ESSAYS IN EMPIRICAL ASSET PRICING

by
MUSTAFA ÖZTEKİN

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ABSTRACT

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MUSTAFA ÖZTEKİN

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Dissertation Supervisor: Prof. K. ÖZGÜR DEMİRTAŞ

Keywords: exchange-traded funds, price discovery, information efficiency, performance evaluation, financial innovation

This dissertation is composed of three articles. The first article presents an overview, a broad literature review and a study on exchange-traded funds (ETFs). In this study, I examine the institutional investors' asset allocation decisions in ETF markets and find that institutional players do not appear to exhibit consistently superior allocation and market timing skills neither specifically in the vicinity of extreme risk appetite periods nor in general. The second article investigates the price discovery role of ETFs and documents a predictive relation between the returns of emerging market ETFs traded in the US and the one-day-ahead returns to their corresponding aggregate local equity indices in a sample that covers 18 countries. This relation, which is more pronounced during periods of higher volatility, is robust after controlling for the non-synchronicity between markets, serial correlation in index returns, and various determinants of aggregate returns. I also find that an out-of-sample rolling window strategy outperforms investing in the market index several-fold in the majority of the markets. The third article focuses on the hedging role of ETFs and provides evidence that compared to a naked long position in a stock (naked strategy) which is expected to release positive earnings news, complementing the position with industry ETF hedges (hedged strategy) improves performance in terms of various reward-to-risk ratios based on downside risks. However, the naked strategy generates higher six-factor alphas and manipulation-proof performance measures. These results hold in various equity subsamples. Finally, both strategies tend to perform better among riskier stocks.

ÖZET

AMPİRİK VARLIK DEĞERLEMESİ ÜZERİNE MAKALELER

MUSTAFA ÖZTEKİN

YÖNETİM BİLİMLERİ DOKTORA TEZİ, TEMMUZ 2022

Tez Danışmanı: Prof. Dr. K. ÖZGÜR DEMİRTAŞ

Anahtar Kelimeler: borsa yatırım fonları, fiyat keşfi, bilgi verimliliği, performans değerlendirmesi, finansal yenilik

Bu tez üç makaleden oluşmaktadır. İlk makalede borsa yatırım fonları (BYF) üzerine genel bir bakış, literatür taraması ve bir çalışma sunulmaktadır. Bu çalışmada, kurumsal yatırımcıların BYF piyasalarındaki varlık tahsisini incelemekteyim ve ne özellikle aşırı risk iştahı dönemleri civarında ne de genel olarak, kurumsal yatırımcıların tutarlı biçimde üstün varlık tahsisi ve piyasa zamanlaması kararları sergilemediği sonucuna ulaşmaktayım. İkinci makale, BYF'lerin fiyat keşfi rolünü araştırmakta ve 18 ülke içeren bir örneklemde, ABD'de işlem gören gelişmekte olan piyasa BYF'lerinin getirileri ile bu BYF'lerin tekabül ettiği yerel hisse endekslerinin ertesi işlem günü getirileri arasında öngörücü bir ilişki olduğunu sergilemektedir. Yüksek oynaklık dönemlerinde daha belirgin olan bu ilişki, piyasalar arasında eş zamanlılık olmamasına, endeks getirilerindeki seri korelasyona ve endeks getirilerinin çeşitli belirleyici faktörlerine karşı dirençlidir. Ayrıca piyasaların çoğunluğunda, bu ilişkiye dayalı örneklem-dışı hareketli pencere alım-satım stratejisinin endekse yapılan pasif yatırıma kıyasla birkaç kat daha fazla getiri sağladığına ulaşmaktayım. Üçüncü makale, BYF'lerin koruma rolüne odaklanmakta ve pozitif finansal sonuçlar açıklaması beklenen bir hissede alınacak çıplak alım pozisyonuna (çıplak strateji) kıyasla, bu pozisyonu sektör BYF satım pozisyonları ile tamamlayan stratejinin (korumalı strateji) risk-getiri profilini aşağı yönlü risklere odaklı çeşitli performans metrikleri açısından iyileştirdiğine dair bulgular sunmaktadır. Ancak çıplak strateji, daha yüksek altı-faktör alfa ve manipüle-edilemez performans ölçütü değerleri sağlamaktadır. Bu sonuçlar çeşitli hisse alt örneklemlerinde geçerliliğini korumaktadır. Son olarak, her iki strateji de daha riskli hisseler arasında daha iyi performans göstermektedir.

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Can Harun ve Seda'ya

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MSCI Morgan Stanley Composite Index . . . 10

MVIS MV Index Solutions . . . 37

NASDAQ National Association of Securities Dealers Automated Quotations . . . 6

NAV Net asset value . . . 2

NYSE New York Stock Exchange . . . 35

PM Post meridiem (after noon) . . . 41

S&P Standard & Poors . . . 2

SEC US Securities and Exchange Commission . . . 1

SIC Standard Industrial Classification . . . 69

SPDR Standard & Poors Depositary Receipts . . . 2

SPY SPDR S&P 500 ETF Trust . . . 2

SUE Standardized Unexpected Earnings . . . 68

T-bills Treasury bills . . . 72

TIPS Toronto Index Participation Shares . . . 2

US United States . . . 2

USD United States Dollar . . . 2

VaR Value-at-Risk . . . 72

1. AN OVERVIEW OF ETFs AND ETF PLAYS OF INSTITUTIONAL INVESTORS

1.1 An Overview of ETFs

1.1.1 Introduction

Exchange-traded funds (ETFs) are one of the greatest innovations of recent times in capital markets. In the broadest sense, an ETF is an investment instrument containing a pool of assets, shares of which can be bought and sold just like common stocks during market trading hours at the exchange(s) the ETF is listed, as the name exchange-traded implies.

ETFs are such a young phenomenon that the first ETFs in the financially developed world were born in 1990s. Towards the end of 1980s, careful examination of the 1987 market crash (commonly known as Black Monday) and its underlying causes urged U.S. Securities and Exchange Commission (the SEC) officials to brainstorm on devising a new instrument, by which investors could conveniently buy or sell baskets of assets intraday, rather than single securities. The goal was to alleviate the firesales/order-sweeping pressures on single securities' orderbooks in potential future market disruption episodes, thereby preventing the reoccurrence of catastrophic events like Black Monday in the future. Interestingly, overcoming the regulatory hurdles to introduce such a product required a great deal of time and negotiation in the U.S. However, that was not the case in Canada and, in the meantime, officials in Toronto Stock Exchange had already become aware of the efforts in the U.S. targeted on the introduction of this new product. Thanks to a less tedious regulatory environment in Canada than in the U.S., they achieved to launch the first ETF in the world in Canada in 1990. (See Balchunas (2016) for further details) This ETF was named the Toronto Index Participation Shares (TIPS). A couple of years later, in 1993, came the first US-based ETF by State Street: SPDR S&P 500 ETF Trust (originally Standard & Poors Depositary Receipts, ticker: SPY). It is commonly referred to as Spider ETF. Spider is currently the largest ETF in the world with an asset size of USD 378 billion as of the end of May 2022. The first ETFs in Japan (Nikkei 300 ETF), Asia-Pacific (ex-Japan) (Hong Kong Tracker Fund) and Europe (LDRs DJ STOXX 50 and LDRs DJ Euro STOXX 50) made their debuts in 1995, 1999 and 2000, respectively.

1.1.2 ETFs vs. Conventional Mutual Funds

ETFs were originally devised as passive investment vehicles. A typical ETF is a fund, a pool of securities, that is designed to track the performance of an index specified by the ETF issuer (also called the ETF sponsor). Tracking error is usually quite low thanks to a cleverly designed arbitrage mechanism, which will be elaborated later. For instance, the first ETF launched in Canada, TIPS, tracked the TSE35 Index, whereas the largest ETF, SPY, tracks the S&P 500 index. In that sense, an investor who aims at betting on the performance of S&P 500 index could do so in a cost-efficient manner by simply purchasing SPY shares in the market. In sum, investing in an ETF is essentially equivalent to investing in the underlying index of that ETF.

It should be noted that this sounds nothing new so far since regular index funds serve the same purpose as well. Now is the time to elaborate on how ETFs differ from mutual funds and what makes them so special that they have become a huge success and stolen market share from their conventional counterparts. It can be argued that in comparison to open-end and closed-end funds, ETFs offer investors the best of both worlds from various aspects. To summarize the prominent ones, an open-end mutual fund does not provide intraday liquidity to its investors. The transactions occur and investors access liquidity only once a day at the close of the trading day. In these end-of-day transactions, investors transact directly with the fund, and deals are settled at NAV (net asset value per share) of the shares netted off any frictions. On the other hand, closed-end mutual funds trade throughout the day and hence provide intraday liquidity to investors. However, the number of shares of a closed-end fund is constant and therefore closed-end funds can trade at wide premiums or discounts (typically discounts) with respect to their net asset values during the day or even for prolonged periods of time. The existence and properties of the closed-end fund discount is an economic puzzle that have been studied heavily by financial economists over years and many alternative suggestions have been proposed as the driver of this empirical regularity. Some of the influential papers in this strand of literature are Lee, Shleifer & Thaler (1991), Berk & Stanton (2007), Cherkes, Sagi & Stanton (2008).[1]

ETFs have a unique recipe thanks to which they can provide intraday liquidity at market prices closely aligned with net asset value of the fund. This recipe is a well-constructed fund structure bringing together a continuous primary market and a continuous secondary market.[2] Definitions and the functioning of these markets will be described in the next section. An open-end fund does not provide intraday liquidity since it lacks a continuous secondary market, whereas a closed-end fund suffers from large discounts or premiums since it lacks a continuous primary market. That is why, ETFs offer the best of both worlds at first glance as they do not suffer the primary shortcoming of open-end funds, which is inability to provide intraday liquidity, and the primary shortcoming of closed-end funds, which is the emergence of large discounts/premiums with respect to NAV.

1.1.3 Two-Tier ETF Market Structure: Primary and Secondary Markets

ETF transactions occur in two separate markets; namely the primary market and the secondary market. The primary market is also called the creation/redemption market. In the primary market, transactions occur only between the ETF sponsor and authorized participants (AP). Each ETF has several authorized participants, which are large institutional players authorized by the ETF sponsor to engage in transactions with the ETF sponsor in the primary market.[3] There are two types of transactions in the primary market. One is the redemption of ETF shares, in which an AP delivers its ETF shares to the sponsor and receives the underlying

[1] Lee et al. (1991), Berk & Stanton (2007), Cherkes et al. (2008) attribute the existence and the fluctuations of the closed-end fund discount to the variations in individual investor sentiment, the interaction between managerial ability and the manager's labor contract and the trade-off between the liquidity benefits of closed-end fund investments and the management fees, respectively.

[2] Here, a continuous primary market refers to a functioning primary market every trading day at pre-determined time intervals and a continuous secondary market refers to uninterrupted intraday liquidity throughout the trading session at the exchange(s) the fund is listed.

[3] Antoniewicz & Heinrichs (2015) report that average (median) number of authorized participants per US-based ETF is 34 (36).

basket of assets in return. The other is the creation of ETF shares, in which an AP delivers the underlying basket of assets and receives newly issued ETF shares from the sponsor in return.[4] The former transaction reduces the ETF's total number of shares outstanding while the latter raises it. Thus, similar to open-end funds, the number of shares of an ETF is not fixed but fluctuates in time as a result of primary market activities.[5] In the absence of this primary market structure, or in a hypothetical scenario where all APs of an ETF cease their activities, that ETF would trade just like a closed-end fund.

On the other hand, secondary market refers to the transactions that occur at the exchanges between all type of market participants during market trading hours. As mentioned earlier, ETFs change hands just like stocks as the name "exchange-traded" suggests. Secondary market transactions do not affect the number of shares outstanding of an ETF. It is worth noting that neither primary market nor secondary market transactions directly induce purchases or sales of the underlying basket of assets in the exchange. As a final note, secondary market transactions dominate the overall ETF trading volume. ICI Investment Company Fact Book (2022) reports that 85% of all ETF activity in US ETF markets during 2021 occurred in the secondary markets.

1.1.4 The ETF Arbitrage Mechanism

The arbitrage mechanism that ensures an ETF's performance closely tracks the performance of its underlying index, i.e. tracking error is kept low, works as follows: Whenever an ETF goes through a relative downward price pressure which causes it to be traded at a discount (at a price lower than its net asset value per share), APs purchase that ETF and simultaneously short-sell the underlying basket of assets in the secondary market. Later, APs transact in the primary market; where they redeem the ETF shares they bought in the secondary market and receive the underlying basket of assets from the ETF sponsor in return, thereby closing out their entire long position in the ETF shares and their entire short position in the underlying basket of assets. In the opposite scenario, whenever an ETF goes through a relative upward price pressure which causes it to be traded at a premium (at a price

[4] The specifications of the creation and redemption baskets are disclosed by the ETF issuer for each trading day.

[5] Complete details on the functioning of the creation/redemption market and the timeline of events during the process can be found in Antoniewicz & Heinrichs (2014).

higher than its net asset value per share), APs short-sell that ETF and simultaneously buy the underlying basket of assets in the secondary market. Later, APs transact in the primary market; where they deliver the underlying basket of assets they bought in the secondary market and receive newly issued ETF shares from the ETF sponsor in return, thereby closing out their entire short position in the ETF shares and their entire long position in the underlying basket of assets. In both cases, APs earn riskless arbitrage profits which are grossly equal to the absolute price difference between the ETF shares and the underlying basket of assets per ETF share transacted. Their net arbitrage profits are the amount remaining after the deduction of any creation/redemption fees and transaction/liquidity costs that arise in due course.

In short, APs absorb the relative supply/demand imbalances in the secondary market and earn riskless arbitrage profits by exploiting the price-NAV divergences in the secondary market and netting out their positions in the primary market. Thanks to this well-incentivized arbitrage mechanism and the competition among various APs for each ETF, many ETFs enjoy very low tracking errors and ETF prices fluctuate in close proximity to their NAVs. That is why, ETFs do not suffer from large discounts or premiums with respect to their NAV, which is a phenomenon frequently observed for closed-end funds.

It goes without saying that APs are not the only parties entitled to act as arbitrageurs in ETF markets. Solely secondary market arbitrage is also possible. Suppose an AP or a non-AP investor observes an ETF is trading at a premium (discount) with respect to its NAV. Accordingly, the investor short-sells the ETF (the underlying basket) and buys the underlying basket (the ETF) in the hope that ETF price and NAV will converge soon and the position can be closed by earning arbitrage profits. In contrast to the riskless arbitrage described in the previous paragraph, this arbitrage action constitutes an example of a risky arbitrage opportunity, because the convergence may never realize or may not realize soon enough for some reason. However, at this point, we need to make a clear distinction between the cases in which the investor is an AP or not. An AP can certainly turn to the primary market and lock in the arbitrage profits, even if the (timely) convergence does not materialize. However, there is no such assurance for a non-AP investor to secure arbitrage profits. That is why we can say that primary market is where the magic happens in the functioning of ETFs. Nevertheless, we should note that, as well as riskless arbitrage by APs, risky arbitrage attempts in the secondary market do contribute to the low tracking errors enjoyed by the ETFs by inducing price pressures in the direction of convergence.

1.1.5 Advantages of ETFs

It is worth noting that the advantages of ETFs are not limited to intraday liquidity and market prices aligned with NAVs as explained earlier. On top of these benefits, ETFs provide easy, transparent, flexible and cost-efficient access to well-diversified portfolios on a large selection of markets, asset classes and strategies. Each of these crucial benefits deserves to be detailed in a paragraph of its own.

ETFs typically track indices measuring the performance of well-diversified portfolios on different asset classes. As such, ETFs facilitate holding well-diversified portfolios for retail and institutional investors. Investors could gain similar exposures with index futures as well. However, futures have an expiration date. Thus, gaining exposure to diversified portfolios via futures bring the additional burden and cost of closing or rolling the positions prior to expiration. In addition, futures are quoted on a limited number of broad market gauges, such as S&P 500 and NASDAQ-100. In contrast, ETFs do not have an expiration date. Furthermore, they track a much wider range of indices than futures.

The fundamental appeal of ETFs for retail and institutional investors emanates from different sources. For retail investors, ETFs democratize the investment landscape and partially equalizes the playground with institutions. Holding well-diversified portfolios containing hundreds or thousands of securities was a privilege of only institutional investors for many decades due to the operational and technological sophistication it requires. Lettau & Madhavan (2018) state that managing an index portfolio was not a cost-effective endeavor even for index fund managers until 1970s. Thanks to ETFs, retail investors now can have easy access to a vast selection of well-diversified portfolios. For institutional investors, ETFs are convenient tools to equitize cash, thereby gaining easy exposure to preferred asset classes and markets without forgoing liquidity. Furthermore, ETFs greatly expand the toolset used by institutional investors for purposes such as strategic or tactical asset allocation moves, portfolio rebalancing and hedging of overall portfolio risks.

Intraday tradability in a sense comes short of adequately describing the strategic flexibility provided by ETFs. Whatever an investor does with stocks, she can do it with ETFs as well. Besides intraday spot transactions, ETF shares can be sold short, can be lent, can be bought on margin. Even options and futures can be bought or written on them. Hence, ETFs effectively enrich the trading strategy set of market participants by facilitating bets on well-diversified portfolios on either direction.

Comprehensive transparency in terms of investment strategy, price, holdings and NAV is another important feature of ETFs. The investment strategy and the underlying index of an ETF is clearly specified by the ETF sponsor at issuance. Since ETFs are exchange-traded, their prices are disclosed in real-time during exchange trading hours. As imposed by related regulations, ETF sponsors disclose their fund holdings every day. Using previous-day's holdings reported by the sponsor and the last recorded market-determined security prices, authorized third-party data vendors calculate and disseminate Intraday Indicative Value (IIV), which is estimated NAV of the fund, every 15 seconds during the trading session. ETFs closely track their underlying indices thanks to a cleverly designed arbitrage mechanism. This mechanism runs smoothly in ETF markets thanks to the timely and transparent dissemination of price, holdings and NAV information. Consequently, an ETF buyer does not suffer from a large premium with respect to NAV, whereas an ETF seller does not suffer from a large discount with respect to NAV when engaging in ETF transactions.

ETFs are low-cost vehicles. As outlined by Prince (2018), there are several cost components pertaining to ETF transactions. Total cost of ETF ownership is composed of expense ratio, brokerage commissions, trading costs, tracking error and taxes accrued when holdings are divested. The expense ratio is equal to the fees charged by the ETF sponsor scaled by the managed asset size. In general, expense ratios of ETFs are comparable to that of index mutual funds, while much cheaper than active mutual funds. Brokerage commissions are paid to the broker-dealer for the execution of ETF transactions at the exchange. Nowadays, some broker-dealers offer very competitive commission rates (zero in some cases) for purchases and sales of certain ETFs with the aim of increasing their market share due to rising popularity of the product. Trading costs are a function of the liquidity of the relevant ETF and they comprise the costs related to bid-ask spreads and depth of the orderbook. ETFs are generally highly liquid instruments and there are many instances of ETF liquidity being greater than that of the underlying securities in some corners of the market like fixed income and foreign assets. Tracking error is the gain or loss stemming from the divergence between the traded price and NAV of the ETF. As mentioned earlier, ETFs often do pretty well on this front and enjoy minimal tracking errors thanks to their special design. As for taxes accrued, ETFs are tax-efficient as well. Since a typical ETF is a passive investment instrument, portfolio turnover is lower than that of actively managed funds. Moreover, most ETF transactions occur in the secondary market where ETF investors trade with each other rather than the fund itself. Therefore, these trades do not translate to actual purchases of underlying basket of assets in the market. In addition, the primary market transactions generally occur in the form of in-kind transfers. Collectively, an ETF structure effectively minimizes the capital gains tax liability falling on its investors. All in all, ETFs are low-cost instruments on the back of their low expense ratios, high liquidity, minimal tracking error and tax-efficiency.

1.1.6 The Epic Growth of ETFs

The strong and broad shift towards passive investments and the benefits of ETFs outlined in the previous section led to a phenomenal growth in the global ETF industry in the new millennium. Novick, Cohen, Madhavan, Bunzel, Sethi & Matthews (2017) attribute the growing popularity of passive investments to three major trends: rising investor awareness of the efficiency of markets and resulting adoption of the "you cannot beat the market" ideology, growing importance of fees and transparency in the eyes of investors and regulators, and transformation of brokerage and advise services in such a way that investment advisers' role shifts away from stock/fund pickers to asset allocators.

In this article, I focus on US-based ETFs. ETFs are identified by a share code of 73 in CRSP Monthly Stock Files. Utilizing this dataset, I have extracted the number and total market value of US-based ETFs in years from 2000 to 2021. Figure 1.1 illustrates the results. According to my calculations based on ETF data provided by CRSP, the number of US-based ETFs have risen from 93 in 2000 to 956 in 2010, and then to 2671 in the end of 2021 while the total market capitalization has skyrocketed from a mere USD 40 billion in 2000 to USD 976 billion in 2010 and then to a remarkable USD 7.2 trillion in the end of 2021. This indicates a CAGR growth in the size of ETF market of 28% over the period from 2000 to 2021 and 20% over the period from 2010 to 2021.

The rise in the market size generates from two components, price appreciation in the underlying securities and net inflows (new share issuances) into the ETFs. Among these two, the latter is the true indicator of the investor demand on ETFs. ICI Investment Company Fact Book (2022) reports that in the last 10 years, net inflows into ETFs amounted to 3.7 trillion, implying that majority of the rise in the total assets of ETFs was driven by increasing investor demand on ETFs.

ICI Investment Company Fact Book (2022) reports that global ETF asset size amounts to USD 10.1 trillion as of the end of 2021 and United States is the largest ETF market in the world with a share of 71%. Europe and Asia-Pacific rank the second and the third with shares of 15% and 11%, respectively. It is also reported that ETF assets comprise 21% of the total assets managed by investment companies in the US.

Figure 1.2, borrowed from ICI Investment Company Factbook (2022), exhibits the breakdown of net assets managed by US-ETFs into main categories as of the end of 2021. US Equity collectively makes up 63% of the total ETF assets, followed by Global/International Equity (18%) and Bond ETFs (17%). Within US equity category, large-cap US equity makes up the largest portion with an asset size of 2.2 trillion and a share of 31% of total ETF assets, and a share of 50% of total US-equity ETF assets.

1.1.7 Types of ETFs

Not only asset size but also the diversity of ETFs has grown considerably in the last couple of decades. Early ETFs were typically designed to track indices, which were mostly cap-weighted broad domestic equity gauges. However, ETFs come in any flavors in the ETF landscape today. The product offering in the industry is so large that it is virtually impossible for an investor not to be able to find an appropriate ETF that fits her own investment objectives.

Every little detail about an ETF is a moving part in today's landscape. To the reader's surprise, a contemporary ETF may even not be a passive investment vehicle as there are many actively managed ETFs in the market currently. That is why, ETFs can be divided into categories with respect to a large set of criteria. Asset class and geographical focus can be counted as the foremost among these. The main asset class options are equity, fixed income, commodities and currency. Hybrid (asset allocation) ETFs that invest in more than one asset class are also available. Within ETFs that invest in domestic equity subclass, broad-based equity ETFs and sector ETFs are the major groups. A large majority of broad-based equity ETFs track cap-weighted indices such as S&P 500, whereas the rest is mostly comprised of smart-beta or actively managed equity ETFs, which will be described later. On the other hand, domestic sector equity ETFs invest a large proportion of their assets consistently on a single sector, as defined by their mandates. Within fixed income, broad market, US government, investment grade, high yield, municipal bonds are major subclasses invested by ETFs. On the commodities front, there are ETFs that provide exposure on precious metals, crude oil and agricultural commodities via either physical backing or using futures contracts. And as for currency ETFs, which comprise a little portion of total ETF assets, investors can easily access instruments for their bets on major currency pairs such as EURUSD and GBPUSD.

As for geographical focus, besides the ones that invest purely in domestic US assets, ETFs that purely or partially invest in developed market equity/bonds, emerging markets equity/bonds and even frontier markets assets exist. Also, there are single country equity ETFs, that track the broad equity market performance of a single country. Antoniewicz & Heinrichs (2014) mention that for both retail and institutional investors, easy access to foreign assets exposure through ETFs is a great value-add. This is because investing in foreign markets directly involves a number of requirements such as having a foreign investor status, a local bank account and a local custodian determined by regulations of the specific countries. Thanks to ETFs that invest in foreign markets, investors seeking exposure to foreign assets conveniently bypass these requirements and delegate their compliance to the ETF sponsor.

Up to this point in this article, we mainly described the functioning of typical ETFs, which are sometimes referred to as vanilla ETFs. These ETFs basically track a well-known index published by a third-party index provider such as Standard & Poors, MSCI and Bloomberg via in-kind creation/redemptions in the primary market. Vanilla ETFs use neither derivative contracts nor leverage. In terms of their holdings, they can either fully replicate the target index or use representative sampling (optimized replication) when it is either costly or hard to obtain some of the securities in the target index. This happens mostly due to illiquidity issues and/or limitations on the ownership of assets.

On the other hand, in today's landscape there are many ETFs which use derivatives like futures, swaps and options in order to yield the performance metric defined by the ETFs objective. We call this synthetic replication as opposed to physical. For instance, some commodity ETFs such as crude oil ETFs use futures contracts to gain exposure on oil due to the practical impossibility of storing this commodity. On the other hand, gold ETFs using either type of replication are available in the market: Some physically hold gold whereas some provide exposure via futures contracts. As for ETFs on conventional asset classes, some present capital preservation feature via use of protective puts. A special class of ETFs that necessarily utilize derivatives are leveraged ETFs. These ETFs deliver approximately a multiple of the performance of the target index. For instance, on a day when S&P 500 return is 1%, a 3x-leveraged ETF on the S&P 500 index yields a daily return close to 3%. Another exotic type of ETF worth mentioning is the inverse ETFs, which deliver a performance inversely related to the performance of the index. ETFs that are both leveraged and inverse are also offered in the market currently. When an ETF employs derivatives for the purpose of achieving their promised performance as specified by its mandate, the creation and redemption baskets that are delivered or received in the primary market by APs, are composed of fully or partially cash.

1.1.8 Breaking Boundaries: Active and Smart Beta ETFs

Arguably, the most interesting categorization of ETFs today is the one in terms of management type since a groundbreaking evolution has gradually materialized in this front over the years. Traditionally, investors view the choice between active and passive management as a binary one. However, ETF diversity has flourished so epically that this convention is not valid anymore.

Earlier ETFs were purely passive investment vehicles that track their specified indices which were mostly cap-weighted equity gauges. On the back of rising demand on ETFs and diverse investment objectives, so-called active (actively-managed) ETFs and smart beta ETFs have begun populating the ETF space for the last decade.

Active ETFs mainly fall under two subgroups. Absolute return targeting ETFs are highly analogous to hedge funds in that the goal is providing positive returns to investors regardless of the price trajectories and states of the invested markets. On the other hand, relative return targeting ETFs have a specific index that they attempt to beat. In this respect, they are akin to active mutual funds. Based on these explanations, absolute return ETFs stand as purely active investments whereas relative return ETFs can be viewed as moderately active investments. What separates active ETFs from their conventional counterparts are mainly their flexibility, intraday liquidity, transparency, and lower fees. For instance, unlike a hedge fund, an absolute-return targeting ETF does not impose a lock-up provision on investors, can be traded intraday, discloses its holdings daily and charges lower fees.

Smart beta ETFs are the major innovation that breaks the once-solid boundary between active and passive investments. By design, they are index-based vehicles as they track certain indices specified by their sponsors in a rule-based and transparent way. However, the indices they track dramatically differ from the traditional cap-weighted broad market gauges tracked by earlier index-based ETFs, or sector indices that concentrate on a specific industry. The investment objective of a smart-beta ETF focuses on a single factor or multiple factors, such as size, style (value/growth), momentum, dividend yield, volatility, etc. Accordingly, indices tracked by smart beta ETFs are essentially factor-weighted indices, constructed using special weighting methodologies based on the relevant factor(s). Attempts at outperforming markets by exploiting factor exposures have traditionally been strategies pursued by conventional active players like hedge funds and active mutual funds. However, thanks to smart beta ETFs, any investor in the market has easy access to gain factor exposures, and hence, pursue active strategies in a passive, index-based manner. As such, smart beta ETFs effectively render the traditional binary view between passive and active investments irrelevant. As noted by Novick et al. (2017), the contemporary investment landscape should be characterized as a continuum of investment styles, each of which should be assessed according to its extent of activity or passivity in the strategies pursued.

1.2 Literature on ETFs

The academic literature on ETFs has been expanding at a rapid pace recently in parallel with the growing popularity of passive investments, and ETFs in particular. In this section, I am going to present a brief overview of some influential research conducted on ETFs.

Since ETFs are a sort of derivative instrument that represent claims to a pool of conventional assets, it is essentially futile to study stand-alone ETF prices or returns. Therefore, theorical or empirical asset pricing studies on ETFs are mostly confined to investigation of the tracking error, i.e. premium or discount of market-determined ETF prices with respect to their net asset values. Dominant views reached by many studies in this literature are that ETF prices commonly diverge from NAV, creating arbitrage opportunities. However, the frequency at which this happens shows considerable variation among different types of ETFs, and the duration of such inefficient pricing is often not long-lived as many of them are corrected intraday. In this strand of literature, Petajisto (2017) provides evidence that ETF prices can significantly diverge from NAV even after controlling for stale pricing in underlying baskets despite the arbitrage mechanism peculiar to ETFs. The author finds that ETFs holding liquid domestic assets are less prone to such pricing inefficiency whereas ETFs with foreign or illiquid holdings suffer from higher tracking errors. Marshall, Nguyen & Visaltanachoti (2013) examine the intraday trading of two S&P 500 ETFs and reach that liquidity (measured by spreads) falls, order imbalance increases and return volatility becomes higher at times when intraday tracking error is high enough to allow arbitrage profits. Furthermore, arbitrageurs correct the intraday mispricings in only 1-2 minutes on average. Blitz & Huij (2012) find that emerging market ETFs exhibit higher tracking errors compared to developed market ETFs. The authors ascribe this finding to the structurally higher cross-sectional dispersion in emerging market stock returns. In a similar vein, Madhavan & Sobczyk (2016) conclude that the magnitudes of premiums or discounts exhibit significant variation across ETFs and is systematically related to cross-sectional measures of liquidity. Finally, Broman (2016) reports that tracking errors of ETFs having similar (distant) investment styles are significantly positively (negatively) correlated.

Apart from studies on the magnitude and drivers of tracking error, the literature on ETFs predominantly revolves around issues related to ETFs' effects on market microstructure. In this respect, volatility, liquidity, price discovery/market efficiency and security co-movement are the foremost aspects heavily studied by scholars.

Malamud (2016) models ETFs with a two-tier market structure composed of a primary and a secondary market in a dynamic general equilibrium setting. The author demonstrates that primary market activities in the form of creations and redemptions serve as a shock propagation channel by which temporary demand shocks in ETF level are propagated to the underlying stocks raising their volatility. Separately, Broman (2016) and Broman & Shum (2018) obtain findings which suggest that there is a clientele effect among ETF investors: the ease of trading diversified baskets and the high liquidity of ETFs attract a new breed of high-frequency, short-horizon, liquidity-oriented investors towards these instruments. A very influential study by Ben-David, Franzoni & Moussawi (2018) corroborate the separate findings of these earlier papers in a well-designed empirical setup. The authors provide evidence that ETFs indeed provide a residence for short-horizon liquidity traders who create relative non-fundamental demand shocks in ETFs. These liquidity shocks are propagated to the underlying securities through the arbitrage mechanism, resulting in elevated non-fundamental volatility for these ETF constituents. Thus, in spite of their many benefits to investors, ETFs are documented to raise the non-fundamental volatilities of their constituent stocks and expose investors to a new source of undiversifiable risk as evidenced by the fact that stocks with higher ETF ownership earn significant risk premiums compared to ones that are held less commonly by ETFs.

The advent of ETFs introduces an extra layer of liquidity on top of the spot transactions in the underlying securities. Research on the liquidity effects of ETFs is mainly devoted to uncovering the possible benefits or costs that come with this extra layer. Agarwal, Hanouna, Moussawi & Stahel (2018) document that ETF ownership drives commonality in the liquidity of constituent stocks of ETFs and the main channel through which this impact occurs is the arbitrage mechanism. The liquidity co-movement among the members of ETF holdings poses a systematic risk for investors as they become deprived of the ability to diversify liquidity risk away. Israeli, Lee & Sridharan (2017) provide evidence that higher ETF ownership brings about lower liquidity in the form of increased trading costs for a stock. They claim this finding stems from uninformed traders' migration to basket market from individual stock trading after the introduction of ETFs. In contrast, Saglam, Tuzun & Wermers (2019) use high-frequency data and document that, in normal times, plain vanilla equity ETFs improve their constituent stocks' liquidity profiles, measured by effective and quoted spreads, Amihud's illiquidity ratio (Amihud, 2002) and implementation shortfall. The authors note that the opposite happens in turbulent times and higher ETF ownership becomes associated with more dramatic liquidity losses for stocks under distressed market conditions such as 2011 US debt ceiling crisis.

Similar to the liquidity aspect, the literature provides mixed evidence regarding the effects of ETFs on price discovery and market efficiency. To begin with research supporting that ETFs adversely impact market efficiency, Israeli et al. (2017) document that ETFs harm market efficiency by making stock prices less responsive and reducing the number of research analysts covering firms that are held by ETFs. Bhattacharya & O'Hara (2018) demonstrate that the additional layer of liquidity and order flow brought by ETFs on illiquid, hard-to-access assets causes persistent price dislocations in the basket assets, and induces herding thereby rendering such illiquid markets more fragile. Bhojraj, Mohanram & Zhang (2020) highlight the role of ETFs in the information transfer across firms around earnings announcement dates and make the distinction that broad-based ETFs exacerbate while sector ETFs enhance informational efficiency of the underlying stocks in this context. Shim (2019) finds that ETFs cause long-lasting distortions in asset prices since factor innovations are reflected in security prices not according to their factor sensitivities but their index weights due to the mechanics of ETF arbitrage mechanism. Brown, Davies & Ringgenberg (2021) show that ETFs with higher net flows underperform ETFs with lower net flows, implying that ETF investors demonstrate a flow-chasing behavior causing non-fundamental positive (negative) demand shocks on recently popular (unpopular) ETFs, which pull the underlying security prices away from their fundamental values.

On the other hand, Glosten, Nallareddy & Zou (2021) find that systematic information is incorporated in a timely manner to prices of stocks that are held by ETFs, and this leads to an improvement in the short-term informational efficiency of these stocks. Shortability of ETFs make them convenient tools to build directional short bets on member securities subject to high short-sale constraints. Karmaziene & Sokolovski (2022) and Li & Zhu (2022) highlight this feature of ETFs and document its positive contribution on market liquidity and market efficiency, respectively, by way of facilitating the expression of negative views on stocks that are hard to short. In a similar spirit, Huang, O'Hara & Zhong (2021) demonstrate how sector ETFs improve market efficiency by expanding hedging capabilities of informed investors such as hedge funds. The authors provide evidence that abnormal hedge fund holdings on stocks which are due to announce positive earnings surprises in the upcoming earnings season climb simultaneously with the short interest of the sector ETFs that hold those stocks. This pattern signifies that "long-the-stock/short-the-sector-ETF" strategy is employed by informed investors to bet on earnings surprises while taking shield from market and sector risks via use of sector ETFs. The paper also documents that sector ETFs reduce post-earnings-announcement-drift, suggesting that sector ETFs contribute to market efficiency by enabling informed investors to short baskets of securities in the same industry in an easy and cost-efficient way. Finally, Novick et al. (2017) maintain in a Blackrock whitepaper that US-based ETFs with international holdings contribute to more efficient pricing of underlying foreign assets every day during the time US exchanges are open and their own local markets are closed.

Another strand of ETF literature is committed to investigation of the impact of ETFs on the correlations among constituent stocks. Unlike the mixed nature of evidence on the liquidity and market efficiency effects of ETFs', this literature is mostly tilted to the verdict that ETFs lead to stronger co-movement in returns of their member stocks. In fact, the finance literature had already documented that component stocks of an index tend to comove strongly even when ETFs were in their infancy. In this context, Morck & Yang (2001) state that index stocks collectively face downward sloping demand curves, Barberis, Shleifer & Wurgler (2005) report that a stock's beta rises considerably once it gets included in the S&P 500 index, and Wurgler (2010) ascribes the increased co-movement of index stocks to the correlated passive investment product flows experienced by these stocks. Bradley & Litan (2010), Israeli et al. (2017), Da & Shive (2018) and Leippold, Su & Ziegler (2016) corroborate this finding in the context of ETFs and conclude that ETFs cause greater co-movement of component stocks. Da & Shive (2018) and Leippold et al. (2016) identify ETF arbitrage mechanism as the main channel driving this enhanced return synchronicity. The former shows that some co-movement may be excessive as evidenced by subsequent price reversals in the data. This finding is in line with that of Baltussen, van Bekkum & Da (2019) who find that the serial dependence in daily to weekly frequency in major stock markets around the world, which was traditionally positive until the 1990s, has turned significantly negative in the new millennium. This change in aggregate pricing behavior is mainly linked to the rise of passive investments, and partly attributable to the mechanics of index arbitrage strategies creating opposite price pressures on the index product and the underlying index assets. To sum up, theoretically, the degree of co-movement between two assets should generate from the correlation between the fundamental exposures between the two. However, the literature provides extensive evidence that indexing, and particularly ETFs, triggers elevated correlations among stocks that participate in common indices. This poses a serious systematic risk for investors by reducing diversification benefits.

1.3 A Research on ETFs: ETF Plays of Institutional Investors

ETFs have been increasingly adopted by both institutional and retail investors in recent times. There is vast academic evidence that institutional investors outperform their retail counterparts in financial markets mainly due to behavioral biases suffered by the latter investor group.[6] ETF space is no exception with regards to this conviction.[7] In this section, I investigate whether the outperformance of institutional investors put forward by academic literature could be verified from a new aspect when one specifically focuses on their aggregate asset allocation decisions in ETF markets.

Accordingly, I conduct research on institutional investors' ETF plays in the vicinity of extreme risk appetite regimes. For that purpose, I obtain the time-series of the evolution of institutional investors' share in US-based ETFs on different asset classes with varying risk levels and investigate the institutional ownership in different ETF categories prior to, during and after the best and worst quarters in terms of

[6] Barber & Odean (2000) conclude that individual investors trade excessively due to overconfidence. Frazzini & Lamont (2008) show that retail investor sentiment is associated with lower future returns and these investors lose wealth by reallocating their capital across funds. Barber & Odean (2013) report that retail traders underperform standard benchmarks, exhibit disposition effect, suffer from limited attention and return chasing behavior, and tend to hold undiversified portfolios. Barber, Lee, Liu & Odean (2009) document that retail investor trades result in systematic and economically large losses, mainly due to their aggressive trades.

[7] In the context of ETFs, Bhattacharya, Loos, Meyer & Hackethal (2017) document that ETFs induce excessive retail trading and retail ETF investors do poorly both in terms of ETF timing and ETF selection. Clifford, Fulkerson & Jordan (2014) report that ETF investors chase returns just like mutual fund investors despite the fact that ETFs are passive vehicles. Brown et al. (2021) present evidence that ETF investors not only chase returns but flows as well, and Broman (2016) shows that noise traders in ETFs lead to commonality in demand shocks causing excessive positive (negative) co-movement of mispricing in ETFs with similar (distant) investment styles.

broad stock market performance. Here, stock market performance is used as a proxy for risk appetite since equities historically constitute the riskiest asset class among conventional asset classes. In this respect, periods of high (low) stock market performance are viewed as high (low) risk appetite periods. Intuitively, one should expect to observe relatively stronger inflows into riskier asset classes and relatively stronger outflows from safer asset classes in high risk appetite periods. Likewise, one should expect to observe relatively stronger inflows into safer asset classes and relatively stronger outflows from riskier asset classes in low risk appetite periods. The asset classes I use are three-fold: US-equity, US-fixed income and gold. In the risk scale, US-equity represents the riskiest, US-fixed income represents the medium-risk and gold represents the safest asset class, comparatively.

My primary goal is to investigate whether institutional investors in ETF markets have historically exhibited superior investment allocation decisions compared to their retail counterparts, by observing their positioning in ETF markets up to four quarters before, during and up to four quarters after boom or bust periods of the stock market. If institutional players excel retail investors in anticipating the prospective market trajectory, we should observe that institutions' share in US-equity ETFs are climbing (sliding) whereas that in gold ETFs are sliding (climbing) while approaching high (low) risk appetite periods. Furthermore, in a subsequent analysis, I relax my focus on the extreme quarters and investigate whether current and lagged changes in institutional ownership can explain stock market returns taking into consideration all the quarters in my sample period.

1.3.1 Data

I obtain data from three sources. I get the quarterly institutional ETF investments (number of shares, market value and asset size) from the Thomson Reuters Institutional Holdings (s34) dataset. This dataset compiles the mandatory 13F reports on institutional holdings, submitted by institutional investors to the SEC and published in EDGAR (Electronic Data Gathering, Analysis, and Retrieval System) on a quarterly basis. My primary source for identification of ETFs belonging to each category, ETF number of shares outstanding, ETF price, ETF assets under management and ETF flows is Bloomberg. Bloomberg serves as a major data source in many ETF-related studies, and Ben-David et al. (2018) maintains that it stands superior to its alternatives concerning the accuracy of number of shares outstanding data. Still, I also utilize CRSP data on ETFs to check the accuracy of data I get from Bloomberg and Thomson Reuters whenever comparison is possible. I merge all three data sources via CUSIP identifiers of the instruments.

The sample period runs from 2000Q1 to 2018Q4. The ETF sample I focus on is the US-based, plain vanilla, passively-managed ETFs that hold either only US equities, or only US fixed income securities or only gold. That is to say, I do not include leveraged ETFs, inverse ETFs, actively-managed ETFs or ETFs that use swaps or other derivatives. This sample choice is in line with that of Ben-David et al. (2018). I also disregard mixed allocation ETFs that invest in multiple asset classes since these would potentially contaminate the findings. My main objective is isolating the institutional flows on ETFs of different asset classes for better characterization of institutional investors' allocation decisions in ETF markets.

1.3.2 Methodology and Results

Table 1.1 divides the quarters in the sample period into 10 deciles based on quarterly returns of the S&P 500 index. The S&P 500 index is a prominent gauge that measures the broad US equity market performance. Decile 1 and decile 10 are identified as the quarters with the worst and best US equity returns, respectively. Here, I use stock market performance as a proxy for the level of risk appetite. Therefore, decile 1 quarters should be considered as risk-off (lowest risk appetite) periods while decile 10 quarters should be viewed as risk-on (highest risk appetite) periods. From this point on, I collectively refer to decile 1 and decile 10 quarters as the extreme quarters. I also refer to decile 1 quarters as the low risk appetite or the worst quarters and decile 10 quarters as the high risk appetite or the best quarters. In my sample period, 2001Q1, 2001Q3, 2002Q2, 2002Q3, 2008Q4, 2010Q2, 2011Q3 and 2018Q4 turn out to be the lowest risk appetite quarters whereas 2003Q2, 2003Q4, 2009Q2, 2009Q3, 2010Q3, 2011Q4 and 2012Q1 turn out to be the highest risk appetite quarters.

Table 1.2 demonstrates the summary statistics of quarterly institutional ownership percentage in US-equity, US-fixed income and gold ETFs. Institutional ownership in a single ETF is calculated as the number of total shares held by institutional investors divided by the total number of shares outstanding of that ETF, or equivalently the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF. Accordingly, aggregate institutional ownership in an ETF category is calculated as the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF category. US-equity ETFs are available throughout the full sample period whereas the first gold ETF was launched in 2004Q4 and the first US-fixed income ETF was launched in 2002Q3. Also, the most recent institutional share data is available as of the end of 2018Q2 for all three ETF categories at the time this study has been conducted. In effect, I have 55, 64 and 74 quarters of institutional ownership data for gold, US-fixed income and US-equity ETFs, respectively. Institutional ownership for gold ETFs ranges between 22% and 50% with an average of 37%. Institutional ownership for US-fixed income ETFs ranges between 31% and 76% with an average of 49%. Finally, institutional ownership for US-equity ETFs ranges between 28% and 71% with an average of 54%. Figure 1.1 exhibits the quarterly evolution of institutional ownership in gold, US-fixed income and US-equity ETFs in the sample period.

Table 1.3 presents the institutional ownership percentage while Table 1.4 presents the change in the institutional ownership percentage in gold, US-fixed income and US-equity ETFs before, during and after extreme quarters, respectively. For gold ETFs, only three and five quarters of data are available for decile 1 and decile 10, respectively. As for the worst quarters, institutional ownership in gold ETFs clearly rises before and during 2011Q3 and starts to decline thereafter in line with ex-ante expectations, whereas it somewhat declines either before or during the quarters 2008Q4 and 2010Q2 and starts to rise thereafter. As for the best quarters, except for 2010Q3 I observe that institutional ownership decreases during the current quarter. However, the trajectory in the previous four quarters and subsequent four quarters do not indicate common patterns.

As for US-fixed income ETFs, three and seven quarters of data are available for decile 1 and decile 10, respectively. Regarding the worst quarters, I observe that for 2008Q4 and 2011Q3 institutional ownership rises in the previous four quarters and the current quarter and declines or stays stagnant after the current quarter in line with ex-ante expectations. However, the trajectory in 2010Q2 is somewhat the opposite. Regarding the best quarters, in five out of seven quarters, I observe that institutional ownership declines up to four quarters before the current quarter, that could imply superiority of institutional investors in anticipation of upcoming high risk appetite period. However, the trajectory of institutional ownership in the current quarter and the following quarters is very heterogeneous among seven cases.

As for US-equity ETFs, seven quarters of data are available both for decile 1 and decile 10. Regarding the worst quarters, I observe that institutional ownership decreases in the previous quarter in six out of seven cases. This may indicate that institutional investors are good at anticipating the upcoming low risk appetite period that is one quarter ahead. However, the trajectory of institutional ownership in the current quarter and the following quarters is very heterogeneous among seven cases. As for the best quarters, I observe that institutional ownership is quite erratic during the previous four quarters, and sharp declines in institutional ownership is a common occurrence in many cases in contrast with ex-ante expectations. This implies institutional investors do not consistently succeed in anticipating the upcoming high risk appetite period. Moreover, one can see that the trajectory of institutional ownership in the current quarter and the following quarters is very heterogeneous and do not show common patterns.

In conclusion, the mixed trend in the trajectory of institutional ownership around extreme quarters for gold ETFs, US-fixed income ETFs and US-equity ETFs does not allow us to obtain convincingly supporting or opposing evidence regarding the superiority of institutional investors in anticipating extreme risk appetite periods ahead of time. Hence, it does not seem possible to reach clear-cut, reliable, and far-reaching conclusions from this analysis. That said, it should be noted that this study is subject to serious sample size limitation since the history of ETFs do not go back far in the past and data frequency can be quarterly at best due to data availability and disclosure frequency.

Therefore, in the next step, I focus on all quarters rather than only the extreme ones and conduct regression analysis to see whether changes in institutional ownership are correlated with risk appetite. Table 1.5 presents the regression results where I regress the current quarterly S&P 500 return on current and lagged changes in institutional ownership percentage to see whether institutional players increase their ownership in risky US-equity ETFs and decrease their ownership in less risky US-fixed income and gold ETFs during and prior to the best quarters and vice versa. The findings reveal that for gold ETFs, which is the safest investment among the three, changes in institutional ownership in the previous three quarters are negatively correlated with risk appetite. This implies that institutions decrease their exposure in the safest asset class prior to high risk appetite periods and vice versa in line with ex-ante expectations. However, none of the coefficients are statistically significant. As for US-fixed income ETFs, the results are rather mixed and signs of the current and lag 1 switch from positive to negative as I add more lags to the specification. In particular, results of the full specification with four lags indicate that the current and previous 4 quarters' change in institutional ownership are negatively correlated to the stock market performance. This could be evidence that institutions adjust their moderate-risk bond exposure downwards prior to high risk appetite periods and vice versa in line with ex-ante expectations. Yet again, none of the coefficients except lag 2 is statistically significant. Finally, changes in institutional ownership in US-equity

ETFs in the current and previous quarter are positively correlated with market performance, while changes in the previous 2 to 4 quarters are positively correlated. This finding, which may be arising from business cycles and resulting cyclicality in the equity market, corroborates the implication that institutions investing in US-equity ETFs do well in anticipating extreme risk appetite periods one quarter ahead of time. Still, none of the coefficients are statistically significant except lag four in the full specification. So, I cannot reach reliable evidence and changes in institutional ETF ownership are not able to predict risk appetite proxied by stock market returns.

In a similar analysis, I alter my explanatory metric from institutional ownership to institutional ETF flows and reconduct the regressions above in a monthly frequency for the sake of alleviating the small sample bias. Institutional ETF flows are calculated by the net change in the value of shares held by institutions adjusted for price movements. Table 1.6 presents the regression results where I regress the current quarterly S&P 500 return (as of the end of each month) on current and lagged institutional ETF flows (as of the end of each month) to see whether institutional ETF flows can explain stock market performance. Yet again, all the coefficients I obtain in contemporaneous and one-lagged specifications are all insignificant. As for full-specifications which include the contemporaneous and lagged institutional flows up to four lags, I observe that negatively significant coefficients are obtained for lag 1, 2 and 3 for US-fixed income ETFs and lag 2 and 3 for US-equity ETFs. This may be an indication that before quarters when stock market performs poorly (strongly), institutional ETF flows into bond funds become stronger (weaker) in the previous three quarters in line with my ex-ante expectations. However, the results of US-equity ETFs suggest the otherwise, which is counterintuitive.

1.3.3 Conclusion

I have examined the positioning of institutional investors in ETF markets of varying risk levels and investigated whether institutional players demonstrate better asset allocation decisions compared to retail players in the vicinity of extreme risk appetite periods and in general. My empirical findings do not allow me to conclude that institutional players outperform retail players in ETF markets in either case. First, I find that institutional investors in ETF markets do not appear to exhibit consistently superior allocation skills in the vicinity of extreme periods. This implies institutional players do not excel in anticipating the upcoming extreme periods, and adjusting their positions accordingly before, during and after these boom and bust periods. Secondly, neither (current and lagged) institutional ownership percentage in US-equity, US-fixed income or gold ETFs; nor institutional ETF flows into US-equity, US-fixed income or gold ETFs are able to explain stock market returns throughout the full sample period. This indicates institutional investors in ETF markets do not appear to exhibit superior market timing and allocation skills in general.

I should note that the results of the study should be taken with a pinch of salt due to several reasons. First and foremost, the ETF market is still a very young and immature market, and it was even more so for most of my sample period. It is highly likely that the adoption level of ETFs as investment instruments by institutions was time-varying and quite different than that by retail investors during my sample period. Secondly, the empirical setup implicitly and naively assumes that institutional investors in ETF markets do not hold non-ETF investments. However, we can think of many plausible scenarios for which that is not the case. For example, Huang et al. (2021) document that many hedge funds are using ETFs as hedging vehicles rather than speculation vehicles, such as holding a stock that is expected to announce a positive earnings surprise in the next quarter and selling the industry or broad market ETFs to hedge that long stock position. Furthermore, many institutional players function as authorized participants, market makers or liquidity providers in ETF markets. It is understandable that the positioning of such institutions in ETFs will not be indicative of their market views. Thirdly, condensing the vast risk scale of investments into three categories as gold, fixed income and equity, to be able to represent low-risk, medium-risk and high-risk investments, is likely an oversimplification. It should be noted that even among the securities within US-fixed income and US-equity asset class, risk levels may wildly differ from each other. Moreover, Treasury bills within US-fixed income class is safer than gold and it is not hard to find defensive stocks in US-equity class that are safer than high-yield or junk bonds within US-fixed income class. Thus, even the risk ladder among gold, US-fixed income and US-equity is not a clean one since none of the asset classes are collectively riskier or safer than the other one with all their constituents.

1.4 Tables and Figures

Table 1.1 Quarterly performance of the S&P 500 index

This table presents quarterly performance of the S&P 500 index in the sample period 2000Q1 – 2018Q4. Decile 1 quarters represent those in which equity market performance is weakest and decile 10 quarters represent those in which the equity market performance is strongest.

Year	Quarter	S&P 500 Return	Decile	Year	Quarter	S&P 500 Return	Decile
2000	1	2.00	6	2009	3	14.99	10
2000	2	-2.93	3	2009	4	5.49	8
2000	3	-1.24	3	2010	1	4.87	7
2000	4	-8.09	2	2010	2	-11.86	1
2001	1	-12.11	1	2010	3	10.72	10
2001	2	5.52	8	2010	4	10.20	9
2001	3	-14.98	1	2011	1	5.42	7
2001	4	10.29	9	2011	2	-0.39	4
2002	1	-0.06	4	2011	3	-14.33	1
2002	2	-13.73	1	2011	4	11.15	10
2002	3	-17.63	1	2012	1	12.00	10
2002	4	7.92	9	2012	2	-3.29	2
2003	1	-3.60	2	2012	3	5.76	8
2003	2	14.89	10	2012	4	-1.01	4
2003	3	2.20	6	2013	1	10.03	9
2003	4	11.64	10	2013	2	2.36	6
2004	1	1.29	5	2013	3	4.69	7
2004	2	1.30	5	2013	4	9.92	9
2004	3	-2.30	3	2014	1	1.30	5
2004	4	8.73	9	2014	2	4.69	7
2005	1	-2.59	3	2014	3	0.62	4
2005	2	0.91	5	2014	4	4.39	7
2005	3	3.15	6	2015	1	0.44	4
2005	4	1.59	5	2015	2	-0.23	4
2006	1	3.73	7	2015	3	-6.94	2
2006	2	-1.90	3	2015	4	6.45	9
2006	3	5.17	7	2016	1	0.77	4
2006	4	6.17	8	2016	2	1.90	5
2007	1	0.18	4	2016	3	3.31	6
2007	2	5.81	8	2016	4	3.25	6
2007	3	1.56	5	2017	1	5.53	8
2007	4	-3.82	2	2017	2	2.57	6
2008	1	-9.92	2	2017	3	3.96	7
2008	2	-3.23	3	2017	4	6.12	8
2008	3	-8.88	2	2018	1	-1.22	3
2008	4	-22.56	1	2018	2	2.93	6
2009	1	-11.67	2	2018	3	7.20	9
2009	2	15.22	10	2018	4	-13.97	1

Table 1.2 Institutional ownership in gold, US-fixed income and US-equity ETFs

This table presents summary statistics of quarterly institutional ownership in gold, US-fixed income and US-equity ETFs. Institutional ownership in a single ETF is calculated as the number of total shares held by institutional investors divided by the total number of shares outstanding of that ETF, or equivalently the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF. Accordingly, aggregate institutional ownership in an ETF category is calculated as the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF category. Data on the number of shares or the market value/asset size held by institutional investors as of the end of each quarter is collected from Thomson Reuters Institutional Holdings (s34) dataset.

	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs
#Quarters	55	64	74
Mean	0.3731	0.4940	0.5362
Std Dev	0.0618	0.0881	0.1002
Min	0.2242	0.3114	0.2801
Max	0.4983	0.7576	0.7147
Skewness	-0.3139	-0.1004	-0.7183
Kurtosis	2.9630	2.8798	2.7724

Table 1.3 Institutional ownership percentage in gold, US-fixed income and US-equity ETFs around extreme quarters

This table presents the institutional ownership percentage in gold, US-fixed income and US-equity ETFs before, during and after extreme quarters. The figures associated with low risk appetite quarters (S&P 500 return decile 1) and high risk appetite quarters (S&P 500 return decile 10) are presented in Panel A and Panel B, respectively.

Panel A. Low risk appetite quarters

Year	Quarter	S&P 500 Return	Return Decile	Quarter (t-4)	Quarter (t-3)	Quarter (t-2)	Quarter (t-1)	Current Quarter	Quarter (t+1)	Quarter (t+2)	Quarter (t+3)	Quarter (t+4)
								GOLD ETFs				
2001	1	-12.11	1	na	na	na	na	na	na	na	na	na
2001	3	-14.98	1	na	na	na	na	na	na	na	na	na
2002	2	-13.73	1	na	na	na	na	na	na	na	na	na
2002	3	-17.63	1	na	na	na	na	na	na	na	na	na
2008	4	-22.56	1	0.3772	0.3527	0.3326	0.3418	0.3584	0.4870	0.4062	0.3952	0.4123
2010	2	-11.86	1	0.4062	0.3952	0.4123	0.4131	0.3765	0.4287	0.4456	0.4658	0.4708
2011	3	-14.33	1	0.4287	0.4456	0.4658	0.4708	0.4983	0.4414	0.4273	0.4409	0.4551
								US-FIXED INCOME ETFs				
2001	1	-12.11	1	na	na	na	na	na	na	na	na	na
2001	3	-14.98	1	na	na	na	na	na	na	na	na	0.4746
2002	2	-13.73	1	na	na	na	na	na	0.4746	0.4359	0.3787	0.5524
2002	3	-17.63	1	na	na	na	na	0.4746	0.4359	0.3787	0.5524	0.3696
2008	4	-22.56	1	0.3206	0.5704	0.5066	0.4879	0.5363	0.3647	0.4355	0.3926	0.3973
2010	2	-11.86	1	0.4355	0.3926	0.3973	0.3834	0.3114	0.3712	0.4414	0.4635	0.4815
2011	3	-14.33	1	0.3712	0.4414	0.4635	0.4815	0.5109	0.5190	0.5083	0.5107	0.5007
								US-EQUITY ETFs				
2001	1	-12.11	1	0.3078	0.3335	0.4100	0.3792	0.4527	0.4126	0.4192	0.4271	0.3962
2001	3	-14.98	1	0.4100	0.3792	0.4527	0.4126	0.4192	0.4271	0.3962	0.2893	0.3605
2002	2	-13.73	1	0.4126	0.4192	0.4271	0.3962	0.2893	0.3605	0.3435	0.3450	0.4267
2002	3	-17.63	1	0.4192	0.4271	0.3962	0.2893	0.3605	0.3435	0.3450	0.4267	0.4533
2008	4	-22.56	1	0.5844	0.7211	0.7119	0.6389	0.6651	0.5889	0.5902	0.5709	0.5879
2010	2	-11.86	1	0.5902	0.5709	0.5879	0.5631	0.4941	0.5861	0.6371	0.6322	0.6452
2011	3	-14.33	1	0.5861	0.6371	0.6322	0.6452	0.6622	0.6215	0.6468	0.5995	0.5932

Panel B. High risk appetite quarters

Year	Quarter	S&P 500 Return	Return Decile	Quarter (t-4)	Quarter (t-3)	Quarter (t-2)	Quarter (t-1)	Current Quarter	Quarter (t+1)	Quarter (t+2)	Quarter (t+3)	Quarter (t+4)
						GOLD ETFs						
2003	2	14.89	10	na	na	na	na	na	na	na	na	na
2003	4	11.64	10	na	na	na	na	na	na	na	na	0.2285
2009	2	15.22	10	0.3326	0.3418	0.3584	0.4870	0.4062	0.3952	0.4123	0.4131	0.3765
2009	3	14.99	10	0.3418	0.3584	0.4870	0.4062	0.3952	0.4123	0.4131	0.3765	0.4287
2010	3	10.72	10	0.3952	0.4123	0.4131	0.3765	0.4287	0.4456	0.4658	0.4708	0.4983
2011	4	11.15	10	0.4456	0.4658	0.4708	0.4983	0.4414	0.4273	0.4409	0.4551	0.4495
2012	1	12.00	10	0.4658	0.4708	0.4983	0.4414	0.4273	0.4409	0.4551	0.4495	0.4063
						US-FIXED INCOME ETFs						
2003	2	14.89	10	na	0.4746	0.4359	0.3787	0.5524	0.3696	0.4576	0.7568	0.4764
2003	4	11.64	10	0.4359	0.3787	0.5524	0.3696	0.4576	0.7568	0.4764	0.5766	0.5852
2009	2	15.22	10	0.5066	0.4879	0.5363	0.3647	0.4355	0.3926	0.3973	0.3834	0.3114
2009	3	14.99	10	0.4879	0.5363	0.3647	0.4355	0.3926	0.3973	0.3834	0.3114	0.3712
2010	3	10.72	10	0.3926	0.3973	0.3834	0.3114	0.3712	0.4414	0.4635	0.4815	0.5109
2011	4	11.15	10	0.4414	0.4635	0.4815	0.5109	0.5190	0.5083	0.5107	0.5007	0.5209
2012	1	12.00	10	0.4635	0.4815	0.5109	0.5190	0.5083	0.5107	0.5007	0.5209	0.5028
						US-EQUITY ETFs						
2003	2	14.89	10	0.2893	0.3605	0.3435	0.3450	0.4267	0.4533	0.4599	0.4911	0.5280
2003	4	11.64	10	0.3435	0.3450	0.4267	0.4533	0.4599	0.4911	0.5280	0.4977	0.4999
2009	2	15.22	10	0.7119	0.6389	0.6651	0.5889	0.5902	0.5709	0.5879	0.5631	0.4941
2009	3	14.99	10	0.6389	0.6651	0.5889	0.5902	0.5709	0.5879	0.5631	0.4941	0.5861
2010	3	10.72	10	0.5709	0.5879	0.5631	0.4941	0.5861	0.6371	0.6322	0.6452	0.6622
2011	4	11.15	10	0.6371	0.6322	0.6452	0.6622	0.6215	0.6468	0.5995	0.5932	0.5980
2012	1	12.00	10	0.6322	0.6452	0.6622	0.6215	0.6468	0.5995	0.5932	0.5980	0.5798

Table 1.4 Change in institutional ownership percentage in gold, US-fixed income and US-equity ETFs around extreme quarters

This table presents the change in institutional ownership percentage in gold, US-fixed income and US-equity ETFs before, during and after extreme quarters. The figures associated with low risk appetite quarters (S&P 500 return decile 1) and high risk appetite quarters (S&P 500 return decile 10) are presented in Panel A and Panel B, respectively.

Panel A. Low risk appetite quarters

Year	Quarter	S&P 500 Return	Return Decile	Last 4 Quarters' Cumulative Change	Last 3 Quarters' Cumulative Change	Last 2 Quarters' Cumulative Change	Last Quarter's Change	Current Quarter's Change	Next Quarter's Change	Next 2 Quarters' Cumulative Change	Next 3 Quarters' Cumulative Change	Next 4 Quarters' Cumulative Change
								GOLD ETFs				
2001	1	-12.11	1	na	na	na	na	na	na	na	na	na
2001	3	-14.98	1	na	na	na	na	na	na	na	na	na
2002	2	-13.73	1	na	na	na	na	na	na	na	na	na
2002	3	-17.63	1	na	na	na	na	na	na	na	na	na
2008	4	-22.56	1	-0.0301	-0.0353	-0.0108	0.0093	0.0166	0.1286	0.0477	0.0368	0.0539
2010	2	-11.86	1	-0.0739	0.0070	0.0179	0.0008	-0.0366	0.0522	0.0691	0.0893	0.0943
2011	3	-14.33	1	0.0943	0.0421	0.0252	0.0050	0.0275	-0.0569	-0.0710	-0.0574	-0.0432
								US-FIXED INCOME ETFs				
2001	1	-12.11	1	na	na	na	na	na	na	na	na	na
2001	3	-14.98	1	na	na	na	na	na	na	na	na	na
2002	2	-13.73	1	na	na	na	na	na	na	na	na	na
2002	3	-17.63	1	na	na	na	na	na	-0.0387	-0.0959	0.0778	-0.1050
2008	4	-22.56	1	0.1406	0.1674	-0.0824	-0.0187	0.0484	-0.1716	-0.1008	-0.1437	-0.1390
2010	2	-11.86	1	0.0187	-0.0521	-0.0092	-0.0138	-0.0720	0.0598	0.1300	0.1521	0.1701
2011	3	-14.33	1	0.1701	0.1103	0.0401	0.0180	0.0294	0.0080	-0.0027	-0.0003	-0.0102
								US-EQUITY ETFs				
2001	1	-12.11	1	na	0.0714	0.0458	-0.0307	0.0735	-0.0401	-0.0336	-0.0257	-0.0565
2001	3	-14.98	1	0.0791	0.0026	0.0334	-0.0401	0.0066	0.0079	-0.0230	-0.1299	-0.0587
2002	2	-13.73	1	-0.0565	-0.0164	-0.0230	-0.0309	-0.1069	0.0712	0.0541	0.0557	0.1374
2002	3	-17.63	1	-0.1233	-0.1299	-0.1378	-0.1069	0.0712	-0.0170	-0.0155	0.0662	0.0928
2008	4	-22.56	1	0.0148	0.0546	-0.0821	-0.0730	0.0261	-0.0762	-0.0749	-0.0941	-0.0772
2010	2	-11.86	1	-0.0257	-0.0271	-0.0078	-0.0248	-0.0690	0.0920	0.1430	0.1381	0.1511
2011	3	-14.33	1	0.1511	0.0591	0.0081	0.0130	0.0170	-0.0407	-0.0154	-0.0627	-0.0690

Panel B. High risk appetite quarters

Year	Quarter	S&P 500 Return	Return Decile	Last 4 Quarters' Cumulative Change	Last 3 Quarters' Cumulative Change	Last 2 Quarters' Cumulative Change	Last Quarter's Change	Current Quarter's Change	Next Quarter's Change	Next 2 Quarters' Cumulative Change	Next 3 Quarters' Cumulative Change	Next 4 Quarters' Cumulative Change
								GOLD ETFs				
2003	2	14.89	10	na	na	na	na	na	na	na	na	na
2003	4	11.64	10	na	na	na	na	na	na	na	na	na
2009	2	15.22	10	0.1343	0.1544	0.1451	0.1286	-0.0808	-0.0109	0.0062	0.0070	-0.0296
2009	3	14.99	10	0.0736	0.0643	0.0477	-0.0808	-0.0109	0.0171	0.0179	-0.0187	0.0335
2010	3	10.72	10	-0.0296	-0.0187	-0.0358	-0.0366	0.0522	0.0169	0.0371	0.0421	0.0696
2011	4	11.15	10	0.0696	0.0526	0.0324	0.0275	-0.0569	-0.0142	-0.0005	0.0136	0.0081
2012	1	12.00	10	-0.0042	-0.0244	-0.0294	-0.0569	-0.0142	0.0137	0.0278	0.0222	-0.0209
								US-FIXED INCOME ETFs				
2003	2	14.89	10	na	na	-0.0959	-0.0572	0.1737	-0.1828	-0.0948	0.2044	-0.0760
2003	4	11.64	10	-0.1050	-0.0663	-0.0091	-0.1828	0.0880	0.2992	0.0188	0.1191	0.1276
2009	2	15.22	10	-0.2056	-0.1419	-0.1232	-0.1716	0.0708	-0.0429	-0.0383	-0.0521	-0.1241
2009	3	14.99	10	-0.0711	-0.0524	-0.1008	0.0708	-0.0429	0.0046	-0.0092	-0.0812	-0.0214
2010	3	10.72	10	-0.1241	-0.0812	-0.0858	-0.0720	0.0598	0.0702	0.0923	0.1103	0.1397
2011	4	11.15	10	0.1397	0.0695	0.0474	0.0294	0.0080	-0.0107	-0.0083	-0.0182	0.0019
2012	1	12.00	10	0.0776	0.0554	0.0374	0.0080	-0.0107	0.0024	-0.0075	0.0126	-0.0054
								US-EQUITY ETFs				
2003	2	14.89	10	-0.0512	0.0557	-0.0155	0.0016	0.0817	0.0266	0.0333	0.0644	0.1014
2003	4	11.64	10	0.0928	0.1098	0.1082	0.0266	0.0067	0.0312	0.0681	0.0378	0.0399
2009	2	15.22	10	-0.1322	-0.1230	-0.0501	-0.0762	0.0014	-0.0193	-0.0023	-0.0271	-0.0961
2009	3	14.99	10	-0.1217	-0.0487	-0.0749	0.0014	-0.0193	0.0170	-0.0078	-0.0769	0.0151
2010	3	10.72	10	-0.0961	-0.0769	-0.0938	-0.0690	0.0920	0.0510	0.0461	0.0591	0.0762
2011	4	11.15	10	0.0762	0.0252	0.0300	0.0170	-0.0407	0.0253	-0.0220	-0.0283	-0.0235
2012	1	12.00	10	-0.0156	-0.0107	-0.0237	-0.0407	0.0253	-0.0473	-0.0536	-0.0488	-0.0670

Table 1.5 Regression analysis with institutional ownership as explanatory variable

This table presents results from the regressions of quarterly S&P 500 returns on current and lagged quarterly changes in institutional ownership percentage in gold, US-fixed income and US-equity ETFs. D.InstOwn is the contemporaneous quarterly change in institutional ownership whereas L1.InstOwn, L2.InstOwn, L3.InstOwn and L4.InstOwn are the change in institutional ownership percentage one, two, three and four quarters ago, respectively. t-statistics, given in parentheses, are adjusted for autocorrelation and heteroskedasticity using the Newey-West (1987) procedure.

	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs
D.InstOwn	-0.3356	0.0935	0.0878	-0.3809	0.1155	0.1618	-0.4130	0.0374	0.1417	-0.4656	0.0656	0.2154	-0.4695	-0.0090	0.3520
	(-1.36)	(0.82)	(0.43)	(-1.15)	(0.85)	(0.76)	(-1.24)	(0.26)	(0.56)	(-1.41)	(0.36)	(0.78)	(-1.28)	(-0.06)	(1.53)
L1.InstOwn				-0.1113	0.0343	0.3680	-0.0698	-0.0852	0.3426	-0.0602	-0.1450	0.3150	-0.0734	-0.7910	0.4885
				(-0.98)	(0.37)	(1.48)	(-0.50)	(-0.81)	(1.33)	(-0.38)	(-1.23)	(0.95)	(-0.38)	(-0.60)	(1.45)
L2.InstOwn							-0.0266	-0.1672	-0.1616	-0.1113	-0.3065	-0.2007	-0.0938	-0.3931	-0.2728
							(-0.16)	(-1.99)	(-0.70)	(-0.45)	(-2.29)	(-0.92)	(-0.34)	(-2.33)	(-1.23)
L3.InstOwn										-0.0993	-0.2656	-0.3844	-0.1287	-0.4349	-0.5109
										(-0.62)	(-1.18)	(-1.10)	(-0.49)	(-1.54)	(-1.41)
L4.InstOwn													0.0107	-0.3489	-0.7435
													(0.04)	(-1.81)	(-4.39)
Intercept	0.0184	0.0217	0.0110	0.0183	0.0206	0.0104	0.0190	0.0222	0.0117	0.0188	0.0213	0.0146	0.0184	-0.0227	0.0188
	(1.84)	(2.30)	(1.12)	(1.78)	(2.18)	(0.99)	(1.82)	(2.36)	(1.15)	(1.78)	(2.42)	(1.55)	(1.76)	(2.50)	(2.14)
#observations	54	63	73	53	62	72	52	61	71	51	60	70	50	59	69

Table 1.6 Regression analysis with institutional flows as explanatory variable

This table presents results from the regressions of quarterly S&P 500 returns on current and lagged quarterly institutional flows into gold, US-fixed income and US-equity ETFs. D.InstFlow is the contemporaneous quarterly institutional flows whereas L1.InstFlow, L2.InstFlow, L3.InstFlow and L4.InstFlow are the institutional flows one, two, three and four quarters ago, respectively. t-statistics, given in parentheses, are adjusted for autocorrelation and heteroskedasticity using the Newey-West (1987) procedure.

	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs	Gold ETFs	US-Fixed Income ETFs	US-Equity ETFs
D.InstFlow	-0.0984	-0.0757	-0.3222	-0.1043	-0.1274	-0.3579	-0.1004	-0.1799	-0.4756	-0.1177	-0.0867	-0.3458	-0.1314	-0.1195	-0.3754
	(-0.89)	(-0.55)	(-1.30)	(-0.92)	(-0.86)	(-1.32)	(-0.88)	(-1.20)	(-1.66)	(-0.96)	(-0.65)	(-1.16)	(-0.98)	(-1.00)	(-1.16)
L1.InstFlow				0.0637	-0.1862	-0.2220	0.0499	-0.3551	-0.2663	0.0504	-0.3829	-0.3347	0.0485	-0.3806	-0.3361
				(0.50)	(-1.53)	(-1.39)	(0.38)	(-2.44)	(-1.36)	(0.38)	(-3.17)	(-1.62)	(0.36)	(-2.89)	(-1.49)
L2.InstFlow							0.0846	-0.5566	-0.4239	0.0945	-0.7420	-0.4807	0.0780	-0.7506	-0.5325
							(0.87)	(-2.93)	(-1.94)	(0.99)	(-4.04)	(-2.22)	(0.77)	(-4.08)	(-2.24)
L3.InstFlow										-0.0775	-0.6199	-0.4149	-0.0722	-0.6447	-0.4018
										(-0.73)	(-4.38)	(-2.06)	(-0.70)	(-4.65)	(-2.04)
L4.InstFlow													-0.1263	-0.1067	-0.1288
													(-0.73)	(-0.48)	(-0.77)
Intercept	0.0178	0.0193	0.0225	0.0169	0.0280	0.0276	0.0150	0.0557	0.0373	0.0167	0.0832	0.0452	0.0185	0.0898	0.0478
	(1.73)	(2.00)	(2.39)	(1.66)	(2.54)	(2.68)	(1.40)	(3.75)	(3.78)	(1.62)	(4.89)	(3.88)	(2.03)	(5.78)	(3.85)
#observations	144	144	144	141	141	141	138	138	138	135	135	135	132	132	132

Figure 1.1 Growth of US-based ETFs

This figure exhibits the total number and the total market capitalization of US-based ETFs as of the end of each year from 2000 to 2021. The figures are calculated using the CRSP monthly stock file. ETF instruments are classified with a share code of 73 in this dataset. Market capitalization of each ETF is computed by multiplying the closing price of the ETF with its number of shares outstanding.

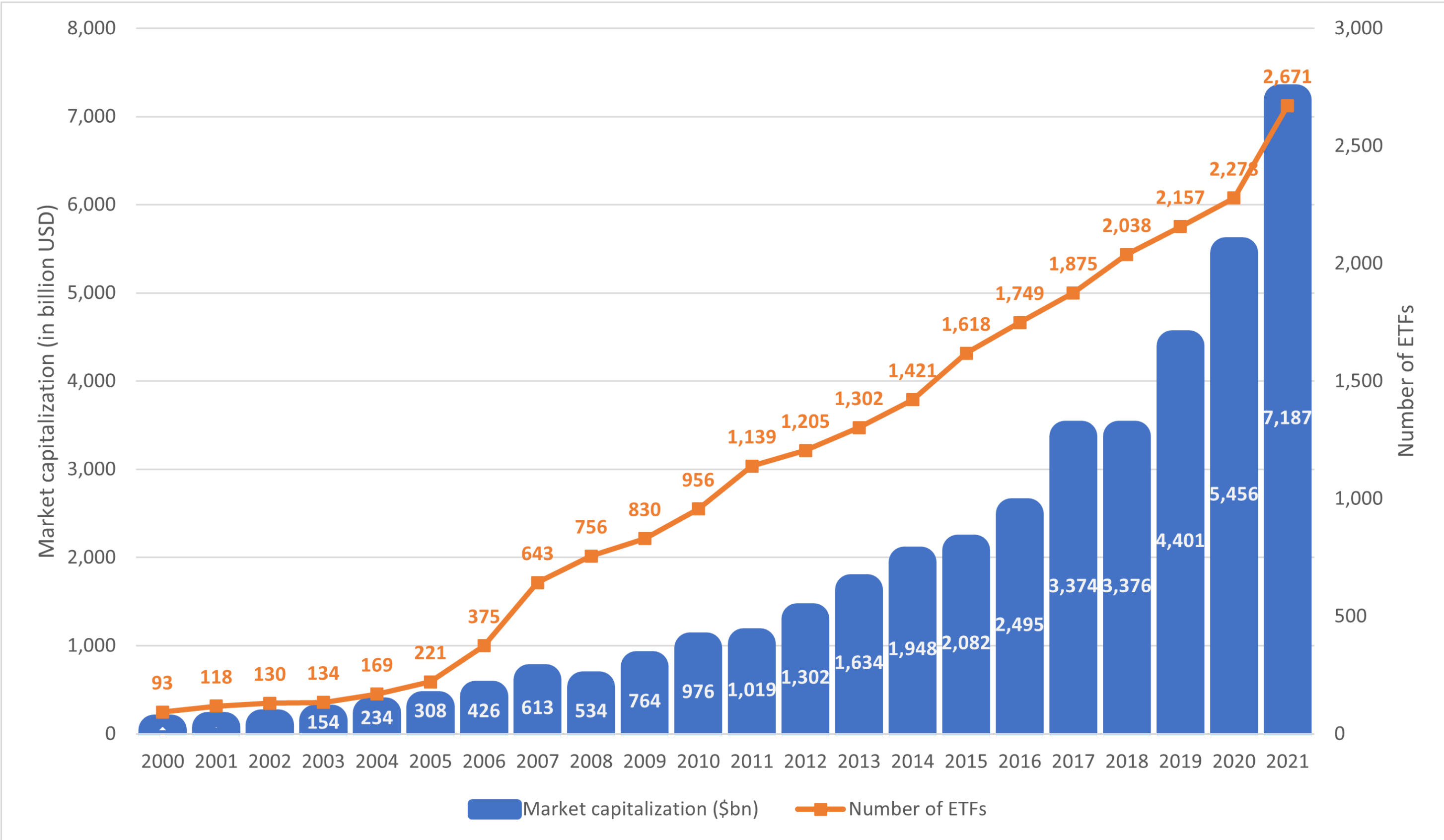


Figure 1.2 Composition of US-based ETFs' net assets

This figure, borrowed from ICI Investment Company Fact Book (2022), exhibits the breakdown of net assets managed by US-based ETFs into main asset subclasses as of the end of 2021.

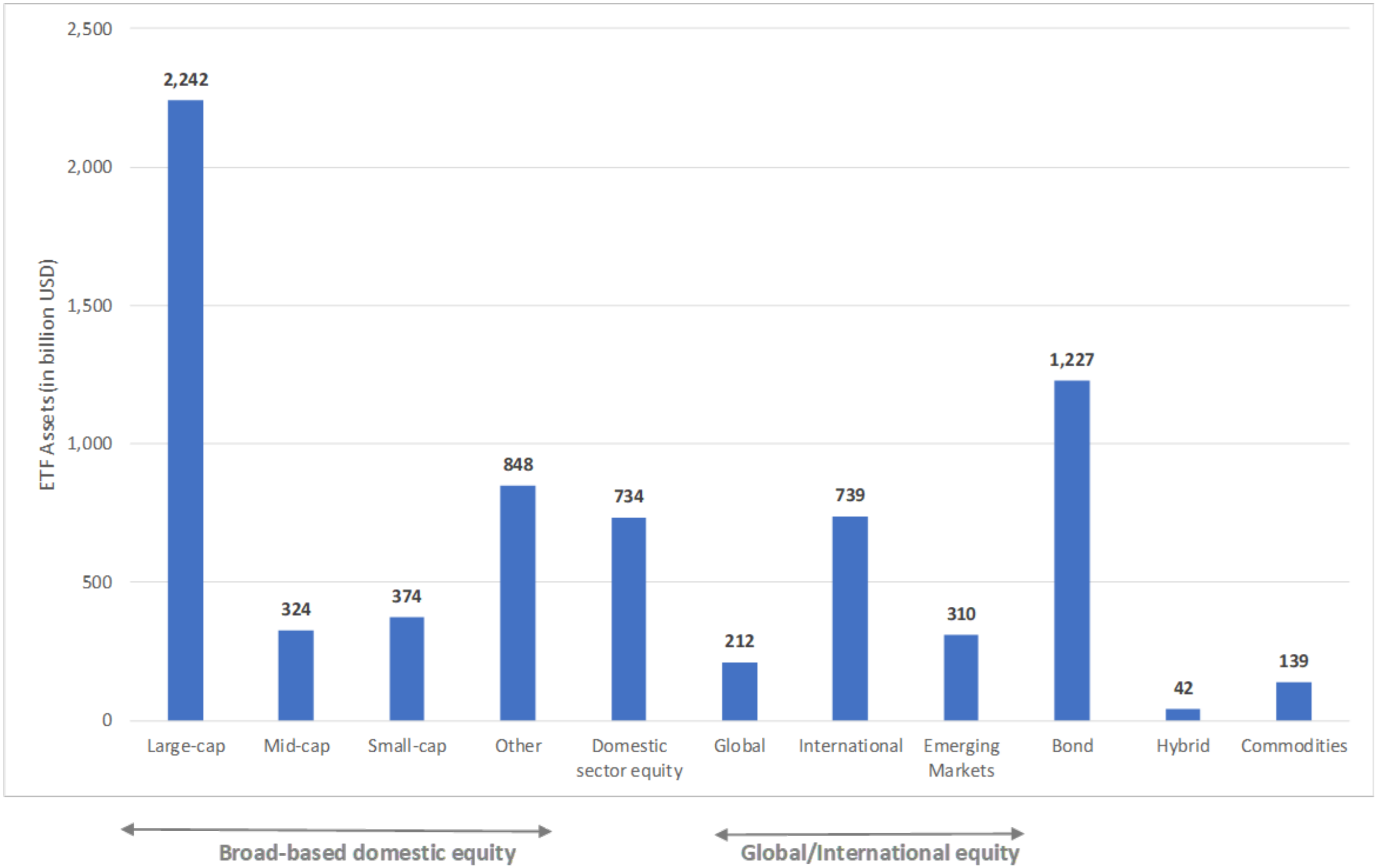
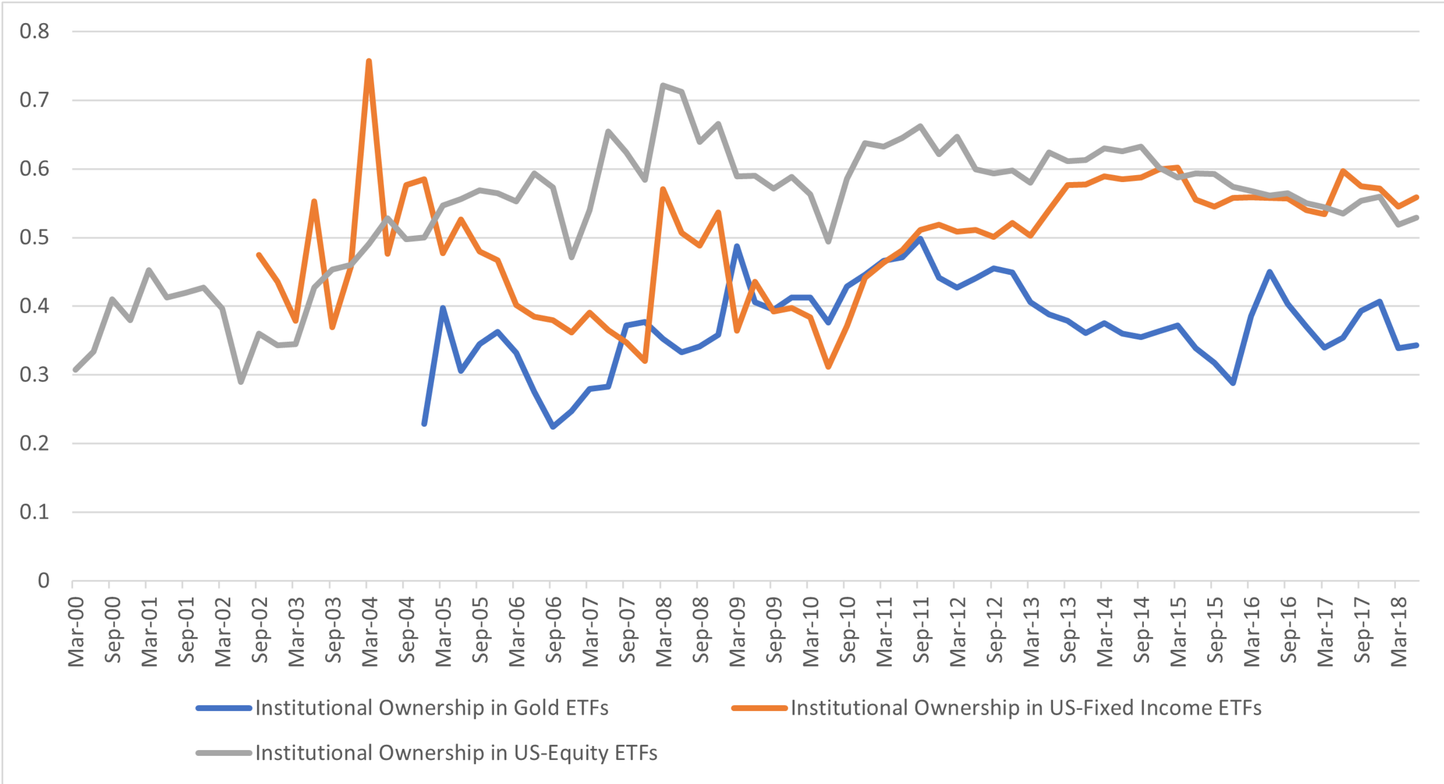


Figure 1.3 Evolution of institutional ownership in gold, US-fixed income and US-equity ETFs

This figure exhibits the evolution of quarterly institutional ownership percentage in gold, US-fixed income and US-equity ETFs during the sample period. Institutional ownership in a single ETF is calculated as the number of total shares held by institutional investors divided by the total number of shares outstanding of that ETF, or equivalently the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF. Accordingly, aggregate institutional ownership in an ETF category is calculated as the total market value/asset size held by institutional investors divided by the total market value/asset size of that ETF category. Data on the number of shares or the market value/asset size held by institutional investors as of the end of each quarter is collected from Thomson Reuters Institutional Holdings (s34) dataset.



2. PRICE DISCOVERY IN EMERGING MARKET ETFs

2.1 Introduction

Exchange-traded funds (ETFs) are investment vehicles that are traded continuously in public exchanges. They are issued by sponsors that are mostly structured as open-end investment companies which allow for the creation and redemption of shares in the fund. Most ETFs aim to track the performance of an index either physically by holding all or a representative sample of the underlying securities of the index or synthetically by utilizing derivative contracts. Since the mid-90s when the first ETF in the US market began trading, assets under management in these vehicles have skyrocketed due to their low transaction costs and high liquidity. This trend has coincided with the increased popularity of passive investing in the asset management industry (French, 2008; Stambaugh, 2014).

Although ETF shares are traded in exchanges like closed-end funds, the discrepancy between their market prices and the net asset values (NAVs) of their underlying portfolios is limited due to the existence of authorized participants (APs). These are institutions that have the privilege of trading directly with ETF sponsors in the primary market. When the ETF price is lower than NAV, APs buy ETF shares and sell short the underlying ETF basket securities simultaneously in the secondary market. Subsequently, they redeem their ETF shares for the underlying securities in the primary market, thereby closing their net position both in the ETF shares and the underlying securities. When NAV is lower than the ETF price, APs buy the underlying securities and sell short the ETF shares simultaneously in the secondary market. Subsequently, they deliver the underlying securities for new ETF shares in the primary market, thereby closing their net position. This arbitrage mechanism does not allow ETF shares to trade at a significant premium or discount. There are also secondary market arbitrageurs such as hedge funds who take opposite positions in an ETF and its underlying index to benefit from any price discrepancies.

One strand of academic research related to ETFs focuses on the price discovery role that these instruments can play. Madhavan & Sobczyk (2016), Broman & Shum (2018) and Lettau & Madhavan (2018) argue that the cost-effective nature of ETFs make them attractive tools for investors who want to make directional bets on particular indices. Thus, ETF prices may reflect new systematic information before their underlying securities. Subsequently, this information will also be impounded in the prices of the index constituents as a result of the arbitrage activities of APs and secondary market arbitrageurs. Studies such as Richie, Daigler & Gleason (2008), Marshall et al. (2013), Li & Zhu (2022) and Glosten et al. (2021) present evidence which is consistent with the hypothesis that ETFs enhance price discovery. On the other hand, Israeli et al. (2017) and Da & Shive (2018) argue that ETFs hinder informational efficiency by documenting that the comovement of stock prices tend to increase once they are part of an index. Moreover, Broman (2016) and Brown et al. (2021) find that the price discrepancy between ETFs and their underlying portfolios are correlated across ETFs.[1]

In this study, we approach the issue of price discovery in ETFs from a new angle by focusing on ETFs that are traded in the US and track various emerging market equity indices. To our knowledge, this is the first study in the literature that focuses on the predictive power of ETFs on country index returns. ETFs present a convenient way to make directional bets on aggregate stock markets of emerging countries and new systematic information may be reflected in the prices of these ETFs before their underlying indices. Subsequent arbitrage activities of market participants would bring ETF prices and the prices of their underlying indices in line. We test this conjecture by collecting time-series return data for 18 emerging market equity ETFs traded in the New York Stock Exchange (NYSE). We hypothesize that returns of these ETFs traded in the US should be able to forecast future index returns determined in the local exchanges if ETFs play a price discovery role. Due to the non-synchronous nature of trading in global financial markets, we make sure that the trading windows for the ETFs precede the trading hours in their corresponding local exchanges. Our results indicate that, for the majority of the markets in our sample, there is a significant predictive relation between ETF returns and one-day-ahead index returns after serial correlation in index returns and various variables that may forecast aggregate returns are controlled for. We also find that this relation

[1] Another contentious area in ETF research is related to the impact of ETFs on the liquidity of their underlying securities. Although studies such as Agarwal et al. (2018) and Pham, Marshall, Nguyen & Visaltanachoti (2021) argue that ownership in ETFs enhances liquidity, Petajisto (2017), Dannhauser (2017), Piccotti (2018) and Evans, Moussawi, Pagano & Sedunov (2019) present evidence that ETF ownership increases transaction costs in the underlying securities due to crowding out effects. Moreover, Ben-David et al. (2018) find that ETFs increase the volatility of their underlying assets through non-fundamental demand.

is stronger during periods of higher market volatility. As would be expected, due to the systematic nature of information reflected in ETF prices and the existence of competitive arbitrageurs, the predictive relation does not extend to horizons longer than one day. We also examine whether predictability exists in the other direction by regressing future ETF returns on lagged local index returns and conducting Granger causality tests, and find that bidirectional spillover effects are weak or non-existent. Finally, a rolling window trading strategy based on the documented predictive relation is able to generate economically superior returns compared to a buy-and-hold strategy in the market indices for the majority of countries in our sample. The returns to this strategy are much larger when it is implemented in the high-volatility sample compared to the low-volatility sample. These results collectively support the conjecture that ETFs play a price discovery role for aggregate equity returns in emerging markets.

The remainder of the paper is organized as follows. Section 2.2 describes the data and variables. Section 2.3 presents the empirical results. Section 2.4 concludes.

2.2 Data and Variables

2.2.1 Data

Our data source for daily ETF and index returns is Bloomberg. All returns are denominated in US dollars. We focus on 18 emerging markets that exhibit wide geographical dispersion. Asia is represented by 7 countries (China, India, Indonesia, Malaysia, Pakistan, Philippines and South Korea) whereas the Americas is represented by 6 countries (Argentina, Brazil, Chile, Colombia, Mexico and Peru) in the sample. 4 countries, namely Greece, Poland, Russia and Turkey, belong to Europe. The final country in our sample is South Africa.

Panel A of Table 2.1 presents the names and codes of ETFs for each country, the names of the indices tracked by these ETFs and the codes of the selected country equity indices. 13 ETFs used in our study are issued by iShares which is the largest issuer of ETFs globally. 4 ETFs are issued by Global X which is a New York-based private provider of global ETFs. For Russia, we utilize the ETF issued by VanEck

Vectors which is another investment management firm headquartered in New York. All 18 ETFs used in our analysis are traded in the NYSE.[2] A large majority of the equity indices that these ETFs track are constructed and calculated by MSCI. A small number of ETFs use FTSE (China, Colombia, Greece) or MVIS (Russia) indices to benchmark their investment performance. The beginning date for the sample period in each country is limited by the availability of ETF return data. The longest sample period belongs to Brazil and begins as early as August 2000. The sample period ends in April 2019 for all markets.

Panel B of Table 2.1 presents the trading hours for the local exchanges in the emerging markets in our sample and the NYSE. Keeping track of the trading hours is crucial because one needs to be cautious that the day $t-1$ trading window in the NYSE for the equity ETFs does not overlap with the day t trading windows in the local exchanges. Since the disperse trading hours around the world pose a problem of non-synchronicity between exchanges, any predictive relation between ETF returns and index returns could just be spurious and this issue requires a tedious treatment. To solve this problem, we follow studies such as Manaster & Rendleman Jr (1982) and Cremers & Weinbaum (2010) and ignore the overnight index returns. Specifically, we calculate daily ETF returns from the closing of the prior trading day $t-1$ to the closing of the current trading day t. We use these ETF returns to forecast index returns from the opening of the next trading day $t+1$ to the closing of the next trading day $t+1$. By doing so, we make sure that the measurement window for our main predictive variable is separated temporally from the measurement window of the variable that is being forecasted. Panel B displays both the local trading hours for each stock exchange and the corresponding trading hours in New York time. The smallest hourly differences between the time that the trading session for ETFs closes in the NYSE and the time that the next-day local equity trading session commences are observed for Asian markets. The difference in real time between the NYSE and local trading sessions varies between 3 and 4 hours in South Korea, Malaysia and Philippines. The analogous time difference is much higher in countries from the Americas. There is a 17.5-hour gap between the ETF trading sessions in the NYSE and local equity sessions in Colombia and Mexico.

For the regression analysis conducted in section 2.3, we obtain additional control variables from Bloomberg at the daily frequency to forecast index returns. First, motivated by studies such as Fama & French (1988), Kothari & Shanken (1997) and Pontiff & Schall (1998) which find evidence for the predictive power of aggregate

[2]For some countries, the NYSE lists multiple ETFs that track the country's equity market's performance. One example is Colombia for which both Global X MSCI Colombia ETF (GXG) and iShares MSCI Colombia ETF (ICOL) exist. In such cases, we choose the ETF with the largest asset size as of April 2019.

fundamental-to-price ratios on market returns, we collect aggregate dividend yield (D/P) and aggregate book-to-market ratio (B/M) data for each market. Second, we collect data for the daily percentage change in the assets under management (ΔAUM) for each ETF to control for possible flow-return relations. Third, we control for the daily percentage change in the exchange rate between the local currency and US dollars (ΔFX). Finally, motivated by the intertemporal CAPM of Merton (1973), we control for the daily conditional volatility of the market return. The measure used to control for conditional volatility is the range-based volatility ($RVol$) defined as the difference between the logarithm of the highest index price and the logarithm of the lowest ETF price each day. As discussed by Brandt & Diebold (2006), range-based volatility is highly efficient, robust to microstructural noise and approximately Gaussian.

2.2.2 Descriptive Statistics

Table 2.2 provides summary statistics for the open-to-close daily index returns and close-to-close daily ETF returns for the emerging markets in our sample. One should be careful not to make comparisons between the markets since the sample periods for different markets do not coincide. Nevertheless, it is possible to observe some general trends in the data. Panel A of Table 2.2 presents summary statistics for the index returns. One can see that, some equity indices such as those of India and Turkey lost value in dollar terms over time with daily average returns of -11 and -7 basis points, respectively. The highest mean return belongs to China with a value of 13 basis points. The median statistics tend to be close to the mean statistics. The standard deviations for the daily index returns are much larger than their central tendency statistics. The standard deviation statistics for Argentina and Russia exceed 2%. Since the index returns are measured at the daily frequency, the minimum and maximum statistics are relatively high in absolute value reflecting short-term jumps. The most extreme daily index fluctuations have been observed in Russia with minimum and maximum statistics of -19.05% and 17.66%, respectively. The long tails of daily equity index return distributions are reflected in the kurtosis statistics with all indices displaying varying degrees of leptokurtosis. The highest kurtosis statistics belong to Peru and Chile with values of 21.65 and 19.18, respectively. The skewness statistics for 14 out of 18 indices are negative but their absolute values are small indicating mildly left-skewed distributions. The most positive skewness statistic belongs to Peru with a value of 1.56.

Panel B of Table 2.2 presents summary statistics for the ETF returns. The patterns for the ETF and index returns are similar with small deviations. The mean daily ETF returns vary between -3 basis points for Pakistan and 7 basis points for South Africa. Median returns are greater than the mean returns for most markets with standard deviations once again much larger than the central tendency statistics. Extreme daily returns are also pronounced for ETFs with two minimum returns below -20% (for Russia and South Africa) and six maximum returns exceeding 20% (largest of which is observed for Brazil). The skewness statistics are small in absolute magnitude and vary between -0.40 for Poland and 0.93 for Peru. Daily ETF return distributions are also leptokurtic with the highest kurtosis statistic belonging to South Korea with a value of 18.19.

Table 2.3 presents correlation coefficients between or among daily index and ETF returns. Panel A of Table 2.3 presents two sets of correlation statistics between index and ETF returns. The first column titled "Lagged" presents the correlations between open-to-close index returns on day t and close-to-close returns on ETFs on day $t-1$ for each market. As such, it constitutes a preliminary test of our primary hypothesis related to the price discovery role of ETFs. We observe that 15 out of 18 correlation coefficients are positive indicating that the one-day-ahead index values tend to move in the same direction with the current ETF returns. The highest correlation statistics belong to Philippines, Russia, Indonesia and Peru with values between 0.25 and 0.28. Negative correlations are observed in Turkey, China and South Korea with values between -0.01 and -0.09. The second column titled "Contemporaneous" presents correlation statistics between close-to-close index and ETF returns on day t. Note that the non-synchronicity between ETF trading hours in the NYSE and equity trading hours in the local exchanges would cause these two sets of "contemporaneous" returns not to be perfectly correlated. Nevertheless, we find that the overwhelming majority of the correlation statistics in the last column of the panel exceed 0.60 with Brazil and Mexico displaying correlations as high as 0.89. The smallest correlation statistic belongs to China with a value of 0.31.

Panel B of Table 2.3 presents cross-correlations of open-to-close returns among the emerging market indices. Despite non-synchronicity, we observe that 150 out of 153 correlation statistics in the panel are positive in line with Morck, Yeung & Yu (2000) who find that equity prices tend to move together in emerging economies. Moreover, return correlations among countries in the same geographical region tend to be higher. For example, three of the four correlation statistics that exceed 0.5 are the pairwise correlations between Brazil, Chile and Mexico. Beside the Americas, a similar regional effect is also observed in the Asia-Pacific as pairwise correlations between Indonesia, Malaysia and Philippines vary between 0.33 and 0.38.

2.3 Empirical Results

2.3.1 Regression Analysis

Table 2.4 presents results for univariate and multivariate predictive regressions that forecast one-day-ahead open-to-close index returns using lagged close-to-close ETF returns and various control variables. Index and ETF returns are winsorized at the 1% level within each market to reduce the effect of outliers. For each regression, we report the slope coefficient of the independent variable(s), the constant term and the associated t-statistics adjusted for autocorrelation and heteroscedasticity via the Newey, West & others (1987) procedure using six lags.

The first two columns of Table 2.4 present results for univariate regressions where lagged ETF returns ($ETFret$) are used to predict one-day-ahead index returns in each market. We observe that 15 out of 18 coefficients associated with $ETFret$ have positive signs with the exception of those for China, South Korea and Turkey. Moreover, 12 out of 15 positive coefficients are significant at the 5% level. The significantly positive coefficients are associated with relatively high t-statistics as 10 out of 12 these statistics exceed 5. The coefficients with the highest magnitudes belong to Peru and Russia with values of 0.2142 and 0.2016, respectively. This indicates that a 1% increase in the returns of an emerging market equity ETF traded in the NYSE is associated with an increase of more than 20 basis points in the returns of the associated country equity index one day later. These findings provide initial evidence for the price discovery role of exchange-traded funds.

Next, we entertain the possibility that the findings from the univariate regressions are driven by serial correlation in index returns. If there is positive serial correlation in daily index returns, a positive coefficient associated with ETF returns in a predictive regression of one-day-ahead index returns may be simply capturing an autocorrelation pattern. This is due to the fact that contemporaneous ETF returns and index returns are highly correlated as seen in the last column of Panel A of Table 2.3 despite the lack of an exact overlap in their measurement windows. To test this possibility, we augment the univariate specification by adding lagged close-to-close index returns ($Indexret$) among the independent variables. The results are presented between the third and fifth columns of Table 2.4. We find that 14 out of 18 coefficients associated with $ETFret$ have positive signs and 11 of these positive coefficients are statistically significant at the 5% level. The largest slope coefficient is observed for Russia with a value of 0.2893 (t-statistic = 9.51). These findings indicate that the price discovery role of ETFs is not simply a manifestation of serial correlation in index returns. We also find that half of the coefficients for lagged index returns have no statistical significance whereas 6 (3) of them are significantly negative (positive).

Next, we estimate the full regression specifications which include controls for aggregate fundamental-to-price ratios, daily changes in assets under management and exchange rates, and conditional volatility. The results of these regressions are presented in the last eight columns of Table 2.4 for each market. The findings indicate that the predictive power of ETF returns observed in the earlier estimations remains intact after additional control variables are added. Specifically, the returns to 12 emerging market equity ETFs are still able to forecast next-day index returns.[3] We do not observe any clear patterns for the coefficients of the other control variables. Aggregate dividend yield and book-to-market ratio exhibit predictive power for one-day-ahead index returns in only 3 and 4 markets, respectively. Similarly, the coefficients associated with range-based volatility are significantly positive in 3 markets.[4]

Emerging markets are not necessarily homogenous in the way that asset pricing phenomena manifest themselves (Demirer, Omay, Yuksel & Yuksel, 2018). Results in Table 2.4 also exhibit some heterogeneity across markets/specifications and some comments to address these differences are in order. First, we should note that the regressions in Table 2.4 constitute a lower bound for the predictive power of ETF returns. This is due to the fact that trading sessions in the local markets and NYSE have some degree of overlap on the same calendar day. For example, on day t, iShares MSCI Turkey ETF begins trading at 9:30 AM in NYSE which corresponds to 4:30 PM local time in Turkey. The equity exchange in Turkey closes at 6:10 PM local time. In other words, there is a certain time window during which the ETF in NYSE and equities in Borsa Istanbul trade simultaneously. One would expect the ETF to track the Turkish index closely during this common time interval and the actual price discovery process in the ETF to occur after trading ends in Borsa Istanbul. In other words, to forecast local index returns on day t+1, close-to-close ETF returns during day t could be a noisier measure compared to open-to-close ETF

[3] We also add the lagged return on the S&P 500 index to the full specification as an additional control variable. The results indicate that 11 slope coefficients retain their significantly positive coefficients. Moreover, we estimate these regressions by excluding *Indexret* from the set of independent variables. We find that 14 out 18 equity ETFs exhibit predictive power for future index returns.

[4] We also estimate panel regressions using data from all markets rather than estimating a single time-series regression for each market. For the univariate specification, *ETFret* has a coefficient of 0.0658 with a t-statistic of 2.86. For the full specification, *ETFret* has a coefficient of 0.0926 with a t-statistic of 2.24.

returns during day t. To investigate this idea, we replace the independent variable of interest in the specifications in Table 2.4 with open-to-close ETF returns. In unreported results, we find that slope coefficients for Mexico, India and Poland are uniformly positive and significant across specifications in contrast to the mixed evidence from earlier. Moreover, ETF returns gain forecasting power for Turkish index returns. Second, as reported in Panel A of Table 2.1, the local market indices we forecast and the indices that emerging market ETFs track are not exactly the same. For example, iShares MSCI Turkey ETF tracks the MSCI Turkey Investable Market Index 25/50 rather than XU030 index itself. We calculate the correlation between these index pairs for each market at the weekly and monthly frequencies to judge their congruity. We find that these correlations are lowest in Argentina and China with values of 0.71 and 0.45 (0.70 and 0.65) at the weekly (monthly) frequency when correlations tend to be at least 0.80 in all other markets. This could partially explain the lower price discovery role that ETFs play for local equity indices in Argentina and China. The relative segmentation of the Chinese stock market from global capital markets (Demirer, Yuksel & Yuksel, 2020) could also be related to the lack of forecasting power of ETF returns in China. Finally, one should note that China, India and South Korea are different from other emerging markets in the sense that there is an abundance of broad and industry-specific ETFs that have large positions in these countries' assets whereas there is only one or two dedicated ETFs that track the local indices of other countries. Since we use the returns of only one particular ETF to investigate price discovery in each country, the forecasting relation between ETF returns and future index returns in China, India and South Korea could be diluted. This could also partially account for the weak or lack of evidence for the price discovery role of ETFs in these countries in Table 2.4.

2.3.2 High-volatility versus Low-volatility

The high incidence of positive slope coefficients associated with ETF returns in Table 2.4 can be interpreted by the conjecture that investors favor the ETF market to reflect systematic information due to the advantages that these markets offer and this market-level information subsequently gets incorporated into index price as a result of the activities of authorized participants and arbitrageurs. To take this conjecture one step further, we hypothesize that the predictive power of ETF returns on future index returns should be more pronounced when there is more index-level information reflected in the market. It is admittedly difficult to construct daily proxies of informational intensity at the aggregate level in an emerging market setting. We proceed with daily index volatility to differentiate between high-information and low-information periods despite the fact that this is a noisy measure since volatility can also be driven by liquidity in addition to information. Specifically, we calculate daily time-series for the range-based volatility measure and divide these time-series into two over the full sample period for each market. If the volatility is higher (lower) than the 70^{th} (30^{th}) percentile on day t, we treat this as a high- (low-) volatility day. Then, we regress day one-day-ahead index returns on lagged ETF returns and other control variables within subsamples that only include high or low volatility days. The results are presented in Table 2.5.

Panel A of Table 2.5 presents results for high-volatility days. It should be recognized that these regressions are estimated for samples which have about 30% of the observations used in Table 2.4 and, thus, their statistical power is reduced. Nevertheless, we find that 10 out 15 positive coefficients observed in the univariate regressions are statistically significant. The largest coefficient belongs to Peru with a value of 0.3865 (t-statistic = 5.45). When lagged index returns are added to the specifications, although predictive power is lost in Chile and Mexico, 8 coefficients associated with ETF returns are still significantly positive. Finally, employing the full set of control variables does not impact the price discovery role of ETFs as there is a positive intertemporal relation between ETF returns and future index returns in 9 markets.

We expect the predictive power of ETF returns to diminish in Panel B of Table 2.5 which presents results for low-volatility days. This is exactly what we find. Although there is still a univariate intertemporal relation between ETF returns and future index returns in 7 emerging markets, the magnitude and statistical significance of the coefficients are reduced. For the 10 markets in which $ETFreturn$ had a significantly positive coefficient in the univariate regressions of Panel A of Table 2.5, the magnitudes of the coefficients drop without exception. The largest drop is observed for Peru from 0.3865 to 0.0484. A similar pattern is observed for the associated t-statistics. Moreover, in the full specifications for the low-volatility days, only one-third of the markets exhibit an intertemporal relation between lagged ETF returns and index returns. These results collectively provide supporting evidence for the price discovery role of ETFs.

2.3.3 Longer-term Predictability

We argue that the predictive power of ETF returns on index returns for the emerging markets in our sample is driven by advance information flow into ETF prices due to the convenience provided by these instruments. If this is the case, we would expect the intertemporal relation between ETF and index returns to be short-lived due to the existence of a large number of competitive arbitrageurs in the market who have the capacity to process any information in ETF prices and reflect them into the prices of their underlying securities quickly. This would especially be true for market-level information. Therefore, in this section, we test whether the predictive relation documented in the previous sections applies to index returns observed two- or three-days ahead.

Panel A of Table 2.6 presents results from specifications in which day $t+2$ index returns are regressed on day t ETF returns and various control variables. We find that all the coefficients associated with ETFret are statistically indistinguishable from zero at the 5% level with the sole exception of Peru. The absolute magnitudes of the coefficients are also small with values between -0.0173 for Brazil and 0.0742 for Peru. When we augment the specification with $Indexret$, we still find that there is no positive intertemporal relation between ETF returns and two-day ahead index returns. The coefficients for $ETFret$ vary between -0.0328 for Indonesia and 0.0264 for Turkey. Adding the full set of control variables does not impact the findings since none of the coefficients associated with $ETFret$ bear any statistical significance. The results in Panel B of Table 2.6 for three-day-ahead index returns complement these findings. Among the 54 coefficients associated with $ETFret$ in this panel, only the one for South Korea in the full specification is significantly positive. These findings collectively suggest that the forecasting power of ETF returns traded in the NYSE for emerging market index returns last only up to one-day.

2.3.4 Bidirectional Spillover Effects

The main hypothesis of this study is that systematic information about the aggregate equity market would be reflected in ETFs prior to the local market indices due to various advantages that ETFs offer in terms of taking positions. Results associated with forecasting regressions for future index returns using past ETF returns provide supporting evidence for this hypothesis. However, it is also possible that informed trading during trading sessions at the local level would only be reflected in the ETF returns at a later point in time when NYSE opens. In other words, due to potential bidirectional spillover effects, directional predictability could manifest itself in both directions.

To investigate this possibility, we interchange the dependent variable and the independent variable of main interest in the specifications estimated in Table 2.4 and test whether local index returns have any forecasting power for one-day-ahead ETF returns. To account for non-synchronicity issues, we again make sure that the closing hour of the local market is prior to the opening hour of the ETF market during which daily returns are calculated. Results are presented in Table 2.7. In the univariate specifications, we find that the slope coefficients associated with local index returns are significantly positive in one-third of the sample countries. Although this suggests the existence of some degree of bidirectional spillover effects, one can also observe that the magnitudes and t-statistics of these significantly positive coefficients are much lower compared to those from the univariate specifications in Table 2.4. Moreover, local index returns exhibit predictive ability in only two countries after controlling for the serial correlation in ETF returns. Only Colombia survives the inclusion of all control variables in the specification. These results provide only feint evidence for bidirectional spillover effects and predictability predominantly flows along the direction from ETF returns to local index returns.

Next, we conduct Granger (1969) causality tests to investigate predictability in both directions. We determine the optimal number of lags of the dependent variable in each market using the Akaike information criterion. First, we test the null hypothesis that ETF returns do not Granger-cause local index returns. Unreported results indicate that this hypothesis is rejected at the 5% level for 12 countries when only one lag of ETF returns is used in the tests. Including all control variables and/or additional lags of ETF returns in the specification generates similar results. On the other hand, when we test the null hypothesis that local index returns do not Granger-cause ETF returns using only one lag of index returns, the hypothesis is rejected for only 3 countries. Again, augmenting the specification with other control variables and/or additional lags of index returns does not have a qualitative impact on the findings. We conclude that the relation between ETF and local index returns is not bidirectional in its nature.

2.3.5 Additional Tests

Given that there is some heterogeneity in our results across markets and model specifications in Table 2.4, in this section, we present our findings in a more compact manner while running some extra robustness tests. First, given the lack of a consensus regarding the optimal number of lags to be used in the Newey-West procedure, we vary the number of lags from 3 to 9 by increasing it one at a time. We repeat this additional test for all three specifications presented in Table 2.4 and for the full, high-volatility and low-volatility subsamples separately. Second, to take the possibility of higher-order serial correlation in daily index returns into account, we include 3 or 5 lags of the dependent variable as explanatory variables in the second and third specifications of Table 2.4 rather than only one lag. Table 2.8 presents the number of countries that support the predictive power of ETF returns at the 1%, 5% and 10% significance levels. First, we find that the number of lags used in the Newey-West procedure does not have a notable impact on the statistical significance of our findings since varying the number of lags causes a change of at most one in the number of positively significant $ETFret$ coefficients. Second, the number of lags of the dependent variable included in the right-hand side of the specification does not affect our results substantially since these alternative models also change the number of positively significant $ETFret$ coefficients by at most one. Last but not least, the main conclusions from sections 2.3.1 and 2.3.2 continue to be valid. These findings collectively support the robustness of our findings.

Next, we examine whether the increasing popularity of ETFs and passive investment over time causes any variation in the forecasting power of ETF returns between the periods before and after the 2007-09 financial crisis. We are able to conduct this analysis for only six markets, namely Brazil, China, Malaysia, Mexico, South Africa and South Korea, for which ETF data pre-dates the global financial crisis (GFC) by at least two years. We allow the pre-GFC sample to end in June 2007 and the post-GFC sample to begin in April 2009 following Ben-David, Franzoni & Moussawi (2012) and Fahlenbrach, Prilmeier & Stulz (2012). In unreported tests, we repeat our baseline predictive regressions for these two subsamples separately. We find that, consistent with the full-sample findings in Table 2.4, slope coefficients associated with ETF returns are significantly positive in both subsamples for Malaysia, Mexico and South Africa with incrementally higher t-statistics in the post-GFC sample. We also observe that the significantly positive $ETFret$ coefficients observed for Brazil in the multivariate specifications are confined to the post-GFC sample. Finally, for South Korea (China), the intertemporal relation between ETF and index returns is significantly negative (insignificant) in both subsamples as in the full sample.

2.3.6 Economic Significance

Welch & Goyal (2008) examine the performance of a wide variety of factors that have been suggested by the literature to be significant predictors of aggregate returns in the US and find that the out-of-sample performance of these predictors would not have helped investors to profitably time the market. To be able to address this issue and observe the economic significance of our findings, we calculate cumulative returns to a rolling window strategy that uses out-of-sample one-day ahead forecasts of open-to-close index returns based on lagged close-to-close ETF returns.[5] The first forecasting regression uses the first half of the sample period in each market. Next, one-day-ahead index return estimates are calculated using an expanding window. Specifically, on each day t after the midpoint of the sample period for each country, the data available up to day t are used to estimate the univariate predictive regression. The estimated coefficients are recorded and used to forecast the index return on day $t+1$. The strategy stays invested in the index both overnight and intraday on days in which the forecasted index return is positive. For the days in which the forecasted index return is negative, the strategy shorts the index at the opening and rebuilds a long index position at the closing of the day. Cumulative returns to this rolling window strategy and the actual returns to the market index in each country are presented in Figure 2.1a in blue and red, respectively.

The plots suggest that the strategy detailed above generates higher cumulative returns compared to investing in the aggregate market portfolio itself for most of the countries in our sample. The exceptions are Argentina, Brazil, China and Poland where the actual returns to the market index are at least as high as the returns to the rolling window strategy. We should point out that these are also the markets for which there was no predictive relation between ETF returns and future index returns in the univariate specifications of Table 2.4.[6] However, these plots are not just mechanical in the sense that they indicate the economic significance of the predictability that we document. In 13 out of 18 markets, the rolling window strategy

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[5]We also calculate out-of-sample R^2 statistics following Campbell & Thompson (2008). Specifically, we use initial windows of varying lengths to estimate univariate or multivariate predictive regressions of one-day-ahead open-to-close index returns to produce the first out-of-sample forecast in each market. Next, we expand the estimation window by one day at a time and repeat this procedure to produce out-of-sample forecasts for the next period until the end of the sample. Out-of-sample R^2 statistics are calculated as one minus the ratio of the sum of squared deviations of actual excess market returns from forecasted excess market returns to the sum of squared deviations of actual excess market returns from their historical average benchmark. We find negative values for the R^2 statistics to be rare indicating that the predictive regressions do not underperform the historical averages in terms of mean squared forecasting errors.

[6]South Korea presents an anomaly in the sense that Table 2.4 indicated a negative intertemporal relation between ETF returns and future index returns in this market. Although this finding is not consistent with the hypothesis of price discovery in ETFs, the rolling window strategy still generates considerable returns due to its long-short nature.

appears to outperform simple index investing by more than 20% annually before transaction costs. For example, in Russia, the value of $1 invested in the market index itself stays flat over the sample period whereas it grows to about $10 under the rolling window strategy. Similarly, $1 grows about seven-fold in Greece and more than four-fold in Chile, India and Malaysia. In other words, the statistical significance uncovered in the regression analysis translates to economic significance based on an out-of-sample trading strategy.[7]

We repeat this analysis for the high-volatility and low-volatility subsamples defined in section 2.3.2 separately and present the results in Figures 2.1b and 2.1c. Since the predictive power of ETF returns has been documented to be stronger during high-volatility days compared to low-volatility days, we expect the strategy to perform better in the high-volatility subsample. Our results confirm this conjecture. As observed in Figure 2.1b, the rolling window strategy generates higher cumulative returns compared to the index buy-and-hold strategy in the high-volatility sample for all markets except Argentina and China. In contrast, Figure 2.1c shows that there are only six countries for which the rolling window strategy outperforms the market index in the low-volatility subsample. The magnitude of average outperformance in terms of annualized returns across markets is 34.6% and 1.6% in the high- and low-volatility subsamples, respectively. Furthermore, with the exception of Argentina and China, the strategy generates higher cumulative returns in 16 markets when implemented in the high-volatility sample compared to the low-volatility sample. Among these markets, the average annualized return of the rolling window strategy is 33% and -2% in the high- and low-volatility subsamples, respectively.

2.4 Conclusion

This study contributes to the literature on the price discovery role of exchange traded funds (ETFs) by hypothesizing that, due to the convenience provided by ETFs to traders, investors may prefer to reflect systematic information about aggregate stock markets to ETFs trading in the US prior to their underlying securities trading in local exchanges. This information would subsequently be reflected in the prices of equity market indices as arbitrage forces play their part. Hence, the price discovery role

[7] We also check the economic significance of our findings by comparing the Sharpe ratios of the rolling window strategy and the aggregate market index for each country. The rolling window strategy again has a superior performance in 14 markets with the exceptions of Argentina, Brazil, China and Poland.

played by ETFs would precipitate an intertemporal relation between ETF returns and future index returns. We test this conjecture on 18 emerging market equity ETFs traded in the NYSE and find that the returns of these ETFs are able to forecast one-day-ahead index returns for a majority of the countries in our sample. This predictive relation is not driven by the non-synchronicity between exchanges, serial correlation in index returns or various determinants of aggregate returns. Moreover, the relation between ETF and local index returns is not bidirectional in its nature and predominantly flows along the direction from ETF returns to local index returns. We also find that the magnitude and significance of this relation is more pronounced during periods of high equity market volatility. Finally, we exhibit the economic significance of our findings by constructing an out-of-sample trading strategy based on the forecasting power of ETF returns and show that this strategy outperforms simple index investing, especially in the high-volatility subsample.

2.5 Tables and Figures

Table 2.1 Index, ETF and trading hour information

This table presents information about the country equity indices and the ETFs that track the aggregate equity markets of the emerging markets in our sample. Panel A presents the names and codes of ETFs for each country, the names of the indices tracked by these ETFs and the codes of the selected country equity indices. The last column presents the sample beginning date for each country. The sample period ends in April 2019 for all countries. Panel B presents the name of the major stock exchange in each country, the time zone and the trading hours of these exchanges in both local time and New York time. The last column presents the time difference (in hours) between when New York Stock Exchange closes in day $t-1$ and when the local exchange opens in day t.

Panel A. Indices and ETFs

Country	ETF Name	ETF Code	Index Tracked By ETF	Equity Index Code	Beginning Date
Argentina	Global X MSCI Argentina ETF	ARGT	MSCI All Argentina 25/50 Index	MERVAL	4.04.2011
Brazil	iShares MSCI Brazil ETF	EWZ	MSCI Brazil 25/50 Index	IBOV	3.08.2000
Chile	iShares MSCI Chile Capped ETF	ECH	MSCI Chile Investable Market Index	IPSA	4.12.2007
China	iShares China Large-Cap ETF	FXI	FTSE China 25 Index	SHCOMP	2.11.2004
Colombia	Global X MSCI Colombia ETF	GXG	FTSE Colombia 20 Index	COLCAP	19.02.2009
Greece	Global X FTSE Greece 20 ETF	GREK	FTSE/Athex 20 Index	ASE	5.01.2012
India	iShares MSCI India ETF	INDA	MSCI India Index	SENSEX	2.03.2012
Indonesia	iShares MSCI Indonesia ETF	EIDO	MSCI Indonesia Investable Market Index	JCI	2.07.2010
Malaysia	iShares MSCI Malaysia ETF	EWM	MSCI Malaysia Index	FBMKLCI	8.01.2001
Mexico	iShares MSCI Mexico ETF	EWW	MSCI Mexico IMI 25/50 Index	INMEX	4.01.2002
Pakistan	Global X MSCI Pakistan ETF	PAK	MSCI All Pakistan Select 25/50 Index	KSE100	30.04.2015
Peru	iShares MSCI Peru ETF	EPU	MSCI All Peru Capped Index	SPBL25PT	24.07.2015
Philippines	iShares MSCI Philippines ETF	EPHE	MSCI Philippines Investable Market Index	PCOMP	4.10.2010
Poland	iShares MSCI Poland ETF	EPOL	MSCI Poland Investable Market Index	WIG20	2.07.2010
Russia	VanEck Vectors Russia ETF	RSX	MVIS Russia Index	RTSI$	4.05.2007
South Africa	iShares MSCI South Africa ETF	EZA	MSCI South Africa Index	TOP40	11.03.2003
South Korea	iShares MSCI South Korea ETF	EWY	MSCI Korea Index	KOSPI	4.01.2002
Turkey	iShares MSCI Turkey ETF	TUR	MSCI Turkey Investable Market Index	XU030	2.04.2008

Panel B. Exchange trading hours

Country	Stock Exchange	Time Zone	Trading Hours (Local)	Trading Hours (NY)	Time Difference
Argentina	Bolsa de Comercio de Buenos Aires	UTC-03:00	11:00 AM - 5:00 PM	09:00 AM - 3:00 PM	17
Brazil	Brasil Bolsa Balcao	UTC-03:00	10:00 AM - 5:00 PM	8:00 AM - 3:00 PM	16
Chile	Bolsa Comercio Santiago	UTC-04:00	9:30 AM - 5:00 PM	8:30 AM - 4:00 PM	16.5
China	Shanghai Stock Exchange	UTC+08:00	9:30 AM - 3:30 PM	8:30 PM - 2:30 AM	4.5
Colombia	Bolsa de Valores de Colombia	UTC-05:00	9:30 AM - 4:00 PM	9:30 AM - 4:00 PM	17.5
Greece	Athens Exchange	UTC+02:00	10:15 AM - 5:20 PM	3:15 AM - 10:20 AM	11.25
India	Bombay Stock Exchange	UTC+05:30	9:15 AM - 3:40 PM	10:45 PM - 5:10 AM	6.75
Indonesia	Indonesia Stock Exchange	UTC+07:00	9:30 AM - 4:00 PM	9:30 PM - 4:00 AM	5.5
Malaysia	Bursa Malaysia	UTC+08:00	9:00 AM - 5:00 PM	8:00 PM - 4:00 AM	4
Mexico	Bolsa Mexicana de Valores	UTC-06:00	8:30 AM - 3:10 PM	9:30 AM - 4:10 PM	17.5
Pakistan	Pakistan Stock Exchange	UTC+05:00	9:30 AM - 3:30 PM	11:30 PM - 5:30 AM	7.5
Peru	Bolsa de Valores de Lima	UTC-05:00	8:30 AM - 3:00 PM	8:30 AM - 3:00 PM	16.5
Philippines	Philippine Stock Exchange	UTC+08:00	9:00 AM - 3:30 PM	8:00 PM - 2:30 AM	4
Poland	Warsaw Stock Exchange	UTC+01:00	9:00 AM - 5:05 PM	3:00 AM - 11:05 AM	11
Russia	Moscow Exchange	UTC+03:00	10:00 AM - 6:50 PM	2:00 AM - 10:50 AM	10
South Africa	Johannesburg Stock Exchange	UTC+02:00	9:00 AM - 5:00 PM	2:00 AM - 10:00 AM	10
South Korea	Korea Exchange	UTC+09:00	9:00 AM - 3:30 PM	7:00 PM - 1:30 AM	3
Turkey	Borsa Istanbul	UTC+03:00	10:00 AM - 6:10 PM	2:00 AM - 10:10 AM	10
USA	New York Stock Exchange	UTC-05:00	9:30 AM - 4:00 PM	9:30 AM - 4:00 PM	0

Table 2.2 Summary statistics

This table provides summary statistics for the open-to-close index returns and close-to-close ETF returns for the emerging markets in our sample. All returns are denominated in US dollars and measured at a daily frequency. The table presents the mean, median, standard deviation, minimum, 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile, maximum, skewness and kurtosis statistics for each country. The sample beginning date is presented in Table 2.1 for each country. The sample period ends in April 2019 for all countries.

Panel A. Index returns

	Mean	Median	St Dev	Min	P25	P75	Max	Skew	Kurt
Argentina	0.09	0.12	2.02	-10.55	-0.98	1.20	9.49	-0.23	5.42
Brazil	0.04	0.06	1.73	-11.39	-0.89	1.03	14.66	0.03	7.81
Chile	-0.01	0.00	0.99	-6.03	-0.47	0.47	12.53	0.52	19.18
China	0.13	0.13	1.48	-7.82	-0.54	0.82	8.18	-0.14	6.48
Colombia	0.03	0.03	0.88	-3.52	-0.41	0.50	4.31	-0.04	5.11
Greece	0.02	0.06	1.93	-13.34	-0.89	0.95	10.84	-0.22	8.65
India	-0.11	-0.11	0.76	-3.70	-0.53	0.35	3.81	-0.13	4.82
Indonesia	0.02	0.04	0.93	-8.84	-0.43	0.50	4.74	-0.74	10.85
Malaysia	0.01	0.02	0.64	-5.59	-0.30	0.33	3.90	-0.42	9.66
Mexico	0.04	0.06	1.21	-6.70	-0.56	0.66	12.85	0.21	11.15
Pakistan	-0.04	-0.07	0.99	-3.99	-0.56	0.50	4.13	-0.06	4.85
Peru	0.04	0.04	1.14	-5.21	-0.50	0.54	12.23	1.56	21.65
Philippines	-0.01	0.02	0.92	-5.01	-0.55	0.55	5.28	-0.25	5.49
Poland	0.01	0.00	1.00	-6.70	-0.57	0.59	5.58	-0.21	6.16
Russia	-0.01	0.06	2.02	-19.05	-0.93	1.00	17.66	-0.49	13.86
South Africa	0.07	0.11	1.28	-7.65	-0.60	0.76	8.01	-0.01	6.93
South Korea	-0.02	-0.01	1.06	-10.73	-0.51	0.50	8.98	-0.24	11.64
Turkey	-0.07	-0.06	1.51	-9.22	-0.89	0.81	7.48	-0.13	5.47

Panel B. ETF returns

	Mean	Median	St Dev	Min	P25	P75	Max	Skew	Kurt
Argentina	0.00	0.04	1.60	-8.93	-0.88	0.90	6.66	-0.11	5.15
Brazil	0.05	0.11	2.45	-19.63	-1.26	1.37	25.58	0.02	10.31
Chile	0.00	0.03	1.60	-12.07	-0.78	0.78	15.69	0.00	14.34
China	0.06	0.07	2.15	-14.85	-0.93	1.03	20.27	0.77	14.59
Colombia	0.04	0.05	1.48	-6.98	-0.77	0.84	7.47	-0.04	5.34
Greece	0.02	0.09	2.56	-16.42	-1.39	1.39	13.21	-0.09	6.56
India	0.01	0.06	1.39	-6.64	-0.82	0.87	6.46	-0.11	4.54
Indonesia	0.03	0.04	1.76	-11.96	-0.90	0.94	9.46	-0.14	6.63
Malaysia	0.02	0.09	1.35	-11.62	-0.69	0.74	8.99	-0.16	8.05
Mexico	0.04	0.08	1.73	-10.99	-0.86	0.94	21.47	0.41	14.09
Pakistan	-0.03	-0.09	1.27	-5.11	-0.77	0.72	6.79	0.06	5.56
Peru	0.06	0.07	1.25	-5.91	-0.64	0.68	10.29	0.93	11.05
Philippines	0.04	0.04	1.33	-8.05	-0.77	0.80	7.20	0.10	5.05
Poland	0.04	0.11	1.71	-10.97	-0.89	0.98	9.01	-0.40	7.25
Russia	0.01	0.10	2.58	-22.32	-1.14	1.23	22.95	-0.34	14.17
South Africa	0.07	0.12	2.20	-20.08	-1.06	1.28	22.92	0.11	13.16
South Korea	0.06	0.09	2.07	-13.82	-0.92	1.08	22.42	0.88	18.19
Turkey	0.02	0.07	2.48	-14.95	-1.17	1.35	17.49	-0.13	8.45

Table 2.3 Correlation matrices

This table presents the correlation matrices between or among index returns and ETF returns for the emerging markets in our sample. Panel A presents the correlations between the returns of the country equity indices and returns of the ETFs that track the aggregate equity markets of these countries. Lagged correlation statistics in the second column refer to the correlations between open-to-close index returns on day t and close-to-close returns on the corresponding ETFs on day $t-1$. Contemporaneous correlation statistics in the third column refer to the correlations between close-to-close index returns on day t and close-to-close returns on the corresponding ETFs on day t. Panel B presents the contemporaneous correlations between open-to-close index returns among all countries.

Panel A. Index-ETF correlations

	Lagged	Contemporaneous
Argentina	0.03	0.69
Brazil	0.02	0.89
Chile	0.20	0.86
China	-0.03	0.31
Colombia	0.17	0.83
Greece	0.18	0.77
India	0.07	0.77
Indonesia	0.25	0.66
Malaysia	0.18	0.54
Mexico	0.11	0.89
Pakistan	0.11	0.77
Peru	0.25	0.77
Philippines	0.28	0.63
Poland	0.04	0.81
Russia	0.26	0.66
South Africa	0.20	0.70
South Korea	-0.09	0.66
Turkey	-0.01	0.80

Panel B. Index cross-correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Argentina	1.00																	
2	Brazil	0.45	1.00																
3	Chile	0.32	0.55	1.00															
4	China	0.11	0.15	0.11	1.00														
5	Colombia	0.29	0.41	0.43	0.14	1.00													
6	Greece	0.09	0.15	0.21	0.03	0.19	1.00												
7	India	0.14	0.18	0.22	0.11	0.17	0.12	1.00											
8	Indonesia	0.10	0.15	0.25	0.15	0.21	0.10	0.23	1.00										
9	Malaysia	0.11	0.18	0.26	0.16	0.23	0.07	0.13	0.38	1.00									
10	Mexico	0.36	0.60	0.55	0.12	0.41	0.16	0.19	0.19	0.20	1.00								
11	Pakistan	0.01	0.04	0.06	0.06	0.08	0.07	0.01	0.07	0.07	0.05	1.00							
12	Peru	0.32	0.37	0.36	0.17	0.34	0.19	0.16	0.17	0.16	0.28	0.12	1.00						
13	Philippines	0.03	0.09	0.22	0.09	0.19	0.07	0.13	0.35	0.33	0.17	0.02	0.13	1.00					
14	Poland	0.20	0.27	0.32	0.05	0.28	0.23	0.20	0.14	0.14	0.35	0.01	0.24	0.09	1.00				
15	Russia	0.34	0.41	0.40	0.13	0.40	0.21	0.25	0.25	0.28	0.43	0.06	0.40	0.15	0.38	1.00			
16	South Africa	0.24	0.36	0.45	0.14	0.38	0.26	0.29	0.27	0.27	0.43	0.07	0.36	0.21	0.39	0.58	1.00		
17	South Korea	0.13	0.21	0.19	0.24	0.19	0.08	0.19	0.25	0.31	0.24	-0.02	0.18	0.20	0.12	0.22	0.22	1.00	
18	Turkey	0.15	0.25	0.25	-0.01	0.21	0.10	0.16	0.11	0.10	0.30	-0.04	0.17	0.09	0.32	0.32	0.29	0.07	1.00

Table 2.4 Regression analysis

This table presents results from the predictive regressions of one-day-ahead open-to-close index returns on lagged close-to-close ETF returns (ETFret), close-to-close index returns (Indexret), aggregate dividend yield (D/P), percentage change in an ETF's assets under management (ΔAUM), aggregate book-to-market ratio (B/M), percentage change in the exchange rate between the local currency and US dollar (ΔFX) and range-based volatility (RVol) calculated as the difference between the logarithms of the highest and lowest daily ETF prices in a day. t-statistics are adjusted for autocorrelation and heteroscedasticity using the Newey-West (1987) procedure.

	ETFret	Const	ETFret	Indexret	Const	ETFret	Indexret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	0.0368	0.0010	-0.0284	0.0659	0.0010	-0.0332	0.0796	-0.0007	0.0020	0.0049	0.1157	0.8799	-0.0006
	(1.04)	(1.99)	(-0.56)	(1.72)	(2.03)	(-0.64)	(1.95)	(-1.74)	(1.79)	(0.14)	(1.10)	(1.36)	(-0.40)
Brazil	0.0164	0.0004	0.0912	-0.0848	0.0004	0.0984	-0.0811	0.0006	0.0020	0.0111	0.0394	-0.2835	-0.0029
	(1.22)	(1.47)	(2.75)	(-2.62)	(1.47)	(3.05)	(-2.41)	(2.45)	(1.73)	(0.56)	(0.91)	(-0.56)	(-2.35)
Chile	0.1278	-0.0001	0.0932	0.0452	-0.0001	0.0945	0.0778	0.0006	0.0033	0.0110	0.1149	-0.1417	-0.0036
	(7.71)	(-0.62)	(2.24)	(0.99)	(-0.65)	(2.23)	(1.59)	(1.10)	(1.70)	(0.79)	(2.85)	(-0.12)	(-2.84)
China	-0.0249	0.0013	-0.0107	-0.0550	0.0013	-0.0172	-0.0530	-0.0010	0.0076	0.0454	0.1926	1.2551	-0.0013
	(-1.57)	(4.92)	(-0.65)	(-2.67)	(4.77)	(-1.01)	(-2.39)	(-0.86)	(1.53)	(1.99)	(1.02)	(2.27)	(-1.05)
Colombia	0.1040	0.0002	0.0734	0.0392	0.0002	0.0768	0.0481	0.0005	-0.0016	0.0100	0.0457	-0.4959	-0.0002
	(6.54)	(1.05)	(2.64)	(1.36)	(1.03)	(2.71)	(1.48)	(1.42)	(-0.93)	(0.73)	(1.19)	(-0.34)	(-0.13)
Greece	0.1291	0.0002	0.1652	-0.0568	0.0002	0.1606	-0.1013	0.0010	0.0006	0.0676	-0.1763	-0.1595	-0.0028
	(5.45)	(0.52)	(4.64)	(-1.39)	(0.52)	(4.54)	(-2.13)	(1.30)	(0.54)	(2.58)	(-1.76)	(-0.21)	(-1.59)
India	0.0403	-0.0011	0.0513	-0.0176	-0.0011	0.0500	-0.0103	-0.0016	0.0271	-0.0016	-0.0061	1.0844	-0.0086
	(2.27)	(-5.62)	(1.65)	(-0.49)	(-5.58)	(1.61)	(-0.27)	(-0.88)	(2.04)	(-0.10)	(-0.11)	(0.63)	(-2.76)
Indonesia	0.1283	0.0002	0.1762	-0.1017	0.0002	0.1726	-0.0685	0.0024	0.0009	-0.0152	0.0655	1.0708	-0.0053
	(8.24)	(0.99)	(8.59)	(-3.45)	(0.96)	(8.32)	(-1.91)	(2.69)	(0.22)	(-1.03)	(0.96)	(1.05)	(-2.38)
Malaysia	0.0849	0.0001	0.0729	0.0317	0.0001	0.0717	0.0445	0.0000	0.0009	0.0031	0.0508	0.6402	-0.0007
	(8.31)	(0.76)	(6.08)	(1.96)	(0.74)	(5.96)	(2.20)	(0.26)	(0.76)	(0.27)	(1.31)	(0.53)	(-0.83)
Mexico	0.0802	0.0003	0.0682	0.0143	0.0003	0.0389	0.0178	-0.0006	0.0032	0.0069	-0.0873	0.4876	-0.0002
	(5.50)	(1.88)	(1.85)	(0.37)	(1.88)	(1.04)	(0.46)	(-1.42)	(1.44)	(0.62)	(-2.05)	(0.71)	(-0.14)
Pakistan	0.0848	-0.0004	0.1031	-0.0261	-0.0004	0.1126	-0.0051	0.0017	-0.0033	-0.0009	-0.1077	5.6061	-0.0084
	(2.68)	(-1.10)	(2.27)	(-0.48)	(-1.10)	(2.49)	(-0.09)	(2.11)	(-0.71)	(-0.06)	(-0.36)	(4.03)	(-2.25)
Peru	0.2142	0.0003	0.1212	0.1265	0.0002	0.1700	0.1444	-0.0009	-0.0003	-0.0271	0.3389	4.0167	0.0022
	(5.73)	(0.66)	(2.72)	(2.37)	(0.68)	(3.05)	(2.16)	(-1.16)	(-0.19)	(-0.46)	(1.92)	(2.17)	(1.26)
Philippines	0.1942	-0.0001	0.2371	-0.0817	-0.0001	0.2376	-0.1009	0.0008	0.0073	0.0066	-0.1414	0.8427	-0.0048
	(11.12)	(-0.65)	(11.39)	(-3.21)	(-0.56)	(11.24)	(-3.27)	(2.24)	(1.54)	(0.45)	(-1.85)	(0.57)	(-2.35)
Poland	0.0230	0.0001	0.0460	-0.0300	0.0001	0.0847	-0.0492	-0.0001	0.0059	0.0350	0.1058	0.8372	-0.0044
	(1.40)	(0.40)	(1.59)	(-1.05)	(0.40)	(2.71)	(-1.51)	(-0.61)	(2.44)	(2.34)	(2.39)	(0.86)	(-2.50)
Russia	0.2016	0.0000	0.2893	-0.1582	0.0000	0.2997	-0.1498	-0.0001	0.0018	0.0333	0.1074	-0.1777	-0.0017
	(9.43)	(-0.12)	(9.51)	(-4.96)	(-0.07)	(9.49)	(-4.46)	(-0.47)	(1.14)	(1.42)	(1.53)	(-0.28)	(-1.25)
South Africa	0.1193	0.0006	0.2171	-0.1608	0.0006	0.2484	-0.1463	0.0004	-0.0010	-0.0169	0.0918	-0.2110	-0.0001
	(9.35)	(3.31)	(11.41)	(-7.06)	(3.23)	(10.81)	(-6.24)	(0.86)	(-0.24)	(-1.31)	(3.10)	(-0.30)	(-0.10)
South Korea	-0.0475	-0.0002	-0.0949	0.0878	-0.0002	-0.0949	0.0867	0.0006	0.0010	0.0096	-0.0011	-0.0158	-0.0021
	(-4.35)	(-1.48)	(-5.80)	(4.34)	(-1.66)	(-5.81)	(3.85)	(1.36)	(0.93)	(0.50)	(-0.02)	(-0.02)	(-1.85)
Turkey	-0.0068	-0.0007	-0.0084	0.0022	-0.0007	0.0013	0.0097	-0.0024	0.0154	0.0003	0.0440	0.9779	-0.0059
	(-0.44)	(-2.34)	(-0.27)	(0.06)	(-2.34)	(0.04)	(0.26)	(-3.35)	(3.61)	(0.01)	(0.64)	(1.74)	(-3.38)

Table 2.5 High volatility versus low volatility

This table presents results from the predictive regressions of one-day-ahead open-to-close index returns on lagged close-to-close ETF returns (ETFret) and various control variables that are defined in Table 2.4. Panels A and B present results for subsamples where the daily range-based volatility is higher than the 70th percentile and lower than the 30th percentile over the sample period, respectively. t-statistics are adjusted for autocorrelation and heteroscedasticity using the Newey-West (1987) procedure.

Panel A. High-volatility sample

	ETFret	Const	ETFret	Indexret	Const	ETFret	Indexret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	0.0935	-0.0001	0.0122	0.0706	0.0000	0.0455	0.1091	-0.0016	0.0081	-0.0693	0.1134	2.0816	-0.0073
	(1.16)	(-0.09)	(0.10)	(0.99)	(-0.03)	(0.36)	(1.44)	(-1.28)	(1.91)	(-0.78)	(0.63)	(2.04)	(-1.50)
Brazil	0.0403	-0.0015	0.1132	-0.0849	-0.0015	0.1209	-0.0708	0.0023	0.0080	0.0196	0.0785	0.1099	-0.0151
	(1.47)	(-2.08)	(1.81)	(-1.37)	(-2.14)	(1.99)	(-1.09)	(3.68)	(3.00)	(0.39)	(0.89)	(0.15)	(-4.63)
Chile	0.1925	-0.0008	0.1111	0.1093	-0.0008	0. 1130	0.1651	0.0004	0.0109	0.0182	0.1820	1.5683	-0.0084
	(6.36)	(-1.80)	(1.69)	(1.58)	(-1.83)	(1.71)	(2.24)	(0.34)	(1.98)	(0.66)	(2.22)	(1.03)	(-2.95)
China	-0.0519	0.0018	-0.0333	-0.0725	0.0017	-0.0410	-0.0743	-0.0016	0.0212	0.1202	0.5616	1.1617	-0.0058
	(-1.78)	(2.40)	(-1.10)	(-2.17)	(2.17)	(-1.36)	(-2.04)	(-0.46)	(1.45)	(1.97)	(0.85)	(1.51)	(-2.34)
Colombia	0.2033	-0.0002	0.1694	0.0406	-0.0002	0.1642	0.0341	0.0017	-0.0052	-0.0113	-0.0412	1.8606	-0.0019
	(6.21)	(-0.40)	(2.05)	(0.50)	(-0.38)	(1.96)	(0.40)	(1.63)	(-1.01)	(-0.30)	(-0.44)	(0.75)	(-0.74)
Greece	0.1762	-0.0005	0.2493	-0.1121	-0.0006	0.2385	-0.1955	0.0020	0.0036	0.1646	-0.2428	0.0387	-0.0109
	(4.06)	(-0.44)	(3.60)	(-1.40)	(-0.48)	(3.34)	(-2.07)	(1.48)	(1.34)	(2.81)	(-1.08)	(0.03)	(-2.67)
India	0.0095	-0.0024	-0.0125	0.0343	-0.0023	-0.0016	0.0001	0.0055	0.0546	-0.0103	-0.1615	3.0028	-0.0308
	(0.23)	(-4.55)	(-0.18)	(0.44)	(-4.27)	(-0.02)	(0.00)	(0.97)	(1.77)	(-0.27)	(-1.28)	(1.07)	(-4.86)
Indonesia	0.1980	-0.0008	0.2714	-0.1539	-0.0009	0.2570	-0.0917	0.0081	0.0012	-0.0193	0.1237	2.0835	-0.0190
	(7.73)	(-1.56)	(8.23)	(-2.81)	(-1.82)	(7.56)	(-1.33)	(2.87)	(0.11)	(-0.57)	(0.78)	(1.36)	(-3.40)
Malaysia	0.1152	-0.0004	0.0801	0.0879	-0.0004	0.0783	0.1031	0.0000	0.0059	-0.0096	0.0650	1.2874	-0.0040
	(6.13)	(-1.39)	(3.58)	(2.90)	(-1.38)	(3.51)	(2.91)	(0.02)	(2.13)	(-0.35)	(0.63)	(0.72)	(-2.38)
Mexico	0.1277	-0.0006	0.1114	0.0192	-0.0006	0.0394	0.0383	-0.0009	0.0077	0.0356	-0.2108	1.4218	-0.0029
	(4.96)	(-1.31)	(1.58)	(0.26)	(-1.30)	(0.54)	(0.52)	(-1.18)	(1.63)	(1.50)	(-2.14)	(1.60)	(-1.27)
Pakistan	0.1126	-0.0003	0.1856	-0.0921	-0.0004	0.2384	-0.0749	0.0034	-0.0011	0.0069	-0.0856	8.9569	-0.0212
	(1.84)	(-0.32)	(1.68)	(-0.78)	(-0.42)	(2.07)	(-0.58)	(1.41)	(-0.10)	(0.18)	(-0.18)	(4.31)	(-1.83)
Peru	0.3865	0.0002	0.2364	0.1746	0.0002	0.3635	0.2264	-0.0012	-0.0024	-0.0582	0.8948	5.8757	0.0040
	(5.45)	(0.22)	(2.12)	(1.77)	(0.17)	(3.06)	(1.80)	(-0.54)	(-0.61)	(-0.52)	(2.27)	(2.74)	(0.73)
Philippines	0.3108	-0.0006	0.3764	-0.1143	-0.0006	0.3680	-0.1178	0.0017	0.0238)	0.0023	-0.2320	2.7115	-0.0146
	(9.13)	(-1.18)	(7.71)	(-1.75)	(-1.19)	(7.26)	(-1.52)	(1.83)	(2.47)	(0.07)	(-1.14)	(0.98)	(-3.04)
Poland	0.0672	0.0002	0.0569	0.0135	0.0002	0.1144	-0.0243	-0.0003	0.0090	0.1096	0.1935	1.7345	-0.0068
	(1.87)	(0.36)	(0.84)	(0.19)	(0.37)	(1.53)	(-0.31)	(-0.53)	(1.40)	(3.15)	(1.72)	(1.12)	(-1.31)
Russia	0.2855	-0.0015	0.3642	-0.1514	-0.0016	0.3865	-0.1452	-0.0006	0.0069	0.0892	0.2122	0.3812	-0.0097
	(8.87)	(-1.61)	(7.98)	(-2.90)	(-1.64)	(7.80)	(-2.54)	(-0.66)	(1.98)	(1.63)	(1.48)	(0.45)	(-2.83)
South Africa	0.1811	-0.0002	0.2702	-0.1632	-0.0005	0.2952	-0.1437	0.0014	-0.0022	-0.0497	0.0807	0.5917	-0.0041
	(8.51)	(-0.50)	(9.09)	(-4.29)	(-1.00)	(8.14)	(-3.72)	(1.08)	(-0.28)	(-1.31)	(1.25)	(0.55)	(-1.82)
South Korea	-0.0698	-0.0014	-0.1395	0.1351	-0.0014	-0.1424	0.1353	0.0002	0.0059	0.0402	-0.0264	0.7723	-0.0077
	(-3.75)	(-3.33)	(-5.15)	(3.88)	(-3.34)	(-5.18)	(3.45)	(0.16)	(2.55)	(0.68)	(-0.28)	(0.78)	(-3.52)
Turkey	-0.0331	-0.0032	-0.0364	0.0045	-0.0032	-0.0307	0.0172	-0.0060	0.0406	-0.0003	0.0258	1.7166	-0.0175
	(-1.22)	(-3.84)	(-0.67)	(0.08)	(-3.85)	(-0.49)	(0.27)	(-3.15)	(3.44)	(-0.01)	(0.18)	(1.85)	(-4.05)

Panel B. Low-volatility sample

	ETFret	Const	ETFret	Indexret	Const	ETFret	Indexret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	0.0175	0.0016	0.0083	0.0129	0.0016	-0.0004	0.0014	-0.0005	0.0001	0.0259	-0.0222	1.1170	0.0018
	(0.82)	(5.49)	(0.29)	(0.51)	(5.42)	(-0.01)	(0.06)	(-2.22)	(0.14)	(1.80)	(-0.44)	(1.57)	(1.81)
Brazil	-0.0190	0.0010	0.0349	-0.0596	0.0011	0.0308	-0.0741	-0.0002	-0.0013	0.0192	-0.0181	1.1547	0.0024
	(-1.81)	(6.05)	(1.45)	(-2.55)	(6.11)	(1.24)	(-3.04)	(-1.27)	(-1.47)	(1.14)	(-0.62)	(1.89)	(2.71)
Chile	0.0180	0.0004	0.0351	-0.0217	0.0004	0.0343	-0.0391	-0.0004	0.0005	0.0173	-0.0094	0.0994	0.0012
	(1.92)	(4.07)	(1.83)	(-1.03)	(4.09)	(1.76)	(-1.63)	(-1.15)	(0.43)	(1.78)	(-0.40)	(0.13)	(1.52)
China	0.0041	0.0007	0.0093	-0.0152	0.0007	0.0087	-0.0202	-0.0010	0.0041	-0.0039	0.0522	1.3981	0.0003
	(0.44)	(4.64)	(0.87)	(-1.09)	(4.68)	(0.77)	(-1.34)	(-1.67)	(1.39)	(-0.32)	(0.64)	(2.51)	(0.27)
Colombia	-0.0021	0.0003	0.0108	-0.0179	0.0003	0.0070	-0.0264	0.0001	-0.0004	0.0228	0.0049	0.2821	0.0002
	(-0.18)	(2.95)	(0.61)	(-0.89)	(2.95)	(0.37)	(-1.20)	(0.59)	(-0.41)	(3.37)	(0.19)	(0.19)	(0.24)
Greece	0.0214	0.0006	0.0420	-0.0363	0.0006	0.0416	-0.0439	0.0005	-0.0007	0.0069	-0.0243	-0.6154	0.0009
	(1.51)	(2.44)	(1.99)	(-1.26)	(2.49)	(1.93)	(-1.41)	(1.19)	(-1.08)	(0.31)	(-0.39)	(-1.31)	(0.90)
India	0.0421	-0.0001	0.0970	-0.0975	0.0000	0.0976	-0.0986	-0.0009	0.0022	-0.0084	-0.0308	-0.8425	0.0006
	(3.58)	(-0.74)	(5.68)	(-4.18)	(-0.12)	(5.69)	(-3.81)	(-0.74)	(0.22)	(-0.83)	(-0.61)	(-0.50)	(0.23)
Indonesia	0.0328	0.0007	0.0371	-0.0105	0.0007	0.0393	-0.0336	0.0013	-0.0083	0.0041	-0.0722	2.4095	0.0013
	(3.92)	(6.08)	(3.57)	(-0.62)	(6.12)	(3.53)	(-1.71)	(2.22)	(-2.36)	(0.38)	(-1.72)	(1.87)	(0.72)
Malaysia	0.0350	0.0003	0.0512	-0.0449	0.0003	0.0509	-0.0428	0.0004	-0.0007	0.0044	0.0100	0.8121	-0.0007
	(4.84)	(4.51)	(6.45)	(-3.90)	(4.67)	(6.40)	(-2.93)	(2.50)	(-0.82)	(0.60)	(0.38)	(0.51)	(-1.01)
Mexico	0.0009	0.0004	-0.0066	0.0095	0.0004	-0.0209	0.0111	-0.0002	-0.0025	-0.0108	-0.0519	1.1967	0.0016
	(0.10)	(4.09)	(-0.32)	(0.45)	(4.04)	(-0.93)	(0.51)	(-0.65)	(-1.67)	(-1.66)	(-2.13)	(1.54)	(2.18)
Pakistan	0.0127	-0.0004	0.0289	-0.0314	-0.0003	0.0338	-0.0129	0.0000	0.0027	-0.0062	0.2134	-2.7560	-0.0017
	(0.48)	(-1.89)	(0.77)	(-0.66)	(-1.68)	(0.89)	(-0.27)	(0.02)	(0.92)	(-0.65)	(0.55)	(-1.50)	(-0.91)
Peru	0.0601	0.0004	0.0411	0.0344	0.0004	0.0541	0.0325	-0.0008	0.0000	-0.0013	0.1367	2.4816	0.0024
	(2.50)	(2.11)	(1.37)	(1.22)	(2.23)	(1.46)	(0.94)	(-2.16)	(0.01)	(-0.04)	(1.53)	(1.56)	(2.67)
Philippines	0.0484	0.0004	0.0771	-0.0621	0.0005	0.0764	-0.0470	-0.0002	-0.0028	-0.0157	-0.0069	-0.2012	0.0020
	(3.72)	(3.21)	(5.22)	(-3.59)	(3.50)	(4.95)	(-2.06)	(-0.82)	(-0.81)	(-1.66)	(-0.13)	(-0.17)	(1.41)
Poland	-0.0146	0.0002	0.0054	-0.0266	0.0002	0.0096	-0.0212	-0.0003	0.0021	-0.0039	0.0183	1.6076	-0.0006
	(-1.12)	(1.70)	(0.26)	(-1.31)	(1.71)	(0.39)	(-0.89)	(-2.32)	(1.24)	(-0.33)	(0.53)	(1.52)	(-0.49)
Russia	0.0442	0.0008	0.0957	-0.0891	0.0009	0.0935	-0.0944	0.0000	-0.0009	-0.0111	-0.0365	0.0297	0.0019
	(3.29)	(3.99)	(4.78)	(-3.85)	(4.31)	(4.53)	(-3.74)	(0.00)	(-1.17)	(-0.70)	(-0.87)	(0.07)	(3.07)
South Africa	0.0273	0.0010	0.0811	-0.0790	0.0010	0.1117	-0.0675	-0.0006	0.0016	-0.0064	0.0773	-0.0179	0.0021
	(3.02)	(7.35)	(5.92)	(-5.00)	(7.73)	(6.67)	(-4.02)	(-1.76)	(0.45)	(-0.67)	(3.26)	(-0.02)	(1.62)
South Korea	-0.0290	0.0001	-0.0359	0.0108	0.0001	-0.0382	0.0087	0.0001	-0.0026	0.0142	0.0314	0.2756	0.0025
	(-3.41)	(1.50)	(-3.15)	(0.92)	(1.46)	(-3.38)	(0.57)	(0.18)	(-3.35)	(1.20)	(1.29)	(0.22)	(3.27)
Turkey	-0.0084	0.0003	0.0153	-0.0305	0.0003	0.0105	-0.0374	-0.0003	0.0020	0.0054	-0.0199	0.9974	-0.0005
	(-0.70)	(1.61)	(0.75)	(-1.41)	(1.64)	(0.46)	(-1.34)	(-0.72)	(0.70)	(0.28)	(-0.44)	(1.17)	(-0.39)

Table 2.6 Longer-term predictability

This table presents results from the predictive regressions of future open-to-close index returns on lagged close-to-close ETF returns (ETFret) and various control variables that are defined in Table 2.4. Panels A and B present results for two-day-ahead and three-day-ahead index returns, respectively. t-statistics are adjusted for autocorrelation and heteroscedasticity using the Newey-West (1987) procedure.

Panel A. 2-day return prediction

	ETFret	Const	ETFret	Indexret	Const	ETFret	Indexret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	-0.0086	0.0010	-0.0113	0.0469	0.0010	-0.0066	0.0584	-0.0008	0.0022	0.0055	0.1271	0.8662	-0.0007
	(-0.24)	(1.91)	(-0.32)	(1.63)	(1.97)	(-0.18)	(1.79)	(-1.75)	(1.80)	(0.16)	(1.11)	(1.28)	(-0.43)
Brazil	-0.0173	0.0004	-0.0171	-0.0017	0.0004	-0.0173	-0.0105	0.0006	0.0018	0.0165	-0.0119	-0.4640	-0.0026
	(-1.16)	(1.48)	(-1.15)	(-0.13)	(1.47)	(-1.14)	(-0.55)	(2.31)	(1.44)	(0.82)	(-0.27)	(-0.86)	(-1.98)
Chile	0.0141	-0.0002	-0.0133	0.1381	-0.0002	-0.0144	0.1711	0.0005	0.0031	0.0099	0.1110	-0.4545	-0.0033
	(0.79)	(-0.87)	(-0.75)	(7.64)	(-1.09)	(-0.81)	(7.61)	(0.93)	(1.56)	(0.70)	(2.70)	(-0.37)	(-2.51)
China	0.0010	0.0013	0.0093	-0.0590	0.0013	0.0106	-0.0578	-0.0011	0.0077	0.0378	0.2021	1.2123	-0.0012
	(0.05)	(4.84)	(0.49)	(-2.85)	(4.68)	(0.55)	(-2.59)	(-0.91)	(1.52)	(1.69)	(1.05)	(2.17)	(-0.92)
Colombia	0.0238	0.0002	0.0057	0.1067	0.0002	0.0036	0.1110	0.0006	-0.0022	0.0120	0.0307	-0.8755	0.0002
	(1.44)	(1.14)	(0.34)	(5.95)	(1.04)	(0.21)	(4.10)	(1.48)	(-1.26)	(0.85)	(0.72)	(-0.56)	(0.15)
Greece	0.0095	0.0002	-0.0109	0.1199	0.0002	-0.0080	0.0676	0.0009	0.0005	0.0652	-0.2130	-0.4383	-0.0024
	(0.49)	(0.48)	(-0.58)	(4.25)	(0.46)	(-0.42)	(2.09)	(1.11)	(0.43)	(2.46)	(-1.99)	(-0.58)	(-1.25)
India	0.0132	-0.0010	0.0080	0.0295	-0.0010	0.0128	0.0397	-0.0017	0.0275	-0.0066	-0.0035	1.2472	-0.0085
	(0.82)	(-5.09)	(0.47)	(1.39)	(-5.22)	(0.74)	(1.41)	(-0.89)	(1.99)	(-0.38)	(-0.06)	(0.71)	(-2.64)
Indonesia	-0.0135	0.0002	-0.0328	0.0770	0.0002	-0.0250	0.1018	0.0028	-0.0007	-0.0196	0.0371	1.0172	-0.0053
	(-0.94)	(1.03)	(-2.04)	(3.11)	(1.05)	(-1.52)	(3.45)	(2.72)	(-0.15)	(-1.25)	(0.52)	(1.00)	(-2.08)
Malaysia	0.0184	0.0000	-0.0013	0.0875	0.0000	0.0000	0.1003	0.0000	0.0007	0.0083	0.0654	0.5255	-0.0005
	(1.95)	(0.42)	(-0.13)	(5.79)	(0.42)	(0.00)	(5.18)	(0.08)	(0.53)	(0.68)	(1.60)	(0.41)	(-0.52)
Mexico	-0.0192	0.0004	-0.0324	0.0912	0.0003	-0.0264	0.0591	-0.0006	0.0032	0.0081	-0.1068	0.2604	0.0000
	(-1.23)	(1.89)	(-2.04)	(5.59)	(1.87)	(-1.63)	(2.79)	(-1.50)	(1.33)	(0.72)	(-2.44)	(0.36)	(0.02)
Pakistan	0.0128	-0.0004	0.0025	0.0576	-0.0004	0.0226	0.0926	0.0019	-0.0033	-0.0081	-0.1452	5.7691	-0.0094
	(0.36)	(-1.08)	(0.07)	(1.54)	(-1.08)	(0.59)	(2.24)	(2.16)	(-0.62)	(-0.45)	(-0.48)	(4.06)	(-2.27)
Peru	0.0742	0.0003	0.0213	0.2074	0.0002	0.0185	0.1902	-0.0010	-0.0006	0.0325	0.2256	3.8508	0.0029
	(1.99)	(0.57)	(0.56)	(4.69)	(0.52)	(0.48)	(2.63)	(-1.36)	(-0.35)	(0.63)	(1.23)	(2.03)	(1.64)
Philippines	0.0058	0.0000	-0.0204	0.0959	0.0000	-0.0220	0.0808	0.0008	0.0069	0.0035	-0.1360	0.6495	-0.0045
	(0.31)	(0.11)	(-0.97)	(3.94)	(-0.03)	(-1.06)	(2.83)	(2.00)	(1.34)	(0.23)	(-1.63)	(0.44)	(-2.04)
Poland	0.0156	0.0001	0.0149	0.0056	0.0001	0.0126	-0.0025	-0.0001	0.0063	0.0344	0.0311	1.0547	-0.0048
	(1.04)	(0.63)	(0.98)	(0.33)	(0.62)	(0.81)	(-0.10)	(-0.41)	(2.49)	(2.27)	(0.73)	(1.03)	(-2.60)
Russia	0.0248	0.0000	0.0056	0.0766	0.0000	0.0072	0.0380	-0.0002	0.0030	0.0228	-0.1124	-0.5305	-0.0026
	(1.13)	(0.10)	(0.25)	(3.57)	(0.08)	(0.32)	(1.38)	(-0.68)	(1.74)	(0.96)	(-1.64)	(-0.76)	(-1.74)
South Africa	-0.0051	0.0007	-0.0083	0.0164	0.0007	-0.0001	-0.0342	0.0004	0.0009	-0.0022	-0.1318	-0.5459	-0.0005
	(-0.37)	(3.54)	(-0.59)	(1.11)	(3.53)	(-0.01)	(-1.76)	(0.68)	(0.18)	(-0.17)	(-4.46)	(-0.69)	(-0.32)
South Korea	-0.0077	-0.0003	-0.0091	0.0070	-0.0003	-0.0109	-0.0036	0.0008	0.0013	0.0072	-0.0454	-0.2609	-0.0027
	(-0.58)	(-1.92)	(-0.69)	(0.52)	(-1.95)	(-0.81)	(-0.22)	(1.90)	(1.25)	(0.36)	(-0.92)	(-0.35)	(-2.44)
Turkey	0.0258	-0.0007	0.0264	-0.0053	-0.0007	0.0300	0.0030	-0.0022	0.0141	-0.0028	0.0129	0.8886	-0.0055
	(1.65)	(-2.40)	(1.67)	(-0.34)	(-2.38)	(1.94)	(0.11)	(-3.08)	(3.35)	(-0.13)	(0.20)	(1.66)	(-3.20)

Panel B. 3-day return prediction

	ETFret	Const	ETFret	Indexret	Const	ETFret	Indexret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	0.0122	0.0010	0.0126	0.0451	0.0010	0.0143	0.0599	-0.0007	0.0020	-0.0030	0.1414	0.8429	-0.0007
	(0.35)	(1.84)	(0.36)	(1.52)	(1.88)	(0.40)	(1.79)	(-1.40)	(1.63)	(-0.08)	(1.18)	(1.21)	(-0.38)
Brazil	-0.0049	0.0003	-0.0049	-0.0016	0.0003	-0.0052	-0.0108	0.0007	0.0021	0.0150	-0.0153	-0.4670	-0.0031
	(-0.34)	(1.13)	(-0.34)	(-0.12)	(1.12)	(-0.37)	(-0.56)	(2.54)	(1.56)	(0.72)	(-0.33)	(-0.87)	(-2.32)
Chile	-0.0345	-0.0002	-0.0345	0.1326	-0.0002	-0.0360	0.1665	0.0006	0.0032	0.0078	0.1092	-0.2052	-0.0035
	(-1.97)	(-0.90)	(-1.96)	(7.10)	(-1.07)	(-2.10)	(7.20)	(0.95)	(1.56)	(0.56)	(2.61)	(-0.16)	(-2.54)
China	0.0195	0.0012	0.0198	-0.0502	0.0012	0.0244	-0.0484	-0.0013	0.0085	0.0395	0.2436	1.3215	-0.0013
	(1.14)	(4.57)	(1.16)	(-2.32)	(4.43)	(1.45)	(-2.12)	(-1.11)	(1.66)	(1.72)	(1.25)	(2.37)	(-0.96)
Colombia	-0.0153	0.0004	-0.0159	0.1041	0.0003	-0.0177	0.1010	0.0007	-0.0035	0.0201	0.0280	-0.7555	0.0007
	(-0.85)	(1.63)	(-0.88)	(5.79)	(1.62)	(-0.99)	(3.71)	(1.77)	(-1.90)	(1.49)	(0.66)	(-0.51)	(0.57)
Greece	0.0450	0.0001	0.0447	0.1197	0.0001	0.0400	0.0703	0.0011	0.0006	0.0596	-0.2610	-0.3381	-0.0030
	(1.89)	(0.20)	(1.90)	(4.30)	(0.13)	(1.72)	(2.18)	(1.31)	(0.44)	(2.25)	(-2.44)	(-0.44)	(-1.57)
India	0.0027	-0.0011	0.0027	0.0334	-0.0011	0.0081	0.0507	-0.0015	0.0310	-0.0093	0.0042	1.2558	-0.0102
	(0.18)	(-4.86)	(0.17)	(1.60)	(-5.03)	(0.52)	(1.72)	(-0.71)	(2.11)	(-0.53)	(0.07)	(0.71)	(-2.92)
Indonesia	-0.0227	0.0002	-0.0225	0.0592	0.0002	-0.0153	0.0962	0.0029	0.0004	-0.0248	0.0627	0.9012	-0.0061
	(-1.37)	(0.95)	(-1.38)	(2.64)	(0.95)	(-0.95)	(3.34)	(2.79)	(0.08)	(-1.68)	(0.83)	(0.87)	(-2.32)
Malaysia	0.0117	0.0000	0.0093	0.0818	0.0000	0.0100	0.0938	0.0000	0.0015	0.0079	0.0540	0.9377	-0.0009
	(1.15)	(0.33)	(0.93)	(5.39)	(0.34)	(1.00)	(4.59)	(0.07)	(1.01)	(0.62)	(1.26)	(0.72)	(-0.98)
Mexico	-0.0180	0.0004	-0.0160	0.0824	0.0004	-0.0161	0.0498	-0.0006	0.0036	0.0058	-0.1164	0.2956	-0.0001
	(-1.17)	(1.96)	(-1.02)	(5.16)	(1.94)	(-1.03)	(2.34)	(-1.60)	(1.48)	(0.50)	(-2.58)	(0.40)	(-0.05)
Pakistan	-0.0259	-0.0007	-0.0272	0.0463	-0.0007	-0.0056	0.0675	0.0015	-0.0054	0.0039	-0.0924	5.8481	-0.0064
	(-0.96)	(-1.76)	(-1.03)	(1.07)	(-1.77)	(-0.20)	(1.50)	(1.35)	(-1.01)	(0.25)	(-0.29)	(4.65)	(-1.30)
Peru	0.0643	0.0002	0.0436	0.2112	0.0001	0.0375	0.1826	-0.0010	-0.0004	0.0410	0.2002	3.9516	0.0025
	(1.49)	(0.38)	(1.12)	(4.72)	(0.32)	(0.97)	(2.40)	(-1.26)	(-0.21)	(0.75)	(1.04)	(2.06)	(1.33)
Philippines	-0.0130	0.0001	-0.0137	0.0851	0.0001	-0.0131	0.0751	0.0010	0.0083	0.0040	-0.0796	0.6349	-0.0055
	(-0.65)	(0.44)	(-0.69)	(3.86)	(0.29)	(-0.67)	(2.70)	(2.65)	(1.53)	(0.23)	(-0.93)	(0.42)	(-2.44)
Poland	0.0010	0.0002	0.0010	0.0063	0.0002	0.0008	0.0024	-0.0001	0.0057	0.0301	0.0396	0.7332	-0.0040
	(0.06)	(0.93)	(0.07)	(0.37)	(0.93)	(0.05)	(0.10)	(-0.57)	(2.27)	(2.02)	(0.90)	(0.71)	(-2.20)
Russia	-0.0110	0.0000	-0.0116	0.0817	-0.0001	-0.0114	0.0370	-0.0003	0.0038	0.0206	-0.1380	-0.6385	-0.0033
	(-0.49)	(-0.09)	(-0.51)	(3.60)	(-0.15)	(-0.50)	(1.26)	(-0.85)	(2.07)	(0.85)	(-1.98)	(-0.87)	(-2.13)
South Africa	-0.0134	0.0007	-0.0132	0.0146	0.0007	-0.0118	-0.0362	0.0004	0.0019	-0.0006	-0.1359	-0.5657	-0.0009
	(-1.09)	(3.58)	(-1.08)	(0.99)	(3.57)	(-0.98)	(-1.82)	(0.64)	(0.38)	(-0.05)	(-4.49)	(-0.70)	(-0.53)
South Korea	0.0249	-0.0003	0.0249	0.0010	-0.0003	0.0260	-0.0076	0.0008	0.0019	0.0103	-0.0366	-0.0132	-0.0033
	(1.94)	(-2.07)	(1.94)	(0.07)	(-2.06)	(2.00)	(-0.44)	(1.90)	(1.78)	(0.50)	(-0.75)	(-0.02)	(-3.05)
Turkey	0.0226	-0.0007	0.0226	0.0000	-0.0007	0.0261	0.0112	-0.0021	0.0136	-0.0021	0.0205	1.0040	-0.0053
	(1.27)	(-2.27)	(1.27))	(0.00)	(-2.27)	(1.42)	(0.41)	(-3.04)	(3.25)	(-0.09)	(0.31)	(1.67)	(-3.03)

Table 2.7 Bidirectional spillover effects

This table presents results from the predictive regressions of one-day-ahead open-to-close ETF returns on lagged close-to-close index returns (Indexret), various control variables that are defined in Table 2.4. t-statistics are adjusted for autocorrelation and heteroscedasticity using the Newey-West (1987) procedure.

	Indexret	Const	Indexret	ETFret	Const	Indexret	ETFret	D/P	B/M	ΔAUM	ΔFX	RVol	Const
Argentina	0.0471	-0.0006	0.0226	0.0497	-0.0006	0.0142	0.0433	-0.0001	0.0012	0.0170	-0.0751	0.1896	-0.0017
	(3.03)	(-2.01)	(1.13)	(1.68)	(-2.02)	(0.67)	(1.44)	(-0.32)	(1.86)	(0.78)	(-1.55)	(0.41)	(-1.88)
Brazil	-0.0187	-0.0005	-0.0260	0.0080	-0.0006	-0.0204	0.0323	0.0012	0.0010	0.0348	0.1106	-0.1068	-0.0050
	(-1.32)	(-2.13)	(-0.82)	(0.26)	(-2.13)	(-0.62)	(0.98)	(4.50)	(0.78)	(2.07)	(2.16)	(-0.21)	(-3.75)
Chile	0.0880	-0.0004	0.1054	-0.0175	-0.0004	0.1174	-0.0174	0.0014	0.0000	0.0119	0.0498	0.1649	-0.0043
	(3.54)	(-1.67)	(1.61)	(-0.29)	(-1.67)	(1.73)	(-0.29)	(1.50)	(0.00)	(0.65)	(0.95)	(0.13)	(-2.11)
China	0.0191	0.0001	0.0314	-0.0310	0.0001	0.0220	-0.0345	-0.0004	0.0019	0.0385	-0.0178	-0.3048	0.0001
	(1.23)	(0.70)	(1.92)	(-1.93)	(0.69)	(1.26)	(-2.15)	(-0.51)	(0.51)	(2.54)	(-0.12)	(-0.73)	(0.09)
Colombia	0.1245	-0.0005	0.1788	-0.0598	-0.0005	0.1735	-0.0604	-0.0003	0.0046	0.0433	0.0518	-0.4276	-0.0026
	(4.87)	(-1.84)	(4.36)	(-1.58)	(-1.82)	(4.14)	(-1.55)	(-0.64)	(1.80)	(2.31)	(0.94)	(-0.21)	(-1.54)
Greece	0.0306	-0.0002	0.0811	-0.0508	-0.0002	0.0676	-0.0531	-0.0011	0.0020	0.0209	-0.0276	-0.3578	-0.0002
	(1.24)	(-0.58)	(2.32)	(-1.62)	(-0.55)	(1.70)	(-1.67)	(-1.55)	(2.05)	(0.71)	(-0.30)	(-0.69)	(-0.16)
India	0.0137	-0.0001	0.0140	-0.0003	-0.0001	-0.0038	0.0020	-0.0010	0.0037	0.0024	-0.0753	1.6749	-0.0002
	(0.68)	(-0.80)	(0.44)	(-0.01)	(-0.80)	(-0.09)	(0.08)	(-0.61)	(0.33)	(0.11)	(-1.17)	(1.10)	(-0.09)
Indonesia	0.0536	-0.0002	-0.0130	0.0715	-0.0002	0.0145	0.0672	0.0001	0.0109	-0.0271	-0.0180	0.1285	-0.0046
	(2.06)	(-0.88)	(-0.32)	(2.87)	(-0.90)	(0.29)	(2.67)	(0.10)	(2.15)	(-1.38)	(-0.21)	(0.11)	(-1.74)
Malaysia	0.0024	0.0002	0.0370	-0.0422	0.0002	0.0235	-0.0421	0.0005	0.0010	0.0185	-0.0505	1.6516	-0.0023
	(0.11)	(1.12)	(1.41)	(-2.15)	(1.13)	(0.74)	(-2.14)	(2.21)	(0.58)	(1.34)	(-0.91)	(1.14)	(-2.27)
Mexico	0.0132	-0.0003	0.0673	-0.0563	-0.0003	0.0720	-0.0802	0.0000	0.0022	0.0048	-0.0714	0.5749	-0.0015
	(0.76)	(-1.72)	(1.48)	(-1.34)	(-1.72)	(1.58)	(-1.87)	(0.08)	(0.78)	(0.44)	(-1.33)	(0.81)	(-0.99)
Pakistan	0.0813	-0.0012	0.0772	0.0047	-0.0012	0.0633	0.0066	0.0014	-0.0116	0.0071	-0.2196	2.0776	-0.0022
	(2.56)	(-3.88)	(1.60)	(0.10)	(-3.93)	(1.31)	(0.15)	(2.20)	(-2.51)	(0.62)	(-0.89)	(1.67)	(-0.77)
Peru	0.1227	0.0001	0.0524	0.0901	0.0001	0.0697	0.1100	0.0003	0.0004	-0.0176	0.1238	1.3122	-0.0014
	(3.04)	(0.26)	(0.94)	(1.73)	(0.23)	(1.01)	(1.83)	(0.38)	(0.29)	(-0.32)	(0.67)	(0.74)	(-0.69)
Philippines	0.0263	0.0001	0.0086	0.0243	0.0001	0.0131	0.0235	0.0004	0.0049	-0.0162	-0.0768	-1.5024	-0.0025
	(1.36)	(0.31)	(0.30)	(1.04)	(0.30)	(0.38)	(1.02)	(1.04)	(1.21)	(-1.17)	(-1.08)	(-1.29)	(-1.37)
Poland	0.0319	0.0003	0.0393	-0.0085	0.0003	0.0121	-0.0020	0.0000	0.0034	0.0325	0.0039	-1.1796	-0.0021
	(2.02)	(1.48)	(1.10)	(-0.26)	(1.49)	(0.30)	(-0.06)	(0.17)	(1.28)	(2.17)	(0.07)	(-1.16)	(-1.10)
Russia	-0.0090	0.0001	0.0239	-0.0400	0.0001	0.0047	-0.0512	0.0003	0.0012	0.0204	-0.1039	0.3381	-0.0026
	(-0.36)	(0.29)	(0.68)	(-1.54)	(0.26)	(0.12)	(-1.87)	(0.77)	(0.74)	(1.07)	(-1.66)	(0.69)	(-2.17)
South Africa	-0.0100	0.0007	0.0060	-0.0197	0.0007	-0.0054	-0.0360	-0.0002	0.0099	0.0275	-0.0378	-0.7166	-0.0030
	(-0.63)	(3.28)	(0.25)	(-0.97)	(3.28)	(-0.21)	(-1.55)	(-0.33)	(1.99)	(1.95)	(-1.03)	(-0.81)	(-1.74)
South Korea	0.0145	-0.0003	0.0343	-0.0249	-0.0003	0.0259	-0.0250	-0.0003	0.0027	0.0443	0.0053	-0.3948	-0.0021
	(0.91)	(-1.63)	(1.62)	(-1.55)	(-1.61)	(0.98)	(-1.54)	(-0.73)	(2.20)	(2.50)	(0.10)	(-0.48)	(-1.63)
Turkey	0.0096	0.0005	0.0313	-0.0249	0.0005	0.0068	-0.0331	-0.0024	0.0187	0.0397	-0.0486	0.0149	-0.0066
	(0.52)	(1.66)	(0.94)	(-0.85)	(1.66)	(0.18)	(-1.03)	(-3.27)	(3.97)	(1.88)	(-0.71)	(0.02)	(-3.29)

Table 2.8 Summary of robustness tests

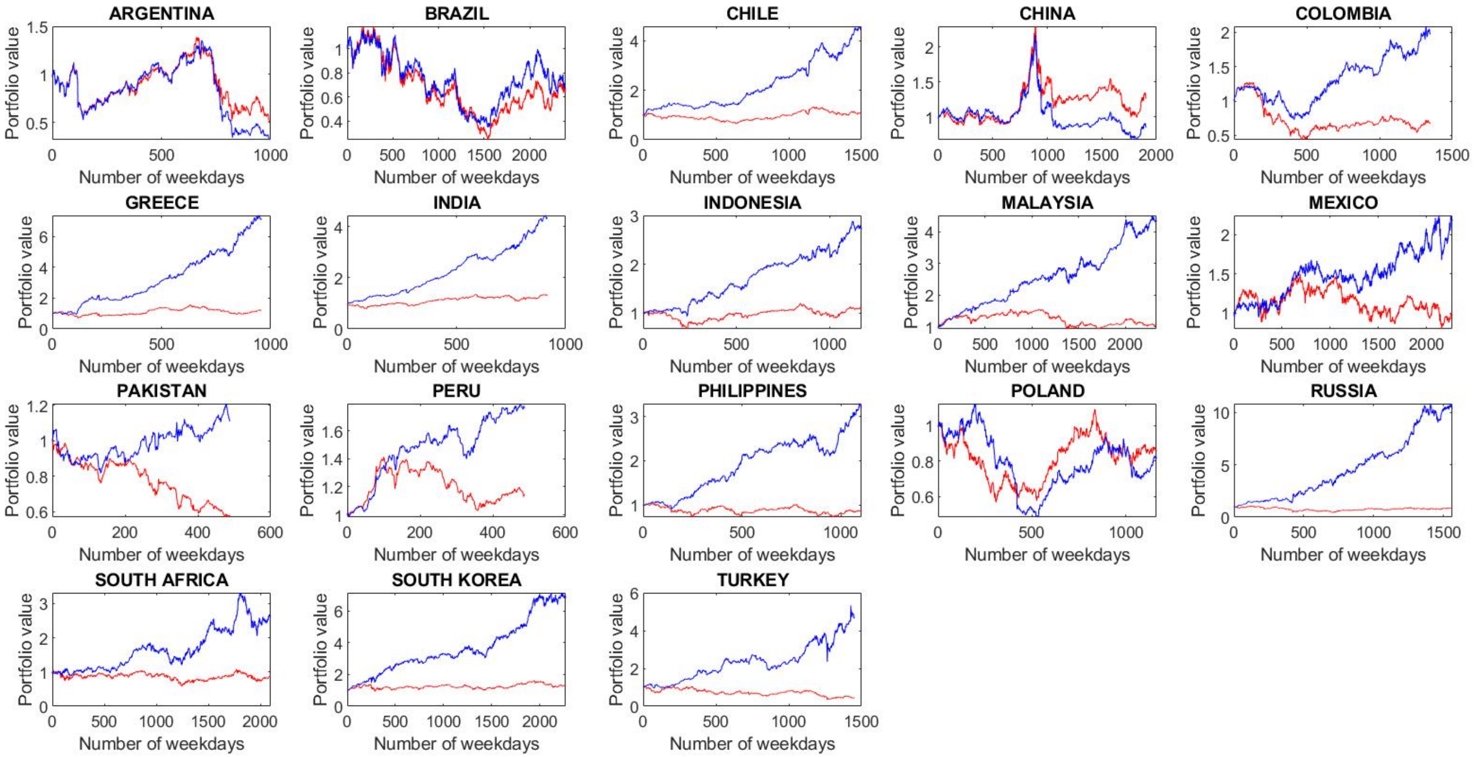
This table provides summary results for predictive regressions of one-day-ahead open-to-close index returns on lagged close-to-close ETF returns and various control variables that are defined in Table 2.4. Each number presented in the table corresponds to the number of countries that support the predictive power of ETF returns at the 1%, 5% and 10% significance levels. Results are presented for a univariate specification, a bivariate specification that controls for lagged index returns and a multivariate specification that includes all control variables. In Panel A, regressions are estimated for the full sample, high-volatility sample and low-volatility sample using various lags for the Newey-West (1987) procedure that adjusts for autocorrelation and heteroscedasticity. In Panel B, regressions are augmented by additional lags of the dependent variable.

	Univariate			Indexret Control			All Controls		
	1%	5%	10%	1%	5%	10%	1%	5%	10%
Panel A									
Full Sample									
NW 3 lags	11	12	12	9	11	13	10	12	12
NW 4 lags	11	12	12	9	11	13	10	12	12
NW 5 lags	11	12	12	9	11	13	10	12	12
NW 6 lags	11	12	12	9	11	12	10	12	12
NW 7 lags	11	12	12	9	11	12	10	12	12
NW 8 lags	11	12	12	9	11	12	10	12	12
NW 9 lags	11	12	12	8	11	12	10	12	12
High Volatility									
NW lags	10	10	12	6	8	10	7	9	11
NW 4 lags	10	10	12	6	8	10	7	9	11
NW 5 lags	10	10	12	6	8	10	7	10	11
NW 6 lags	10	10	12	6	8	11	7	9	11
NW 7 lags	10	10	12	6	8	11	7	9	11
NW 8 lags	10	10	12	6	8	11	7	9	11
NW 9 lags	10	10	12	6	8	11	7	9	11
Low Volatility									
NW 3 lags	7	7	8	6	6	8	6	6	8
NW 4 lags	7	7	8	6	6	8	6	6	8
NW 5 lags	6	7	8	6	7	8	6	6	8
NW 6 lags	6	7	8	6	7	8	6	6	8
NW 7 lags	6	7	8	6	7	8	6	6	8
NW 8 lags	6	7	8	6	7	8	6	7	8
NW 9 lags	6	7	9	6	7	8	6	7	8
Panel B									
3 lags of Indexret									
NW 3 lags				8	11	12	11	12	12
NW 4 lags				9	11	12	11	12	12
NW 5 lags				9	11	12	11	12	12
NW 6 lags				9	11	12	11	12	12
NW 7 lags				9	11	12	11	12	12
NW 8 lags				9	11	12	11	12	12
NW 9 lags				9	11	12	11	12	12
5 lags of Indexret									
NW 3 lags				8	11	13	11	12	12
NW 4 lags				9	11	13	11	12	12
NW 5 lags				9	11	13	11	12	12
NW 6 lags				9	11	13	11	12	12
NW 7 lags				9	11	13	11	12	12
NW 8 lags				9	11	13	11	12	12
NW 9 lags				9	11	13	11	12	12

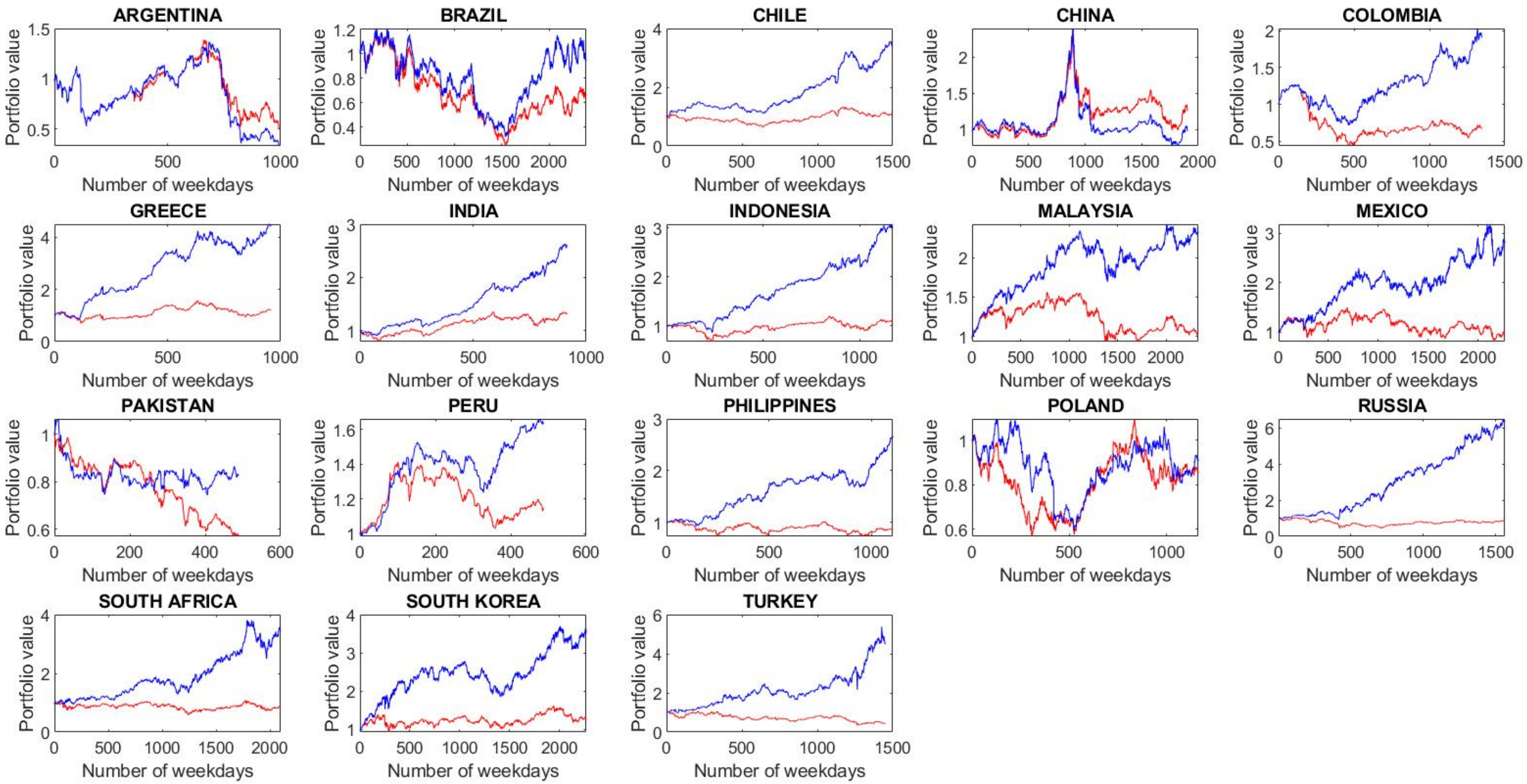
Figure 2.1 Economic significance

This figure presents cumulative returns to a rolling window strategy that uses the out-of-sample one-day ahead forecasts of open-to-close index returns based on lagged close-to-close ETF returns. The first forecasting regression uses the first half of the sample period in each market. Then, the one-day-ahead index return estimates are calculated using an expanding window. Specifically, on each day t after the midpoint of the sample period for each country, the data available up to day t are used to estimate the univariate predictive regression. The estimated coefficients are recorded and used to forecast the index return at day $t+1$. The strategy stays invested in the index both overnight and intraday on days in which the forecasted index return is positive. For the days in which the forecasted index return is negative, the strategy shorts the index at the opening and rebuilds long index position at the closing of the day. The cumulative returns to this rolling window strategy are presented in blue whereas the actual returns to the market index are presented in red for each country. Panels A, B and C present results for the full sample, high-volatility sample and low-volatility sample, respectively.

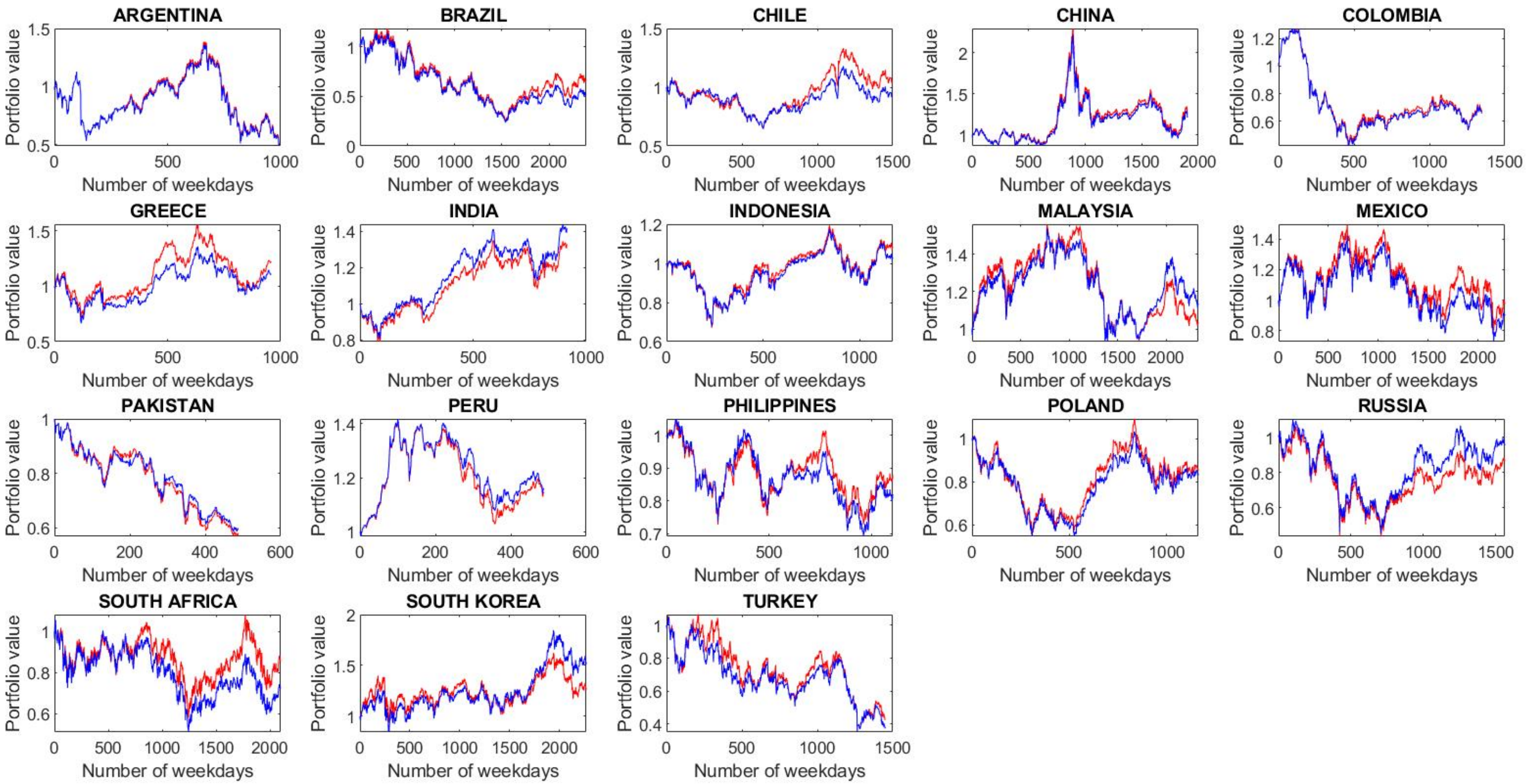
(a) Full sample



(b) High-volatility sample



(c) Low-volatility sample



3. HEDGING WITH INDUSTRY ETFs

3.1 Introduction

Exchange-traded funds (ETFs) have been one of the most successful recent financial innovations with about $10 trillion worth of assets managed globally under nearly 9,000 ETFs. Structured as continuously traded open-end investment companies which allow for the creation and redemption of fund shares, ETFs have disrupted the asset management industry due to their low transaction costs, high liquidity and flexibility. Moreover, due to the existence of primary market arbitrage undertaken by authorized participants, market prices and net asset values of ETFs do not diverge in contrast to closed-end funds. In line with the increased popularity of these passive investing vehicles, the academic literature focusing on ETFs has expanded significantly in recent years. Some studies such as Madhavan & Sobczyk (2016), Broman & Shum (2018), Lettau & Madhavan (2018) and Glosten et al. (2021) focus on the price discovery role of ETFs and how they contribute to market efficiency. Li & Zhu (2022) provide evidence that ETFs provide an avenue for investors to circumvent short-sale constraints. Other studies such as Ben-David et al. (2018), Da & Shive (2018) and Brown et al. (2021) argue that ETFs increase volatility and return co-movement in financial markets. There are also studies such as Israeli et al. (2017), Dannhauser (2017), Piccotti (2018) which suggest that ETFs may have a dampening effect on liquidity. Ben-David, Franzoni & Moussawi (2017) provide a comprehensive review of the earlier empirical literature on ETFs.

Huang et al. (2021) (HOZ, 2021) focus on an underappreciated role of ETFs in financial markets: hedging. The authors conjecture that an informed trader who wants to benefit from private and favorable firm-specific information would want to manage market risk and sector risk. Market risk can be hedged by index futures or index ETFs whereas industry ETFs provide a convenient way to hedge sector risk. Consistent with these ideas, the study documents that hedge funds' holdings in stocks with upcoming positive earnings news and short interest in associated industry ETFs spike simultaneously before earnings announcements with positive content. Moreover, this type of "long-the-stock/short-the-ETF" activity is more pronounced among stocks with higher industry exposure. The study also provides evidence that such activity enhances market efficiency as the reduction in post-earnings-announcement drift is more pronounced among member stocks with higher industry exposure after the inception of industry ETFs. Furthermore, the inception of industry ETFs reduces the arbitrage risk of member stocks.

In this study, we build on the findings of HOZ (2021) and obtain the perspective of a hypothetical hedge fund that can perfectly forecast earnings announcements with positive news which are defined as those that have standardized unexpected earnings that rank in the top quartile within a quarter. The fund follows one of two strategies. In the naked strategy, the fund constructs an equal-weighted portfolio consisting of long positions in all stocks with upcoming positive earnings news. For each stock, the long position is taken n trading days before the announcement and unwound n trading days after the announcement where n varies from 10 to 60 in increments of ten. For the hedged strategy, each long stock position is complemented by short positions in corresponding industry ETFs.

We compare the performances of these two strategies between 2010 and 2021 based on six metrics calculated using either daily or monthly strategy returns. Four of these metrics are reward-to-risk ratios where the average excess strategy return is divided by standard deviation or three downside risk measures, namely downside deviation, value-at-risk and maximum drawdown. The fifth metric is six-factor alpha, the intercept term from a regression of excess strategy returns on the five factors of Fama & French (2015) and momentum factor. The final metric is the manipulation-proof performance measure (MPPM) of Goetzmann, Ingersoll, Spiegel & Welch (2007). We calculate these metrics either as point estimates over the full sample or time-series averages using a rolling window approach.

Our results indicate that the hedged strategy produces higher reward-to-risk ratios compared to the naked strategy and the differences between two strategies is more pronounced for shorter holding windows. This finding highlights the importance of using industry ETFs to hedge sector exposure in terms of reducing especially downside risk. On the other hand, using short positions in ETFs to complement long positions in stocks with upcoming positive earnings news does not have a boosting effect on six-factor alphas or MPPM. In fact, the naked strategy generates higher MPPM values for all holding windows. We also compare the performances of the strategies when they are executed among certain equity subsamples and find that both generate higher performance metrics for stocks with higher risk such as those with smaller market capitalizations, lower liquidities and higher book-to-market ratios. More importantly, the superior performance of the hedged (naked) strategy based on reward-to-risk ratios (alpha and MPPM) is robust in an overwhelming majority of the subsamples we examine.

The paper is structured as follows. Section 3.2 discusses data and sample composition. Section 3.3 describes the naked/hedged strategies and the performance metrics. Section 3.4 presents the empirical results. Section 3.5 concludes.

3.2 Data and Sample Composition

Our study uses ETF- and stock-level data collected from multiple resources and covers the period between 2010 and 2021. We begin by describing the stock level data. First, we obtain quarterly company earnings data from COMPUSTAT for all ordinary common shares listed on NYSE, AMEX and NASDAQ. If there is more than one quarterly earnings report for a certain firm-quarter, we consider only the one with the latest announcement date. We impose several restrictions to this data following HOZ (2021). We require that price-per-share at the fiscal quarter end is available from COMPUSTAT and is greater than \$1. We also require that market value of equity at the fiscal quarter end is available and greater than \$5 million. We also eliminate observations for which earnings announcement date is missing, earnings announcement date is more than 100 days later than the fiscal quarter end, and CRSP data is not available. For this sample, we follow Livnat & Mendenhall (2006) and define earnings surprises as the standardized unexpected earnings (SUE) following a seasonal random walk model. As such, the SUE of a stock at the end of a quarter is defined as the difference in earnings per share between the current quarter and four quarters earlier scaled by price per share at the end of the current quarter. A stock with a positive earnings announcement is defined as one whose SUE ranks in the top quartile. We determine these quartile breakpoints within each quarter rather than over the entire sample period to avoid having a disproportionately higher number of observations during periods of accelerated aggregate economic activity. These procedures leave us a total of 39,412 positive earnings surprises originating from 4,710 distinct stocks. Panel A of Table 3.1 presents the annual distribution of observations with positive earnings surprises.

Next, we move on to constructing the ETF sample. First, we obtain a list of US equity ETFs from Bloomberg by selecting fund type to be "ETF", fund asset class to be "Equity" and fund geographical focus to be "USA". In order to restrict the sample to plain vanilla US equity ETFs, we further filter out ETFs that are actively-managed, leveraged or inverse or that invest in swaps or other derivatives. We cross-check this list with etfdb.com and etf.com to eliminate any ETFs that do not invest predominantly in US common stocks and add any ETFs that are missing from Bloomberg. Then, we extract the fund CUSIP number and portfolio number of these ETFs using the CRSP Fund Identifiers dataset. Finally, we download the holdings of these ETFs from the CRSP Survivor-Bias-Free Mutual Fund database. Panel B of Table 3.1 presents the annual distribution of plain vanilla US equity ETFs with available holdings data. Note that the number of ETFs with holdings data almost doubles during our sample period.[1]

To identify industry ETFs, we utilize fund holdings following the approach of HOZ (2021). First, we extract the SIC codes of all US equities from COMPUSTAT and CRSP. We prioritize COMPUSTAT codes when available and CRSP codes otherwise. If neither SIC code is available, we disregard that holding and do not assign it to any specific industry. Then, we merge these SIC codes with the ETF holdings data and map the SIC codes to their corresponding Fama-French (FF) 12 industries. Next, for each ETF holding report, we sum the percent allocated to stocks with the same FF-12 industry to get the industry allocation of each US equity ETF. To be classified as an industry ETF, a fund needs to invest at least 30% of its assets under management to a certain FF-12 industry in each available holding report. We eliminate those ETFs whose name includes words such as "smart beta", "factor", "momentum", "volatility", "value", "yield", "dividend", "growth" and "dynamic" to avoid smart beta ETFs whose primary goal is providing a factor exposure rather than concentrating on a specific sector. Finally, we exclude those ETFs that have less than 30 different stocks within their holdings in any of their holding reports so that firm-specific risk is largely diversified away. As a result, we end up with 119 distinct industry ETFs (only one of which is dedicated to two sectors at the same time) covering 10 FF-12 industries which is almost identical to the number of industry ETFs that HOZ (2021) identify. The distribution of industry ETFs across FF-12 industries is provided in Panel C of Table 3.1.

In the final step, we match industry ETFs and stocks to determine the number of earnings announcements that the hypothetical hedge fund is going to act upon. An

[1]The number of ETFs with available holdings data is only 25 and 26 in 2008 and 2009, respectively. The low number of observations in these years should be attributed to a scarcity of holdings data in CRSP rather than a reduction in the number of ETFs trading in the market during the global financial crisis. This motivates our choice of 2010 as the starting year of the sample.

industry ETF and a stock constitute a pair if the stock appears in our positive earnings surprise sample, the stock is included within the holdings of the ETF at least once in our sample[2], and the dedicated FF-12 industry is the same for the ETF and the stock.[3] Following this procedure, we obtain 11,464 distinct ETF-stock pairs. Note that a stock can be matched with multiple ETFs and an ETF can be matched with multiple stocks. Next, for each industry ETF-stock pair, we collect daily equity and ETF returns from CRSP. We allow only up to 5 consecutive trading days of missing observations in either the equity or ETF return series which reduces the number of eligible ETF-stock pairs to 11,376. Finally, when we merge our daily ETF-stock return pairs with the positive earnings surprise sample to mark the earnings announcement dates, we end up with 18,824 matching cases.[4] In other words, the hypothetical hedge fund in our study will anticipate 18,824 positive earnings surprises to execute its strategy over our sample period.

3.3 Methodology

3.3.1 Strategy Construction

Our hypothetical hedge fund is dedicated to a single strategy which is betting on positive earnings surprises. We assume that this fund can perfectly anticipate every positive earnings surprise and rebalances its stock portfolio on a daily basis. In our analysis, we compare the performance of two competing strategies. For the naked strategy, the fund takes a long position in all stocks with upcoming positive earnings surprises. We conduct our analysis for six holding windows ranging from 10 to 60 trading days before and after earnings announcement dates. For a stock

[2]The reason why we impose this particular requirement is that FF-12 industries tend to constitute broad categories. For example, a household appliances company and a motor vehicle company would both be assigned to the consumer durables industry and we want to reduce the possibility that our hypothetical hedge fund would hedge the risk of a long position in a household appliances stock by shorting an ETF that tracks the automotive sector.

[3]We eliminate those stocks whose FF-12 industry is not stable during the sample period.

[4]This leaves 20,588 unmatched positive earnings surprises. These surprises originate from 2,423 distinct stocks. 2,222 of these are not a part of any eligible ETF-stock pair because they are stocks not held by industry ETFs. The remaining unmatched cases stem primarily from either missing return data or paired industry ETF being not established at the announcement date of the earnings surprise.

that announces its earnings on day t and a 10-day radius for the holding window, the fund takes a long position in the stock at the beginning of day $t-10$, holds it for 21 trading days and divests it at the end of day $t+10$. We allow a maximum radius of 60 trading days for the holding window so that the fund would add a stock to its portfolio before the earlier earnings announcement date and most likely sell it before the next earnings announcement date. For the hedged strategy, the fund manages the sector risk associated with these long stock positions by simultaneously taking short positions in corresponding industry ETFs.

In terms of implementation, for each alternative holding window, we determine the collection of stocks with upcoming positive earnings surprises that should be held in the naked portfolio on a daily basis. We also determine the collection of matched industry ETFs that should be shorted in the hedged portfolio on a daily basis. If there are more than one eligible industry ETFs to be shorted against a stock, we assign equal weights to each of them. Daily return of the naked strategy is calculated as the simple arithmetic average of the daily returns of the stocks in the naked portfolio such that each stock is invested the same dollar amount on a given day. Daily return of the ETF portfolio is calculated as the weighted average of the daily returns of the ETFs in the hedged portfolio where weights are determined by the number of ETFs that are used to hedge each long stock position. For example, suppose that, on day t, the naked portfolio contains stocks A, B and C with upcoming positive earnings announcements. Assume further that stock A is hedged by ETF X only, stock B is hedged by ETFs X and Y, and stock C is hedged by ETFs X, Y and Z.[5] In this case, each stock is assigned a weight of 1/3 whereas ETF X is assigned a weight of 11/18 (=1/3 + 1/6 + 1/9), ETF Y is assigned a weight of 5/18 (=1/6 + 1/9) and ETF Z is assigned a weight of 1/9. Daily return of the hedged strategy is equal to the difference between the daily returns of the naked strategy and the ETF portfolio. After calculating a daily return series for the naked and hedged strategies from 2010 to 2021, we also generate a monthly return series by compounding daily returns within the same calendar month.

[5] In this situation, all three stocks and all three ETFs should be dedicated to the same FF-12 industry. However, it is possible that stock A was never in the holdings of ETFs Y and Z and stock B was never in the holdings of ETF Z whereas stock A was in the holdings of ETF X, stock B was in the holdings of ETFs X and Y and stock C was in the holdings of all three ETFs at least in one reporting period during the sample period.

3.3.2 Performance Metrics

We calculate six performance metrics for both daily and monthly returns of the naked and hedged strategies over six alternative holding windows. Four of the six performance metrics are reward-to-risk ratios that measure how much excess return a strategy generates per unit of risk where risk is defined in alternative ways. The first metric, Sharpe ratio, adjusts for total portfolio risk and is equal to the average excess return over the full sample period divided by the standard deviation of excess returns. Standard deviation treats favorable and unfavorable return realizations equally and ignores the non-normality of the distribution of investment returns. Thus, we calculate three additional reward-to-risk ratios that adjust for downside risk. Sortino ratio is equal to the average excess return over the full sample period divided by the downside deviation of excess returns where downside deviation only takes excess returns lower than zero into account. Return-to-VaR is equal to the average excess return over the full sample period divided by the value-at-risk of excess returns where value-at-risk is defined as the 1$^{\text{st}}$ percentile of excess returns. Finally, Calmar ratio is equal to the average excess return over the full sample period divided by maximum drawdown where maximum drawdown is equal to the percentage decline in the value of an investment from its historical peak to its historical trough.[6] The risk-free rate used to calculate excess returns is the interest rate on one-month US T-bills and obtained from Kenneth French's website.

We calculate two additional performance metrics that are not defined as reward-to-risk ratios. The first one is six-factor alpha which is the intercept term from a regression of daily or monthly strategy returns on the market, size, value, profitability and investment factors of Fama & French (2015) plus the momentum factor of Carhart (1997). The data for these factors is again obtained from Kenneth French's website. The second one is the manipulation-proof performance measure of Goetzmann et al. (2007).

$$MPPM = \hat{\Theta} = \frac{1}{(1-\rho)\Delta t} \ln\left(\frac{1}{T}\sum_{t=1}^{T}[(1+r_t)/1+r_{ft}]^{(1-\rho)}\right) \tag{3.1}$$

where r_t and r_{ft} are the per-period investment return and risk-free interest rate at time t. This metric is transformed such that it can be interpreted as the annualized continuously compounded excess return certainty equivalent of the portfolio. In other words, a risk-free portfolio that earns $\exp[\ln(1+r_{ft})+\Theta\Delta t]$ each period would

[6] Although we calculate these metrics over the full sample period in our baseline tests, we also allow for the time-varying nature of strategy performance and calculate them on a rolling window basis in section 3.4.3.

have a manipulation-proof performance measure equal to Θ. Δt is chosen to be 1/252 and 1/12 for daily and monthly calculations, respectively. Goetzmann et al. (2007) define ρ in terms of the return on a benchmark portfolio and equate it to 3 in their simulations based on historical data for the CRSP value-weighted market index. We also use a relative risk aversion value of 3 in our baseline analysis.

3.4 Empirical Results

3.4.1 Full Sample Analysis

Panel A of Table 3.2 presents performance metrics for the daily return series of the naked and hedged strategies that utilize six alternative holding windows. We begin our discussion by focusing on the reward-to-risk ratios. First, we observe that the hedged strategy generates a higher average excess return per unit risk compared to the naked strategy for all holding windows. For example, the naked strategy has Sortino, Return-to-VaR and Calmar ratios of 0.2150, 0.0513 and 1.4199 for the shortest holding window, respectively. The analogous values are 0.3065, 0.0743 and 1.5452 for the hedged strategy. This overperformance persists as the holding window becomes wider. Second, we observe that the performance of both strategies deteriorate as the holding window of stocks with positive earnings surprises becomes wider. In other words, average excess return does not increase enough to compensate for additional risk as the hypothetical hedge fund carries a stock for a longer duration in its portfolio. For example, the Sharpe ratio for the naked strategy decreases almost monotonically from 0.1320 to 0.0798 as the radius of the holding window increases from 10 to 60 trading days. Similarly, the Sharpe ratio for the hedged strategy decreases from 0.1735 to 0.0941 as the holding window expands.

These findings can be digested more easily by referring to Figure 3.1 which provides a graphical representation for the performance metrics in Panel A of Table 3.2. As can be seen, as the holding window expands along the x-axis, reward-to-risk ratios tend to decline almost uniformly. Moreover, the line for the hedged strategy stays above that for the naked strategy without any exceptions. Furthermore, the distance between the lines generally shortens as the holding window expands which indicates that strategies' performances tend to converge as the hedge fund takes a long position in stocks with positive earnings announcements earlier and divests them later.

Next, we discuss the other two performance metrics that are not defined as reward-to-risk ratios. We again observe that strategy performance is weaker for longer holding windows. Alpha (MPPM) of the naked strategy decreases from 0.0015 to 0.0006 (0.4305 to 0.2129) from the shortest to the longest holding window whereas alpha (MPPM) of the hedged strategy decreases from 0.0015 to 0.0005 (0.3416 to 0.1217). However, these numbers also indicate that the relative ranking of the two strategies switches for these metrics. Alpha is almost identical between the two strategies for all holding windows. Figure 3.1 indicates that the alpha profiles nearly coincide and, if anything, the line for the naked strategy lies slightly above that of the hedged strategy. For MPPM, the naked strategy clearly outperforms the hedged strategy for all holding windows and the MPPM lines do not seem to converge as the holding window is expanded.[7]

Panel B of Table 3.2 presents performance metrics for the monthly returns series for the naked and hedged strategies. Patterns associated with daily strategy returns generally hold up for the monthly frequency. First, for the reward-to-risk ratios, the hedged strategy generates higher values compared to the naked strategy with the sole exception of Calmar ratio for the (-10,+10) trading window. Third, for alpha and MPPM, relative performances flip and the naked strategy generates higher values. For example, for the longest holding window, alpha of the naked (hedged) strategy is equal to 0.0120 (0.0108) whereas MPPM of the naked (hedged) strategy is equal to 0.2188 (0.1230). Second for all six metrics, the performances of both strategies tend to diminish for longer holding windows. As a final note, one can observe that for the four reward-to-risk ratios, values for the monthly return series are larger than those for the daily return series since average excess returns in the numerator tend to increase faster with investment horizon compared to the risk measures in the denominator. Alphas show a similar pattern since abnormal returns also accumulate with investment horizon. However, MPPM is roughly stable between the daily and monthly return series as it is designed to be so.

These results collectively suggest that using short positions in industry ETFs to hedge the sector risk associated with long positions in stocks with upcoming posi-

[7] We entertain alternative values for the ρ parameter used to calculate MPPM since we calculate the daily (monthly) estimate for ρ to be 4.95 (7.09) during our sample period based on the formula provided by Goetzmann et al. (2007). First, we find that MPPM values tend to decrease for both strategies and all holding windows as the relative risk aversion estimate is increased from 3 to 5 to 7. Second, we find that the outperformance of the naked strategy gets less pronounced as ρ increases. When $\rho = 7$, MPPM values for the strategies are almost identical.

tive earnings surprises provides a better performance when the performance metric explicitly adjusts for downside risk as in Sortino, Return-to-Var and Calmar ratios. This suggests that shorting industry ETFs proves itself useful for insulating the hypothetical hedge fund from considerably unfavorable industry shocks. However, except the Sharpe ratio, when the performance metric does not explicitly adjust for downside risk, hedging with industry ETFs has a dampening effect on strategy performance. For alpha, this is consistent with studies such as Kelly & Jiang (2014), Bali, Cakici & Whitelaw (2014) and Chabi-Yo, Ruenzi & Weigert (2018) which find that downside risk is not accounted for by traditional factor models. The situation is similar for MPPM which utilizes lognormally distributed strategy outcomes in its specific functional form.

3.4.2 Subsample Analysis

In this section, we investigate how the performances of the naked and hedged strategies compare to each other across equity subsamples formed based on various firm-specific attributes. We also examine whether the strategies produce higher performance metrics in certain equity subsamples compared to others. For these analyses, we utilize six attributes which are measured at the end of the month preceding the first day of the holding period for a stock. Firm size is equal to stock price times number of shares outstanding. Liquidity (LIQ) is equal to the negative of the daily ratio of absolute stock return to its dollar volume averaged over the last 12 months. We require a minimum of 200 daily observations to calculate LIQ. Market beta is equal to the slope coefficient from a regression of monthly excess stock returns on monthly excess market returns during the past 60 months. Idiosyncratic volatility (IVOL) is the standard deviation of residual terms from a regression of monthly excess stock returns on the market, size and value factors of Fama & French (1993) during the past 60 months. We require a minimum of 24 monthly observations to calculate market beta and IVOL. For months from June of year t to May of year $t+1$, book-to-market ratio (BM) is defined as book value of equity for the fiscal year ending in calendar year $t-1$ divided by market capitalization at the end of calendar year $t-1$. Book value of equity is equal to stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock. Finally, momentum (MOM) is the cumulative stock return during the 11-month period up to but not including the current month. We split all stocks in the CRSP universe into deciles based on each attribute and form two groups based on whether a stock is included in the top or bottom five deciles at the end of a month.[8]

Table 3.3 presents Sharpe, Sortino, Return-to-VaR and Calmar ratios for the naked and hedged strategies across subsamples based on various attributes. First, as in the full sample, the hedged strategy continues to generate higher reward-to-risk ratios compared to the naked strategy for a vast majority of subsamples and holding horizons. There is a total of 288 combinations of performance metrics, holding windows and equity subsamples and the hedged strategy is associated with a better performance in 265 (92.0%) of these combinations. Out of the 23 cases in which the hedged strategy does not overperform the naked strategy, 16 cases are associated with the longest holding window. This is expected as we observed in Figure 3.1 that the reward-to-risk ratios of the two strategies converge as the holding window expands. Other notable exceptions are encountered in the shortest holding window for which the naked strategy has higher Sharpe and Return-to-VaR ratios for low beta stocks and higher Calmar ratios for smaller and more liquid stocks. These results suggest that hedging via short positions in industry ETFs improves total risk- and downside risk-adjusted performance ratios of long positions in stocks with upcoming positive earnings in a large majority of equity subsamples.

Second, we find that both strategies tend to generate higher reward-to-risk ratios in specific equity subsamples. For example, all four ratios are larger for both strategies when they are executed among small stocks rather than large stocks. In other words, independent from the decision of the hypothetical hedge fund to use industry ETFs for hedging purposes, taking long positions in small stocks with upcoming positive earnings generates higher reward-to-risk ratios. A similar pattern exists for less liquid stocks and stocks with higher book-to-market ratios as the strategies perform better in these subsamples. As far as small size, low liquidity and a high value-to-price ratio proxy for different aspects of equity risk, it can be argued that the hedge fund's strategy is more successful in subsamples of stocks with higher risk. With the exception of the shortest holding window, the strategies produce higher reward-to-risk ratios among equities with lower market betas which is consistent with the betting-against-beta anomaly of Frazzini & Pedersen (2014). Findings for idiosyncratic volatility (momentum) are ambiguous since the naked strategy tends to perform better for equities with higher IVOL (lower MOM) whereas the hedged strategy tends to perform better for equities with lower IVOL (higher MOM).

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[8]Note that we conduct the decile sorts across all common stocks in the CRSP universe rather than the stocks in our industry ETF-stock pairs to be able to assess the relative magnitude of an attribute in a more comprehensive manner. As a result, the subsamples we analyze do not always contain the same number of stocks. For example, since ETFs tend to hold larger and more liquid stocks in their portfolios, the number of stocks in the high size or high LIQ subsamples is about 50% higher than the number of stocks in the low size or low LIQ subsamples. Our results are qualitatively the same if the decile sorts are conducted across the stocks in the industry ETF-stock pairs.

In Table 3.4, we compare six-factor alphas and manipulation-proof performance measures for the naked and hedged strategies across equity subsamples. In Panel A, one can observe that the difference between the alphas of the two strategies is miniscule within all equity subsamples for all holding horizons. In other words, as observed for the full sample in Table 3.2, hedging with industry ETFs does not improve the hypothetical hedge fund's strategy in any substantial manner. In Panel B, a clear pattern emerges as one compares MPPM values of the naked and hedged strategies. For 72 out of 72 possible MPPM comparisons, the naked strategy generates a higher value compared to the hedged strategy. This again reiterates the full sample findings in Table 3.2. Finally, in both panels, one can observe that both naked and hedged strategies perform better among stocks in certain subsamples, especially those with smaller firm size, lower liquidity and higher idiosyncratic volatility.

3.4.3 Rolling Window Analysis

The analysis up to this point implicitly assumes that performances of the strategies are stable through time since we calculated a single value for each performance metric by using the entire time series of strategy returns. However, it is possible investment performance has a time-varying nature and we take this possibility into account by calculating each performance metric on a rolling window basis. Specifically, for the daily return series, we calculate each performance metric at a daily frequency using the strategy returns during the prior 250 trading days. For the monthly return series, we calculate each performance metric at a monthly frequency using the strategy returns during the prior 36 months. In Table 3.5, we report the averages of these daily and monthly performance metrics for six alternative holding windows. This procedure also allows us to conduct tests of statistical significance since we obtain a time series for each performance metric rather than a single point estimate.

For the metrics based on daily returns in Panel A, one can see that the hedged strategy generates significantly greater reward-to-risk ratios compared to the naked strategy. The average Sharpe ratio associated with the naked (hedged) strategy in the shortest window is 0.1629 (0.2060) and the t-statistic for a two-tailed test of equality for these values is -59.18. Although the difference gets smaller in terms of absolute magnitude as the holding window expands, the analogous t-statistic is -22.12 for the longest holding window. Similar patterns are observed for downside risk-adjusted Sortino, Return-to-VaR and Calmar ratios. The naked minus hedged performance spread is significantly negative for all three ratios and six holding windows. The narrowest spread is observed for the Calmar ratio and the longest holding window which is still highly significant with a t-statistic of -4.01. As in Tables 3.2 and 3.3, the overperformance of the hedged strategy vanishes when we focus on six-factor alpha and MPPM. However, different from those tables, even visibly small differences in alpha magnitudes between the strategies correspond to substantial levels of statistical significance. For example, in the shortest holding window, the naked (hedged) strategy produces an alpha of 0.0017 (0.0016) and the difference between these alphas has a t-statistic of 18.64. The naked strategy clearly outperforms the hedged strategy in terms of MPPM since the naked minus hedged MPPM spread has a t-statistic between 35.74 and 42.88 over the holding windows. These patterns are summarized graphically in Figure 3.2. For the metrics based on monthly returns in Panel B, although the reported t-statistics get smaller in terms of absolute value, all of the abovementioned conclusions are intact.

3.5 Conclusion

In this study, we construct two competing trading strategies inspired by Huang et al. (2021) who document that hedge funds increase their short positions in industry ETFs simultaneously with their holdings on member stocks before these firms announce positive earnings surprises. We test whether this hedging activity for sector risk deemed as "long-the-stock/short-the-ETF" results in a superior performance profile compared to an unhedged or naked strategy that only takes long stock positions before positive earnings announcements. To do so, we take the perspective of a hypothetical hedge fund which is able to foresee upcoming favorable earnings news impeccably and assume that the fund includes a stock with such news in its naked portfolio for various windows around the announcement date. For the hedged portfolio, these long stock positions are complemented by short positions in corresponding industry ETFs. Results indicate that the hedged strategy generates greater reward-to-risk ratios when mean strategy returns are scaled by standard deviation, downside deviation, value-at-risk or maximum drawdown. These patterns highlight the role of industry ETFs in managing portfolio risk, especially downside risk. However, these findings are not observed for alternative performance metrics such as six-factor alpha and manipulation-proof performance measure. Alphas associated with the hedged strategy are slightly lower than those of the naked strategy whereas the latter strategy clearly overperforms the former in terms MPPM. These findings continue to hold in a large majority of equity subsamples sorted based on various firm-specific attributes. Finally, both strategies generate higher performance metrics when they are executed within certain equity subsamples such as smaller stocks with lower liquidities and higher book-to-market ratios.

3.6 Tables and Figures

Table 3.1 Sample composition

This table presents details about the composition of the industry ETF-stock sample utilized in this study. Panel A presents the annual distribution of observations with positive earnings surprises. A stock has to have a price-per-share of at least $1 and a market value of equity of at least $5 million to be included in this sample. Stocks with missing earnings announcement dates and return data are also eliminated. Earnings surprise is measured by standardized unexpected earnings (SUE) which is equal to the difference in earnings per share between the current quarter and four quarters earlier scaled by price per share at the end of the current quarter. Stocks with positive earnings surprises are defined as those with SUE values in the top quartile within each quarter. Panel B presents the annual distribution of plain vanilla US equity ETFs with available holdings data. Panel C presents the distribution of industry ETFs across the Fama-French-12 industries. An industry ETF is one that invests at least 30% of its assets under management to a certain sector, whose name does not include words associated with strategies other than tracking a certain sector, and contains at least 30 distinct stocks within its holdings.

Panel A. Positive earnings surprises

Year	#	Year	#
2010	3,317	2016	3,265
2011	3,261	2017	3,249
2012	3,195	2018	3,298
2013	3,183	2019	3,249
2014	3,290	2020	3,230
2015	3,345	2021	3,530

Panel B. Plain vanilla US equity ETFs

Year	#	Year	#
2010	343	2016	515
2011	406	2017	593
2012	402	2018	626
2013	398	2019	652
2014	403	2020	658
2015	460	2021	642

Panel C. Industry ETFs

Industry	#	Industry	#
Consumer Nondurables	7	Utilities	6
Manufacturing	12	Wholesale and Retail	10
Energy	8	Healthcare	16
Chemicals	6	Finance	25
Business Equipment	29	Other	1

Table 3.2 Performance metrics - Full sample

This table presents performance metrics for a hypothetical hedge fund that can anticipate positive earnings surprises as defined in Table 3.1. For the naked strategy, the fund takes a long position in stocks with upcoming positive earnings surprises for holding windows ranging from 10 to 60 trading days before and after their earnings announcement dates. Daily return of the naked strategy is equal to the arithmetic average of the daily returns of the stocks in the portfolio. For the hedged strategy, the fund complements its long stock positions with short positions in corresponding industry ETFs. Daily return of the ETF portfolio is equal to the weighted average of the daily returns of the ETFs in the portfolio where weights are determined by the number of ETFs that are used to hedge each long stock position. Daily return of the hedged strategy is equal to the difference between the daily returns of the naked strategy and the ETF portfolio. Monthly strategy returns utilized in Panel B are compounded from daily strategy returns. Sharpe, Sortino, Return-to-VaR and Calmar ratios are defined as the average excess return (over the risk-free rate) per unit of standard deviation, lower partial moment, 1% value-at-risk and maximum drawdown, respectively. Alpha is the intercept term from the regression of strategy returns on market, size, value, investment, profitability and momentum factors. MPPM is the manipulation-proof performance measure of Goetzmann et al. (2007).

Panel A. Metrics based on daily returns

		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
Sharpe	Naked	0.1320	0.1024	0.0877	0.0884	0.0865	0.0798
	Hedged	0.1735	0.1452	0.1182	0.1213	0.1117	0.0941
Sortino	Naked	0.2150	0.1640	0.1391	0.1406	0.1379	0.1270
	Hedged	0.3065	0.2642	0.2099	0.2199	0.2085	0.1688
Return-to-VaR	Naked	0.0513	0.0412	0.0345	0.0344	0.0339	0.0312
	Hedged	0.0743	0.0638	0.0497	0.0522	0.0504	0.0408
Calmar	Naked	1.4199	0.9162	0.7704	0.7924	0.7798	0.7141
	Hedged	1.5452	1.2100	0.9748	1.0907	1.0269	0.7990
Alpha	Naked	0.0015	0.0009	0.0007	0.0007	0.0007	0.0006
	Hedged	0.0015	0.0009	0.0007	0.0007	0.0006	0.0005
MPPM	Naked	0.4305	0.2968	0.2413	0.2433	0.2370	0.2129
	Hedged	0.3416	0.2068	0.1523	0.1538	0.1463	0.1217

Panel B. Metrics based on monthly returns

		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
Sharpe	Naked	0.6035	0.4857	0.4108	0.4186	0.4086	0.3822
	Hedged	0.6908	0.6036	0.4772	0.5070	0.4640	0.4079
Sortino	Naked	1.3623	1.0868	0.8411	0.8517	0.8296	0.7587
	Hedged	1.6956	1.6818	1.1055	1.3374	1.2524	0.9692
Return-to-VaR	Naked	0.2443	0.3088	0.1799	0.1929	0.1845	0.1665
	Hedged	0.3979	0.4317	0.1960	0.2776	0.2616	0.2196
Calmar	Naked	2.2251	1.4762	1.2370	1.3321	1.2835	1.1525
	Hedged	1.5781	2.9152	1.3562	2.6553	2.3559	1.3139
Alpha	Naked	0.0324	0.0190	0.0141	0.0141	0.0138	0.0120
	Hedged	0.0315	0.0178	0.0130	0.0131	0.0127	0.0108
MPPM	Naked	0.4302	0.3025	0.2446	0.2479	0.2414	0.2188
	Hedged	0.3400	0.2081	0.1530	0.1553	0.1475	0.1230

Table 3.3 Sharpe, Sortino, Return-to-Var and Calmar ratios - Subsamples

This table presents Sharpe, Sortino, Return-to-VaR and Calmar ratios for a hypothetical hedge fund that can anticipate positive earnings surprises. Daily returns to the naked/hedged strategies and performance metrics are defined in Table 3.2. However, for the naked strategy, the fund takes long positions only in stocks that are either in the top five or bottom five deciles in the CRSP universe for various firm-specific attributes. *Size* is defined as the market value of common equity. *Beta* is the slope coefficient from the regression of monthly excess equity returns on monthly excess market returns during the past 60 months. *IVOL* is idiosyncratic volatility defined as the standard deviation of residual terms from the regression of monthly excess equity returns on monthly market, size and value factors during the past 60 months. *BM* is the book-to-market ratio of equity. *LIQ* is stock liquidity measured as negative of the daily ratio of absolute stock return to its dollar volume averaged over the last 12 months. *MOM* is momentum return measured as the cumulative return during the past 11 months skipping one month.

		Panel A. Sharpe Ratio						Panel B. Sortino Ratio					
		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)	(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
High Size	Naked	0.1082	0.0855	0.0713	0.0712	0.0640	0.0617	0.1787	0.1350	0.1123	0.1127	0.1009	0.0975
	Hedged	0.1397	0.1243	0.0950	0.0939	0.0726	0.0614	0.2656	0.2232	0.1677	0.1681	0.1274	0.1079
Low Size	Naked	0.1451	0.1147	0.1067	0.1060	0.1066	0.0977	0.2563	0.1902	0.1734	0.1725	0.1766	0.1579
	Hedged	0.1510	0.1300	0.1213	0.1221	0.1170	0.1054	0.2920	0.2400	0.2181	0.2240	0.2311	0.1907
High LIQ	Naked	0.1071	0.0831	0.0730	0.0691	0.0661	0.0617	0.1751	0.1314	0.1156	0.1094	0.1044	0.0976
	Hedged	0.1363	0.1153	0.0989	0.0861	0.0777	0.0598	0.2361	0.2003	0.1789	0.1528	0.1385	0.1055
Low LIQ	Naked	0.1419	0.1164	0.1032	0.1050	0.1032	0.0959	0.2596	0.1927	0.1668	0.1706	0.1695	0.1550
	Hedged	0.1449	0.1350	0.1188	0.1247	0.1168	0.1062	0.3009	0.2491	0.2120	0.2294	0.2231	0.1903
High Beta	Naked	0.1311	0.0929	0.0801	0.0816	0.0805	0.0750	0.2182	0.1498	0.1277	0.1303	0.1294	0.1202
	Hedged	0.1681	0.1211	0.0999	0.1047	0.0993	0.0854	0.3152	0.2176	0.1769	0.1865	0.1838	0.1533
Low Beta	Naked	0.1224	0.1093	0.0996	0.0999	0.0932	0.0864	0.2098	0.1764	0.1582	0.1596	0.1481	0.1367
	Hedged	0.1181	0.1240	0.1242	0.1263	0.1081	0.0834	0.2132	0.2339	0.2271	0.2398	0.2006	0.1390
High IVOL	Naked	0.1326	0.1022	0.0899	0.0915	0.0894	0.0815	0.2274	0.1665	0.1438	0.1472	0.1444	0.1304
	Hedged	0.1533	0.1278	0.1077	0.1126	0.1018	0.0880	0.2905	0.2345	0.1906	0.2037	0.1848	0.1528
Low IVOL	Naked	0.1258	0.0940	0.0784	0.0756	0.0718	0.0679	0.2116	0.1495	0.1239	0.1194	0.1131	0.1073
	Hedged	0.1586	0.1454	0.1178	0.1070	0.0954	0.0758	0.3089	0.2764	0.2161	0.1907	0.1703	0.1384
High BM	Naked	0.1399	0.1045	0.0915	0.0903	0.0867	0.0807	0.2395	0.1680	0.1453	0.1439	0.1398	0.1287
	Hedged	0.1681	0.1458	0.1335	0.1326	0.1140	0.0978	0.3255	0.2685	0.2439	0.2456	0.2311	0.1733
Low BM	Naked	0.1087	0.0909	0.0770	0.0787	0.0764	0.0722	0.1791	0.1466	0.1237	0.1264	0.1229	0.1159
	Hedged	0.1138	0.1088	0.0828	0.0867	0.0801	0.0721	0.1972	0.1962	0.1463	0.1549	0.1432	0.1309
High MOM	Naked	0.1259	0.1003	0.0859	0.0845	0.0805	0.0752	0.2046	0.1593	0.1355	0.1331	0.1270	0.1184
	Hedged	0.1541	0.1382	0.1152	0.1142	0.1008	0.0787	0.2730	0.2520	0.2042	0.2031	0.1776	0.1308
Low MOM	Naked	0.1234	0.1014	0.0878	0.0897	0.0884	0.0817	0.2159	0.1669	0.1422	0.1464	0.1481	0.1343
	Hedged	0.1345	0.1243	0.1035	0.1076	0.0945	0.0902	0.2613	0.2283	0.1879	0.2012	0.2100	0.1779

		Panel C. Return-to-VaR Ratio						Panel D. Calmar Ratio					
		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)	(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
High Size	Naked	0.0453	0.0332	0.0269	0.0267	0.0243	0.0236	0.9798	0.7107	0.6023	0.6178	0.5452	0.5235
	Hedged	0.0567	0.0531	0.0380	0.0383	0.0284	0.0230	1.1446	0.8547	0.6728	0.7501	0.4790	0.4234
Low Size	Naked	0.0555	0.0469	0.0436	0.0435	0.0438	0.0396	2.1330	1.1518	1.0205	1.0156	1.0576	0.9467
	Hedged	0.0634	0.0554	0.0504	0.0524	0.0540	0.0425	1.9561	1.3967	1.0805	1.3091	1.3611	0.8538
High LIQ	Naked	0.0435	0.0317	0.0277	0.0266	0.0251	0.0236	1.0030	0.6958	0.6248	0.5902	0.5626	0.5190
	Hedged	0.0595	0.0511	0.0414	0.0351	0.0311	0.0230	0.9239	0.8928	0.8456	0.7562	0.5763	0.4090
Low LIQ	Naked	0.0589	0.0491	0.0423	0.0429	0.0430	0.0392	2.0916	1.1704	0.9764	1.0228	1.0292	0.9442
	Hedged	0.0621	0.0591	0.0522	0.0529	0.0525	0.0436	3.4386	1.1908	1.1711	1.3509	1.3461	0.9396
High Beta	Naked	0.0514	0.0374	0.0314	0.0328	0.0320	0.0291	1.5358	0.8412	0.7120	0.7366	0.7384	0.6756
	Hedged	0.0693	0.0506	0.0426	0.0457	0.0449	0.0376	2.0430	0.9184	0.7767	0.8736	0.8862	0.7124
Low Beta	Naked	0.0492	0.0437	0.0384	0.0385	0.0352	0.0330	1.3635	0.9515	0.8499	0.8878	0.8187	0.7717
	Hedged	0.0484	0.0545	0.0563	0.0603	0.0482	0.0369	2.0757	1.3032	1.1211	1.2476	0.9789	0.3990
High IVOL	Naked	0.0527	0.0429	0.0361	0.0368	0.0360	0.0321	1.6910	0.9748	0.8195	0.8710	0.8648	0.7797
	Hedged	0.0638	0.0546	0.0448	0.0473	0.0444	0.0351	2.5409	1.0788	0.8501	1.0360	0.9962	0.6265
Low IVOL	Naked	0.0519	0.0359	0.0288	0.0278	0.0270	0.0259	1.2354	0.8199	0.6718	0.6384	0.6019	0.5603
	Hedged	0.0661	0.0606	0.0486	0.0451	0.0393	0.0314	2.1733	1.3053	1.0733	0.9780	0.8482	0.6058
High BM	Naked	0.0569	0.0414	0.0358	0.0357	0.0346	0.0318	1.6541	0.9402	0.7895	0.7871	0.7557	0.6914
	Hedged	0.0754	0.0607	0.0586	0.0566	0.0527	0.0405	2.4661	1.3550	1.0994	1.2199	1.0227	0.6646
Low BM	Naked	0.0414	0.0364	0.0300	0.0312	0.0303	0.0285	1.2940	0.8551	0.7171	0.7544	0.7359	0.6868
	Hedged	0.0532	0.0466	0.0338	0.0369	0.0342	0.0341	1.5460	1.0005	0.5130	0.7736	0.8027	0.6468
High MOM	Naked	0.0485	0.0399	0.0330	0.0327	0.0310	0.0288	1.3125	0.8639	0.7529	0.7365	0.7107	0.6631
	Hedged	0.0630	0.0577	0.0501	0.0485	0.0417	0.0309	1.5674	1.0540	0.8117	0.9061	0.8739	0.4867
Low MOM	Naked	0.0493	0.0411	0.0348	0.0361	0.0367	0.0328	1.5865	0.9997	0.7983	0.8596	0.8607	0.7703
	Hedged	0.0594	0.0546	0.0430	0.0471	0.0483	0.0397	2.0455	1.2943	0.6961	0.9936	1.2183	0.7446

Table 3.4 Alpha and manipulation-proof performance measure - Subsamples

This table presents alpha and manipulation-proof performance measures for a hypothetical hedge fund that can anticipate positive earnings surprises. Daily returns to the naked/hedged strategies and performance metrics are defined in Table 3.2. However, for the naked strategy, the fund takes long positions only in stocks that are either in the top five or bottom five deciles in the CRSP universe for various firm-specific attributes. *Size* is defined as the market value of common equity. *Beta* is the slope coefficient from the regression of monthly excess equity returns on monthly excess market returns during the past 60 months. *IVOL* is idiosyncratic volatility defined as the standard deviation of residual terms from the regression of monthly excess equity returns on monthly market, size and value factors during the past 60 months. *BM* is the book-to-market ratio of equity. *LIQ* is stock liquidity measured as negative of the daily ratio of absolute stock return to its dollar volume averaged within a month. *MOM* is momentum return measured as the cumulative return during the past 11 months skipping one month.

		Panel A. Alpha						Panel B. MPPM					
		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)	(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
High Size	Naked	0.0011	0.0007	0.0004	0.0004	0.0003	0.0003	0.3431	0.2370	0.1831	0.1825	0.1555	0.1468
	Hedged	0.0011	0.0006	0.0004	0.0004	0.0003	0.0003	0.2675	0.1597	0.1078	0.1050	0.0790	0.0677
Low Size	Naked	0.0023	0.0013	0.0011	0.0011	0.0011	0.0010	0.5599	0.3549	0.3163	0.3124	0.3200	0.2836
	Hedged	0.0022	0.0012	0.0010	0.0010	0.0010	0.0009	0.4564	0.2511	0.2102	0.2082	0.2145	0.1799
High LIQ	Naked	0.0012	0.0006	0.0005	0.0004	0.0004	0.0003	0.3423	0.2292	0.1895	0.1744	0.1631	0.1469
	Hedged	0.0011	0.0006	0.0004	0.0004	0.0003	0.0002	0.2663	0.1521	0.1136	0.0952	0.0859	0.0659
Low LIQ	Naked	0.0022	0.0013	0.0010	0.0011	0.0011	0.0010	0.5493	0.3616	0.3050	0.3108	0.3071	0.2782
	Hedged	0.0021	0.0012	0.0009	0.0010	0.0010	0.0009	0.4445	0.2570	0.2020	0.2106	0.2056	0.1788
High Beta	Naked	0.0018	0.0009	0.0007	0.0007	0.0007	0.0006	0.4812	0.2865	0.2291	0.2353	0.2307	0.2080
	Hedged	0.0018	0.0009	0.0007	0.0007	0.0007	0.0006	0.4113	0.2150	0.1572	0.1642	0.1579	0.1321
Low Beta	Naked	0.0014	0.0009	0.0007	0.0007	0.0006	0.0006	0.3835	0.2843	0.2498	0.2484	0.2308	0.2107
	Hedged	0.0013	0.0008	0.0006	0.0006	0.0006	0.0005	0.2731	0.1713	0.1380	0.1362	0.1175	0.0945
High IVOL	Naked	0.0019	0.0011	0.0009	0.0009	0.0009	0.0007	0.4956	0.3202	0.2659	0.2719	0.2643	0.2321
	Hedged	0.0019	0.0011	0.0008	0.0008	0.0008	0.0007	0.4218	0.2406	0.1820	0.1883	0.1749	0.1444
Low IVOL	Naked	0.0013	0.0007	0.0005	0.0005	0.0004	0.0004	0.3809	0.2491	0.1956	0.1860	0.1742	0.1611
	Hedged	0.0012	0.0006	0.0004	0.0004	0.0004	0.0003	0.2810	0.1514	0.1033	0.0931	0.0838	0.0676
High BM	Naked	0.0019	0.0010	0.0008	0.0008	0.0008	0.0006	0.4900	0.3074	0.2552	0.2511	0.2405	0.2168
	Hedged	0.0018	0.0010	0.0007	0.0007	0.0007	0.0006	0.4021	0.2207	0.1706	0.1678	0.1568	0.1267
Low BM	Naked	0.0013	0.0008	0.0006	0.0006	0.0006	0.0005	0.3675	0.2634	0.2069	0.2122	0.2043	0.1891
	Hedged	0.0013	0.0008	0.0005	0.0005	0.0005	0.0005	0.2801	0.1790	0.1186	0.1217	0.1139	0.1043
High MOM	Naked	0.0015	0.0009	0.0007	0.0006	0.0006	0.0005	0.4199	0.2898	0.2362	0.2299	0.2164	0.1969
	Hedged	0.0015	0.0008	0.0006	0.0006	0.0005	0.0004	0.3388	0.2015	0.1496	0.1444	0.1300	0.1021
Low MOM	Naked	0.0017	0.0010	0.0008	0.0008	0.0008	0.0007	0.4297	0.3053	0.2462	0.2528	0.2527	0.2246
	Hedged	0.0016	0.0010	0.0007	0.0007	0.0007	0.0006	0.3331	0.2151	0.1546	0.1592	0.1589	0.1373

Table 3.5 Performance metrics - Rolling window

This table presents performance metrics for a hypothetical hedge fund that can anticipate positive earnings surprises. Daily returns to the naked/hedged strategies and performance metrics are defined in Table 3.2. Performance metrics are calculated on a rolling window basis using daily returns of each strategy during the past 250 trading days (Panel A) or monthly returns of each strategy during the past 36 months (Panel B). The table reports the averages of these daily/monthly performance metrics for six alternative holding periods ranging from 10 to 60 trading days before and after earnings announcement dates. *t-statistics* associated with two-tailed tests for the equality of performance metrics between the naked and hedged strategies are presented in parentheses.

Panel A. Metrics based on daily returns

		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
Sharpe	Naked	0.1629	0.1228	0.1072	0.1046	0.1006	0.0961
	Hedged	0.2060	0.1699	0.1430	0.1369	0.1261	0.1142
	t-stat	(-59.18)	(-52.04)	(-40.10)	(-39.88)	(-31.92)	(-22.12)
Sortino	Naked	0.2968	0.2129	0.1837	0.1786	0.1714	0.1637
	Hedged	0.4377	0.3322	0.2744	0.2592	0.2371	0.2142
	t-stat	(-72.56)	(-61.35)	(-46.29)	(-46.35)	(-39.45)	(-29.96)
Return-to-VaR	Naked	0.0645	0.0483	0.0412	0.0398	0.0385	0.0366
	Hedged	0.1012	0.0746	0.0659	0.0612	0.0553	0.0497
	t-stat	(-68.74)	(-58.56)	(-46.33)	(-44.99)	(-38.45)	(-30.29)
Calmar	Naked	6.7578	4.5258	3.8076	3.6322	3.4795	3.2704
	Hedged	8.6471	6.3562	4.6676	4.3005	3.8430	3.4604
	t-stat	(-25.37)	(-27.24)	(-15.98)	(-12.85)	(-7.22)	(-4.01)
Alpha	Naked	0.0017	0.0010	0.0008	0.0007	0.0007	0.0006
	Hedged	0.0016	0.0009	0.0007	0.0007	0.0006	0.0006
	t-stat	(18.64)	(38.05)	(63.82)	(63.07)	(62.08)	(63.19)
MPPM	Naked	0.4624	0.3088	0.2548	0.2478	0.2364	0.2200
	Hedged	0.3663	0.2150	0.1630	0.1549	0.1433	0.1266
	t-stat	(42.88)	(38.06)	(36.06)	(36.20)	(35.75)	(35.74)

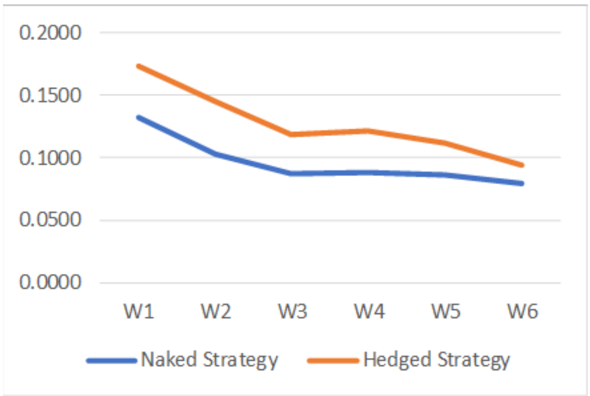
Panel B. Metrics based on monthly returns

		(-10,+10)	(-20,+20)	(-30,+30)	(-40,+40)	(-50,+50)	(-60,+60)
Sharpe	Naked	0.7679	0.5572	0.4651	0.4503	0.4296	0.4103
	Hedged	0.9090	0.7288	0.5772	0.5603	0.5062	0.4566
	t-stat	(-11.18)	(-10.87)	(-10.02)	(-10.79)	(-7.98)	(-4.90)
Sortino	Naked	2.5737	1.4541	1.0747	0.9976	0.9288	0.8739
	Hedged	6.0758	2.6206	1.4377	1.3664	1.2228	1.0611
	t-stat	(-13.20)	(-9.44)	(-10.12)	(-11.30)	(-9.13)	(-6.00)
Return-to-VaR	Naked	0.5489	0.3524	0.2665	0.2378	0.2204	0.2091
	Hedged	1.3363	0.6263	0.3576	0.3420	0.2929	0.2617
	t-stat	(-11.99)	(-9.88)	(-9.58)	(-12.95)	(-9.20)	(-7.43)
Calmar	Naked	7.4692	3.5988	2.6500	2.4130	2.1979	2.0203
	Hedged	18.8667	6.7782	3.9820	3.7460	3.0950	2.3102
	t-stat	(-12.04)	(-11.74)	(-8.14)	(-9.67)	(-6.94)	(-2.23)
Alpha	Naked	0.0341	0.0187	0.0139	0.0128	0.0119	0.0107
	Hedged	0.0333	0.0179	0.0133	0.0122	0.0112	0.0099
	t-stat	(8.73)	(8.51)	(7.92)	(7.43)	(7.74)	(9.73)
MPPM	Naked	0.4573	0.2915	0.2373	0.2308	0.2179	0.2034
	Hedged	0.3631	0.1991	0.1491	0.1413	0.1283	0.1127
	t-stat	(22.59)	(21.21)	(18.94)	(19.57)	(19.64)	(19.90)

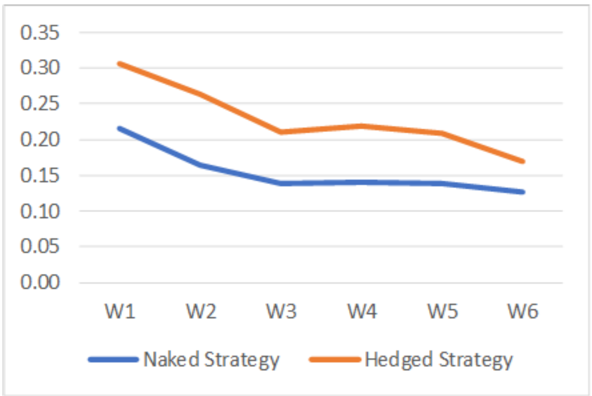
Figure 3.1 Performance metrics - Full sample

This figure presents performance metrics for a hypothetical hedge fund that can anticipate positive earnings surprises. Daily returns to naked/hedged strategies and performance metrics are defined in Table 3.2. Performance metrics are calculated over the full sample and for six alternative holding windows ranging from 10 (W1) to 60 (W6) trading days before and after earnings announcement dates.

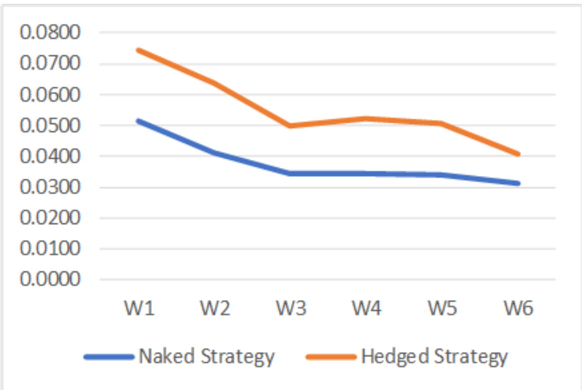
a. Sharpe ratio



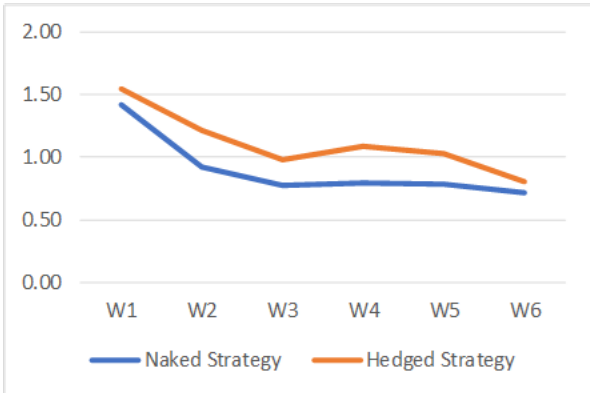
b. Sortino ratio



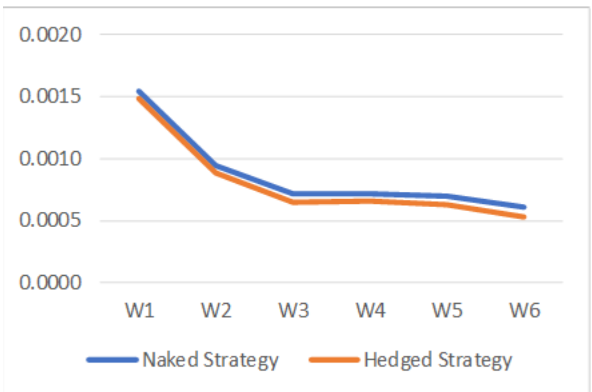
c. Return-to-VaR ratio



d. Calmar ratio



e. Alpha



f. MPPM

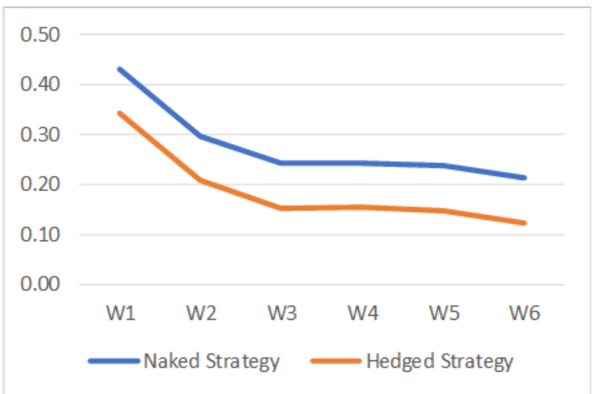
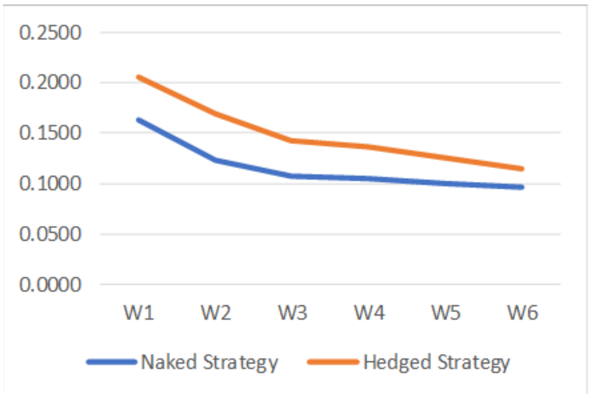


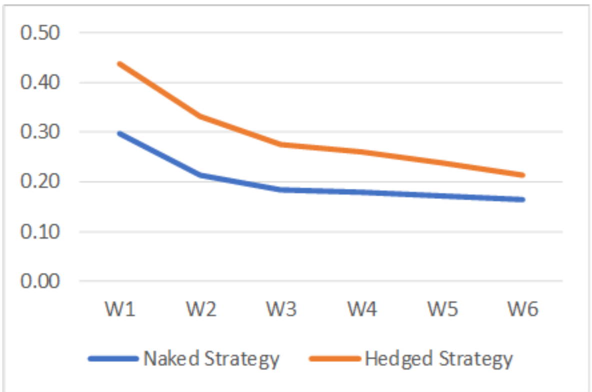
Figure 3.2 Performance metrics – Rolling window

This figure presents performance metrics for a hypothetical hedge fund that can anticipate positive earnings surprises. Daily returns to naked/hedged strategies and performance metrics are defined in Table 3.2. Performance metrics are calculated on a rolling window basis (250 trading days) and for six alternative holding windows ranging from 10 (W1) to 60 (W6) trading days before and after earnings announcement dates.

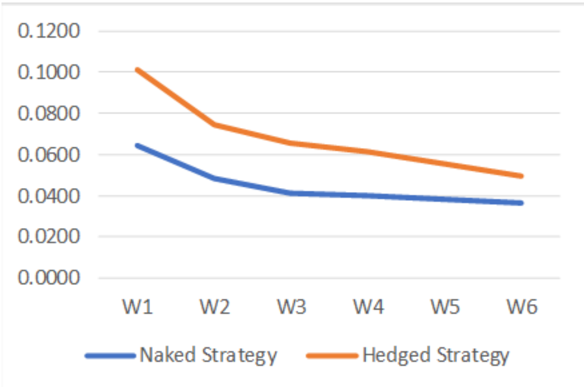
a. Sharpe ratio



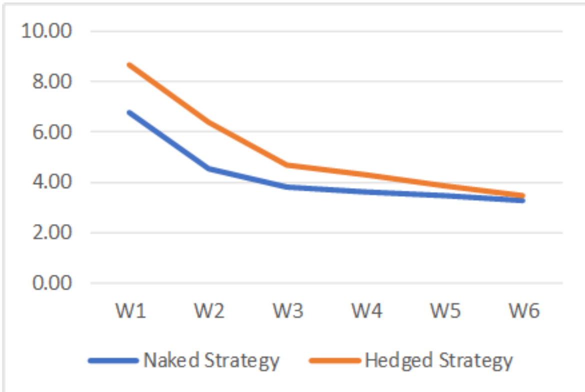
b. Sortino ratio



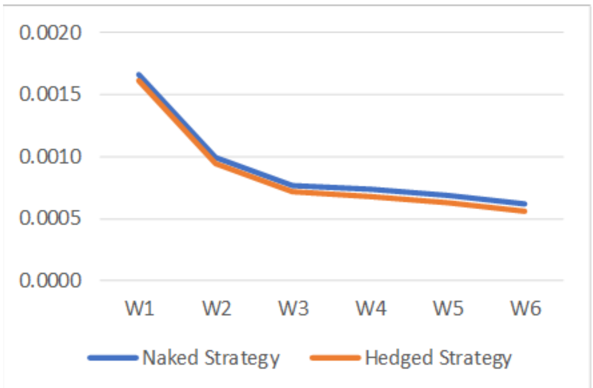
c. Return-to-VaR ratio



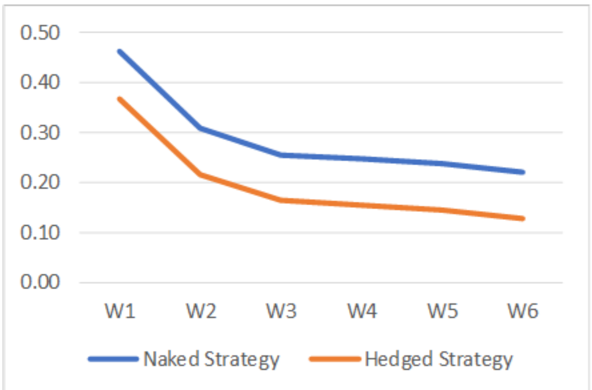
d. Calmar ratio



e. Alpha



f. MPPM



BIBLIOGRAPHY

Agarwal, V., Hanouna, P., Moussawi, R., & Stahel, C. W. (2018). Do ETFs increase the commonality in liquidity of underlying stocks? In *28th Annual Conference on Financial Economics and Accounting, Fifth Annual Conference on Financial Market Regulation*.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Antoniewicz, R. & Heinrichs, J. (2015). The role and activities of authorized participants of exchange-traded funds. Technical report, Investment Company Institute, Washington, DC. http://www.ici.org/pdf/ppr_15_aps_etfs. pdf.

Antoniewicz, R. S. & Heinrichs, J. (2014). Understanding exchange-traded funds: How ETFs work. Technical report, Investment Company Institute, Washington, DC. http://www.ici.org/system/files/attachments/per20-05.pdf.

Balchunas, E. (2016). The ETF files: How the US government inadvertently launched a USD 3 trillion industry. *Bloomberg Markets*, *7*.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2014). Hybrid tail risk and expected stock returns: When does the tail wag the dog? *The Review of Asset Pricing Studies*, *4*(2), 206–246.

Baltussen, G., van Bekkum, S., & Da, Z. (2019). Indexing and stock market serial dependence around the world. *Journal of Financial Economics*, *132*(1), 26–48.

Barber, B. M., Lee, Y.-T., Liu, Y.-J., & Odean, T. (2009). Just how much do individual investors lose by trading? *The Review of Financial Studies*, *22*(2), 609–632.

Barber, B. M. & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, *55*(2), 773–806.

Barber, B. M. & Odean, T. (2013). The behavior of individual investors. In *Handbook of the Economics of Finance*, volume 2 (pp. 1533–1570). Elsevier.

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283–317.

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). Hedge fund stock trading in the financial crisis of 2007–2009. *The Review of Financial Studies*, *25*(1), 1–54.

Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-traded funds. *Annual Review of Financial Economics*, *9*(1), 169–189.

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs increase volatility? *The Journal of Finance*, *73*(6), 2471–2535.

Berk, J. B. & Stanton, R. (2007). Managerial ability, compensation, and the closed-end fund discount. *The Journal of Finance*, *62*(2), 529–556.

Bhattacharya, A. & O'Hara, M. (2018). Can ETFs increase market fragility? Effect of information linkages in ETF markets. Working paper.

Bhattacharya, U., Loos, B., Meyer, S., & Hackethal, A. (2017). Abusing ETFs. *Review of Finance*, *21*(3), 1217–1250.

Bhojraj, S., Mohanram, P., & Zhang, S. (2020). ETFs and information transfer across firms. *Journal of Accounting and Economics*, *70*(2-3), 101336.

Blitz, D. & Huij, J. (2012). Evaluating the performance of global emerging markets equity exchange-traded funds. *Emerging Markets Review*, *13*(2), 149–158.

Bradley, H. S. & Litan, R. E. (2010). Choking the recovery: Why new growth companies aren't going public and unrecognized risks of future market disruptions. Technical report, Ewing Marion Kauffman Foundation.

Brandt, M. W. & Diebold, F. X. (2006). A no-arbitrage approach to range-based estimation of return covariances and correlations. *Journal of Business*, *79*(1).

Broman, M. S. (2016). Liquidity, style investing and excess comovement of exchange-traded fund returns. *Journal of Financial Markets*, *30*, 27–53.

Broman, M. S. & Shum, P. (2018). Relative liquidity, fund flows and short-term demand: evidence from exchange-traded funds. *Financial Review*, *53*(1), 87–115.

Brown, D. C., Davies, S. W., & Ringgenberg, M. C. (2021). ETF arbitrage, non-fundamental demand, and return predictability. *Review of Finance*, *25*(4), 937–972.

Campbell, J. Y. & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, *21*(4), 1509–1531.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82.

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2018). Crash sensitivity and the cross section of expected stock returns. *Journal of Financial and Quantitative Analysis*, *53*(3), 1059–1100.

Cherkes, M., Sagi, J., & Stanton, R. (2008). A liquidity-based theory of closed-end funds. *The Review of Financial Studies*, *22*(1), 257–297.

Clifford, C. P., Fulkerson, J. A., & Jordan, B. D. (2014). What drives ETF flows? *Financial Review*, *49*(3), 619–642.

Cremers, M. & Weinbaum, D. (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis*, *45*(2), 335–367.

Da, Z. & Shive, S. (2018). Exchange traded funds and asset return correlations. *European Financial Management*, *24*(1), 136–168.

Dannhauser, C. D. (2017). The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs). *Journal of Financial Economics*, *125*(3), 537–560.

Demirer, R., Omay, T., Yuksel, A., & Yuksel, A. (2018). Global risk aversion and emerging market return comovements. *Economics Letters*, *173*, 118–121.

Demirer, R., Yuksel, A., & Yuksel, A. (2020). The US term structure and return volatility in emerging stock markets. *Journal of Economics and Finance*, *44*(4), 687–707.

Evans, R. B., Moussawi, R., Pagano, M. S., & Sedunov, J. (2019). ETF short interest and failures-to-deliver: Naked short-selling or operational shorting? Working paper.

Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance*, *67*(6), 2139–2185.

Fama, E. F. & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), 3–25.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Frazzini, A. & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, *88*(2), 299–322.

Frazzini, A. & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25.

French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, *63*(4), 1537–1573.

Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, *67*(1), 22–47.

Goetzmann, W., Ingersoll, J., Spiegel, M., & Welch, I. (2007). Portfolio performance manipulation and manipulation-proof performance measures. *The Review of Financial Studies*, *20*(5), 1503–1546.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 424–438.

Huang, S., O'Hara, M., & Zhong, Z. (2021). Innovation and informed trading: Evidence from industry ETFs. *The Review of Financial Studies*, *34*(3), 1280–1316.

Investment Company Fact Book (2022). Investment Company Fact Book: A review of trends and activities in the investment company industry. Technical report, Investment Company Institute, Washington, DC.

Israeli, D., Lee, C., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? An information perspective. *Review of Accounting Studies*, *22*(3), 1048–1083.

Karmaziene, E. & Sokolovski, V. (2022). Short-selling equity exchange traded funds and its effect on stock market liquidity. *Journal of Financial and Quantitative Analysis*, *57*(3), 923–956.

Kelly, B. & Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, *27*(10), 2841–2871.

Kothari, S. P. & Shanken, J. (1997). Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial Economics*, *44*(2), 169–203.

Lee, C. M., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, *46*(1), 75–109.

Leippold, M., Su, L., & Ziegler, A. (2016). How index futures and ETFs affect stock return correlations. Working paper.

Lettau, M. & Madhavan, A. (2018). Exchange-traded funds 101 for economists. *Journal of Economic Perspectives*, *32*(1), 135–54.

Li, F. W. & Zhu, Q. (2022). Short Selling ETFs. *The Review of Asset Pricing Studies*. raac005.

Livnat, J. & Mendenhall, R. R. (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, *44*(1), 177–205.

Madhavan, A. & Sobczyk, A. (2016). Price dynamics and liquidity of exchange-traded funds. *Journal of Investment Management*, *14*(2), 1–17.

Malamud, S. (2016). A dynamic equilibrium model of ETFs. Working paper.
Manaster, S. & Rendleman Jr, R. J. (1982). Option prices as predictors of equilibrium stock prices. *The Journal of Finance*, *37*(4), 1043–1057.
Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2013). ETF arbitrage: Intraday evidence. *Journal of Banking & Finance*, *37*(9), 3486–3498.
Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, *41*, 867–887.
Morck, R. & Yang, F. (2001). The mysterious growing value of S&P 500 membership. Technical report, National Bureau of Economic Research.
Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, *58*(1-2), 215–260.
Newey, W. K., West, K. D., et al. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708.
Novick, B., Cohen, S., Madhavan, A., Bunzel, T., Sethi, J., & Matthews, S. (2017). Index investing supports vibrant capital markets. Technical report, BlackRock.
Petajisto, A. (2017). Inefficiencies in the pricing of exchange-traded funds. *Financial Analysts Journal*, *73*(1), 24–54.
Pham, S. D., Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2021). The liquidity of active ETFs. *Global Finance Journal*, *49*, 100572.
Piccotti, L. R. (2018). ETF premiums and liquidity segmentation. *Financial Review*, *53*(1), 117–152.
Pontiff, J. & Schall, L. D. (1998). Book-to-market ratios as predictors of market returns. *Journal of Financial Economics*, *49*(2), 141–160.
Prince, D. (2018). Navigating today's ETF landscape (September-2018). Technical report, BlackRock.
Richie, N., Daigler, R. T., & Gleason, K. C. (2008). The limits to stock index arbitrage: Examining S&P 500 futures and SPDRS. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *28*(12), 1182–1205.
Saglam, M., Tuzun, T., & Wermers, R. (2019). Do ETFs increase liquidity? Working paper.
Shim, J. J. (2019). Arbitrage comovement. Working paper.
Stambaugh, R. F. (2014). Presidential address: Investment noise and trends. *The Journal of Finance*, *69*(4), 1415–1453.
Welch, I. & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), 1455–1508.
Wurgler, J. (2010). On the economic consequences of index-linked investing. Technical report, National Bureau of Economic Research.