bad) via their affiliate banks' corporate loan services.

It is interesting to compare the informativeness of ETF trading to that of mutual funds. Affiliations with banks are known to accrue information to active open-end mutual funds (OEFs) in the mutual fund industry (e.g., Irvine, Lipson and Puckett (2007), Massa and Rehman (2008), Massa and Zhang (2012)), which is in spirit close to our finding in the ETF industry. However, this seemingly similar observation could imply drastically different incentives and normative implications in the two industries. On the one hand, it is perhaps not surprising for active mutual funds to collect superior information in order to create better performance for their investors. On the other hand, the same intuition does not directly apply to the ETF industry, as ETFs do not have the fiduciary duty to generate index-adjusted performance for investors. Rather, any performance that is not delivered to investors will be ultimately paid back to affiliated banks, for instance through the aforementioned swap design. Moreover, unlike OEFs, most ETFs are affiliated with bank conglomerates (as opposed to specialized asset management companies). These institutional differences imply that ETFs could be exposed more to the incentives to help affiliated financial conglomerates, which we can term as "*pro-conglomerate incentives*", than to the incentives of delivering superior performance to investors, which we label "*pro-investor incentives*". It is therefore critical to ask whether the surprising selection ability of ETFs reflects the former incentives because, if so, regulators and practitioners do have grounds to worry about the role played by ETFs in the financial market.

To better understand the incentives associated with ETFs, we investigate three issues. First, how pervasive are the pro-conglomerate incentives – i.e., is ETF activeness limited only to the collection of information through the bank-loan channel, or could there be other mechanisms leading ETFs to deviate from their public image of index tracker as well? Second, do investors benefit or suffer from these mechanisms? Note that even though ETFs deliver index return in general, they can still share additional benefits with the investors through reductions in fees. In other words, pro-conglomerate and pro-investor incentives are not necessarily mutually exclusive. Investors can still benefit or suffer from pro-investor or pro-conglomerate incentives through variations in fees. Finally, how do investors respond to ETF incentives? Pro-conglomerate incentive does not necessarily mean conflict of interest as long as investors do not get hurt. But do investors nonetheless worry about such incentives? Addressing these questions will help us to understand the potential opportunities and risks associated with the ETF industry.

Regarding the first question, we find that pro-conglomerate incentives are quite widely observed through several distinctive mechanisms. Similar to what we have observed in the bank-loan channel, ETFs investment in the stocks of the affiliated bank is related to better performance: an increase in abnormal ownership of affiliated ETFs predicts higher performance of the bank stock. ETF investments in stocks with high ownership of the affiliated OEFs also appear informative. However, in addition to these informative trading mechanisms, ETFs also seem to engage in cross-trades with affiliated OEFs. All these mechanisms can potentially benefit the affiliated conglomerate. Unlike informative trading, cross-trading is typically related to negative performance as opposed to positive performance for ETFs. Therefore, cross-trades with OEFs, far from helping the ETFs are in fact very damaging to them. It is the OEFs that benefit from these cross-trades: a one-standard-deviation increase in ETF/OEF cross-trades leads to an annualized 5.9% higher return and 13.84% higher inflow for the affiliated OEFs. Cross-trades therefore offer an even more drastic example of pro-conglomerate incentivized activeness to subsidize affiliated poor-performing OEFs.

In order to explore the second question, we link the major benefits and costs of ETF investments from investors' perspective, including the degree of inaccuracy (or risk) in tracking benchmarks as well as the level of ETF fees, to the aforementioned mechanisms of ETF's pro-conglomerate activeness –i.e., ETF's investment in stocks with affiliated bank-loan services, ETF's investment in stocks of affiliated bank, and the performance of affiliated OEFs. We find that all these mechanisms are positively associated with tracking errors. Moreover, investment in affiliated bank-loan stocks and affiliated bank stocks allow ETFs to generate performance from their holdings, but fees are largely unaffected. In other words, the potential benefits associated with the selection ability of ETFs are not passed on to the investors through the reduction in fees. Even worse, every 1% negative return of affiliated OEFs is associated with 14 bps of additional ETF fees, potentially reflecting the cost of cross-trades shared by ETF investors.

Overall, these results suggest that ETFs do not seem to pass on additional benefit to the investors either as reduced fees or in terms of lower tracking errors, yet ETF investors may face some risk of negative performance when ETFs need to subsidize affiliated OEFs. In this regard, ETF assets provide a sort of "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 ETF.

Finally, we ask whether the investors are aware of this pro-conglomerate incentives and worry about it. To address this last issue is not easy, as it is highly complex (if not impossible) to quantify the risk implications of each off-benchmark operation. However, we can derive some indirect evidence with a sort of "revealed preference approach" analysis of investor demand that exploits a unique feature of the ETF industry: unlike the case for OEFs, ETF flows are typically associated with sophisticated institutional investors. More explicitly, although investors can both trade ETFs in the market (which leads to trading volume but not ETF flows) and invest/redeem their ETF shares at the fund level (which directly transform into inflows/outflows), the high capital request of the latter is affordable only to the institutional investors.[5] Hence, ETF flows provide a relatively clean measure of the demand of sophisticated institutional investors. This allows us to gauge the impact of subsidization by examining whether sophisticated investors penalize potential subsidization by reducing their demand.

To perform our analysis, we also construct an indirect measure to gauge the impact of potential subsidization as the difference between the holding-based return that ETFs can generate and the gross-of-fee reported return of the ETFs that investors can receive. A positive difference implies a

[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". In this case, retail investors tend to buy and sell ETFs shares in the market and the process of creation/redemption of shares is mostly reserved to sophisticated institutional investors. ETF flows are often regarded as a built-in arbitrage mechanism to ensure that ETF market prices do not deviate substantially from NAVs.

potential transfer of benefits from the ETFs to the affiliated financial conglomerate – hence we refer to this difference as *Swapped Transfer* when there is no confusion. In the lack of explicit information on the actual transactions across affiliated parties, this variable provides a rough approximation of what could be transferred, directly – e.g., by a formal swap contract – or indirectly – e.g., by cross-trade – from the ETFs to the affiliated financial conglomerate. More importantly, it captures the potential concern that investors and regulators may have on subsidizations – that is, ETFs may transfer benefits to their affiliated financial conglomerates rather than to their investors.

We find that positive *Swapped Transfer* is typically associated with higher ETF outflows. A one-standard-deviation increase in *Swapped Transfer* is associated with an annual outflow of 3.56%. In other words, investors seem to have concerns when affiliated financial conglomerates, rather than investors, benefit from the off-benchmark activities of ETFs. The magnitude of the effect is in line with investors' response to their direct losses: a one-standard-deviation increase in ETF fees is associated with an annual outflow of 8.61%. Moreover, ETF investors also withdraw capital when the affiliated bank's rating or return on assets (ROA) drops. A one-standard-deviation deterioration in bank rating translates into 9.18% lower flows per year. More importantly, the outflow sensitivity with respective to *Swapped Transfer* increases with a worsening of the ratings and ROA of the affiliated bank. These patterns suggest that investors regard potential subsidizations between ETFs and affiliated banks as detrimental especially when the latter become risky.

Overall, these findings suggest that the global ETF industry is much more complicated than a simple offering of index trackers might indicate. They are the first – to the best of our knowledge – to provide evidence in support of recent regulatory concerns on the incentives of ETFs using alternative strategies to replicate their benchmarks (e.g., FSB (2011), IMF (2011), Ramaswamy (2011)). One caveat here is that some of our tests are indirect – for instance those associated with the third question. However, even these indirect observations suggest that the popularity of ETFs among investors and their active 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)).

In doing so, we also contribute to the burgeoning literature on ETFs. Although the entire ETF industry only has less than three decades of history, its growth speed has dwarfed other types of asset management firms and, subsequently, attracted tremendous academic attention (e.g., Boehmer and Boehmer (2003), Ben-David, Franzoni and Moussawi (2014), Da and Shive (2015), Israeli, Lee and Sridharan (2015)). Most existing studies focus on ETFs as a trading instrument, from market traders' perspective. Our paper investigates the incentives of these funds instead.

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. 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 (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 first briefly describe the industry and then we define our data variables.

A. 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 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.[6]

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

[6] 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)).

"Broker/Investment Bank Asset Management" in Factset.[7] 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),[8] 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 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. 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 pro-conglomerate incentives could be more influential in Europe.

The last two columns of Panel A report the fraction of ETFs for which we are able to construct the benchmarks.[9] 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

[7] 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".

[8] 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.

[9] 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. Use of the actual weights of explicitly indexed funds tracking the benchmark has the advantage that some of the weights in the official benchmark include stocks that in practice may not be fully investable by mutual funds due to illiquidity or other constraints.

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.[10]

B. Data Sources

Our data are drawn from different sources. The ETF and OEF holdings data are from the Factset/Lionshares database.[11] The Factset/Lionshares holdings data on international funds are sparse before 2001, so our sample is restricted to the 2001–2009 period. 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 variables quoted in USD. 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.

[10] 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.

[11] 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.

C. Variables

We will define the main variables in the subsequent sections as we use them. Here, we just summarize the main control variables we will use in this paper as well as the measures of performance.

We consider measures of both ETF and stock performance. The measures of ETF performance are the gross-of-fee *NAV-based Return*, the benchmark-adjusted fund return, DGTW-adjusted *Holding-based Return* and the *ActiveShr Performance*. *Holding-based Return* of an ETF is defined as the investment value-weighted average of the returns of the stocks in its portfolio. It represents the return the ETF would have earned based on the stocks in its portfolio. The *ActiveShr Performance* is computed as the difference between the holding-based return of an ETF and that of its benchmark. It captures the abnormal return that an ETF can generate by deviating from the holding portfolio of its benchmark.

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 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).[12] The construction of these international factors is in the spirit of Griffin (2002). We extend these international factors to 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.[13]

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

[12] 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.

[13] 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)).

its style average to compute its DGTW-adjusted return. Finally, we obtain portfolio-level *DGTW-adjusted Return* as the investment value-weighted average of stock-level DGTW-adjusted returns for all the stocks in the portfolio.

We 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.

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, 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.

The *DGTW-adjusted Return* for the 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. The Surprising Selection Ability of ETFs

In this section, we document a surprising selection ability of ETFs based on their affiliations with banks and discuss its implications. To capture the potential information benefits accruing from the affiliation with the bank conglomerate, we use the LPC DealScan data and define a dummy variable, $CorporateLoanDummy_{i,f,t}$, 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 information that ETFs may obtain from their affiliated banks based on such banks' processing of corporate loans.

Then, we use this dummy to define bank loan-related abnormal (i.e., benchmark adjusted) stock ownership for all the ETFs as follows: $ETFadjOwn(Loaned\ Corp)_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times CorporateLoanDummy_{i,f,t}$, where $ETFadjOwn(Loaned\ Corp)_{i,t}$ refers to bank loan-related abnormal ETF ownership for stock i in period t, $h_{i,f,t}$ and $\hat{h}_{i,f,t}$ refer to the real and benchmark-implied ownership of ETF f in stock i, respectively. If the bank-loan channel is indeed motivated by information, a positive change in abnormal ownership should predict higher stock returns out-of-sample. We therefore estimate the annual panel regression:

$$Perf_{i,t} = \alpha + \beta \times \Delta ETFadjOwn(Loaned\ Corp)_{i,t-1} + \gamma M_{i,t-1} + e_{i,t}, \qquad (1)$$

where $Perf_{i,t}$ is the average monthly DGTW-adjusted return of a stock in year t, and $\Delta ETFadjOwn(Loaned\ Corp)_{i,t-1}$ refers to changes in abnormal ETF ownership of stock i in year $t-1$ 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 2. Models 1 through 4 report the full sample results. The results document that bank loan-related abnormal ownership of ETFs can generate significant performance out of sample: in Model 2, for instance, each 1% increase in bank loan-related abnormal ownership of ETFs can be transferred to a 12 bps higher DGTW-adjusted return per year.[14]

As a "Placebo" test, we also construct the abnormal ETF ownership unrelated to affiliated bank loan services as follows:

$$ETFadjOwn(Unloaned\ Corp)_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times (1 - CorporateLoanDummy_{i,f,t}) \quad ,$$

in which all variables are defined the same as in $ETFadjOwn(Loaned\ Corp)_{i,t}$. The results reported in Models 3 and 4 show that the abnormal ETF ownership changes unrelated to affiliated bank loan services 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 Models 5 to 8, we break down the analysis into different subsamples. In Models 5 and 6, we consider the synthetic and sampling ETFs, whereas in Models 7 and 8, we consider U.S. and 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 confirmed to be good (bad) via the affiliate banks' corporate loan services. In brief, ETFs trading exhibits a surprising selection ability.

Although active open-end mutual funds (OEFs) are known to accrue information from affiliated banks (e.g., Irvine, Lipson and Puckett (2007), Massa and Rehman (2008), Massa and Zhang (2012)),

[14] The dependent variable is reported as a percentage of monthly abnormal return. Thus, the impact of a 1% increase in $\Delta ETFadjOwn(Loaned\ Corp)$ can be estimated for Model 2, for instance, as $1.014\% \times 12 \times 1\% = 12.17$ bps. Unreported tests using raw stock return lead to very similar results, and each 1% increase in bank loan-related abnormal ownership of ETFs can be transferred to a 11 bps higher return per year.

their incentives are very different. Active OEFs want to collect superior information to deliver better performance to their investors. By contrast, ETFs do not have the fiduciary duty to generate index-adjusted performance for investors. Why, in this case, do ETFs have incentives to collect information?

It is important to understand the incentives behind the surprising selection ability of ETFs, not the least because the latter may indicate an incentive to help affiliated financial conglomerates (i.e., "*pro-conglomerate incentives*") as opposed to deliver superior performance to investors (i.e., "*pro-investor incentives*"). Indeed, precisely because ETFs do not have any duty to deliver extra benefits to their investors, the benefits generated from this surprising selection ability could be ultimately delivered back to affiliated conglomerate through, for instance, the swap design between ETFs and their affiliated conglomerates. In this case, conglomerates have incentives to accrue information to their affiliated ETFs, allowing the former to indirectly benefit from the information advantage that they obtain from the financial services they offer. In this regard, compared to OEFs, ETFs provide a more suitable instrument to implement *pro-conglomerate incentives* because of the combination of their index-tracking fiduciary duty (i.e., extra benefits do not need to be passed on to investors) and the potential swap designs between ETFs and affiliated conglomerates.

The rest of our paper examines three important questions which will allow us to better portrait ETF incentives. First, how pervasive are pro-conglomerate incentives? In addition to the bank-loan channel as described in this section, could there be other pro-conglomerate incentivized mechanisms in which ETFs actively deviate from their public image of index tracker? Second, do investors benefit or suffer from these mechanisms – i.e. could pro-conglomerate incentives also benefit investors? Finally, how do investors respond to pro-investor incentives? We examine these three questions in the following three sections, respectively.

IV. How Pervasive Are Pro-conglomerate Incentives ?

We start with the first question of how pervasive is ETF activeness that could be related to pro-conglomerate incentives. We extend the investigation to stocks on which ETFs may derive information from their affiliations: stocks of the affiliated bank as well as stocks (co-)invested by the affiliated OEFs. We also explore the channel of cross-trading between affiliated ETFs and OEFs.

A. Selection Ability on Affiliated Bank Stocks

ETFs may directly derive information (from their affiliated conglomerate) on the stocks of their affiliated bank. Does their trading predict abnormal performance of the bank stock as the bank loan channel? To address this issue, we estimate the following panel specification:

$$Perf_{b,q} = \alpha + \beta \times \Delta ETFadjOwn(Affiliated\ Bank)_{b,q-1} + \gamma M_{b,q-1} + e_{b,q}, \tag{2}$$

where $Perf_{b,q}$ is the average monthly DGTW-adjusted return of a bank stock in quarter q, and $\Delta ETFadjOwn(Affiliated\ Bank)_{b,q-1}$ refers to changes in abnormal ETF ownership in bank b by the affiliated ETFs (by netting out their benchmark-implied ownership). The vector M stacks all other stock and fund control variables as defined previously. We add quarter and bank fixed effects, and cluster the errors at the bank level.

We report the results in Table 3. Models 1 through 4 report the full sample results. Especially, Models 1 and 2 document that an increase in abnormal ownership of affiliated ETFs predicts higher performance of the bank stock. Models 3 and 4 present a "Placebo" test, where we construct $\Delta ETFadjOwn(Unaffiliated\ Bank)_{b,q-1}$ as the change in percentage abnormal stock ownership held by the ETFs for *unaffiliated* banks. Models 5 to 8 further apply Model 4 to subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs. We see that affiliated ETF abnormal ownership changes forecast bank performance in all sub-groups except for the case of U.S. ETFs. In contrast, if we focus on ETFs unaffiliated with the bank, their abnormal ownership changes do not predict bank return. This provides evidence of selection ability related to superior information.[15]

B. Co-ownership and Cross-Trading between ETFs and Affiliated OEFs

[15] This evidence is also consistent with the possibility of bank support – i.e., the investment of the ETF is used to prop up the value of the shares of the affiliated bank. While this is possible, still the effect for the fund is to invest in assets whose price goes up in value. In the presence of pure price support, it is not clear this will translate in a consistent positive relationship between investment and future return.

Another potential source of information for the ETFs are the affiliated OEFs. We therefore investigate if there is any relation between the stock selection of the ETFs and the stakes of the affiliated OEFs. More specifically, we estimate:

$$Perf_{i,t} = \alpha + \beta \times \Delta ETFadjOwn(High\ ETF/OEF\ Co\text{-}Ownership)_{i,t-1} + \gamma M_{i,t-1} + e_{i,t}, \quad (3)$$

where $\Delta ETFadjOwn(High\ ETF/OEF\ Co\text{-}Ownership)_{i,t-1}$ refers to changes in abnormal ETF ownership in stocks in which the affiliated OEFs have high degree of co-investment (i.e., co-ownership). High and Low co-ownership are constructed according to the median breakpoint in the cross section of each period. For stocks in which ETFs and OEFs have high co-ownership, we expect the ETF trading to be informative because information could be accrued from affiliated OEFs or conglomerate for these relative "important" stocks. The use of this information is beneficial to affiliated conglomerate in a way that is similar to the bank-loan channel.

Another important way of benefiting affiliated conglomerate is cross-trading ("cross-trades"), through which ETFs and affiliated OEFs could swap trading benefits/losses (see Gaspar, Massa and Matos (2006) for the cross-trading mechanism within the OEF industry). To explore whether this channel also exists, we also construct a variable $\Delta ETFadjOwn(High\ ETF/OEF\ CrossTrades)_{i,t}$, referring to changes in abnormal ETF ownership in stocks in which the affiliated OEFs have high degree of cross-trading, where cross-trading is defined following Gaspar, Massa and Matos (2006) – Appendix A provides the detailed definition. We then link stock performance to this cross-trading related ownership variable by replacing the co-ownership variable with this variable in Equation (3).

We report the results in Table 4. Models 1 through 4 report the results for the co-ownership-based variable and Models 5 to 8 report the results for the cross-trades-based variable. We find that changes in abnormal ETF ownership in stocks also heavily held by affiliated OEFs increase the subsequent ETF performance. For instance, each 1% increase in ETF/OEF co-ownership-based abnormal ownership of ETFs is related to a 4.5 bps higher DGTW-adjusted return per year (Model 4). On the other hand, cross-trade between ETFs and affiliated OEFs is related to negative performance. In particular, each 1% increase in abnormal ownership of ETFs in stocks with low ETF/OEF cross-trades activities is related to a 3 bps higher DGTW-adjusted return per year (Model 8).

Given that the ETF/OEF co-ownership could result from the information spillover between affiliated OEFs and ETFs, while ETF/OEF cross-trades are largely driven by the need to subsidize affiliated OEFs, we further investigate their joint effect when we separately consider either the stocks of firms that borrow from the affiliated bank or the stocks of firms which do not borrow from the affiliated bank. The results are reported in the Internet Appendix (Table IN1). We find that changes in abnormal ETF ownership in stocks with high co-ownership and low cross-trades predict higher DGTW-adjusted return in the full sample as well as in all the sub-samples, while high co-ownership and high cross-trades are associated with superior performance only in the case of stocks of lending-related firms. This further suggests that ETFs and OEFs receive common information related to bank loans from the affiliated bank.

C. Pro-conglomerate Incentives behind ETF/OEF Cross-Trades

Our results so far suggest that cross-trades with OEFs, far from helping the ETFs are in fact very damaging to them. Before we move on to investigate investors' benefit/cost associated with this mechanism (which is the goal of our next section), we want to explore further how cross-trades could benefit affiliated conglomerate.

Our conjecture is that cross-trade may also be used to help bad performing OEFs in the same group. By help promoting OEFs' performance, cross-trades from ETFs could effectively help OEFs to avoid outflows/attract new flows.[16] We test this hypothesis in a two-stage framework. In the first stage, we consider the possibility that both ETFs and OEFs deviate from their benchmark to allow for convenient cross-trading. In this case, their portfolios exhibit off-benchmark active shares in the spirit of Cremers and Petajisto (2009). To conduct cross-trading on a particular stock, however, both parties need to deviate on the same stock. Hence, we need to go beyond the original active share measure and investigate how *common* active ownership between ETFs and OEFs (which we label *ETF/OEF*

[16] Note that it makes sense for performance to be transferred from a "closed-end" instrument to an "open-end" fund, as the former will not suffer from outflows due to the "closed-end" property while the latter will gain inflows due to the "open-end" property. ETFs are effectively "closed-end" funds to retail investors as explained in Footnote 5, making this subsidization feasible. The opposite direction of trading is unlikely to happen, as it will lead to outflows for the latter without obvious inflows of the former. Based on the same argument, this mechanism is unlikely to benefit two "closed-end" instruments, an implication we will use to conduct a Placebo test. The mechanism could benefit two "open-end" funds; see, e.g., Gaspar, Massa and Matos (2006).

Co-ActiveShr) is related to cross-trades between the affiliated entities. In the second stage, we explore how this cross trades help affiliated OEFs. In other words, 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):

$$\text{First stage: } CrossTrades_{f,t} = \alpha + \beta \times Co\text{-}ActiveShr_{f,t} + \gamma M_{f,t} + e_{f,t}, \quad (4)$$

$$\text{Second stage: } Fund\_Char_{f,t+1} = \alpha + \beta \times \widehat{CrossTrades}_{f,t} + \gamma M_{f,t} + e_{f,t+1}, \quad (5)$$

where $CrossTrades_{f,t}$ in the first stage 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)), and $\widehat{CrossTrades}_{f,t}$ in the second stage is its projected value from the first stage. $Co\text{-}ActiveShr_{f,t}$ is the benchmark-adjusted common active shares between an OEF f and its affiliated ETF(s), which is defined as $\sum_{i\in\{f\cap ETF\}} DivStock_{i,f,t} = \sum_{i\in\{f\cap ETF\}} \left|w_{i,f,t} - \widehat{w}_{i,f,t}\right|/2$ for all stock i that is held by both OEF f and its affiliated ETF(s), 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. $Fund\_Char_{f,t+1}$ 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 5. 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 as reported in Model 1, we find that common active share 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.[17] A one-standard-deviation increase in ETF/OEF cross-trades instrumented using $Co\text{-}ActiveShr$ leads to an annualized 5.9% higher return and 13.84% higher inflow. Notably, the enhanced return and flow are achieved at the cost of higher

[17] (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.

benchmark-adjusted return volatility, whereas net-of-risk performance remains mostly unchanged. Overall, these results lend support to a cross-subsidization channel from ETFs to affiliated OEFs in promoting the flows of the latter.

As noted in Footnote 16, this type of subsidization can only occur from ETFs to OEFs. It makes less sense, from the conglomerate's perspective, to let ETFs to conduct similar cross-subsidization. Panel B provides a Placebo test based on this intuition. There, we tabulate the formation (first stage) and influence (second stage) of cross-trades between affiliated ETFs. 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.

Next, as a robustness check, we split the sample by type of ETF and report the results in Table 6. 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 significant for optimized sampling ETFs but not for synthetic ETFs. U.S. ETFs are not subject to this problem; instead, the problem is concentrated in European ETFs.

Overall, we find that pro-conglomerate incentives are quite pervasive and take the form of several distinctive mechanisms. Similar to what we have observed in the bank-loan channel, ETFs investment in the stocks of the affiliated bank are related to better performance. ETF investments in stocks with high co-ownership of affiliated OEFs also appear informative. Finally, in addition to these informative trading mechanisms, ETFs also seem to engage in cross-trades with affiliated OEFs.

Although these mechanisms could arise to benefit conglomerates, we are yet to text their impact on investors. In principle, pro-conglomerate and pro-investor incentives may not be mutually exclusive. Our next section, therefore, takes on the task of investigating the impact of these mechanisms on ETFs investors.

V. Investors' Benefits and Costs

In order to explore the second question of whether investors benefit or suffer from ETF activeness, we link major benefits/costs of ETF investments (from investors' perspective) to aforementioned mechanisms of pro-conglomerate incentives –i.e., ETF's investment in stocks with affiliated bank-loan services, ETF's investment in stocks of affiliated bank, and the need to help affiliated OEFs proxied by the performance of affiliated OEFs. The major benefits/costs of ETF investments include: the degree of ETFs' deviation from their benchmarks in terms of holdings (i.e., active share of Cremers and Petajisto (2009)), the degree of ETFs' deviation from their benchmarks in terms of returns (i.e., *Tracking Error*), and ETF fees.

Active share (*ActiveShr*) is constructed following Cremers and Petajisto (2009). To construct fund *Tracking Error*, we obtain the fund's total return (net of fees) in U.S. dollars from Morningstar. We add back the fees, and we refer to the resulting gross-of-fee return as the *NAV-based Return*.[18] We then 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.

Since investors use ETFs to track index returns, more deviations imply a risk of tracking the underlining index from investors' perspective. A lower fee, by contrast, implies extra benefits delivered by the ETF. Note that investors will view active share as a risk – similar to tracking error except in the holding space – in the ETF industry. Active share is a risk from investors' perspective because, different from the OEF industry, its performance will not be automatically distributed to investors unless fees are reduced. More active share in the holding portfolio, in this regard, only imposes a potential risk for an ETF not to deliver index return in bad economic scenarios (i.e., a counterparty risk if the swap counterparty of the ETF fail to deliver index return in bad economic states).

A. Mechanisms of Pro-conglomerate Incentives vs. Tracking Error

[18] 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.

We first investigate the link between ETFs' tracking risk and the three mechanisms of information and subsidization. To capture the information benefits accruing from the affiliation with the bank conglomerate, we use $CorporateLoanDummy_{i,f,t}$, defined as before, to proxy for the information that ETFs may obtain from their affiliated banks based on such banks' processing of corporate loans. To capture the informational advantages for the ETFs to invest in affiliated banks, we define a dummy variable $AffiliatedBankStockDummy_{i,f,t}$ that equals one if ETF f holds the stock of its affiliated bank i in year t and zero otherwise. To proxy for the need to engage in cross-trades with the affiliated OEFs, we define a variable $AffiliatedOEFPerformance_{f,t}$ 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 the 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.

Since most of our tests are conducted at the stock level, here we also provide similar tests by aggregating ETF tracking risk and pro-conglomerate mechanisms at the stock level. We then estimate the annual panel regression as follows:

$$ActiveShr_{i,t} \text{ } or \text{ } Tracking \text{ } Error_{i,t} = \alpha + \beta \times Channels_{i,t-1} + \gamma \times M_{i,t-1} + e_{i,t}, \quad (6)$$

where the dependent variable measures tracking risk (*ActiveShr*, *Tracking Error*) and $Channels_{i,t-1}$ is the vector that contains proxies for pro-conglomerate mechanisms (i.e., *CorporateLoanDummy*, *AffiliatedBankStockDummy*, and *AffiliatedOEFPerformance*). 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 defined before. We estimate a panel specification with year and stock fixed effects and clustering at the stock level.

The results are reported in Table 7, Panel A, for active share (*ActiveShr*), and Panel B for *Tracking Error*. In Models 1 to 3, we separately report the three channels, whereas we consider a specification with all the channels in Model 4. Model 5 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 the variables that proxy for the channels and the proxies for deviation. In particular, across the different specifications, we find a strong positive relationship between *CorporateLoanDummy* and *ActiveShr* and a similar pattern between *CorporateLoanDummy* and *Tracking Error*. ETFs that own stocks in firms that receive corporate loan services from the bank affiliated with the applicable ETF present a higher *ActiveShr* (*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. Also, the stocks of affiliated banks display an *ActiveShr* (*Tracking Error*) that is higher by 18.9% (30.6 bps).

Finally, there is a negative relationship between deviation and the performance of the affiliated OEFs – i.e., *AffiliatedOEFPerformance*. A benchmark-adjusted performance of the affiliated OEFs that is worse by one standard deviation raises *ActiveShr* (*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 previous results suggest that the assistance is transferred to OEFs through cross-trades.

Unreported results further investigate the role played by stock lending. Stock-lending fees are negatively correlated with both *ActiveShr* and *Tracking Error*. This effect is also economically relevant: a one-standard-deviation higher level of fees reduces *ActiveShr* (*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.

B. Mechanisms of Pro-conglomerate Incentives vs. Fees

We now move on to the performance side of ETF activeness. When positive performance is generated, the ETFs can pass on this additional benefit to the investors as reduced fees. Because ETFs are only required to deliver gross-of-fee returns as high as index returns, reductions in fees (as well as better tracking error) provide the only way for ETFs to benefit their investors. Therefore, we must consider

ETF fees jointly with performance to derive an overall picture. A side-by-side examination of the two variables allows us to understand both the overall benefit of ETF active share (*ActiveShr*) and the part that is passed on to the ETF investors.

We begin with performance (*ActiveShr Performance*), and report the results in Panel A of Table 8. The layout of the columns is the same as that of Table 8. We find that the information channel is positively related to performance. This result is expected as higher quality information derived from bank loans can be used to generate performance that outperforms the benchmark. In contrast, there is no link between performance and *AffiliatedBankStockDummy*. Moreover, affiliated OEF performance is negatively related to ETF performance, implying a "substitute" effect between ETF and OEF return.

We then investigate the annual ETF expense ratio in Panel B. Here, the dependent variable reflects the fees charged by the ETF. We find that the benefit of the information channel does not accrue to ETF investors – i.e., the *CorporateLoanDummy* is uncorrelated with fees. Additionally, there is no direct link between fees and excess investment in the stock of affiliated banks. Instead, there is a strong negative relationship between fees and *AffiliatedOEFPerformance*: every 1% negative return of affiliated OEFs is associated with 14 bps of additional ETF fees. Since negative performance of affiliated OEFs implies a higher chance for ETFs to subsidize OEFs, the negative correlation could be interpreted as the cost of subsidization. In unreported results, it is interesting to notice that investors get some solace from the stock lending activity. Indeed, security lending fee 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.

Overall, these results suggest that ETF investors do not benefit from ETF activeness associated with pro-conglomerate incentives. Therefore, the systematic holdings difference involves a transfer between the ETF and its sponsor (and affiliated OEFs). This provides a sort of "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 ETF. However, the investors may face the credit risk related to this behavior. Are they aware of it? This is the topic of the next subsection.

VI. The Market Reaction to ETF's Activeness

Our findings suggest that ETFs deviate from the benchmark to leverage their information advantage from the affiliated bank, and to help other members of their financial conglomerate. Although the information-motivated active share 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. The remaining question, therefore, is whether this *pro-conglomerate incentive* is perceived by sophisticated ETF investors as detrimental.

To answer this question, we relate the ETF flows[19] – a proxy for the sophisticated ETF investor demand – to the potential impact of ETF pro-conglomerate incentives in the following regression with year fixed effects and clustering at the fund level:

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

where $Flow_{f,t}$ refers to the average monthly flows of ETF f in year t; $Welfare_{f,t}$ refers to the potential impact of ETF off-benchmark activities which we will specify shortly. $Rating_{f,t}$ refers to the S&P long-term domestic issuer credit rating of its affiliated bank and proxies for distress risk (we also use bank ROA to replace bank rating in a few specifications). 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 =

[19] Although ETF investors typically exit by selling the ETF in the market as opposed to redeeming the shares (see footnote 4), investors can nonetheless create inflows and outflows at the fund level. This feature allows us to use ETF flows to proxy for fund demand. We compute monthly ETF flows as $Flow_{f,m} = [TNA_{f,m} - TNA_{f,m-1} \times (1 + R_{f,m})]/TNA_{f,m-1}$, 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.

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. Vector *M* stacks control variables.[20]

There are two important effects: any additional benefits or costs generated by the off-benchmark activities of ETFs can be transferred to investors or to affiliated conglomerates. We have already discussed that ETF fees provide a reasonable proxy for the beneficial effect that can be received by ETF investors. What is still missing is a measure on the beneficial impact of such activities on the affiliated conglomerates. Ideally, we will need explicit cash flow transaction data between ETFs and affiliated conglomerates to construct such a measure. However, such transaction-level data are unavailable to our best knowledge. Hence, we propose to construct an indirect measure to gauge the overall effect of potential subsidization.

More explicitly, we construct a new variable, *Swapped Transfer*, as the difference between the holding-based return that ETFs can generate and the gross-of-fee reported return of the ETFs that investors can receive. The intuition is as follows: a positive difference – or a positive value of *Swapped Transfer* – implies a "transfer" from ETFs to affiliate conglomerates, since there are some capitals accumulated by ETFs that are not distributed to investors.[21] Note that it is improper to equalize a positive *Swapped Transfer* to real cash flows transferred from ETFs to banks. Rather, this variable tells the relative *direction* of the transfer: a positive value implies that the transfer is from ETFs to affiliated financial conglomerates, rather than to the ETF investors. This transfer may take a direct (e.g., explicit swap contracts) or indirect form (e.g., cross-trades). To further verify this interpretation, we test the flow implication of *Swapped Transfer* side by side with ETF *Fees*. We also directly test the flow implication of tracking risk (i.e., *ActiveShr*, *Tracking Error*) in order to

[20] Since authorized participants create and redeem shares to exploit the arbitrage profits from the price discrepancy between ETF market price and NAV, we further control for the ETF premium, defined as $Premium_{f,m} = (Price_{f,m} - NAV_{f,m})/NAV_{f,m}$, where $Price_{f,m}$ refers to the market price of fund f in month m, $NAV_{f,m}$ refers to the net asset value in the same month.

[21] *Swapped Transfer* is also 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.

understand whether investors care more about tracking risk *per se* or its implication in terms of subsidization.

Table 9 presents the results. Models 1 to 5 illustrate that ETF flows are uncorrelated with *ActiveShr* or *Tracking Error* but are negatively related to both *Swapped Transfer* and *Fees*. It is reasonable that investors are not particularly worried about tracking risk *per se* because tracking risk may be related to superior information, as we have discussed above, which does not necessarily hurt investors. However, positive *Swapped Transfer* and higher *Fees* signal a net detrimental effect to the investor, 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 3.56% (8.61%) in Model 3 (Model 4). 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 9.18% 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 the investors, then deterioration in bank performance should also appear detrimental to the 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.

[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.

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. As a robustness check, we also estimate a Fama-MacBeth specification with Newey-West adjustment. The (unreported) results are similar to the reported results.

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 exhibit a surprising selection ability in particular and display a significant degree of activeness in general. ETFs systematically deviate from their benchmark to both exploit the information gathered by the affiliated bank through its lending activities as well as direct investment in affiliated bank stocks, and to promote the flows of affiliated OEFs. Even the extra-performance due to the information advantage is not passed on to the ETF investors through lower fees or better tracking error, but is transferred to the affiliated sponsor. The market awareness of this 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.
ActiveShr Performance	ETF holding-based return minus the holding-based return of index funds tracking the same benchmark.
Holding-based 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. Active Share Measure	
ActiveShr	Active share in a given year t is computed as follows: $ActiveShr_{f,t} = \sum_{i \in f} DivStock_{i,f,t} = \sum_{i \in f} \lvert w_{i,f,t} - \widehat{w}_{i,f,t} \rvert / 2$, where $DivStock_{i,f,t}$ refers to the stock-level active share 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 active share 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.
ETF Premium (in %)	ETF premium in a given month m is computed as follows: $Premium_{f,m} = (Price_{f,m} - NAV_{f,m}) / NAV_{f,m}$, where $Price_{f,m}$ refers to the market price of fund f in month m, $NAV_{f,m}$ refers to the net asset value in the same month. The annual premium is the average of monthly premium within a year.
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.
Affiliated ETF Ownership (in %)	Affiliated 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.
Affiliated OEF Performance (Benchmark adjusted, in %)	Monthly affiliated OEF total returns as reported by Morningstar, minus the average return of the open-end funds tracking the same benchmark. 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.
F. Stock Characteristics	
ETFadjOwn(Loaned Corp)	ETF Benchmark adjusted Ownership of Loaned Corporation in a given year t is computed as follows: $ETFadjOwn(Loaned\ Corp)_{i,t} = \sum_f (h_{i,f,t} - \hat{h}_{i,f,t}) \times CorporateLoanDummy_{i,f,t}$, 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 $CorporateLoanDummy_{i,f,t}$ is a dummy variable that takes the value of one if the affiliated bank of ETF f provides 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.
ETFadjOwn(Unloaned Corp)	ETF Benchmark adjusted Ownership of None-Loaned Corporation in a given year t is computed as follows: $ETFadjOwn(Unloaned\ Corp)_{i,t} = \sum_f \left(h_{i,f,t} - \hat{h}_{i,f,t}\right) \times (1 - CorporateLoanDummy_{i,f,t})$, where all variables are defined the same as in ETF Benchmark adjusted Ownership of Loaned Corporation.
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
ActiveShr Performance	0.045	0.449	-0.343	-0.078	-0.002	0.090	0.453
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							
ActiveShr	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
ETF Premium (in %)	0.035	0.187	-0.080	-0.031	0.004	0.056	0.229
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							
DGTW-adjusted Bank Return (in %)	-0.222	4.130	-4.917	-2.225	-0.240	1.862	4.459
Market-to-Book Ratio	1.640	0.821	0.661	1.124	1.495	2.100	2.782
Affiliated 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
Corporate Loan Dummy	0.019	0.136	0.000	0.000	0.000	0.000	0.000
Affiliated 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 Stock Selection Based on Bank Lending (Stock Level)

This table 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,

$$Perf_{i,t} = \alpha + \beta_1 \Delta ETFadjOwn(Loaned\ Corp)_{i,t-1} + \beta_2 \Delta ETFadjOwn(Unloaned\ Corp)_{i,t-1} + \gamma M_{i,t-1} + e_{i,t},$$

where $Perf_{i,t}$ is the average monthly DGTW-adjusted return of a stock in year t, $\Delta ETFadjOwn(Loaned\ Corp)_{i,t-1}$ is the change in bank loan–related abnormal ETF ownership of stock i in year $t-1$, and $\Delta ETFadjOwn(Unloaned\ Corp)_{i,t-1}$ 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. Models 5 to 8 further apply Model 4 to subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Out-of-sample DGTW-adjusted Stock Return (in %) Regressed on ΔAbnormal ETF Ownership of Lending-Related Stocks								
	Full Sample				Synthetic	Sampling	U.S.	European
	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***	19.181***	19.352***	19.786***	19.029***
	(38.99)	(20.06)	(39.00)	(20.07)	(37.81)	(40.09)	(41.20)	(37.00)
ΔETFadjOwn(Loaned Corp)	0.976**	1.014**	0.967**	1.008**	0.360*	1.105**	-1.746	0.593**
	(2.12)	(2.19)	(2.11)	(2.19)	(1.72)	(2.37)	(-0.14)	(2.46)
ΔETFadjOwn(Unloaned Corp)			-0.076	-0.043	-0.111	-0.192**	-0.027	0.115
			(-0.93)	(-0.53)	(-1.63)	(-2.03)	(-0.33)	(1.53)
Log (Stock Size)	-3.088***	-3.084***	-3.087***	-3.083***	-2.871***	-2.845***	-2.832***	-2.874***
	(-38.85)	(-38.79)	(-38.81)	(-38.75)	(-41.51)	(-40.65)	(-40.44)	(-41.59)
Turnover	-1.398***	-1.322***	-1.396***	-1.321***	-1.681***	-1.657***	-1.698***	-1.767***
	(-5.08)	(-4.79)	(-5.07)	(-4.79)	(-6.52)	(-6.46)	(-6.62)	(-6.88)
Log (Net Income)	0.077***	0.078***	0.077***	0.078***	0.073***	0.071***	0.069***	0.073***
	(7.95)	(8.11)	(7.95)	(8.11)	(7.98)	(7.71)	(7.52)	(7.95)
Log (Sales)	0.170*	0.171**	0.170*	0.171**	0.099	0.085	0.089	0.103
	(1.96)	(1.97)	(1.96)	(1.97)	(1.17)	(0.99)	(1.05)	(1.20)
Log (Total Assets)	-0.113	-0.136	-0.114	-0.136	-0.197**	-0.191**	-0.189**	-0.193**
	(-1.26)	(-1.52)	(-1.27)	(-1.53)	(-2.39)	(-2.31)	(-2.29)	(-2.33)
Log (Fund TNA)		-0.067		-0.068	-0.008	0.112***	0.032	-0.094***
		(-1.62)		(-1.62)	(-0.32)	(6.04)	(1.44)	(-6.93)
Log (Fund Age)		0.220*		0.217*	-0.037	-0.685***	-0.232**	0.473***
		(1.74)		(1.72)	(-0.27)	(-6.84)	(-2.04)	(7.21)
Expense Ratio		0.417		0.414	0.369	0.685***	0.517***	0.258
		(1.64)		(1.63)	(0.30)	(3.43)	(2.65)	(0.60)
Fund Return		-0.140***		-0.140***	-0.172***	-0.096***	-0.013	-0.126***
		(-3.59)		(-3.59)	(-3.08)	(-4.37)	(-0.58)	(-6.47)
Fund Flow		-0.012**		-0.012**	0.008***	-0.022***	-0.008	0.023***
		(-1.99)		(-1.99)	(3.65)	(-3.98)	(-1.16)	(7.35)
R-squared	0.168	0.170	0.168	0.170	0.162	0.162	0.160	0.163
Obs	46,198	46,198	46,198	46,198	46,198	46,198	46,198	46,198

Table 3: ETF Stock Selection of Affiliated Bank Stocks (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 level,

$$Perf_{b,q} = \alpha + \beta_1 \Delta ETFadjOwn(Affiliated\ Bank)_{b,q-1} + \beta_2 \Delta ETFadjOwn(Unaffiliated\ Bank)_{b,q-1} + \gamma M_{b,q-1} + e_{b,q},$$

where $Perf_{b,q}$ is the average monthly DGTW-adjusted return of bank b in quarter q, $\Delta ETFadjOwn(Affiliated\ Bank)_{b,q-1}$ is the change in percentage abnormal bank ownership held by the affiliated ETFs (by netting out their benchmark-implied ownership), $\Delta ETFadjOwn(Unaffiliated\ Bank)_{b,q-1}$ is the change in percentage abnormal bank ownership held by the ETFs not affiliated with the bank. 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. Models 5 to 8 further apply Model 4 to subsamples of ETFs, including synthetic replication ETFs, optimized sampling ETFs, U.S. ETFs, and European ETFs. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Out-of-sample DGTW-adjusted Bank Stock Return (in %) Regressed on ΔAbnormal ETF Ownership of Affiliated Bank Stocks								
	Full Sample				Synthetic	Sampling	U.S.	European
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-3.224	-9.743	-3.095	-9.643	-9.851	-9.872	-10.235	-9.621
	(-0.58)	(-1.10)	(-0.55)	(-1.08)	(-1.11)	(-1.11)	(-1.12)	(-1.08)
ΔETFadjOwn(Affiliated Bank)	0.062***	0.060***	0.065***	0.063***	0.066***	0.064***	-5.398*	0.065***
	(2.78)	(2.86)	(2.85)	(2.92)	(3.16)	(2.99)	(-1.84)	(3.20)
ΔETFadjOwn(Unaffiliated Bank)			-0.029	-0.028	-0.030	-0.034	-0.143	-0.027
			(-1.31)	(-1.23)	(-1.10)	(-1.18)	(-1.09)	(-1.21)
Log (Stock Size)	0.648*	0.421	0.659*	0.435	0.428	0.433	0.407	0.432
	(1.73)	(1.19)	(1.75)	(1.22)	(1.21)	(1.22)	(1.08)	(1.22)
Turnover	2.254	1.905	2.237	1.891	1.893	1.904	2.195	1.875
	(0.70)	(0.62)	(0.70)	(0.62)	(0.62)	(0.62)	(0.73)	(0.61)
Log (Net Income)	0.071	0.085	0.072	0.085	0.085	0.085	0.089	0.085
	(1.19)	(1.55)	(1.22)	(1.58)	(1.56)	(1.57)	(1.58)	(1.58)
Log (Sales)	0.174	0.203	0.214	0.242	0.240	0.240	0.243	0.241
	(0.22)	(0.25)	(0.27)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Log (Total Assets)	-0.401	-0.463	-0.452	-0.514	-0.499	-0.509	-0.489	-0.509
	(-0.47)	(-0.52)	(-0.52)	(-0.58)	(-0.56)	(-0.57)	(-0.54)	(-0.57)
Log (Fund TNA)		0.053		0.063	0.066	0.071	0.077	0.060
		(0.20)		(0.24)	(0.25)	(0.27)	(0.28)	(0.22)
Log (Fund Age)		1.843**		1.778**	1.785**	1.775**	1.830**	1.787**
		(2.28)		(2.20)	(2.20)	(2.19)	(2.22)	(2.21)
Expense Ratio		-1.044		-0.941	-0.927	-0.905	-1.226	-0.947
		(-0.77)		(-0.70)	(-0.68)	(-0.67)	(-0.89)	(-0.71)
Fund Return		0.186		0.188	0.190	0.190	0.197	0.188
		(0.60)		(0.61)	(0.62)	(0.62)	(0.64)	(0.62)
Fund Flow		0.030		0.028	0.029	0.028	0.027	0.029
		(1.51)		(1.44)	(1.45)	(1.42)	(1.32)	(1.47)
R-squared	0.145	0.149	0.147	0.152	0.151	0.152	0.153	0.152
Obs	785	785	785	785	785	785	785	785

Table 4: ETF Stock Selection Based on Affiliated OEFs (Stock Level)

Models 1 to 4 present 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,

$$Perf_{i,t} = \alpha + \beta_1 \Delta ETFadjOwn(High\ ETF/OEF\ Co\text{-}Ownership)_{i,t-1} + \gamma M_{i,t-1} + e_{i,t},$$

where $Perf_{i,t}$ is the average monthly DGTW-adjusted return of a stock in year t, $\Delta ETFadjOwn(High\ ETF/OEF\ Co\text{-}Ownership)_{i,t-1}$ is the change in abnormal ETF ownership in stocks in which the affiliated OEFs have high degree of co-investment (i.e., co-ownership). High (Low) ETF/OEF co-ownership refers to the stock with above (below) median common ownership between ETFs and affiliated OEFs in the cross section of each period. 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. Models 5 to 8 present similar statistics when $\Delta ETFadjOwn(High\ ETF/OEF\ Co\text{-}Ownership)$ is replaced with $\Delta ETFadjOwn(High\ ETF/OEF\ CrossTrades)$, referring to changes in abnormal ETF ownership in stocks in which the affiliated OEFs have high degree of cross-trading, and cross-trading is defined following Gaspar, Massa and Matos (2006). Appendix A provides detailed definitions of each variable. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Out-of-sample DGTW-adjusted Stock Return (in %) Regressed on ΔAbnormal ETF Ownership of OEF-Related Stocks								
OEF-Related Corp =	ETF/OEF Co-Ownership				ETF/OEF Cross-Trades			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	22.656***	21.717***	22.660***	21.693***	22.645***	21.697***	22.661***	21.647***
	(40.65)	(23.27)	(40.64)	(23.24)	(40.65)	(23.25)	(40.65)	(23.20)
ΔETFadjOwn(High OEF-Related Corp)	0.360***	0.362***	0.369***	0.373***	-0.088	-0.098	-0.068	-0.077
	(4.38)	(4.38)	(4.41)	(4.41)	(-0.54)	(-0.60)	(-0.42)	(-0.47)
ΔETFadjOwn(Low OEF-Related Corp)			0.077	0.088			0.244***	0.255***
			(1.06)	(1.21)			(3.93)	(4.07)
Log (Stock Size)	-3.127***	-3.130***	-3.128***	-3.131***	-3.125***	-3.127***	-3.127***	-3.130***
	(-37.93)	(-37.92)	(-37.92)	(-37.91)	(-37.92)	(-37.90)	(-37.92)	(-37.91)
Turnover	-1.812***	-1.806***	-1.811***	-1.805***	-1.817***	-1.811***	-1.816***	-1.809***
	(-6.20)	(-6.18)	(-6.20)	(-6.18)	(-6.22)	(-6.20)	(-6.22)	(-6.20)
Log (Net Income)	0.076***	0.076***	0.076***	0.076***	0.076***	0.077***	0.076***	0.077***
	(7.71)	(7.76)	(7.72)	(7.76)	(7.72)	(7.77)	(7.72)	(7.77)
Log (Sales)	0.083	0.081	0.083	0.081	0.083	0.081	0.083	0.081
	(0.86)	(0.84)	(0.86)	(0.84)	(0.87)	(0.85)	(0.86)	(0.84)
Log (Total Assets)	-0.208**	-0.214**	-0.208**	-0.215**	-0.209**	-0.215**	-0.209**	-0.215**
	(-2.22)	(-2.28)	(-2.22)	(-2.28)	(-2.22)	(-2.28)	(-2.23)	(-2.29)
Log (Fund TNA)		-0.040		-0.039		-0.044		-0.039
		(-1.07)		(-1.03)		(-1.16)		(-1.04)
Log (Fund Age)		0.288***		0.289***		0.293***		0.295***
		(2.95)		(2.97)		(3.00)		(3.03)
Expense Ratio		0.480		0.486		0.505		0.513
		(1.32)		(1.34)		(1.39)		(1.41)
Fund Return		-0.030		-0.030		-0.025		-0.028
		(-0.95)		(-0.94)		(-0.81)		(-0.88)
Fund Flow		0.006		0.006		0.006		0.006
		(1.08)		(1.09)		(1.09)		(1.10)
R-squared	0.175	0.176	0.175	0.176	0.175	0.175	0.175	0.176
Obs	40,608	40,608	40,608	40,608	40,608	40,608	40,608	40,608

Table 5: 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: $CrossTrades_{f,t} = \alpha + \beta ETF/OEF\ Co\text{-}ActiveShr_{f,t} + \gamma M_{f,t} + e_{f,t}$,

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

where $CrossTrades_{f,t}$ is the average quarterly cross-trades of fund f with other affiliated ETF(s) in year t. $ETF/OEF\ Co\text{-}ActiveShr_{f,t}$ is the benchmark-adjusted common active shares between an OEF f and its affiliated ETF(s), defined as $\sum_{i\in\{f\cap ETF\}} DivStock_{i,f,t} = \sum_{i\in\{f\cap ETF\}} \left|w_{i,f,t} - \widehat{w}_{i,f,t}\right|/2$ for all stock i that is held by both OEF f and its affiliated ETF(s), 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. $OEF\_Char_{f,t+1}$ 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, $\widehat{CrossTrades}_{f,t}$ is the projected value of $CrossTrades_{f,t}$ from the first stage, 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: $CrossTrades_{f,t} = \alpha + \beta ETF/ETF\ Co\text{-}ActiveShr_{f,t} + \gamma M_{f,t} + e_{f,t}$,

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

where $ETF/ETF\ Co\text{-}ActiveShr_{f,t}$ is the benchmark-adjusted common active shares between an ETF f and other affiliated ETF(s), $ETF\_Char_{f,t+1}$ 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 5—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-adj Volatility	Return	BMK-adj	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 Co-ActiveShr	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-adj Volatility	Return	BMK-adj	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 Co-ActiveShr	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 6: 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,

$$\text{First stage: } CrossTrades_{f,t} = \alpha + \beta ETF/OEF\ Co\text{-}ActiveShr_{f,t} + \gamma M_{f,t} + e_{f,t},$$

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

where $CrossTrades_{f,t}$ is the average quarterly cross-trades of fund f with other affiliated ETF(s) in year t. $ETF/OEF\ Co\text{-}ActiveShr_{f,t}$ is the benchmark-adjusted common active shares between an OEF f and its affiliated ETF(s). $OEF\_Char_{f,t+1}$ refers to the OEF characteristics including average monthly flow, monthly return and risk-adjusted OEF return (by subtracting the DGTW portfolio return), $\widehat{CrossTrades}_{f,t}$ is the projected value of $CrossTrades_{f,t}$ from the first stage, 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 Co-ActiveShr	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 Co-ActiveShr	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 7: Impact of Pro-conglomerate Incentives on Tracking Risk (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,

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

where $ActiveShr_{i,t}$ is the average quarterly active share of stock i in year t, $Channel_{i,t-1}$ refers to three channels of impact: Corporate Loan Dummy (a dummy variable taking a value of one if it is a lending-related stock), Affiliated Bank Stock Dummy (a dummy variable taking a value of one if the ETF invests in its affiliated bank), and Affiliated OEF Performance (the benchmark-adjusted return of other affiliated OEFs). The Stock-level Corporate Loan Dummy, ActiveShr, and Affiliated Bank Stock Dummy (Affiliated OEF Performance) 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 $Tracking\ Error_{i,t}$, 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 7—Continued

Panel A: Out-of-sample Active Share Regressed on Stock and ETF Characteristics					
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.120***	-0.140***	-0.149***	-0.127***	0.022
	(-4.99)	(-5.51)	(-5.82)	(-5.28)	(0.76)
Corporate Loan Dummy	0.118***			0.118***	0.112***
	(7.65)			(7.63)	(7.39)
Affiliated Bank Stock Dummy		0.189***		0.180***	0.171***
		(4.13)		(4.06)	(3.77)
Affiliated OEF Performance			-0.045***	-0.045***	-0.045***
			(-4.73)	(-4.80)	(-4.70)
Log (Stock Size)	0.007***	0.008***	0.008***	0.007***	0.005***
	(5.48)	(5.81)	(5.63)	(5.27)	(3.58)
Stock Return	0.000**	0.000*	0.000**	0.000**	0.000***
	(1.98)	(1.79)	(2.06)	(2.22)	(3.18)
Turnover	0.003	0.006	0.006	0.004	
	(0.73)	(1.22)	(1.36)	(0.87)	
Log (Stock Illiquidity)					-0.030***
					(-7.95)
Log (Net Income)	0.001**	0.000	0.000	0.001**	0.000
	(2.06)	(1.54)	(1.58)	(2.08)	(1.58)
Log (Sales)	-0.004**	-0.005***	-0.005***	-0.005**	-0.005***
	(-2.48)	(-2.90)	(-2.83)	(-2.53)	(-2.72)
Log (Total Assets)	-0.002	-0.001	-0.001	-0.001	-0.001
	(-0.76)	(-0.40)	(-0.41)	(-0.65)	(-0.54)
Log (Fund TNA)	0.008***	0.009***	0.009***	0.007***	0.006***
	(7.48)	(7.97)	(7.75)	(7.14)	(5.63)
Log (Fund Age)	-0.021***	-0.024***	-0.025***	-0.021***	-0.018***
	(-10.77)	(-11.31)	(-11.59)	(-10.98)	(-9.45)
Expense Ratio	0.028***	0.028***	0.031***	0.030***	0.039***
	(4.21)	(4.29)	(4.64)	(4.60)	(5.82)
Fund Flow	0.000***	0.000***	0.000***	0.000***	0.000***
	(8.22)	(8.09)	(8.00)	(8.09)	(7.27)
R-squared	0.088	0.072	0.072	0.091	0.099
Obs	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
Intercept	-0.843***	-0.859***	-0.924***	-0.906***	-0.685***
	(-10.78)	(-10.87)	(-11.63)	(-11.52)	(-7.40)
Corporate Loan Dummy	0.094***			0.094***	0.081***
	(4.34)			(4.34)	(3.76)
Affiliated Bank Stock Dummy		0.306***		0.292***	0.277***
		(6.82)		(5.97)	(5.96)
Affiliated OEF Performance			-0.349***	-0.349***	-0.352***
			(-11.85)	(-11.84)	(-11.93)
Stock and Fund Controls	Y	Y	Y	Y	Y
R-squared	0.378	0.378	0.382	0.383	0.383
Obs	46,526	46,526	46,526	46,526	46,526

Table 8: Impact of Pro-conglomerate Incentives on Performance 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,

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

where $Perf_{i,t}$ is the average monthly active share performance (ActiveShr Performance) of stock i in year t, and all other specifications are those described in Table 8. 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 Active Share Performance (in %) Regressed on Stock and ETF Characteristics					
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.024	-0.034	-0.095	-0.085	-0.328***
	(-0.37)	(-0.52)	(-1.42)	(-1.27)	(-4.32)
Corporate Loan Dummy	0.057***			0.058***	0.067***
	(4.48)			(4.49)	(5.05)
Affiliated Bank Stock Dummy		-0.020		-0.032	-0.018
		(-0.46)		(-0.61)	(-0.36)
Affiliated OEF Performance			-0.335***	-0.335***	-0.336***
			(-12.22)	(-12.22)	(-12.34)
Stock and Fund Controls	Y	Y	Y	Y	Y
R-squared	0.244	0.243	0.250	0.251	0.252
Obs	46,434	46,434	46,434	46,434	46,434

Panel B: Out-of-sample Fees (in %) Regressed on Stock and ETF Characteristics					
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.583***	0.583***	0.571***	0.571***	0.626***
	(33.80)	(33.69)	(33.55)	(33.66)	(30.12)
Corporate Loan Dummy	0.000			0.001	-0.001
	(0.05)			(0.10)	(-0.23)
Affiliated Bank Stock Dummy		0.026		0.023	0.020
		(0.75)		(0.75)	(0.65)
Affiliated OEF Performance			-0.142***	-0.142***	-0.142***
			(-21.81)	(-21.79)	(-21.70)
Stock and Fund Controls	Y	Y	Y	Y	Y
R-squared	0.354	0.354	0.368	0.368	0.369
Obs	46,526	46,526	46,526	46,526	46,526

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,

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

where $Flow_{f,t}$ refers to the average monthly flow of fund f in year t, $Welfare_{f,t}$ refers to the potential welfare impact of ETF off-benchmark activities, including the average quarterly active share in ETF holdings, Tracking Error, average monthly Swapped Transfer, and annualized percentage Fee (expense ratio), Corporate Loan Dummy (a dummy variable taking the value of one when the ETF holds a lending-related stock), Affiliated Bank Stock Dummy (a dummy variable taking the value of one if the ETF invests in its affiliated bank), and Affiliated OEF Performance (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 ETF Premium, Log(Stock Size in Fund), Log(Stock Illiquidity 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	6.701*	5.772	9.387***	11.216***	15.577***	9.512***	4.757	9.522***	7.911***	13.774***	13.280***	14.433***	13.814***	14.874***
	(1.97)	(1.47)	(3.67)	(3.25)	(4.88)	(2.91)	(1.56)	(3.57)	(3.01)	(4.32)	(3.94)	(3.51)	(4.20)	(4.35)
ActiveShr	0.161				-0.282					-0.225	-0.397	-0.421	-0.442	-0.679
	(0.34)				(-0.55)					(-0.38)	(-0.75)	(-0.81)	(-0.69)	(-1.28)
Tracking Error		0.527			-0.909*					-0.305	-0.605	-0.366	-0.123	-0.589
		(1.00)			(-1.86)					(-0.45)	(-1.29)	(-0.70)	(-0.18)	(-1.26)
Swapped Transfer			-0.654**		-0.737***			0.728*	-1.155***	0.703*	-1.242***	-0.203	0.681	-1.094**
			(-2.44)		(-2.78)			(1.72)	(-2.69)	(1.67)	(-2.97)	(-0.97)	(1.62)	(-2.52)
Expense Ratio				-5.517***	-5.675***					-4.027***	-4.300***	-7.733***	-5.410***	-5.828***
				(-3.93)	(-4.13)					(-3.14)	(-3.13)	(-5.01)	(-3.84)	(-4.02)
Bank Rating						-0.575***		-0.821***		-0.718***			-0.592***	
						(-3.70)		(-5.89)		(-5.02)			(-3.85)	
Bank ROA							2.309***		0.858**		0.314			0.091
							(2.62)		(2.48)		(0.85)			(0.25)
Swapped Transfer × Bank Rating								-0.212***		-0.202***			-0.175**	
								(-2.89)		(-2.77)			(-2.37)	
Swapped Transfer × Bank ROA									0.661**		0.670**			0.629**
									(2.16)		(2.23)			(2.07)
Corporate Loan Dummy												2.287**	1.514	1.834**
												(2.38)	(1.53)	(2.02)
Affiliated Bank Stock Dummy												-2.000***	-1.794**	-0.762
												(-3.40)	(-2.27)	(-1.38)
Affiliated OEF Performance												4.321***	3.115**	3.564**
												(2.82)	(2.08)	(2.33)
ETF Premium	0.003	0.003	-0.016*	0.005	-0.016*	0.003	-0.006	-0.002	-0.005	-0.000	-0.005	-0.001	-0.000	-0.004
	(0.43)	(0.44)	(-1.92)	(0.70)	(-1.96)	(0.41)	(-1.00)	(-0.18)	(-0.96)	(-0.03)	(-0.86)	(-0.16)	(-0.03)	(-0.65)
Log (Stock Size in Fund)	0.069	0.107	0.126	0.080	0.058	0.065	0.138	0.073	0.140	0.023	0.088	0.167	0.151	0.172
	(0.43)	(0.63)	(0.81)	(0.55)	(0.39)	(0.44)	(0.95)	(0.39)	(0.98)	(0.12)	(0.64)	(1.06)	(0.76)	(1.21)
Log (Stock Illiquidity in Fund)	-0.177	-0.198	-0.115	-0.441***	-0.391**	-0.152	-0.162	-0.140	-0.079	-0.363***	-0.309*	-0.417**	-0.341**	-0.272*
	(-1.20)	(-1.53)	(-0.95)	(-2.92)	(-2.23)	(-1.25)	(-1.33)	(-1.25)	(-0.69)	(-2.61)	(-1.91)	(-2.51)	(-2.46)	(-1.73)
Log (Fund TNA)	0.616***	0.639***	0.350**	0.529***	0.220*	0.638***	0.418***	0.662***	0.326**	0.566***	0.219	0.384***	0.499***	0.164
	(3.85)	(3.96)	(2.26)	(3.80)	(1.71)	(4.79)	(2.94)	(4.83)	(2.20)	(3.95)	(1.64)	(2.71)	(3.31)	(1.27)
Log (Fund Age)	-3.897***	-3.955***	-3.355***	-4.283***	-3.596***	-4.136***	-3.795***	-4.117***	-3.438***	-4.281***	-3.517***	-4.063***	-4.219***	-3.575***
	(-6.67)	(-6.87)	(-4.86)	(-7.44)	(-5.43)	(-7.29)	(-5.77)	(-8.56)	(-5.29)	(-8.86)	(-5.60)	(-6.92)	(-8.75)	(-5.68)
Fund Return	-0.675***	-0.672***	-0.556***	-0.651***	-0.505**	-0.659***	-0.436*	-0.283***	-0.281***	-0.353***	-0.299***	-0.546***	-0.360***	-0.298***
	(-3.85)	(-3.82)	(-2.80)	(-3.81)	(-2.61)	(-3.87)	(-1.92)	(-3.65)	(-3.26)	(-4.41)	(-3.41)	(-3.31)	(-4.48)	(-3.35)
Fund Flow	-0.021	-0.020	0.018	-0.019	0.016	-0.023	0.004	-0.026**	0.008	-0.020	0.011	-0.015	-0.020*	0.001
	(-1.48)	(-1.41)	(0.34)	(-1.43)	(0.31)	(-1.64)	(0.07)	(-2.12)	(0.16)	(-1.62)	(0.22)	(-1.10)	(-1.67)	(0.03)
R-squared	0.177	0.178	0.204	0.204	0.234	0.204	0.214	0.205	0.213	0.221	0.23	0.233	0.236	0.245
Obs	704	704	704	704	704	704	704	704	704	704	704	704	704	704