BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 952

Passive funds affect prices: Evidence from the most ETF-dominated asset classes

by Karamfil Todorov

Monetary and Economic Department

July 2021

JEL classification: G11, G13, G23.

Keywords: ETF, leverage, commoditization, VIX, futures.

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Passive Funds Affect Prices: Evidence from the Most ETF-dominated Asset Classes

KARAMFIL TODOROV*

ABSTRACT

This paper studies exchange-traded funds' (ETFs) price impact in the most ETF-dominated asset classes: volatility (VIX) and commodities. I propose a model-independent approach to replicate the VIX futures contract. This allows me to isolate a non-fundamental component in VIX futures prices that is strongly related to the rebalancing of ETFs. To understand the source of that component, I decompose trading demand from ETFs into three parts: leverage rebalancing, calendar rebalancing, and flow rebalancing. Leverage rebalancing has the largest effects. It amplifies price changes and exposes ETF counterparties negatively to variance.

Keywords: ETF, leverage, commoditization, VIX, futures

JEL classification: G11, G13, G23

---

*London School of Economics and Political Science, Department of Finance and Bank for International Settlements. Correspondence: Bank for International Settlements, Centralbahnplatz 2, 4051 Basel, Switzerland; e-mail: karamfil.todorov@bis.org. This paper was previously circulated under the title "Passive Funds Actively Affect Prices: Evidence from the Largest ETF Markets". Some of the leverage rebalancing results from the old version are in Kyle and Todorov (2020). I am grateful to Igor Makarov, Christian Julliard, Dimitri Vayanos, Jean-Pierre Zigrand, Ron Anderson, Zahi Ben-David, Thummim Cho, Francisco Gomes, Steve Heston, Dirk Jenter, Pete Kyle, Dong Lou, Ananth Madhavan, Ian Martin, Martin Oehmke, Daniel Paravisini, Cameron Peng, Andreas Schrimpf, Andrea Tamoni, Andreas Uthemann and Kathy Yuan for their useful advice and comments. I am also thankful to the scientific committees of the BlackRock Applied Research Award and the 7th SUERF/UniCredit Foundation Research Prize for selecting this paper as the winner in these competitions. I am also grateful to seminar participants at the London School of Economics, the Bank of England, BIS, BlackRock, Boston College, CEMFI, HEC Paris, Indiana University, PIMCO, UniCredit, University of Florida, University of Houston, University of Maryland, University of Notre Dame, and Washington University in St. Louis for their helpful feedback. The views expressed in this article are those of the author and do not necessarily reflect the views of the Bank for International Settlements.

Introduction

Recent years have seen a surge in passive investing through ETFs. As of 2019, these funds were managing more than \$6 trillion globally compared with only \$0.2 trillion in 2004.[1] ETFs are progressively being used by retail and institutional investors to obtain a cost-efficient exposure to portfolios of assets or asset strategies. On the one hand, commoditization of assets through ETFs makes investing simple and cost-efficient, thereby attracting new capital and possibly increasing liquidity. On the other hand, commoditization could reduce price informativeness and create systemic risks if the presence of large investors with similar objectives leads to crowded trading, especially during extreme market times. The increasing presence of ETFs in various asset classes has led to a growing number of market participants and academics expressing concerns about the potential distorting impact on underlying assets.

Assessing the impact of ETFs on prices is difficult because it is hard to estimate the fundamental value of the underlying asset. The existing literature has almost exclusively focused on equity markets, where fundamental values are difficult to measure and where ETFs still hold a relatively small share. Most papers have tried to quantify non-fundamental price distortions due to ETFs by looking at price reversals or variance ratios (e.g., Ben-David et al., 2018). One concern with such an approach is that stock prices do not have to revert to some unobserved fundamental value over a pre-defined horizon of several days. In the research presented here, I take a different route and use the beneficial setting of the futures market, where non-fundamental price distortions are easier to measure. In contrast to stock prices, futures prices must convert to the spot price at expiration because futures contracts have finite maturity. In addition, there is only one fundamental cash flow: the spot price,

[1] Source: Morningstar and own calculations. Some of the exchange-traded products (ETPs) analyzed in this research are structured in the form of an exchange-traded note (ETN) rather than an exchange-traded fund. The institutional differences between the two structures do not affect the analysis since ETPs' exposure is transmitted to the underlying futures market irrespective of the legal structure of the product as I show in section IA.2 in the Internet Appendix. I use the term ETF (instead of ETP) to refer to a general exchange-traded product throughout the paper as the term is more familiar to the general public.

which is observable.

I construct a unique data set to identify the size and source of the ETF impact on prices in the most ETF-dominated asset classes: volatility (VIX) and commodities. These ETFs have two beneficial features that make them a useful laboratory to quantify the effects of ETFs on prices. First, ETFs in VIX and commodities hold a much larger share of the market compared to equities. The fraction of ETFs in the market for VIX futures often exceeds 40%, whereas it is less than 2%[2] in the Standard and Poor's (S&P) 500 Index. Several episodes from the VIX market in 2018 and the oil market in 2020 suggest that large ETF-induced trading can exacerbate price changes in turbulent times.[3] Second, using the specifics of futures contracts, I directly test whether the ETF-influenced futures price is informative about the fundamental cash flow (spot price) at expiration. The setting of the futures market also allows me to test specific predictions about the price impact of ETFs on the slope of the futures curve.

This paper documents and studies several new ETF-related phenomena. First, I show that ETFs put pressure on prices of underlying assets in VIX and commodity markets. Trading demand from ETFs (called ETF demand hereafter) is strongly related to futures prices at a daily frequency. The effects are robust to a large set of controls and to different sub-periods.

Second, I show that ETF price impact is not related to price discovery but manifests itself through an increase in the non-fundamental part of prices. To identify ETF-induced price distortions, I propose a model-independent approach for replicating the fundamental value[4] of a VIX futures contract. I simply use the definition of variance and construct a synthetic futures contract from option prices on the S&P 500 Index and VIX. One advantage of my framework is that I make no parametric or distributional assumptions: the results are

[2]On average, for the period 2009–2018. The average proportion of the US stock market held by all equity ETFs is close to 6% for the same period.

[3]See, for example, Pagano et al. (2019), FT (2018), Reuters (2018), FT (2020) and Bloomberg (2020).

[4]Throughout the paper, "fundamental value" of the futures denotes a value that is a more precise measure of the fundamental spot price at maturity compared to the observed, ETF-influenced futures price. Among others, Ben-David et al. (2018) use a similar definition of fundamental value in the context of equities by looking at price reversals.

also valid in the presence of jumps. This is an important strength of my approach, given that VIX futures often experience large spikes.

The synthetic futures contract is not directly influenced by ETF demand since there are no ETFs in the market for options. I show that the synthetic contract is a more precise measure of the fundamental cash flow compared to the observed, ETF-influenced contract. I illustrate that the difference between the prices of the two contracts is strongly related to ETF demand and call this difference the *ETF futures gap (EFG)*. The EFG is also related to measures of funding liquidity. The size of the gap is 0.61 volatility points for the first futures contract, and 0.89 volatility points for the second, on average. These are large in relative terms: 113% of the first-month basis (difference between the first futures and the spot) and 62% of the second-month basis, respectively. A simple strategy of trading VIX futures based on the sign of the EFG delivers a Sharpe ratio of 1.78.

Third, to study the source of the EFG and the risks faced by ETF counterparties, I analyze trading by ETFs and propose a novel decomposition of their demand into three major components: calendar rebalancing, flow rebalancing, and leverage rebalancing. Calendar rebalancing arises because futures are finite-maturity instruments and ETFs have to gradually roll expiring contracts into longer-dated ones to maintain their exposure. ETFs sell portions of the first-month futures and buy portions of the second-month futures on a daily basis, thereby rolling their exposure from the first to the second contract. Flow rebalancing is driven by fund flows: ETFs have to scale up their exposure in case of inflows, and scale it down in case of outflows. Leverage rebalancing arises due to the maintenance of a constant daily leverage by leveraged ETFs and is a new, under-researched type of mechanic institutional demand.

I show that leverage rebalancing has the largest impact on the EFG. This type of ETF demand amplifies price changes and introduces unhedgeable risks for ETF counterparties (called arbitrageurs hereafter). Leveraged ETFs mechanically have to buy the underlying asset after price increases and sell it after price decreases, similar to agents hedging gamma. This creates a potential feedback channel for prices: ETF demand and price changes reinforce each other, pushing prices away from fundamentals. Trading against leveraged ETFs is, in essence, providing liquidity to investors with short horizons, who follow momentum-like strategy. This type of trading exposes arbitrageurs negatively to variance.

Due to leverage rebalancing, the potential distorting effect of ETFs on prices can be large even in a market with a zero net share of ETFs (size of long ETFs equals size of inverse ETFs). A prominent real-world example of this effect was the VIX market in February 2018. The net market share of ETFs then was close to zero, but the potential price impact due to leverage rebalancing was *133% of the total market size* for the first two futures contracts.

Calendar rebalancing inherits part of the non-linearity of leverage rebalancing and also mechanically exposes arbitrageurs to the risk of widening price discrepancies since ETF counterparties have to close futures positions before expiration. Calendar rebalancing puts upward pressure on the second-month EFG and downward pressure on the first-month EFG. Flow rebalancing has a direct effect on prices and also an indirect effect by changing the size of ETFs, and the amount of their calendar rebalancing in future periods. Flow rebalancing moves the second month EFG in the direction of flows: inflows increase the gap, whereas outflows decrease it.

ETFs put pressure on prices also in commodity markets. Leverage rebalancing has the largest impact on the first-month basis in the oil market and the largest impact on the spread between the second and the first futures contracts in the natural gas market. Calendar rebalancing has negative impact on the first month basis for gas, oil and silver.

My main results have several implications. First, they illustrate that price is strongly related to ETF trading demand, when ETFs constitute a large share of the market. In turbulent times, significant leverage-induced rebalancing contributes to extreme market movements and creates a feedback effect on prices. Thus, crowded trading by ETFs moves prices away from fundamentals. This result contributes to the policy debate on the desirability of commoditization. Going forward, the evidence of ETF impact on prices in VIX and commodities can be useful for predicting the potential effects of ETFs on stock and bond markets, should these funds develop a larger share of these traditionally studied asset classes.

Second, my results lead to a more nuanced view of the information content of VIX and the VIX futures premium (the difference between the futures price and the spot). VIX and its derivatives are often perceived as a barometer of financial stress by large financial institutions and are used as an input in stress-tests and various risk models. However, my results suggest that the prices of VIX futures contracts are significantly disrupted by non-fundamental mechanical ETF demand. Third, my findings show how to decompose trading demand from ETFs and study different aspects of their price impact. I also demonstrate how to quantify the potential distorting impact of leverage rebalancing.

The rest of the paper is organized as follows. Section I summarizes the literature and section II describes the data. Section III studies ETF impact in the VIX market. Section IV describes the decomposition of ETF demand. Section V presents robustness checks, trading strategies, and the results for commodity markets. Section VI concludes.

I. Literature review

The research presented here contributes to the literature in four main areas: studies on ETFs, VIX and the variance risk premium (VRP), futures markets, and limits to arbitrage. First, it is related to studies on ETFs. A major drawback of the existing ETF literature is that it is almost exclusively focused on equities, where these funds are a relatively small proportion of the market (less than 6%, on average) and where non-fundamental price deviations are hard to measure. Ben-David et al. (2018) study the volatility effects of ETFs in stocks and argue that ETF arbitrage transmits noise trader risk to underlying securities. Malamud (2015) demonstrates that ETFs can create a transmission mechanism for non-fundamental shocks to the underlying securities. Cheng and Madhavan (2009) show that the returns on leveraged ETFs are path-dependent. Tuzun (2012) finds that the rebalancing of leveraged ETFs can increase the volatility of constituent stocks. Recently, Sushko and Turner (2018) document the increase in the share held by ETFs in several markets and study the impact for liquidity and volatility.

The greater presence of ETFs in VIX and commodity markets makes them a natural candidate for studying the impact of ETF demand on prices and risk premiums. And yet, these ETFs have received little attention in the literature to date. Most papers in the existing literature analyze VIX ETFs by relying on some parametric model (e.g., Bialkowski et al., 2018 and Fernandez-Perez et al., 2018). A related paper by Dong (2016) studies the price impact of VIX ETFs and finds that dealers pass hedging pressure to underlying futures. Similar to the research presented here, Dong (2016) uses a result from Carr and Wu (2006) to estimate the fair value of a VIX futures. However, he does not establish that the fair value relates more closely to fundamentals than the VIX futures price, and does not rule out alternative explanations to ETF demand. The paper also does not study the source of the premium in VIX futures prices. In particular, it ignores the impact of leverage rebalancing. Compared to the existing studies on VIX ETFs, the research presented here relies on a model-independent framework to estimate the impact of ETFs, and proposes a new way to test whether deviations are related to price discovery based on the specifics of the futures market. Another gap in the existing ETF literature is that, to the best of my knowledge, none of the studies has decomposed the demand from ETFs to study the source of their price impact. The research presented here aims to fill this gap by examining different types of trading demand by ETFs in the most ETF-dominated markets.

Second, my paper contributes to the literature on VIX. Cheng (2019) analyzes the VIX premium and finds that, in turbulent times, dealers and asset managers reduce their long volatility positions, whereas hedge funds reduce their short volatility positions. Mixon and Onur (2015) study volatility markets and claim that the long volatility bias of asset managers acts to put upward pressure on VIX futures prices. Alexander and Korovilas (2012) find that ETFs increase the volatility of VIX futures. Bardgett et al. (2019) and Hülsbusch and Kraftschik (2018) illustrate that S&P 500 Index options and VIX derivatives have different information about prices and volatility at different time horizons. Eraker and Wu (2017) develop a model with diffusive and jump shocks to explain the large negative returns on VIX ETFs. However, most papers ignore the impact of ETFs on prices of underlying futures or rely on some parametric assumptions to calculate risk premiums. In the research presented here, I show that the mechanics of ETF rebalancing distorts futures prices, and I measure the resulting gap in a model-independent way.

Third, my research adds to the literature on futures markets and the financialization of commodities. Tang and Xiong (2012), Basak and Pavlova (2016) study the financialization of commodities due to institutional flows. Singleton (2013) argues that flows from institutional investors have contributed significantly to the increase in oil prices prior to 2008. Mou (2011) studies commodity roll of index funds. Most studies on hedging pressure in futures markets use lower-frequency data (quarterly or weekly) on investors' positions to analyze price impact. However, hedging pressure is more likely to be pronounced over short time horizons in the current era of high-frequency trading. Using ETFs to analyze the impact on prices allows the capture of these transitory price effects, since trading demand is observed on a daily basis. The research presented here shows that in markets with a high proportion of ETFs, the demand from these funds is strongly related to the futures premium.

Fourth, my paper also adds to the extensive literature on limits to arbitrage and slow-moving capital. Shleifer and Vishny (1997) develop a simple model with noise trader risk and show that arbitrage could persist. Garleanu et al. (2009) show that dealers provide liquidity in option products and charge for the unhedgeable risks they take due to the impossibility of trading continuously, and due to transaction costs. Gromb and Vayanos (2018) develop a theoretical framework in which financially constrained arbitrageurs exploit price-discrepancies across segmented markets. In the research presented here, I document segmentation in the VIX futures market and illustrate that price discrepancies can persist due to the risk of trading against ETFs.

II. Data and institutional details

I construct a unique data set on ETFs and their underlying securities in VIX and commodities: US natural gas, silver and oil. The data come from several sources. Daily prices, flows, holdings, assets under management, volume of trading, and other characteristics of ETFs come from the websites of the sponsors, from the Center for Research in Security Prices (CRSP), and from Bloomberg. Daily data on futures prices, open interest, and volume of trading are from the Chicago Board Options Exchange (CBOE). Daily data on S&P 500 Index options come from OptionMetrics. The data on futures and spot prices for commodities are from Bloomberg and the US Energy Information Administration (EIA). The analyzed period is generally June 2004 to February 2018 for VIX and June 2006 to June 2020 for commodities; however, some data are only available for a shorter time period as indicated in the figures and tables.

A. The presence of ETFs in different markets

Figure 1 shows the proportion of ETFs in the total market capitalization for several markets. The black lines on the graphs show that the proportion of ETFs periodically exceeds 40% of the total market capitalization for VIX, natural gas and oil. The share of ETFs in equities is much smaller and constitutes less than 2%, on average, for most equity indices. Panel A of Table I summarizes the proportion of ETFs in the total market capitalization and in daily trading volume across several markets. In the following analysis, I focus mainly on VIX ETFs and ETFs in the markets for natural gas, oil and silver given their larger share of the respective market.

[Figure 1 and Table I about here]

B. Institutional details

Unlike most equity ETFs that physically invest in the underlying assets, VIX and commodity ETFs obtain price exposure by entering into positions in futures contracts. Most ETFs follow a benchmark based on the first two futures contracts.[5] They gradually roll their exposure from the first-month contract to the second-month contract (daily for VIX and over a period of five days each month for commodity markets). Some ETFs also aim to maintain a constant daily leverage ratio, L, which can also be negative (for inverse ETFs). For example,

[5]There are also silver ETFs that hold physical silver: I exclude these from the analysis since they do not rebalance on a daily basis, but physically hold the asset. Some VIX ETFs invest in fourth to seventh-month futures contracts but their share is much lower. I analyze these in section IA.3 in the Internet Appendix.

if the benchmark return is 5%, a double-leveraged ($L = 2$) ETF should return 10%, whereas an inverse ETF ($L = -1$) should return -5%. I analyze the exact trading motives of ETFs further in section IV. ETFs are limited to trade in the futures contracts in a mechanical way to minimize their tracking errors. This can lead to a reduction in price informativeness.

C. Summary statistics

Panel B of Table I presents summary statistics for VIX. The VIX futures market is in contango (futures larger than spot) 78% of the time. The distribution of VIX futures is positively-skewed, particularly for short maturities. The average slope of the short end of the futures term structure steepened after the introduction of ETFs. The first-month futures basis[6] went up from 0.06 to 0.79, and the spread between the second and the first-month futures contracts increased from 0.46 to 1.37. The spreads for other futures maturities that are not influenced by ETFs, are little changed. The plot in Figure IA.1 shows that the realized VIX futures premium (the return for an investor who sells short a fully collateralized VIX futures contract and holds it until maturity $\frac{F_{t,T}-F_{T,T}}{F_{t,T}}$) has increased since the introduction of ETFs in January 2009 for the most ETF-influenced maturities of one and two months. The effects are similar even if I exclude the 2008–2009 financial crisis. These facts provide initial evidence that the introduction of ETFs is related to the increase in premiums embedded in VIX futures prices.

In the next three sections, I focus my analysis predominantly on VIX given that this is the most ETF-dominated market in the world. Another benefit of the VIX market is that I can construct a model-free synthetic futures contract that is not directly influenced by ETFs, which allows me to disentangle ETF-induced price distortions. In section V., I present the results for commodity ETFs as a robustness check.

[6]For convenience, I call $F_{t,T} - S_t$ basis throughout the paper. Since the VIX futures term structure is in contango most of the time, it is more convenient to work with $F_{t,T} - S_t$ rather than $S_t - F_{t,T}$. T is maturity, $F_{t,T}$ is time t's price of a futures contract expiring at T, S_t is time t's spot price.

III. The impact of ETFs on futures prices in the VIX market

In this section, I study the impact of trading demand by ETFs on VIX futures prices. I isolate a non-fundamental component of the futures premium and show that this component is strongly related to ETFs' rebalancing.

A. Details on VIX

VIX is an important asset for investors because it provides a natural hedge against market downturns. VIX_t^2 is a portfolio of options that measures risk-neutral expectation of realized variance of the S&P 500 Index return (assuming no jumps) over the next month: $VIX_t^2 = \mathrm{E}_t^{\mathrm{Q}}(Rvar_{t,t+30})$.[7] In a world with jumps, VIX_t^2 measures risk-neutral entropy of the S&P 500 Index return as Martin (2015) demonstrates. Thus, by construction, VIX increases in turbulent times when volatility spikes and aggregate economic uncertainty increases. An important feature of the market for VIX futures, which distinguishes it from traditional futures markets, is that there is no cost-of-carry relation because the spot asset is, in essence, not physically tradable. Since the portfolio of options underlying the VIX calculation is changing almost continuously, in practical terms it is impossible to trade VIX due to large transaction costs. The simplest way to get exposure is by trading VIX futures.

The market for VIX derivatives has grown considerably over the past decade and has become the largest market for volatility for short maturities (e.g., Mixon and Onur, 2015). As of 2018, the total notional value of VIX futures exceeded that of variance swaps for maturities of less than one year. The total dollar volatility exposure (in terms of vega) of VIX futures was close to $8 billion (bn) per month. Part of the massive increase in volatility investing was due to the rise of ETFs, which provided a simple and cost-efficient way to invest in VIX. Figure IA.2 in the Internet Appendix shows the large increase in open interest of VIX futures after the introduction of ETFs, particularly for the most ETF-influenced maturities of one and two months.

[7] As realized variance is a consistent estimator of quadratic variation (e.g., Cheng, 2019).

The inception of ETFs was a market innovation that allowed many retail investors who could not easily trade volatility before, to enter the VIX futures market. Data from Thomson Reuters Institutional Holdings show that the fraction of institutional holdings in VIX ETFs was less than 24%, on average, in 2009–2018. The case of VIX provides a useful laboratory to study the effects of large ETF share in the underlying market and the consequences of letting retail investors enter more sophisticated markets through ETFs. These effects can be useful to predict the impact of larger ETF presence in other markets that were less accessible to retail investors before, e.g., less-liquid corporate bond markets. I discuss further the features of ETFs that allow retail investors to easily enter more sophisticated markets in section V.

B. The impact of ETF demand on futures prices

I start the analysis by studying the effect of ETF rebalancing demand on the VIX futures curve and run the following regression:

$$b_{t,i} = \alpha + \beta_1 D^{\$,all}_{t,i} + \beta_2 b^H_{t,i} + \gamma Ctrl_{t,i} + \epsilon_{t,i}, \tag{1}$$

where $b_{t,i}$ is either the absolute basis for maturity one month ($b_{t,1} = F_{t,T_1} - S_t$), or the spread between two subsequent futures (most results are with the second-month spread: $b_{t,2} = F_{t,T_2} - F_{t,T_1}$). In some specifications $b_{t,i}$ is the relative basis or the relative spread ($b_{t,1} = \frac{F_{t,T_1} - S_t}{S_t}$, $b_{t,2} = \frac{F_{t,T_2} - F_{t,T_1}}{F_{t,T_1}}$). S_t is the spot price, F_{t,T_1} is the price of the first futures contract and F_{t,T_2} is the price of the second one. I use basis as the main dependent variable, instead of the raw futures price, to isolate price movements mostly related to futures premiums as opposed to the spot price. I analyze separately first-month basis and spread, instead of first and second-month bases (as in Mixon and Onur, 2015) to disentangle the local effects of ETF demand on different parts of the curve.[8]

[8]Since the second-month basis is the first-month basis plus spread ($F_{t,T_2} - S_t = F_{t,T_2} - F_{t,T_1} + F_{t,T_1} - S_t = b_{t,2} + b_{t,1}$), using the second-month basis as the dependent variable could capture some of the effects of ETF demand on the first-month basis. Therefore, I focus on spread to isolate the residual price impact between the first and the second-month contracts. The estimates of the second-month basis regressed on $D^{\$,all}_{t,2}$ are also strongly statistically significant.

$D_{t,i}^{\$,all}$ is the net dollar demand from all ETFs for maturity i at time t computed as the sum of changes in dollar holdings of futures contracts from $t-1$ to t for all ETFs. To isolate the effect of a larger share of ETF demand from a pure increase in the size of the overall market, I normalize the demand from ETFs by market capitalization. $b_{t,i}^{H}$ is the basis or spread of a hedge asset. The hedge asset is a synthetic VIX futures contract with the same maturity as the traded one but not influenced by ETF demand: the next subsection explains the exact replication. $b_{t,i}^{H}$ absorbs any asset-specific shocks. $Ctrl_t$ are controls for spot price, open interest, days to maturity, variance of the benchmark, and liquidity (bid-ask spreads). If ETF demand has an impact on futures prices, $\beta_1 \neq 0$.

The results from regression (1) are presented in Table II. For comparison, I standardize all independent variables. Columns 1 and 6 show that one standard deviation rise in ETF demand as fraction of total market capitalization (2.42% for the first-month futures contract and 5.73% for the second) increases the front-month basis by 0.21 volatility points (27% in relative terms) and the spread by 0.10 volatility points (9% in relative terms). The estimates for the relative basis are larger in magnitude as seen from columns 2 and 6. The effect is robust to using absolute ETF demand (columns 3 and 7) and to other checks: demand calculated with lagged returns, and relative basis and spread scaled by days to maturity (unreported for brevity). The fact that $\beta_1 > 0$ is evidence of the impact of ETF demand on the price of underlying futures contracts.

[Table II about here]

The effects of ETF demand are significant only for the respective maturities in which ETFs invest, but there is limited evidence of significant changes in the slopes of other parts of the curve: the estimates for the spreads of third, fourth, fifth and sixth-month futures contracts are mostly insignificant.[9]

[9]The results for VIX ETFs investing in midterm maturities of the futures (section IA.3 of the Internet Appendix) show that their demand is significant for $b_{t,5}$, $b_{t,6}$ but less significant for $b_{t,4}$ and $b_{t,7}$.

C. The ETF futures gap

Table II illustrates that an increase in ETF demand pushes up short-term basis and spread. Although the OLS regressions control for a large set of observable characteristics, the estimates could be biased due to endogeneity if both ETF demand and futures prices are influenced by a fundamental omitted variable. To address this concern, I disentangle the non-fundamental component of prices and analyze whether the effect of ETF demand manifests itself through an increase in that component.

One of the benefits of analyzing the VIX market is that I can directly measure deviations in the futures price due to ETF demand by constructing a synthetic futures contract from a market with no ETFs, and comparing its price to that of the ETF-influenced futures contract. The idea is simple. I calculate $\mathrm{E}_t^{\mathrm{Q}}(S_T)$ (Q is the risk-neutral measure) from option prices without making any parametric or distributional assumptions. By comparing $F_{t,T}$ and $\mathrm{E}_t^{\mathrm{Q}}(S_T)$, I can isolate the component of the VIX futures premium that is different between the futures market and the options market. Then, I test directly which of the two futures prices (the ETF-influenced one $F_{t,T}$, or the synthetically constructed one $\mathrm{E}_t^{\mathrm{Q}}(S_T)$) is a less-biased estimate of the fundamental spot price at expiration. To illustrate the approach, note that basis can be decomposed as follows:[10]

$$F_{t,T} - S_t = \underbrace{F_{t,T} - \mathrm{E}_t^{\mathrm{Q}}(S_T)}_{\textbf{ETF futures gap}} + \overbrace{\underbrace{\mathrm{E}_t^{\mathrm{Q}}(S_T) - S_T}_{\textit{Realized VIX premium}} + \underbrace{S_T - S_t.}_{\textit{Spot VIX change}}}^{\textit{Synthetic basis}} \tag{2}$$

The decomposition shows that time t's basis consists of the **ETF futures gap (EFG)**, the realized VIX premium (RVP), and the spot VIX change. The element of interest in this decomposition is the EFG. This component is different from zero if there is market segmentation or other frictions. I show that ETF demand manifests itself through an increase in this non-fundamental part of the futures price in sections C.2 and C.3.

[10] Spread can be decomposed as follows: $F_{t,T_2} - F_{t,T_1} = F_{t,T_2} - S_t - (F_{t,T_1} - S_t) = (EFG_{t,T_2} - EFG_{t,T_1}) + (RVP_{t,T_2} - RVP_{t,T_1}) + (S_{T_2} - S_{T_1})$.

C.1 Calculating the EFG

To calculate the EFG for maturity T_1, I measure $\mathrm{E}_t^{\mathrm{Q}}(S_{T_1}) = \mathrm{E}_t^{\mathrm{Q}}(VIX_{T_1\to T_2})$ using the definition of variance:[11]

$$\begin{aligned} \mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1\to T_2}) &= \mathrm{E}_t^{\mathrm{Q}}\left(VIX^2_{T_1\to T_2}\right) - \left(\mathrm{E}_t^{\mathrm{Q}}(VIX_{T_1\to T_2})\right)^2 \\ \iff \mathrm{E}_t^{\mathrm{Q}}(VIX_{T_1\to T_2}) &= \sqrt{\mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1\to T_2}) - \mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1\to T_2})}. \end{aligned} \tag{3}$$

The first term under the square root can be calculated using portfolios of S&P 500 Index options with maturities T_1 and $T_2 = T_1 + 30$ *days* that replicate $VIX^2_{t\to T_1}$ and $VIX^2_{t\to T_2}$, respectively (analogous to the calculation of forward rates from spot rates):

$$\begin{aligned} (T_2 - T_1)\mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1\to T_2}) &= (T_2 - t)(VIX^2_{t\to T_2}) - (T_1 - t)(VIX^2_{t\to T_1}) \\ \iff \mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1\to T_2}) &= \frac{(T_2 - t)VIX^2_{t\to T_2} - (T_1 - t)VIX^2_{t\to T_1}}{T_2 - T_1}. \end{aligned} \tag{4}$$

Alternatively, one can use variance swap prices to estimate $\mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1\to T_2})$. By using the definition of VIX as a measure of risk-neutral entropy of the S&P 500 Index return, it is straightforward to show that the result is also valid with jumps (the proof is in the Appendix, section A.1). Full details about the empirical calculation of the synthetic VIX futures are in sections A.1, A.2 of the Appendix and IA.1 of the Internet Appendix.

The second term under the square root in Eq. (3) can be calculated using a static portfolio of out-of-the-money (OTM) VIX options and applying a result from Breeden and Litzenberger (1978) similar to Martin (2017):

$$\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1\to T_2}) = 2R_{f,t\to T_1}\left(\int_{K=0}^{F_{t,T_1}} put_{t,T_1}(K)dK + \int_{K=F_{t,T_1}}^{\infty} call_{t,T_1}(K)dK\right), \tag{5}$$

where $R_{f,t\to T_1}$ is the constant gross risk-free rate. An important point is that the results in Eq. (3), Eq. (4), and Eq. (5) rely on no parametric or distributional assumptions about the

[11] Similar to Carr and Wu (2006) and Dong (2016).

S&P 500 Index or VIX.

[Figure 2 about here]

Figure 2 shows the dynamics of the EFG for maturities at 1–2 months.[12] Figure A2 shows the EFG scaled by the futures price since VIX futures prices are lower for the period after 2013, on average. The last two columns of Panel B in Table I present summary statistics for the EFG. The numbers illustrate that the EFG is positive, on average, but highly volatile and positively-skewed. The first-month EFG is 0.61 volatility points (113% of the first-month basis), and the second-month EFG is 0.89 volatility points (62% of the second-month basis), on average. The largest EFGs were observed during the 5th February 2018 VIX spike (the so-called "Volmageddon"), when the gap exceeded 20 volatility points for both maturities as seen from the daily plots in Figure IA.3 in the Internet Appendix.

[Figure 3 about here]

The decomposition of basis in Eq. (2) shows that the positive impact of ETF demand observed from Table II must happen either through changes in the EFG, or the synthetic basis $\mathrm{E}_T^Q(S_T) - S_t$, or both.

C.2 Does ETF demand manifest itself through the EFG?

Figure 3 shows that the EFG and the rebalancing demand from ETFs move together. To test whether ETF demand manifests itself through the EFG, I run regression of the EFG on ETF demand:

$$EFG_{t,i} = \alpha + \beta_1 D_{t,i}^{\$,all} + \beta_2 EFG_{t-1,i} + \gamma Ctrl_{t,i} + \epsilon_{t,i}. \tag{6}$$

[12]Unfortunately, there are often no VIX options with expirations of five, seven, and eight months and it is thus impossible to calculate $\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1 \to T_2})$ without interpolating the volatility surface. The quality of the VIX options data for three, four, six months and nine months are also worse than that for one and two months. For these reasons, the graphs show the EFG for 1–2 months.

I scale the EFG by the futures price to address potential concerns about the magnitude of the effects being driven by fluctuations in the futures price (the results with the unscaled EFG are similar) and add the lagged EFG to account for autocorrelation. The estimates from columns 1 and 4 of Table III show that one standard deviation rise in ETF demand as a share of market capitalization is related to a contemporaneous increase in the EFG by 0.55% (0.17 volatility points) for the first month and by 1.09% (0.23 volatility points) for the second month. The effects are robust to using demand not scaled by open interest (columns 2 and 6), and are greater in magnitude: 0.70% and 1.15%, respectively. The positive and statistically significant estimates show that the rebalancing of ETFs increases the non-fundamental component of prices.

The first-month EFG is related to funding liquidity: a standard deviation rise in the TED spread (spread between 3-month LIBOR in USD and the interest rate of Treasury bills) increases the gap by 0.37–0.47%. These results suggest that part of the gap could be due to arbitrageurs' inability to close positions easily in times of crisis when liquidity dries up, or could be due to funding constraints consistent with Garleanu and Pedersen (2011) and Gromb and Vayanos (2002). I discuss other potential explanations for the EFG (discretization errors, illiquidity, difference in margin requirements) in section V.

[Table III about here]

The last two columns in Table III show that ETF demand has no significant impact on the synthetic basis $\mathrm{E}_t^{\mathrm{Q}}(S_{T_1}) - S_t$ and spread $\mathrm{E}_t^{\mathrm{Q}}(S_{T_2}) - \mathrm{E}_t^{\mathrm{Q}}(S_{T_1})$ from Eq. (2). This fact illustrates that ETF demand manifests itself through an increase in the non-fundamental component of prices (EFG). The synthetic futures contract captures the part of the price that is not related to ETF demand.

C.3 EFG-fundamental or non-fundamental?

The existence of the ETF futures gap is evidence that the risk-neutral measure imputed from S&P 500 Index and VIX option prices (Q) gives a different forecast of the realized spot price at maturity compared to the risk-neutral measure from the VIX futures market.

However, a priori, the mere presence of the gap does not mean that the futures price $F_{t,T}$ is a poor estimate of the fundamental value. It is possible that price discovery takes place in the ETF-influenced market, and therefore, the gap exists because of fundamental information about the realized spot instead of non-fundamental price pressure in the futures market.

Compared to most studies on price discovery in equity markets that usually rely on information shares (Hasbrouck, 1995) or price reversals and variance ratios (Ben-David et al., 2018), this paper makes use of the beneficial setting of the futures market where price discovery is easier to measure. In equity markets, the horizon over which prices convert to the fundamental value is not fixed and they can theoretically deviate for many periods, since stocks do not have a fixed maturity. Moreover, the fundamental value itself is hard to observe. In contrast, in futures markets, futures prices must convert to the spot price at expiration, since futures contracts have finite maturity. In addition, there is only one fundamental cash flow: the spot price, which is observable.

Since at maturity T, both $\mathrm{E}_T^{\mathbb{Q}}(S_T)$ and $F_{T,T}$ are equal to S_T, the only cash flow (spot price) of the synthetic and the ETF-influenced contract is exactly the same. Thus, I can directly test which of the two futures prices (synthetic or observed) is more informative about that cash flow. If the EFG exists because of price discovery, the ETF-influenced futures would be a better predictor of the realized spot price at maturity. Checking this prediction is straightforward.

Using the identity $F_{t,T} - S_t = F_{t,T} - F_{T,T} + S_T - S_t$ and without making any assumptions, I test whether time t's basis $F_{t,T} - S_t$ predicts subsequent changes of the spot $S_T - S_t$ (fundamental information), or the futures $F_{t,T} - F_{T,T}$ (non-fundamental premium), or both. I run two simple predictive regressions in the spirit of Fama and Bliss (1987):[13]

$$S_T - S_t = \alpha_1 + \beta_1 (X_{t,T} - S_t) + \epsilon_{1,t}, \tag{7}$$

[13]Running regressions (7) and (8) with $S_T - S_t$, $F_{T,T} - F_{t,T}$ and $F_{t,T} - S_t$ scaled by the time to maturity of the futures yields similar results. The results are also unchanged if I control for lags of VIX, time to maturity of the futures, liquidity, open interest, and other factors.

$$X_{T,T} - X_{t,T} = \alpha_2 + \beta_2(X_{t,T} - S_t) + \epsilon_{2,t}, \tag{8}$$

where $X_{t,T}$ is either the observed futures $F_{t,T}$, or the synthetic one $E_t^Q(S_T)$. By subtracting Eq. (8) from Eq. (7), we see that $\beta_1 - \beta_2$ should be equal to one. The closer β_1 is to 1, the more predictive power the futures price has for the fundamental cash flow (spot price at maturity) and the less information it has about the non-fundamental premium. Higher R^2 in Eq. (7) also means that $X_{t,T}$ contains more information about the spot change.

[Table IV about here]

Table IV shows the results from the two regressions. The estimates show that β_1 is closer to one for the synthetic futures compared to the traded one: e.g., $\beta_1 = 1.03$ compared to $\beta_1 = 0.83$ for the second futures. β_1 is not statistically different from one for the synthetic futures at the 5% level. R^2 is 1.5 times larger for the synthetic contract relative to the traded one, which illustrates that the synthetic contract has a larger explanatory power for the spot price change. These results show that the synthetic futures contract is a better predictor of the fundamental cash flow than the traded futures contract. In other words, the EFG is not related to price discovery.

These findings can be justified by the differences between the VIX futures market and the S&P 500 and VIX option markets. First, the S&P 500 and VIX option markets are more than three times larger (in terms of dollar vega) than the VIX futures market for maturities below 2 months, on average for 2009–2018. Second, the option market is dominated by banks, hedge funds, and other more sophisticated investors compared to the VIX futures market which is largely dominated by ETFs.

Since the EFG is not due to price discovery, the only explanation for the gap is then variation in risk premiums: it could be riskier to trade against ETFs in the futures market (due to unhedgeable risks as in Garleanu et al. (2009) or downward-sloping demand curves as in Shleifer (1986)). I show in subsection B of section V. that trading strategies to extract the EFG earn high Sharpe ratios, which is consistent with the risk-premium explanation. Since ETFs passively follow the exact rolling rules of the indices they track to minimize the tracking error, they have a large hedging demand. If ETF counterparties have a limited capacity to absorb this demand, they would require a premium for providing liquidity and trading in the opposite direction. That premium would be incorporated in the futures price and would make it a worse predictor of the only cash flow of the asset, giving rise to the EFG. To investigate this explanation, I next study the motives of ETFs' trading and the inherent risks for arbitrageurs.

IV. Understanding the EFG: decomposition of ETF demand

To understand the source of the EFG, I decompose the rebalancing demand from ETFs into three major components: calendar rebalancing, leverage rebalancing and flow rebalancing, and study the risks associated with each one.

A. Calendar rebalancing

Since futures have an expiration date, to maintain their exposure, VIX and commodity ETFs need to roll out of the maturing contracts before these contracts expire and initiate new positions in longer-maturity contracts. Calendar rebalancing is mechanical and arises exogenously due to futures expiration. Most ETFs in VIX and commodity markets are based on a benchmark that is rolling from the first-month futures contract to the second one over a period of several days. For VIX, the benchmark is a constant-maturity weighted average position: every day, a typical long ETF invests fraction α_t of its wealth in the first-month futures contract, and $1-\alpha_t$ fraction in the second one, s.t. $\alpha_t T_1 + (1-\alpha_t)T_2 \approx 21$ days. T_1 is the time to maturity of the first-month futures contract in business days, T_2 is the time to maturity of the second one, and 21 is the typical number of business days in the rebalancing period (month). For example, suppose that today (t) $T_1 = 21$ days, $T_2 = 42$ days and consider a long ETF: $\alpha_t = 1,\ 1-\alpha_t = 0$. Tomorrow, both futures contracts are closer to maturity: $T_1 = 20$ days, $T_2 = 41$ days, so to keep the duration of the portfolio constant at (roughly) one month, the ETF allocates wealth as follows: $\alpha_{t+1} = \alpha_t - \frac{1}{21} = \frac{20}{21},\ 1-\alpha_{t+1} = \frac{1}{21}$. After 21 business days, $T_1 = 0$ days, $T_2 = 21$ days, the long ETF has completely rolled out of the expiring contract and is 100% invested in the new one month contract, and then the cycle starts again. S&P500 (2019) provides more information on the benchmark of VIX ETFs.

Calendar rebalancing of ETFs can be seen from the dynamics of open interest in the VIX futures market.[14] Before ETFs were introduced, the change in open interest did not have a clear pattern. The left panel of Figure A4 in the Appendix shows typical dynamics before the introduction of ETFs. However, in the post-ETF period, the change in open interest follows a typical pattern, as shown in the right panel: open interest spikes as soon as the futures has two months till expiration and ETFs start to buy it. Once the contract has less than one month till expiration, ETFs start to sell it and open interest declines. The hump-shaped dynamics can be well identified with net ETF positions.

B. Leverage rebalancing

Another important feature of ETFs in VIX and commodity markets is that many of them are leveraged, or inverse, which makes it possible to estimate the impact of leverage-induced trading on prices. Leverage rebalancing is mechanical and arises exogenously due to the maintenance of a constant leverage at a high frequency.[15] Leveraged ETFs aim to return Lr_{t+1} every day, where r_{t+1} is the daily return on the benchmark from t to $t+1$ and L is the leverage (fixed in the prospectus for each leveraged ETF and constant over time). AUM at time $t+1$ should then be $A_{t+1} = A_t(1 + Lr_{t+1})$. An important feature of leveraged ETFs is that, to maintain a constant leverage, they always have to rebalance in the same direction as the benchmark. This is true both for leveraged long ($L > 1$) and inverse ($L < 0$)

[14]Calendar rebalancing is not perfectly predictable as the exact rebalancing amount depends on the assets under management (AUM) of the ETF, which in turn depend on the contemporaneous realized return as I show in part C of this section.

[15]Most ETFs use swaps to obtain a levered exposure. The swaps' exposure is transmitted to the futures market by the swap counterparties. Leveraged funds seek to deliver L multiplied by the daily performance of the benchmark index before fees and expenses. With fees and expenses, their effective leverage can be slightly different from L. The analysis is largely unchanged, however, as L can be replaced with $\hat{L} = L(1 - \phi)$, where ϕ is the tracking error due to fees and expenses. Leverage rebalancing throughout the paper focuses on the rebalancing to maintain a constant leverage with respect to the benchmark but ignores the leverage implicit in futures positions for simplicity.

ETFs: if the benchmark increases (decreases), long ETFs have to increase (decrease) their long position, whereas inverse ETFs have to close (open) some short positions. The derivation is straightforward (Cheng and Madhavan, 2009). At time t, the exposure of a leveraged ETF is LA_t. One period later, the actual exposure is $LA_t(1 + r_{t+1})$, whereas the desired exposure is $LA_{t+1} = LA_t(1+Lr_{t+1})$. Hence, to maintain a constant leverage, the ETF has to rebalance by

$$\delta_{t+1} = LA_{t+1} - LA_t(1 + r_{t+1}) = L(L-1)A_t r_{t+1}. \tag{9}$$

For example, consider a double-leveraged ($L = 2$) ETF with \$10 of AUM (A_t). The ETF buys \$20 worth of futures by borrowing another \$10. Suppose that the price goes up by 10%, then the futures position is worth \$22. Now, the leverage is $1.83 = 22/12$. To maintain the leverage constant at 2, the ETF has to borrow additional \$2($= L(L-1)A_t r_{t+1}$) and use it to buy \$2 of futures contracts. This brings back the leverage to $2 = 24/12$.

Since $L(L-1) > 0$ for any leverage $L \notin [0, 1]$, Eq. (9) shows that rebalancing demand is of the *same* sign as r_{t+1}. This means that trading demands by long and inverse ETFs do not offset, but instead reinforce each other. Since they trade in the same direction, leveraged ETFs can magnify price changes, creating a feedback channel for prices. This mechanism is similar to gamma hedging.

To quantify the potential impact of leverage rebalancing of all N ETFs in a given market, I calculate the leverage rebalancing multiplier $\Gamma_t = \sum_{j=1}^{N} L_j(L_j - 1)A_{j,t}$. The red line in Figure 1 shows Γ_t as a share of the market across several assets. This number is around 1.33 for the VIX market at the beginning of February 2018, which means that if the benchmark spiked by 10%, 13.3% of the total market capitalization would be the additional buying demand from all ETFs due to leverage rebalancing. A similar situation was observed in the oil market in April 2020 when the potential amplification due to leverage rebalancing was 53% of the market size. Leveraged ETFs are present in a variety of asset classes beyond VIX and commodities: equities, bonds and currencies (Kyle and Todorov, 2020). However, their share of the underlying market is the largest in VIX and commodities.

Leverage rebalancing is, essentially, a momentum trade, as it involves buying after price increase and selling after price decrease. Market-makers who trade against ETFs are then contrarian and carry the risk of meeting ETF demand in case of large price changes. Risk-averse arbitrageurs would demand a premium for bearing this risk. If there are flows u_{t+1}, the total rebalancing demand by a leveraged ETF from t to $t+1$ becomes $\delta_{t+1} = L(L-1)A_t r_{t+1} + Lu_{t+1}$.

C. Total ETF demand decomposition

To understand the motives of ETFs' trading, I decompose the daily rebalancing demand by an ETF with a leverage of L ($L = 1$ for a non-leveraged ETF) during the rolling period of K days ($K = 21$ for VIX, $K = 5$ for most commodity markets). Full derivation details are in section A.3 of the Appendix. In dollar terms, the total rebalancing demand for the first-month futures contract (computed as dollar change in holdings from t to $t+1$) is:

$$D^{\$}_{t+1,1} = F_{t+1,T_1}\left(\frac{L(\alpha_t - \frac{1}{K})A_{t+1}}{F_{t+1,T_1}} - \frac{L\alpha_t A_t}{F_{t,T_1}}\right) = \alpha_t\Big(LA_t(1+Lr_{t+1}) + Lu_{t+1} - LA_t(1+r^{F_1}_{t+1})\Big) - \frac{L}{K}A_{t+1}$$
$$= \underbrace{-\frac{L}{K}A_t(1+Lr_{t+1})}_{calendar\ reb.} + \underbrace{\alpha_t A_t L(L-1)r_{t+1}}_{leverage\ reb.} + \underbrace{(\alpha_t - \frac{1}{K})Lu_{t+1}}_{flow\ reb.} + \underbrace{\alpha_t(1-\hat{\alpha}_t)LA_t(r^{F_2}_{t+1} - r^{F_1}_{t+1})}_{remainder}, \tag{10}$$

where $r^{F_1}_{t+1}$, $r^{F_2}_{t+1}$ are the net returns on the first-month and the second-month futures contracts, respectively, $\hat{\alpha}_t = \frac{\alpha_t F_{t,T_1}}{\alpha_t F_{t,T_1} + (1-\alpha_t)F_{t,T_2}}$, and $r_{t+1} = \hat{\alpha}_t r^{F_1}_{t+1} + (1-\hat{\alpha}_t)r^{F_2}_{t+1}$ is the net return on the benchmark.

Eq. (10) illustrates that the total rebalancing demand can be decomposed into four components: calendar rebalancing due to the roll from the first-month to the second-month futures contract, leverage rebalancing to maintain a constant leverage L, flow rebalancing due to inflows or outflows, and a remainder. Analogously, the total dollar rebalancing demand for the second-month futures contract is:

$$D^{\$}_{t+1,2} = \underbrace{\frac{L}{K}A_t(1+Lr_{t+1})}_{calendar\ reb.} + \underbrace{(1-\alpha_t)A_t L(L-1)r_{t+1}}_{leverage\ reb.} + \underbrace{(1-\alpha_t+\frac{1}{K})Lu_{t+1}}_{flow\ reb.} - \underbrace{\hat{\alpha}_t(1-\alpha_t)LA_t(r^{F_2}_{t+1} - r^{F_1}_{t+1}).}_{remainder} \tag{11}$$

The total dollar rebalancing of all N ETFs in a given market is: $D^{\$,\ all}_{t+1,1} = \sum_{j=1}^{N} D^{\$,\ j}_{t+1,1}$, $D^{\$,\ all}_{t+1,2} = \sum_{j=1}^{N} D^{\$,\ j}_{t+1,2}$.

Calendar rebalancing is exactly the opposite for the first-month and the second-month futures contracts. In a market where ETFs are net buyers of futures ($\sum_{j=1}^{N} L_j A_{j,t} > 0$), calendar rebalancing decreases $D^{\$,all}_{t+1,1}$ and increases $D^{\$,all}_{t+1,2}$ (except for extreme realizations of r_{t+1}). Leverage rebalancing is always in the same direction as the realized return on the benchmark. Inflows (rise in flow rebalancing) increase both $D^{\$,all}_{t+1,1}$ and $D^{\$,all}_{t+1,2}$, whereas outflows decrease both of them. The effect of the remainder is due to the fact that the ETF benchmark is a weighted average of the first-month and the second-month futures contracts. Therefore, the return on the second-month futures contract can have an impact on prices for the first (and vice versa) through ETF demand.

On average, in the VIX market, the largest component of rebalancing demand is calendar rebalancing. Flow rebalancing is also large, and sometimes exceeds 75% of the total rebalancing demand from VIX ETFs, as seen from Figure 4. Leverage rebalancing has been growing since 2012, and represented more than 40% of total demand at the start of 2018. The remainder has been historically low (less than 5%). There are several pieces of evidence that ETFs follow their benchmarks and rebalance in the way described in this part as I show in section IA.2 in the Internet Appendix.

[Figure 4 about here]

The decomposition of ETF demand developed in this section is flexible, and can accommodate various types of ETFs. It is not a feature of VIX and commodity ETFs, but can be used to analyze the impact of ETF demand in other asset classes. All ETFs have to rebalance due to investor flows and hence, flow rebalancing is present in ETFs across asset classes. The same holds for leverage rebalancing because leveraged ETFs are present in equity, fixed income, and foreign exchange markets, albeit with a smaller proportion. Calendar rebalancing also has a close analogue in equity and fixed income markets. In VIX and commodity markets, this type of demand arises because futures contracts expire and ETFs have to substitute the positions with new contracts. Analogously, equity ETFs have to rebalance in case of inclusions or exclusions of stocks in the benchmark index. Fixed income ETFs also have to rebalance in a similar way when underlying bonds expire, or when there is a change in the benchmark index due to the inclusion or exclusion of bonds. Thus, the effect of different types of ETF rebalancing can also be studied in other markets.

D. ETFs can affect prices even in a market with a zero net share of ETFs

Eq. (10) and Eq. (11) illustrate that the composition of the market (the proportion of ETFs with different leverages) matters in determining the total rebalancing demand and, as a result, the ETF impact on futures prices. For example, consider a market where there are no flows and the size of all long ETFs is exactly equal to the size of all inverse ETFs so that the net share of ETFs is zero ($\sum_{j=1}^{N} L_j A_{j,t} = 0$). However, the net ETF demand in that case will not be zero as Eq. (10) and Eq. (11) show. In such a market, flow rebalancing, remainder, and the predictable part of calendar rebalancing ($\frac{L}{K} A_t$) are all zero. The only sources of rebalancing are leverage rebalancing and the leverage-induced part of calendar rebalancing ($\frac{1}{K} A_t L^2 r_{t+1}$), both of which can be quite large despite the equal size of all the long and inverse ETFs. Moreover, since leverage rebalancing is always in the same direction as the benchmark return, even in an equal-sized market the potential amplification of price changes can be substantial.

This observation is in contrast to the ordinary view that ETFs have no price impact if the size of long ETFs is exactly equal to that of inverse ETFs. In fact, providing liquidity in such a market should be compensated by a large risk premium because the potential distorting effects of leverage rebalancing are substantial. For example, a market with \$100 of $L = 1$ ETFs is exactly the same in net demand terms to a market with \$100 in $L = 2$ ETFs (with a total exposure of $2 \cdot \$100$) and \$100 in $L = -1$ ETFs. However, the potential leverage rebalancing in the first market is zero, whereas in the second market, it is *four* times the size of the market ($\$400 = 2 \cdot (2 - 1) \cdot \$100 + (-1) \cdot (-1 - 1) \cdot \$100$) multiplied with the realized return on the benchmark. A 10% spike in the benchmark has no feedback effects in the first market, but leads to an additional buying pressure of 40% ($4 \cdot 10\%$) of the whole market size due to mechanical leverage rebalancing in the second market.

E. Example: the VIX market in 2018

A prominent real-world example of these effects was the VIX market in the beginning of February 2018. The net share of ETFs then was close to zero, but the potential distorting effect due to leverage rebalancing was *133% of the total market* (as shown in Figure 1). On 5 February 2018, the ETF benchmark spiked by 96%, which means that more than 127% of the market was allocated to buying VIX futures contracts purely due to mechanical leverage rebalancing. This additional buying pressure contributed to the price increase, pushing the EFG to more than 20 volatility points as shown in Figure IA.3. Following the spike, the largest inverse VIX ETF at that time (XIV) was delisted after dropping more than 90% in price (e.g., Bloomberg, 2018).

F. Risks posed by ETF demand

Consider arbitrageurs who trade against ETFs in the futures market. If agents are competitive and could hedge perfectly (as in a standard Black-Scholes economy), ETF demand pressure would have no effect. However, in practice, arbitrageurs cannot do that as they face incomplete markets because of discrete trading, transaction costs, jumps in the underlying, and other factors (e.g., Garleanu et al., 2009). If arbitrageurs cannot perfectly hedge the ETF exposure, they bear non-fundamental risk of ETF demand shocks on three main fronts.

The first and most important one is leverage rebalancing. This is a relatively new type of rebalancing by institutional investors with a large market share that has been under-researched, partly because leverage ratios of mutual funds or hedge funds are rarely publicly observable. Leveraged ETFs provide a useful laboratory to study the effects of leverage-induced trading on a daily basis. An important observation is that arbitrageurs cannot hedge the leverage rebalancing of ETFs by matching long and inverse ETF demands, since the two are of the same sign as r_t (as $L(L-1) > 0$). Kyle and Todorov (2020) show that leverage rebalancing exposes investors to higher-order cumulants and thus introduces a source of convexity that is not easy to hedge similar to Garleanu et al. (2009).

Intuitively, since both long and inverse ETFs are momentum traders, arbitrageurs who trade against ETFs are contrarian ("carry") traders. If the underlying asset is volatile but ends close to the initial value during the trading period, arbitrageurs collect the "carry" gains. However, if the underlying asset drifts steadily in either direction with little volatility, arbitrageurs lose money due to the negative exposure to squared realized returns (momentum loss). In option terminology, arbitrageurs have a positive vega but negative gamma. Figure A5 illustrates the idea on a simple binomial tree. For an extensive discussion of the risks and returns of the market-making strategy that trades against leveraged ETFs in VIX, commodities, equities, bonds and currencies, see Kyle and Todorov (2020).

Hedging the exposure to leveraged ETFs would require frequent trading in a rolling position of one-month and two-months options on futures, and rebalancing the position on a daily basis (and even more frequently around market close). In turbulent times the hedge portfolio would still be imprecise since ETF tracking errors are magnified (Kyle and Todorov, 2020). Thus, trading against leverage rebalancing exposes arbitrageurs to unhedgeable risks due to the impossibility of trading continuously in the benchmark, transaction costs, and tracking errors. Agents would require premium for bearing these risks. Leverage rebalancing amplifies price changes by moving prices in the direction of benchmark returns: positive returns increase F_{t,T_1} and F_{t,T_2} (as well as $EFG_{t,1}$ and $EFG_{t,2}$), whereas negative returns decrease both prices and EFGs.

The second area of risk for arbitrageurs is calendar rebalancing. This type of demand depends on realized returns and is not perfectly predictable. Maintaining a constant leverage by leveraged ETFs impacts also calendar rebalancing. The non-linear response of calendar rebalancing arises because leveraged ETFs track benchmark returns multiplied with the respective leverage (the term Lr_{t+1} in the brackets for calendar rebalancing from Eq. (10) and Eq. (11)). Hence, calendar rebalancing inherits the non-linearity of leverage rebalancing (in L, and, in continuous time, in the realized return r_{t+1}). Thus, part of this rebalancing could also be hard to hedge.

Another feature of calendar rebalancing is that arbitrageurs mechanically bear the risk of widening price discrepancies before expiration. By trading against the calendar demand from ETFs, ETF counterparties would typically sell the two-months futures contract and then buy it back from ETFs once the contract becomes a one-month futures contract. The right graph in Figure A4 illustrates that usually the increase in open interest for the second-month contract is similar in size to the decrease in open interest for the first-month contract. This observation shows that the new contract positions initiated by ETFs when the futures has maturity of two months, are closed before expiration, once the futures has maturity of one month. This fact suggests that ETF counterparties also close the futures position before maturity and bear the risk of widening price gaps.

If ETFs are net long futures (as for most of the sample), calendar rebalancing would push up $EFG_{t,2}$ and push down $EFG_{t,1}$ over time. In some periods between the end of 2014 and 2016, net ETF demand is short futures due to the rise of inverse ETFs. In those episodes, ETFs sell the two-months contract and buy the one-month contract: calendar rebalancing works in the opposite direction. The selling pushes two-months futures prices lower and decreases the two-months EFG as shown in Figure 2.

The third area of risk for arbitrageurs is flow rebalancing. The effects of this rebalancing could be pronounced if inflows happen at times when arbitrageurs are more constrained. For example, inflows to VIX ETFs when VIX spikes would require arbitrageurs to short-sell VIX futures at a time when financial constraints could be binding. Risk-averse investors would require a premium for increasing their short VIX positions at such times. Flow rebalancing could also have indirect effects through calendar rebalancing. For example, inflows increase ETFs AUM and raise the amount of calendar rebalancing that ETFs perform in future periods. Prices would react in anticipation of these effects. Flow rebalancing would push futures prices and EFGs in the direction of flows. Inflows would increase these variables, whereas outflows would decrease them. The price impact of the three major types of ETF rebalancing is illustrated in Figure 4.

Short-term price impact can translate into longer-term price deviations (futures premium and EFG) through at least two channels. First, leverage rebalancing and flows could make arbitrageurs' financial constraints binding. For example, a temporary spike in price due to leverage rebalancing could trigger financial constraints if arbitrageurs have a short position from the previous period. In anticipation of this risk, prices can deviate for several periods. Second, both leverage rebalancing and flows ultimately end up as parts of calendar rebalancing since they change the AUM of the ETF and these AUM end up rolling from the first-month to the second-month futures contract. Calendar rebalancing is a lower-frequency component of price impact. Moreover, it mechanically introduces short-termism of arbitrageurs since they cannot wait until expiration as explained above. This short-termism can lead to long-term price deviations as shown in Shleifer and Vishny (1997), and Gromb and Vayanos (2002).

G. Empirical evidence on the impact of demand components

The estimates from columns 3 and 6 of Table III show that leverage rebalancing has the largest impact on the EFG: one standard deviation rise is related to an increase of 0.91% (0.24 volatility points) in the first-month EFG and 1.38% (0.35 volatility points) in the second-month EFG. Calendar rebalancing has a negative impact on the front-month gap and a positive impact on the second but the coefficients are much smaller. Flow rebalancing has a positive impact on the second month EFG: one standard deviation rise is related to 0.20% higher EFG. The signs are as predicted in section F. Unreported variance decomposition of the EFG also shows that it is most sensitive to leverage rebalancing. These results indicate that the non-fundamental, ETF-induced pat of futures prices is most strongly related to leverage rebalancing, consistent with the unhedgeable risks faced by ETF counterparties.

V. Robustness checks, trading strategies, and commodity ETFs

In this section, I explore alternative explanations for the EFG and construct trading strategies based on the EFG. I also study the effects of ETFs in commodity markets.

A. Other explanations for the EFG

Several factors could explain the EFG, in addition to ETF demand. First, there is a discretization error when computing $\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1 \to T_2})$ in Eq. (5), since a continuum of strikes is not observable in practice, and the integral is approximated with a sum. However, due to the convexity of call and put option prices, this error would bias the risk-neutral variance downwards, pushing the EFG even higher. Therefore, my calculations would underestimate the true gap. I perform several robustness checks to deal with truncation and discretization errors as described in section IA.1 of the Appendix.

The second possible explanation is that the EFG is driven by illiquidity in the options market. To replicate $\mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1 \to T_2})$ and $\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1 \to T_2})$, one has to trade deep OTM options. Lack of liquidity in those options and higher transaction costs could explain the existence of the gap. However, Figure A3 shows that this is not the case: the EFG calculated with bid and ask option prices is nearly identical to the one from Figure 2.

Another plausible explanation for the gap could be the difference in margin requirements between futures and options markets. The margin-based explanation alone would struggle to explain why the gap takes both positive and negative values, since margins are unlikely to be higher in the futures market than in the options market (typically, futures margins are much smaller). However, funding constraints could explain some of the time variation in the EFG. Shleifer and Vishny (1997) and Gromb and Vayanos (2002) show that when arbitrage capital is scarce, price gaps can exist and persist. Investors could scale back positions during crisis times and could be reluctant to engage in arbitrage if fearful of undesired liquidation of positions at a loss, in case the price discrepancy widened. Garleanu and Pedersen (2011) argue that price discrepancies between two identical assets should depend on the shadow cost of capital, which is often proxied by the TED spread (e.g., Barras and Malkhozov, 2016). The positive coefficient on the TED spread for the first-month EFG in Table III shows that funding constraints might explain some of the variation in the gap.

I present additional robustness checks in subsection A.4 in the Appendix. The results show that the EFG is not driven by hedging pressure in the options market. The positive impact of ETF demand on the EFG is robust to different sub-periods and is greater after 2013, when ETFs become a larger share of the market.

B. Trading strategy

The replicating portfolio for the synthetic futures in Eq. (3) involves buying S&P 500 options with maturity T_2 and selling S&P 500 and VIX options with maturity T_1. This portfolio replicates variance as it gives $(\mathrm{E}_t^{\mathrm{Q}}(S_{T_1}))^2$, whereas VIX futures are quoted in volatility units. Investors can adapt the number of contracts to profit from the EFG in the following way. If the EFG is positive, buying one unit of the replicating portfolio and selling $\mathrm{E}_t^{\mathrm{Q}}(S_{T_1})$ units of VIX futures contracts has a positive payoff today: $\mathrm{E}_t^{\mathrm{Q}}(S_{T_1})F_{t,T_1} - (\mathrm{E}_t^{\mathrm{Q}}(S_{T_1}))^2 = \mathrm{E}_t^{\mathrm{Q}}(S_{T_1})EFG_{t,1} > 0$ and zero payoff at maturity T_1 (ignoring transaction costs and assuming continuum of option strikes). If the the EFG is negative, the strategy involves buying $\mathrm{E}_t^{\mathrm{Q}}(S_{T_1})$ units of VIX futures contracts and selling the replicating portfolio. The Sharpe ratios of the strategy with $T_1 = 47$ days (one of the most frequent durations of the second-month futures) is 1.22. The high Sharpe ratio of the strategy is consistent with the analysis in subsection F of section IV. as investors face significant unhedgeable risk by trading against ETFs and are compensated for bearing it.

Table AIII in the Appendix shows that a higher EFG decreases realized futures returns till maturity: a 1% increase in the EFG predicts 1.66% lower return for the first-month futures contract, and 1.59% lower return for the second. These effects are strongly statistically significant and robust to various factors. Therefore, another strategy to benefit from the EFG is to short-sell VIX futures when the EFG is positive, and to buy VIX futures when the EFG is negative. The Sharpe ratio of this strategy is 1.78 with an annualized return of 51% for the second-month futures.

C. Commodity ETFs

A possible concern is that the impact of ETFs on prices documented so far could be particular to the VIX market due to the special nature of the underlying contract. This raises the question about the applicability of the results to other markets. To address this concern, in this section I study several commodity ETFs with a relatively high share of the respective futures market: natural gas, oil and silver. Relative to VIX ETFs, these ETFs represent a smaller fraction of the market and one would expect a lower price impact.

Compared with the VIX market, in commodity markets it is harder to construct a synthetic futures contract with exactly the same price at expiration as the traded one. I control for asset-specific fundamental shocks by including in the regression the closest futures contract with no ETFs traded for each commodity. For US natural gas futures traded on the New York Mercantile Exchange (NYMEX), I use Intercontinental Exchange (ICE) gas futures (81% correlation). For silver, there was only one liquid futures contract specification before 2011, so I use the closest precious metal: gold (93% correlation). For US crude oil, I use Brent oil (99.7% correlation). I align contracts so that they are expressed in the same units and account for differences in expiration dates. I use relative basis as the dependent variable, instead of the difference between the ETF-influenced futures price and that of the control contract, due to the concern that some systematic factors have changed the pricing across the two markets as explained in section IA.4 in the Internet Appendix.

The results of regression (1) using relative basis and spread for each commodity market are presented in Table V. The estimates show that ETF rebalancing is related to commodity futures prices, which illustrates that the impact of ETFs on prices is a general observation as opposed to being a feature of the VIX market alone. The lower magnitude of the estimates in Table V compared to Table II is related to the lower share of ETFs in commodity markets relative to the VIX market.

[Table V about here]

Compared to the other demand components, leverage rebalancing has the largest impact on basis in the oil market, and on spread in the natural gas market. Calendar rebalancing has significant impact on basis for natural gas, oil and silver, with the largest coefficient for natural gas.[16] Flow rebalancing is less statistically significant in all three markets.

[16]The rolling period for commodity markets is usually from the 6th to the 10th business day of each

D. What is so special about ETFs?

The reader might be wondering what is so special about the price impact of ETFs compared to that of other investment vehicles like mutual funds. There are several important features that distinguish ETFs from traditional mutual funds. First, ETFs make it easier for retail investors to enter the market. ETFs usually have lower investment minimums than index mutual funds, which decreases the barrier to entry for smaller investors. ETFs also allow these investors to avoid the special accounts and documentation required for mutual funds. ETFs are also beneficial for retail investors because they eliminate the need to manage collaterals and expiration dates.

Second, ETFs have lower expense ratios than index mutual funds and can be traded intradaily as opposed to just once per day like mutual funds. The fact that ETFs can be traded like a stock allows investors to use them for short-term bets. Leveraged ETFs also make it easier for investors to lever up, which could be beneficial for investors that could not obtain leverage otherwise. These features make it easier for retail investors to enter the market, consistent with the empirical evidence reported in section II. The influx of retail investors can have impact on the price formation process in futures markets (Aramonte and Todorov, 2021). Third, ETFs follow a passive investment strategy and trade in a mechanical way to minimize tracking errors. Mutual funds generally follow more active strategies.

There is a difference between a market dominated by ETFs and that dominated by other investors who roll out of futures before expiration. The fact that ETFs are mechanically forced to roll out on a daily basis to minimize tracking error creates crowded trades in similar instruments at the same time: the passive strategy of ETFs could move prices. In contrast, a market where investors roll out of contracts in a non-coordinated way is likely to have less pronounced impact on prices since the trades can be executed at different times. The anticipation of concentrated selling by ETFs before expiration could decrease prices and lead

month. This is the case for ETFs that follow benchmarks based on S&P Goldman Sachs Commodity Indices. Some ETFs follow Dow Jones Commodity Indices and rebalance from the 5th to the 9th business day of each month.

to counter-intuitive price dynamics. A prominent example of these effects was the drop of oil prices below zero in April 2020 (Aramonte and Todorov, 2021) and the consequent terminations of several oil ETFs.

VI. Conclusion

This paper shows that ETFs put pressure on prices in the most ETF-dominated asset classes: VIX and commodities. The research uses a model-independent approach for replicating the value of a VIX futures to isolate a non-fundamental gap in prices that is strongly related to the rebalancing of ETFs. The paper proposes a simple test based on the specifics of the futures market to show that the gap is not related to price discovery. Trading strategies to benefit from the gap deliver Sharpe ratios above one.

The paper also provides a decomposition of ETF demand into three main components: calendar rebalancing due to the roll from one futures contract to another, flow rebalancing due to inflow/outflow of money to the fund, and leverage rebalancing due to the maintenance of a constant daily leverage. The framework is flexible to accommodate various types of ETFs, including equity and fixed income ETFs. The results show that leverage rebalancing has the largest impact on the price gap. This type of ETF trading amplifies price changes and introduces unhedgeable risks for ETF counterparties, exposing them negatively to variance.

The results from this research show that ETFs affect prices of underlying assets in the current era of an increasingly large ETF presence. While ETFs can increase liquidity and trading volume by attracting new capital, they also withdraw liquidity during extreme market times. These effects could be magnified if ETFs were used by unsophisticated, short-horizon investors. The recent termination of the largest inverse VIX ETF in 2018 and the extreme events and ETF closures in the oil market in 2020 are prominent examples of such effects. ETFs are transforming the financial industry and increasingly acting as a "wrapper of views" rather than a "wrapper of assets" by allowing investors to get exposure to various trading strategies across traditional, and alternative asset classes. Time and future research will help us understand the consequences of greater ETF presence across asset classes.

Figures

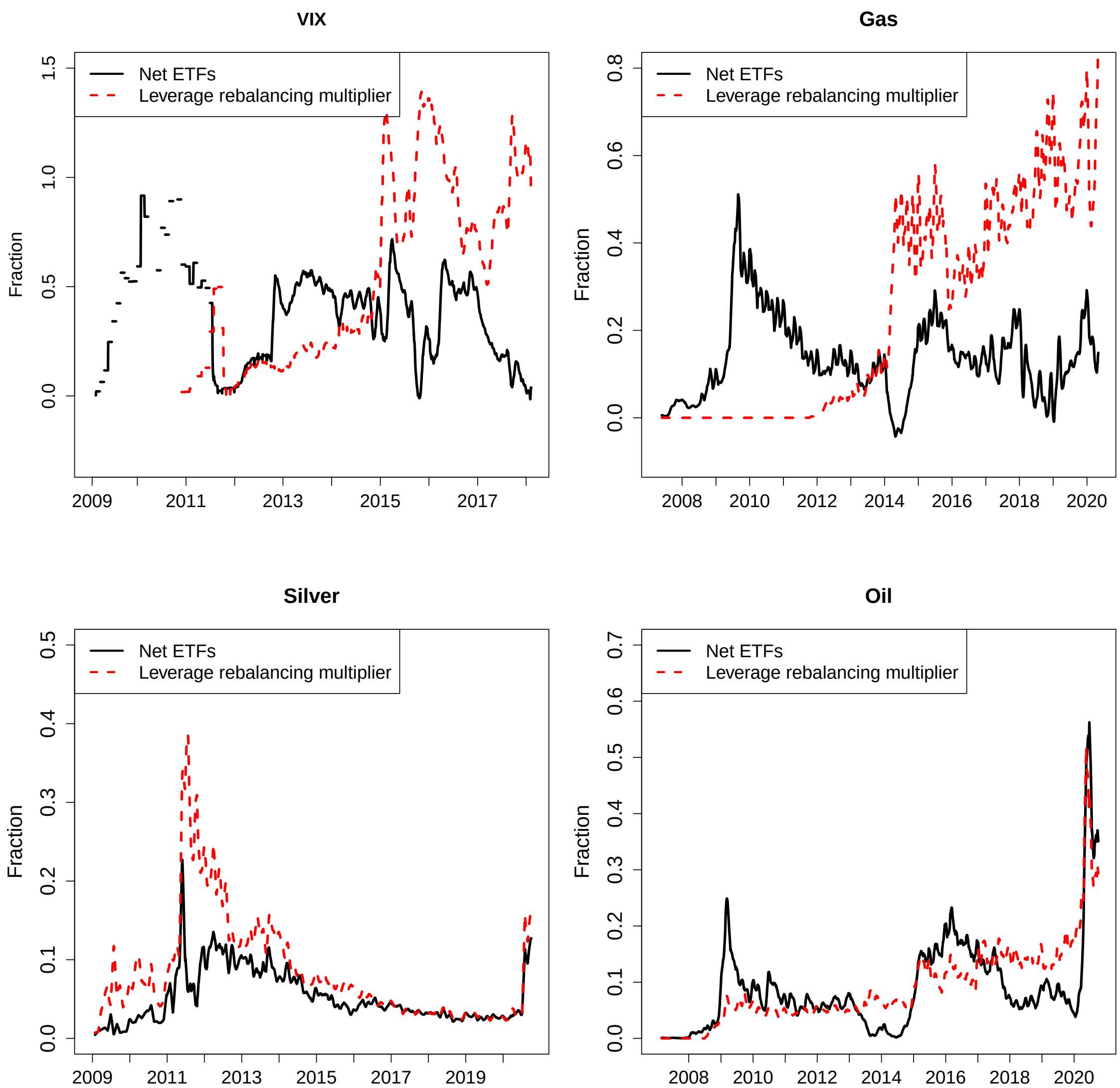

Figure 1. ETF fractions of total market capitalization and the potential impact of leverage rebalancing for VIX, gas, silver and oil. Monthly averages for the two front contracts. The market capitalization is calculated as number of futures contracts multiplied by the futures price. The solid black line shows net ETF fraction (long ETFs minus inverse ETFs) in the total market capitalization of the first and second futures contracts: $\sum_{j=1}^{N} L_j A_{j,t}/Mkt\ cap_t$, where L_j is the leverage of ETF j ($L_j<0$ for inverse ETFs) and $A_{j,t}$ are its assets under management (AUM) at time t. The data for the largest VIX ETF (VXX) are reported irregularly before July 2011, which explains the gaps for VIX before that date. The dashed red line is $\Gamma_t/Mkt\ cap_t$: a measure of the total rebalancing demand by leveraged ETFs (explained in part B of section IV.) scaled by market capitalization.

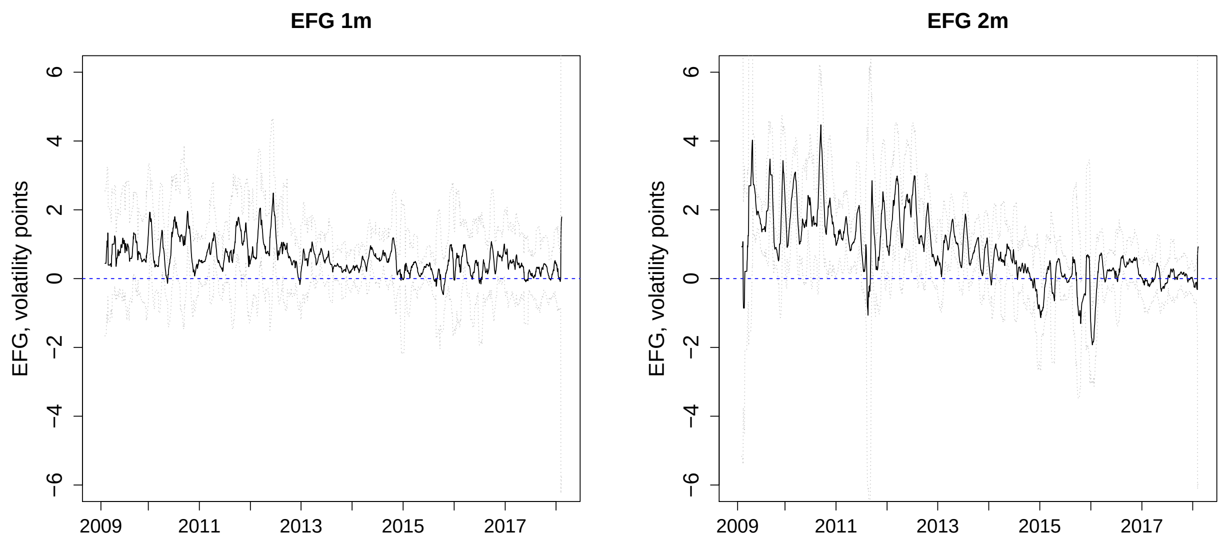

Figure 2. ETF futures gap: monthly averages. The figure shows the dynamics of the ETF futures gap (EFG) for one and two months maturities after the introduction of the first VIX ETF (29 January 2009). The grey dotted lines indicate two standard deviations. EFG is in volatility points.

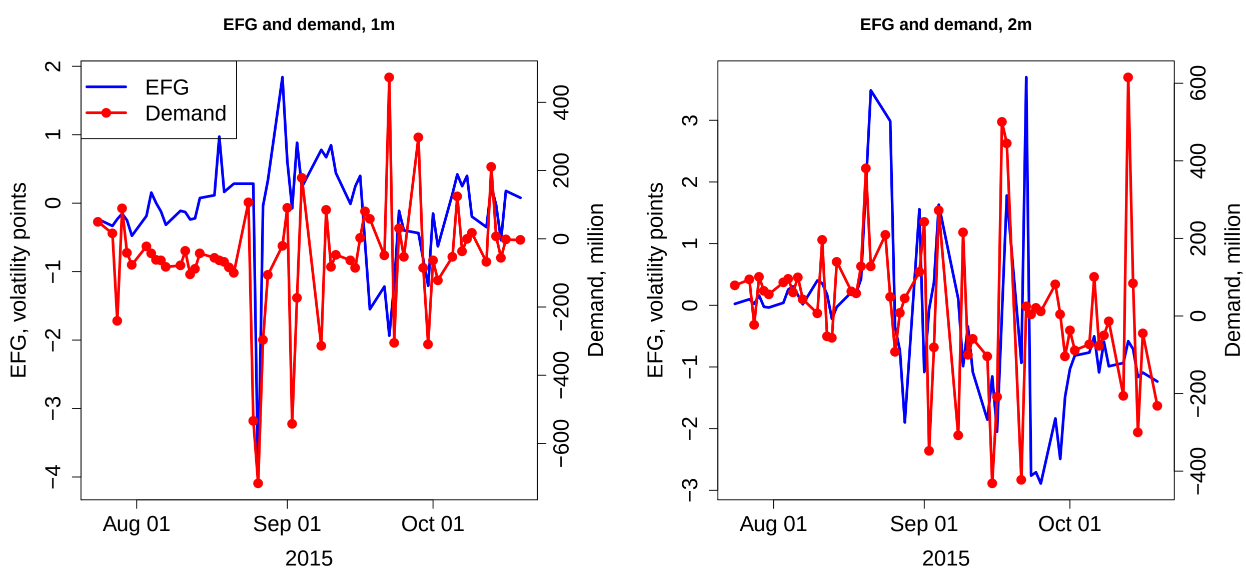

Figure 3. EFG and rebalancing demand from ETFs. The left panel illustrates the daily dynamics of the first-month EFG, the right panel of the second-month EFG. Demand is daily, in million USD. The graphs show a representative sample (August 2015 – October 2015) to illustrate the typical pattern since it is harder to see the dynamics with daily data over long periods.

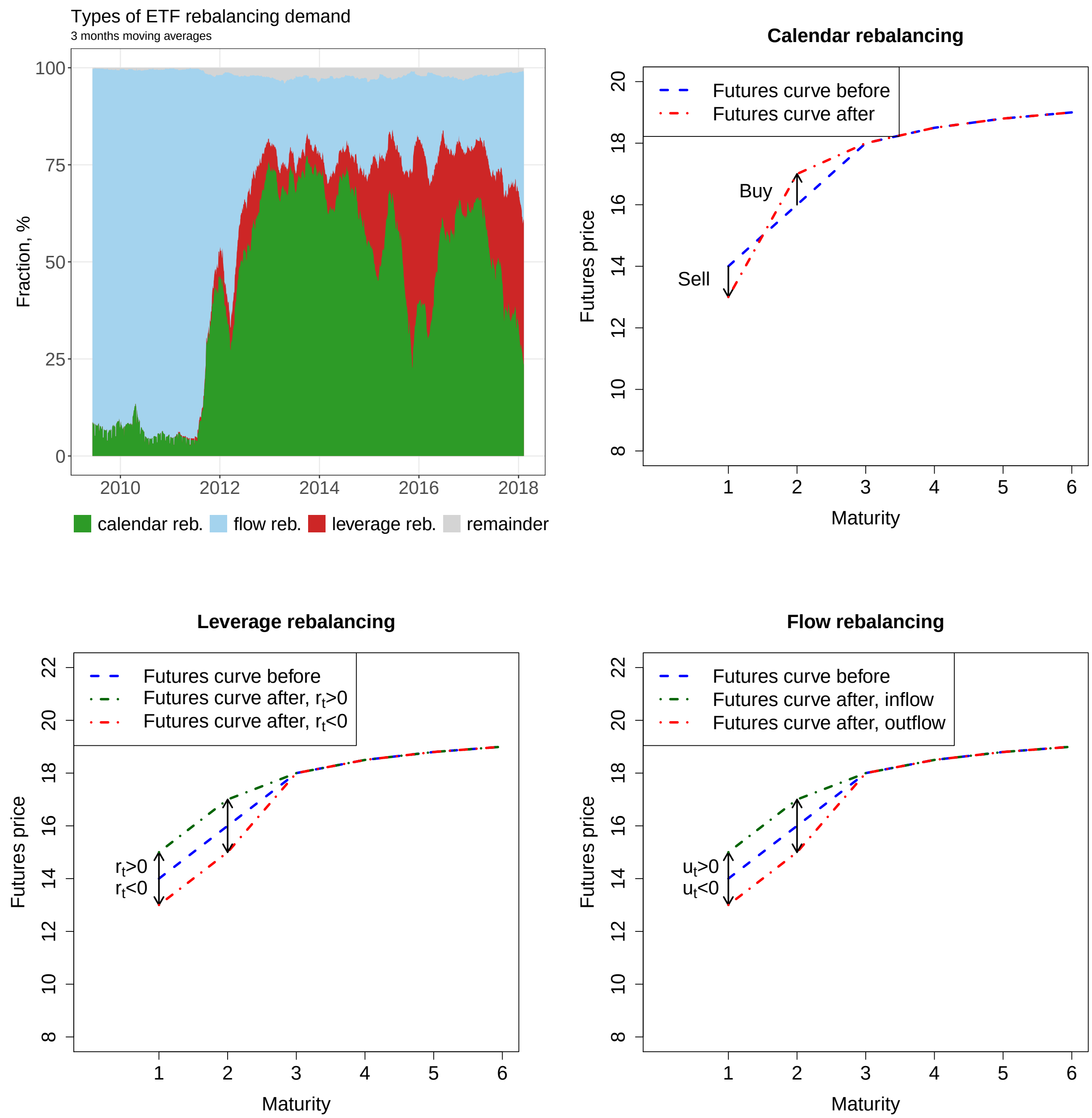

Figure 4. Decomposition of ETF demand. The top left panel illustrates the dynamics of VIX ETFs' demand decomposition. Demand is in absolute values. The top right panel and the two bottom panels show the effects of change in calendar, leverage, and flow rebalancing on the futures curve: assuming ETFs are net long VIX futures ($\sum_{j=1}^{N} L_j A_{j,t} > 0$) and with illustrative numbers. The blue line illustrates the curve before the impact of the rebalancing demand, the red and green ones after it. Maturity is in months, futures price in volatility points.

Tables

Table I

Summary statistics

The table presents summary statistics. Panel A shows the average fraction (over time) of ETFs in total market capitalization and in volume of trading for several markets. The fraction in total market capitalization is calculated as dollar size of all ETFs divided by the dollar capitalization of the benchmark index. ETF fraction in trading volume is calculated similarly. The data are at a daily frequency, from the first ETF trading date in a given asset to June 2020 (February 2018 for VIX). Panel B shows summary statistics for the VIX market. S is spot VIX, F_{T_1}, F_{T_2} are the first and second generic futures, respectively. All prices are in volatility points. Basis is $F_{T_1} - S$, spread is $F_{T_2} - F_{T_1}$. r^{VXX} is the daily return on the largest long VIX ETF (ticker VXX), EFG_{T_1} and EFG_{T_2} are the ETF futures gaps for the first and second-month contracts, respectively. The units (except skewness, kurtosis and number of observations) for spot, futures, basis, spread, EFG_{T_1} and EFG_{T_2} are volatility points, the units for r^{VXX} are %. The lowest EFGs were observed during the peak of the 2008 financial crisis, the largest ones during the VIX spike on 5 February 2018. The data are at a daily frequency and the sample ends in February 2018. The starting dates are determined by the first date when the data become available: June 2004 for the first five columns, February 2009 for r^{VXX}, and March 2006 for the last two columns. The "before ETFs" period is prior to 29 January 2009. The "after ETFs" period is after 29 January 2009 and the length of the period is the same as the one for the "before ETFs" period for each time series. The "before ETFs, excl. crisis" period is prior to 15 September 2008.

Panel A: ETFs' fraction in several markets

Market	Long ETFs fraction (%)	Inverse ETFs fraction (%)	Net ETFs fraction (%)	ETFs fraction in trading volume (%)
VIX	40.89	16.42	24.47	206.68
Natural Gas	16.88	2.72	14.16	19.12
Oil	13.49	2.06	11.43	12.57
Silver	7.16	1.97	5.19	22.63
Gold	3.56	0.62	2.94	10.12
Nasdaq	1.96	0.01	1.95	36.61
S&P 500	1.14	0.04	1.10	21.59
Russell 2000	0.09	0.05	0.04	12.30
Treasuries 7-10 years	0.00	0.00	0.00	0.00

Panel B: Summary statistics for the VIX market

	S	F_{T_1}	F_{T_2}	Basis	Spread	r^{VXX}	EFG_{T_1}	EFG_{T_2}
Mean	18.57	19.11	20.00	0.54	0.89	-0.17	0.61	0.89
Mean, before ETFs	18.87	18.93	19.38	0.06	0.46		0.63	1.18
Mean, before ETFs, excl. crisis	16.70	17.15	17.96	0.45	0.81		0.78	1.26
Mean, after ETFs	23.63	24.42	25.78	0.79	1.37		0.87	1.60
Std. dev.	9.13	8.34	7.53	1.79	1.76	3.20	1.05	1.48
Min	9.14	9.60	11.32	-23.31	-21.10	-14.25	-7.72	-7.08
Max	80.86	67.95	59.77	4.98	5.45	33.44	20.83	20.39
10%	11.43	12.20	13.13	-0.64	-0.55	-3.47	-0.23	-0.40
50%	15.60	16.22	17.50	0.69	1.01	0.00	0.46	0.70
90%	28.27	28.10	29.39	2.01	2.35	28.33	1.77	2.52
Skewness	2.57	2.26	1.87	-4.72	-3.96	1.45	2.46	2.37
Kurtosis	11.84	9.50	7.35	43.71	32.9	13.53	60.90	27.17
Observations	3,442	3,442	3,397	3,442	3,397	2,260	2,619	2,636

Table II

Impact of ETF demand in the VIX market

The table presents regression results for the first-month basis $b_{t,1}$ (Columns 1–4), and the spread between the first-month and the second-month futures contracts $b_{t,2}$ (Columns 5–8). Columns 1 and 5 present the regressions for absolute basis and spread, the rest for relative basis and spread. $D_{t,i}^{\$,all}$ is the ETF demand for the $i-$th futures contract. Columns 3 and 7 use raw demand, whereas all other columns use demand scaled by total market capitalization. Calendar rebalancing, leverage rebalancing, flow rebalancing, and remainder are calculated based on Eq. (10) and Eq. (11). All demand components are scaled by market capitalization. The estimates on the four components do not exactly add up to the estimate for total demand because the variables are standardized. $b_{t,i}^{H}$ is the relative basis of a hedge asset (synthetic futures contract constructed from options), $\sigma_{bmk,t}^2$ is intra-day variance of the ETF benchmark (calculated using 5-minute intervals), $OI_{t,i}$ is open interest for futures i, S_t is spot price. Liquidity (Liq$_{t,i}$) is the relative bid-ask spread ($\frac{Ask-Bid}{Mid}$) of the VIX futures contract. α_t is the fraction of ETF wealth invested in the front-month futures contract. All independent variables are standardized. Here and in all subsequent tables standard errors are computed using the Newey-West (e.g., Newey and West, 1987) estimator with three lags. The major results were unchanged with more lags. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Here and in all subsequent tables the number of observations is less than the number of days in the sample due to missing data for some of the explanatory variables. Daily frequency, February 2009 – February 2018.

Dependent variables	$b_{t,1}$				$b_{t,2}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D_{t,i}^{\$,all}$	**0.21*****	**1.04*****	**0.89*****		**0.10****	**0.13****	**0.29*****	
	(0.07)	(0.18)	(0.16)		(0.05)	(0.07)	(0.11)	
Calendar reb$_{t,i}$				**-0.81*****				**0.15***
				(0.13)				(0.09)
Leverage reb$_{t,i}$				**0.36****				0.07
				(0.17)				(0.13)
Flow reb$_{t,i}$				**0.77*****				**0.40*****
				(0.11)				(0.15)
Remainder$_{t,i}$				0.29*				0.24
				(0.16)				(0.23)
$b_{t,i}^{H}$	0.98***	4.63***	4.83***	4.38***	0.64***	3.04***	3.10***	2.71***
	(0.13)	(0.22)	(0.21)	(0.19)	(0.05)	(0.17)	(0.16)	(0.16)
$\sigma_{bmk,t}^2$	0.08	0.13	0.08	0.004	-0.06*	-0.20	-0.24	-0.30**
	(0.06)	(0.15)	(0.19)	(0.15)	(0.03)	(0.14)	(0.16)	(0.14)
OI$_{t,i}$	-0.19***	-0.49**	-0.16	0.03	-0.44***	-1.25***	-1.54***	-1.25***
	(0.05)	(0.24)	(0.21)	(0.20)	(0.04)	(0.20)	(0.20)	(0.20)
S$_t$	-0.35***	-2.46***	-1.49***	-1.80***	-0.66***	-3.34***	-2.98***	-3.02***
	(0.11)	(0.29)	(0.19)	(0.21)	(0.08)	(0.25)	(0.20)	(0.20)
Liq$_{t,i}$	-0.18***	-0.48***	-0.15	-0.18	-0.14***	-0.63***	-0.38***	-0.53***
	(0.05)	(0.16)	(0.12)	(0.12)	(0.03)	(0.13)	(0.13)	(0.11)
α_t	0.03	0.20	-0.13	-0.21	-0.13***	-0.46***	-0.54***	-0.60***
	(0.04)	(0.17)	(0.16)	(0.15)	(0.03)	(0.14)	(0.13)	(0.13)
Observations	1,882	1,882	1,882	1,882	1,839	1,839	1,839	1,839
R^2	0.71	0.73	0.65	0.67	0.47	0.51	0.50	0.52

Table III

Impact of ETF demand on EFG

The table presents regression results for the one and two-months ETF futures gap (EFG) scaled by the futures price ($\frac{EFG_{t,1}}{F_{t,T_1}}$ and $\frac{EFG_{t,2}}{F_{t,T_2}}$). Columns 1–3 show the results for $EFG_{t,1}$, columns 4–6 for $EFG_{t,2}$. The last two columns present the results of regression (1) for the synthetic basis and spread. Columns 2 and 5 use raw demand, whereas all other columns use demand (or demand components) scaled by total market capitalization. TED_t is the spread between 3-month LIBOR in USD and the interest rate of Treasury bills. Refer to Table II for other variable definitions. All independent variables are standardized. Daily frequency, February 2009 – February 2018.

Dependent variables	$EFG_{t,1}$			$EFG_{t,2}$			$b_{t,1}$, synt	$b_{t,2}$, synt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{\$,all}_{t,i}$	**0.55****	**0.70****		**1.09****	**1.15***		0.17	0.01
	(0.22)	(0.32)		(0.45)	(0.64)		(0.11)	(0.04)
Calendar $\text{reb}_{t,i}$			**-0.09***			**0.08***		
			(0.05)			(0.05)		
Leverage $\text{reb}_{t,i}$			**0.91****			**1.38****		
			(0.44)			(0.64)		
Flow $\text{reb}_{t,i}$			-0.05			**0.20***		
			(0.08)			(0.12)		
$\text{Remainder}_{t,i}$			0.16			0.37		
			(0.25)			(0.27)		
$\sigma^2_{bmk,t}$	0.25	0.26	0.26	-0.19	-0.21	-0.25	-0.38***	-0.07
	(0.44)	(0.44)	(0.34)	(0.68)	(0.61)	(0.55)	(0.15)	(0.05)
$\text{OI}_{t,i}$	-0.65***	-0.74***	-0.89***	0.16	-0.17	-0.11	-0.32***	-0.36***
	(0.22)	(0.20)	(0.17)	(0.24)	(0.14)	(0.18)	(0.10)	(0.07)
S_t	0.01	-0.07	-0.77***	0.63***	0.55***	0.30	-1.33***	-0.99***
	(0.17)	(0.10)	(0.20)	(0.24)	(0.20)	(0.23)	(0.16)	(0.11)
$\text{Liq}_{t,i}$	-0.001	-0.14	0.03	-0.06	-0.10	-0.16	-0.29***	-0.03
	(0.14)	(0.10)	(0.08)	(0.13)	(0.11)	(0.13)	(0.07)	(0.05)
TED_t	0.47***	0.37***	0.45***	-0.21	-0.26	-0.21		
	(0.16)	(0.11)	(0.11)	(0.13)	(0.19)	(0.15)		
$EFG_{t-1,i}$	0.42***	0.42***	0.43***	0.64***	0.64***	0.64***		
	(0.06)	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)		
α_t	-0.40**	-0.05	0.35***	0.35***	0.50***	0.46***	0.41***	-0.12**
	(0.16)	(0.10)	(0.11)	(0.10)	(0.11)	(0.13)	(0.07)	(0.05)
Observations	1,817	1,817	1,817	1,817	1,817	1,817	1,817	1,817
R^2	0.23	0.20	0.27	0.44	0.46	0.47	0.46	0.26

Table IV

Predictive power of basis

The table presents the results from a predictive regression of spot or futures price changes on basis with daily frequency. S_t is spot price, $X_{t,T}$ is either the traded futures $F_{t,T}$ for maturity T, or the synthetic futures $\mathrm{E}_t^{\mathrm{Q}}(S_T)$. The first two columns in each panel show the results for the traded futures, whereas the last two present the results for the synthetic futures. Daily frequency, February 2009 – February 2018.

Panel A: Spot VIX on basis: $S_T - S_t = \alpha_1 + \beta_1(X_{t,T} - S_t) + \epsilon_{1,t}$

	$X_{t,T} = F_{t,T}$		$X_{t,T} = \mathrm{E}_t^{\mathrm{Q}}(S_T)$	
	T=1m	T=2m	T=1m	T=2m
β_1	0.81***	0.83***	0.93***	1.03***
	(0.08)	(0.07)	(0.07)	(0.07)
R^2	0.10	0.15	0.16	0.25
Observations	1,817	1,817	1,817	1,817

Panel B: VIX futures on basis: $X_{T,T} - X_{t,T} = \alpha_2 + \beta_2(X_{t,T} - S_t) + \epsilon_{2,t}$

	$X_{t,T} = F_{t,T}$		$X_{t,T} = \mathrm{E}_t^{\mathrm{Q}}(S_T)$	
	T=1m	T=2m	T=1m	T=2m
β_2	-0.19	-0.17*	-0.07	0.03
	(0.09)	(0.07)	(0.08)	(0.07)
R^2	0.01	0.01	0.00	0.00
Observations	1,817	1,817	1,817	1,817

Table V

Impact of ETF demand in commodity markets

The table presents regression results for commodity markets. Calendar rebalancing, leverage rebalancing, flow rebalancing, and remainder are calculated based on Eq. (10) and Eq. (11). All independent variables are standardized. $b_{t,1}$ is relative basis, $b_{t,2}$ is relative spread, $b^H_{t,i}$ is the relative basis or spread of a synthetic futures contract: all in %. Controls include time to maturity, variance of benchmark, spot price, open interest, and liquidity measured by bid-ask spreads. For gas and oil, I also control for the difference in spot prices of the control asset versus the traded contract. Daily frequency, from the first ETF introduction date in a given market to June 2020.

Panel A: Total effect

Dependent variables	Gas		Oil		Silver	
	$b_{t,1}$	$b_{t,2}$	$b_{t,1}$	$b_{t,2}$	$b_{t,1}$	$b_{t,2}$
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{\$,all}_{t,i}$	0.11	0.12**	0.08***	0.15**	0.02	0.01
	(0.08)	(0.06)	(0.02)	(0.07)	(0.02)	(0.01)
$b^H_{t,i}$	1.05***	0.62***	0.44**	1.65***	0.05***	0.03***
	(0.27)	(0.10)	(0.21)	(0.47)	(0.01)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,703	2,749	2,743	2,958	2,548	2,545
R^2	0.31	0.34	0.33	0.44	0.31	0.54

Panel B: Split on components

Dependent variables	Gas		Oil		Silver	
	$b_{t,1}$	$b_{t,2}$	$b_{t,1}$	$b_{t,2}$	$b_{t,1}$	$b_{t,2}$
	(1)	(2)	(3)	(4)	(5)	(6)
Calendar reb$_{t,i}$	-0.31**	0.15	-0.04***	0.00	-0.03**	0.02
	(0.14)	(0.20)	(0.01)	(0.01)	(0.01)	(0.02)
Leverage reb$_{t,i}$	0.22	0.35***	0.17**	0.11	0.07	0.04
	(0.17)	(0.10)	(0.07)	(0.09)	(0.05)	(0.04)
Flow reb$_{t,i}$	0.28	0.31**	0.01	0.01***	0.01*	0.00
	(0.22)	(0.14)	(0.01)	(0.00)	(0.01)	(0.00)
Remainder$_{t,i}$	0.27	0.35	0.00	0.00	0.17	0.01
	(0.22)	(0.32)	(0.00)	(0.00)	(0.18)	(0.02)
$b^H_{t,i}$	0.82**	0.51***	0.38***	1.85***	0.05***	0.03**
	(0.34)	(0.15)	(0.11)	(0.53)	(0.01)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,673	2,736	2,721	2,941	2,523	2,519
R^2	0.33	0.30	0.34	0.57	0.32	0.54

REFERENCES

Aït-Sahalia, Y., Karaman, M., Mancini, L., 2018. The term structure of variance swaps and risk premia. Unpublished working paper.

Alexander, C., Korovilas, D., 2012. Understanding ETNs on VIX futures. Unpublished working paper.

Andersen, T., Bondarenko, O., Gonzalez-Perez, M., 2011. A corridor fix for VIX: Developing a coherent model-free option-implied volatility measure. Unpublished working paper.

Aramonte, S., Todorov, K., 2021. Futures-based commodity ETFs when storage is constrained. BIS Bulletin 41.

Bardgett, C., Gourier, E., Leippold, M., 2019. Inferring volatility dynamics and risk premia from the S&P 500 and VIX markets. Journal of Financial Economics 131, 593–618.

Barras, L., Malkhozov, A., 2016. Does variance risk have two prices? Evidence from the equity and option markets. Journal of Financial Economics 121, 79–92.

Basak, S., Pavlova, A., 2016. A model of financialization of commodities. Journal of Finance 71, 1511–1556.

Ben-David, I., Franzoni, F., Moussawi, R., 2018. Do ETFs increase volatility? Journal of Finance 73, 2471–2535.

Bialkowski, J., Dang, H., Wei, X., 2018. Does the Tail Wag the Dog? Evidence from Fund Flow to VIX ETFs and ETNs. Journal of Derivatives 24, 31–47.

Bloomberg, 2018. https://www.bloomberg.com/news/articles/2018-02-06/credit-suisse-is-said-to-consider-redemption-of-volatility-note. Last accessed: April 2020.

Bloomberg, 2020. https://www.bloomberg.com/news/articles/2020-04-22/how-etfs-new-whales-of-the-oil-market-are-roiling-crude-prices. Last accessed: April 2020.

Breeden, D., Litzenberger, R., 1978. Prices of state contingent claims implicit in options prices. Journal of Business 51, 621–651.

Carr, P., Wu, L., 2006. A tale of two indices. Journal of Derivatives 13, 13–29.

Carr, P., Wu, L., 2009. Variance risk premiums. Review of Financial Studies 22, 1311–1341.

Cheng, I.H., 2019. The VIX premium. Review of Financial Studies 32, 180–227.

Cheng, M., Madhavan, A., 2009. The dynamics of leveraged and inverse exchange-traded funds. Journal of Investment Management 7, 43–62.

Dong, X.S., 2016. Price impact of ETP demand on underliers. Unpublished working paper, Princeton University.

Eraker, B., Wu, Y., 2017. Explaining the negative returns to volatility claims: An equilibrium approach. Journal of Financial Economics 125, 72–98.

Fama, E.F., Bliss, R.R., 1987. The information in long-maturity forward rates. American Economic Reviews 77, 680–692.

Fernandez-Perez, A., Frijns, B., Tourani-Rad, A., Webb, R.I., 2018. Does increased hedging lead to decreased price efficiency? The case of VIX ETPs and VIX futures. Financial Review 54, 477–500.

FT, 2018. https://www.ft.com/content/be68aac6-3d13-11e8-b9f9-de94fa33a81e. Last accessed: August 2019.

FT, 2020. https://www.ft.com/content/a8a7dc16-1a9a-48f9-9bfa-89269f94218a. Last accessed: April 2020.

Garleanu, N., Pedersen, L.H., 2011. Margin-based asset pricing and deviations from the law of one price. Review of Financial Studies 24, 1980–2022.

Garleanu, N., Pedersen, L.H., Poteshman, A.M., 2009. Demand-based option pricing. Review of Financial Studies 22, 4259–4299.

Gromb, D., Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. Journal of Financial Economics 66, 361–407.

Gromb, D., Vayanos, D., 2018. The dynamics of financially constrained arbitrage. Journal of Finance 73, 1713–1750.

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery. Journal of Finance 50, 1175–1199.

Hülsbusch, H., Kraftschik, A., 2018. Consistency between S&P500 and VIX derivatives: Insights from model-free VIX futures pricing. Journal of Futures Markets 38, 977–995.

Kadan, O., Tang, X., 2020. A bound on expected stock returns. Review of Financial Studies 33, 1565–1617.

Kyle, A.S., Todorov, K., 2020. From Black-Scholes to cumulant risk premium: Evidence from leveraged ETFs. Unpublished working paper, University of Maryland and the London School of Economics.

Malamud, S., 2015. A dynamic equilibrium model of ETFs. Unpublished working paper, Swiss Finance Institute.

Martin, I., 2015. Simple variance swaps. Unpublished working paper, London School of Economics.

Martin, I., 2017. What is the expected return on the market? Quarterly Journal of Economics, Oxford University Press 132, 367–433.

Mixon, S., Onur, E., 2015. Volatility derivatives in practice: Activity and impact. Unpublished working paper, Commodity Futures Trading Commission.

Mou, Y., 2011. Limits to arbitrage and commodity index investment: Front-running the Goldman roll. Unpublished working paper, Columbia University.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite heteroscedasticity and autocorrelation-consistent covariance matrix. Econometrica 55, 703–708.

Ni, S.X., Pearson, N.D., Poteshman, A.M., White, J., 2021. Does option trading have a pervasive impact on underlying stock prices? Review of Financial Studies 34, 1952–1986.

Pagano, M., Sanchez Serrano, A., Zechner, J., 2019. Can ETFs contribute to systemic risk?

Report of the Advisory Scientific Committee 9, European Systemic Risk Board.

Reuters, 2018. https://www.reuters.com/article/us-global-markets-volatility/explainer-investors-burned-as-bets-on-low-market-volatility-implode-idUSKBN1FQ2GL. Last accessed: August 2019.

Shleifer, A., 1986. Do demand curves for stocks slope down? Journal of Finance 41, 579–590.

Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. Journal of Finance 52, 35–55.

Singleton, K.J., 2013. Investor flows and the 2008 boom/bust in oil prices. Management Science 60, 300–318.

S&P500, 2019. https://us.spindices.com/indices/strategy/sp-500-vix-short-term-index-mcap. Last accessed: August 2019.

Sushko, V., Turner, G., 2018. The implications of passive investing for securities markets. BIS Quarterly Review, March 2018.

Tang, K., Xiong, W., 2012. Index investment and the financialization of commodities. Financial Analysts Journal 68, 54–74.

Tuzun, T., 2012. Are leveraged and inverse ETFs the new portfolio insurers? Working Paper, Board of Governors, Federal Reserve System.

Appendix

A.1. Forward VIX derivations

$R_{T_1\to T_2}$ is the gross return on the S&P 500 Index, $R_{f,t\to T} = e^{r_f(T-t)}$ is the constant gross risk-free rate. Using $R_{T_1\to T_2} = \frac{R_{t\to T_2}}{R_{t\to T_1}}$, $\mathrm{E}_t^{\mathrm{Q}} R_{T_1\to T_2} = \mathrm{E}_t^{\mathrm{Q}}(\mathrm{E}_{T_1}^{\mathrm{Q}} R_{T_1\to T_2}) = R_{f,T_1\to T_2}$, and the definition of VIX as a measure of risk-neutral entropy (e.g., Martin, 2015):

$$\begin{aligned}
\mathrm{E}_t^{\mathrm{Q}}(VIX^2_{T_1\to T_2}) &= \frac{2}{T_2-T_1}\mathrm{E}_t^{\mathrm{Q}}\Big(\log \mathrm{E}_{T_1}^{\mathrm{Q}} R_{T_1\to T_2} - \mathrm{E}_{T_1}^{\mathrm{Q}} \log R_{T_1\to T_2}\Big)\\
&= \frac{2}{T_2-T_1}\mathrm{E}_t^{\mathrm{Q}}\Big(\log \mathrm{E}_t^{\mathrm{Q}} R_{T_1\to T_2} - \mathrm{E}_t^{\mathrm{Q}} \log R_{T_1\to T_2}\Big)\\
&= \frac{2}{T_2-T_1}\mathrm{E}_t^{\mathrm{Q}}\Big((T_2-t)r_f - (T_1-t)r_f - (\mathrm{E}_t^{\mathrm{Q}} \log R_{t\to T_2} - \mathrm{E}_t^{\mathrm{Q}} \log R_{t\to T_1})\Big)\\
&= \frac{2}{T_2-T_1}\Big(\log \mathrm{E}_t^{\mathrm{Q}} R_{t\to T_2} - \mathrm{E}_t^{\mathrm{Q}} \log R_{t\to T_2} - (\log \mathrm{E}_t^{\mathrm{Q}} R_{t\to T_1} - \mathrm{E}_t^{\mathrm{Q}} \log R_{t\to T_1})\Big)\\
&= \frac{1}{T_2-T_1}\Big((T_2-t)VIX^2_{t\to T_2} - (T_1-t)VIX^2_{t\to T_1}\Big).
\end{aligned} \tag{A1}$$

A.2. Calculating $\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1\to T_2})$

Based on a result from Breeden and Litzenberger (1978), the price of any function $g(S_T)$ satisfies:

$$\frac{1}{R_{f,t\to T}}E_t^{\mathrm{Q}}(g(S_T)) = \frac{1}{R_{f,t\to T}}g(E_t^{\mathrm{Q}}(S_T)) + \int_{K=0}^{F_{t,T}} g''(K)put_{t,T}(K)dK + \int_{K=F_{t,T}}^{\infty} g''(K)call_{t,T}(K)dK. \tag{A2}$$

Take $g(S_T) = S_T^2$, then:

$$\begin{aligned}
\frac{1}{R_{f,t\to T}}\left(E_t^{\mathrm{Q}}(S_T^2) - (E_t^{\mathrm{Q}}(S_T))^2\right) &= 2\left(\int_{K=0}^{F_{t,T}} put_{t,T}(K)dK + \int_{K=F_{t,T}}^{\infty} call_{t,T}(K)dK\right)\\
\mathrm{Var}_t^{\mathrm{Q}}(S_T) &= 2R_{f,t\to T}\left(\int_{K=0}^{F_{t,T}} put_{t,T}(K)dK + \int_{K=F_{t,T}}^{\infty} call_{t,T}(K)dK\right).
\end{aligned} \tag{A3}$$

Another way to get the same equation is by using $R_T = \frac{S_T}{S_t}$ in Eq. (11) of Martin (2017).

Take $T = T_1,\ T_2 = T_1 + 30\ days,\ S_{T_1} = VIX_{T_1 \to T_2}$, then:

$$\mathrm{Var}_t^{\mathrm{Q}}(VIX_{T_1 \to T_2}) = 2R_{f,t\to T_1}\left(\int_{K=0}^{F_{t,T_1}} put_{t,T_1}(K)dK + \int_{K=F_{t,T_1}}^{\infty} call_{t,T_1}(K)dK\right), \tag{A4}$$

where F_{t,T_1} – time t's price of a futures on $VIX_{T_1\to T_2}$ with maturity T_1,
$put_{t,T_1}(K)$ – time t's price of a put option on $VIX_{T_1\to T_2}$ with maturity T_1 and strike K,
$call_{t,T_1}(K)$ – time t's price of a call option on $VIX_{T_1\to T_2}$ with maturity T_1 and strike K.
The underlying asset of the call and put options is the futures on the VIX since at maturity T_1, $F_{T_1,T_1} = S_{T_1} = VIX_{T_1\to T_2}$, and there are no dividends.

A.3. Derivations of ETF demand decomposition

At time t, the ETF has a dollar position of $L\alpha_t A_t$ in the first-month futures contract and $L(1-\alpha_t)A_t$ in the second. It holds $\frac{L\alpha_t A_t}{F_{t,T_1}}$ units of the first-month contract and $\frac{L(1-\alpha_t)A_t}{F_{t,T_2}}$ units of the second. At time $t+1$, the ETF holds $\frac{L(\alpha_t - \frac{1}{K})A_{t+1}}{F_{t+1,T_1}}$ units of the first-month contract and $\frac{L(1-\alpha_t+\frac{1}{K})A_{t+1}}{F_{t+1,T_2}}$ of the second. The total rebalancing demand (in number of contracts) for the first-month contract from t to $t+1$ is then:

$$\begin{aligned}
D_{t+1,1} &= \frac{L(\alpha_t - \frac{1}{K})A_{t+1}}{F_{t+1,T_1}} - \frac{L\alpha_t A_t}{F_{t,T_1}} \\
&= \frac{1}{F_{t+1,T_1}}\left(\alpha_t\Big(LA_t(1+Lr_{t+1}) + Lu_{t+1} - LA_t(1+r_{t+1}^{F_1})\Big) - \frac{L}{K}A_{t+1}\right) \\
&= \frac{1}{F_{t+1,T_1}}\left(\alpha_t\Big(LA_t(Lr_{t+1} - r_{t+1} + r_{t+1} - r_{t+1}^{F_1}) + Lu_{t+1}\Big) - \frac{L}{K}A_t(1+Lr_{t+1}) - \frac{L}{K}u_{t+1}\right) \\
&= \frac{1}{F_{t+1,T_1}}\left(-\frac{L}{K}A_t(1+Lr_{t+1}) + \alpha_t A_t L(L-1)r_{t+1} + (\alpha_t - \frac{1}{K})Lu_{t+1} + \alpha_t(1-\hat{\alpha}_t)LA_t(r_{t+1}^{F_2} - r_{t+1}^{F_1})\right).
\end{aligned} \tag{A5}$$

I used the fact that $r_{t+1} - r_{t+1}^{F_1} = (1-\hat{\alpha}_t)(r_{t+1}^{F_2} - r_{t+1}^{F_1})$, where $r_{t+1}^{F_1}$ is the net return on the first-month futures contract, $r_{t+1}^{F_2}$ is the net return on the second, $\hat{\alpha}_t = \frac{\alpha_t F_{t,T_1}}{\alpha_t F_{t,T_1} + (1-\alpha_t)F_{t,T_2}}$, and $r_{t+1} = \frac{\alpha_t F_{t+1,T_1} + (1-\alpha_t)F_{t+1,T_2}}{\alpha_t F_{t,T_1} + (1-\alpha_t)F_{t,T_2}} - 1 = \hat{\alpha}_t r_{t+1}^{F_1} + (1-\hat{\alpha}_t)r_{t+1}^{F_2}$ is the net return on the benchmark.

In dollar terms, the rebalancing demand is:

$$\begin{aligned} D^{\$}_{t+1,1} &= D_{t+1,1}F_{t+1,T_1} \\ &= \underbrace{-\frac{L}{K}A_t(1+Lr_{t+1})}_{calendar\ rebalancing} + \underbrace{\alpha_t A_t L(L-1)r_{t+1}}_{leverage\ rebalancing} + \underbrace{(\alpha_t - \frac{1}{K})Lu_{t+1}}_{flow\ rebalancing} + \underbrace{\alpha_t(1-\hat{\alpha}_t)LA_t(r^{F_2}_{t+1} - r^{F_1}_{t+1})}_{remainder}. \end{aligned} \tag{A6}$$

Analogously, the total dollar rebalancing demand for the second futures is:

$$\begin{aligned} D^{\$}_{t+1,2} &= D_{t+1,2}F_{t+1,T_2} \\ &= \underbrace{\frac{L}{K}A_t(1+Lr_{t+1})}_{calendar\ rebalancing} + \underbrace{(1-\alpha_t)A_t L(L-1)r_{t+1}}_{leverage\ rebalancing} + \underbrace{(1-\alpha_t + \frac{1}{K})Lu_{t+1}}_{flow\ rebalancing} \underbrace{-\hat{\alpha}_t(1-\alpha_t)LA_t(r^{F_2}_{t+1} - r^{F_1}_{t+1})}_{remainder}. \end{aligned} \tag{A7}$$

Eq. (A6) and Eq. (A7) can be rewritten in a way to isolate the terms multiplying L^2. For Eq. (A6):

$$D^{\$}_{t+1,1} = \underbrace{(\alpha_t - \frac{1}{K})}_{\geq 0} A_t L^2 r_{t+1} - \alpha_t A_t L r_{t+1} - \frac{L}{K}A_t + (\alpha_t - \frac{1}{K})Lu_{t+1} + \alpha_t(1-\hat{\alpha}_t)LA_t(r^{F_2}_{t+1} - r^{F_1}_{t+1}). \tag{A8}$$

Running the main regressions with the non-linear terms instead of calendar and leverage rebalancing still shows that the predictable part of calendar rebalancing ($\frac{L}{K}A_t$) is statistically significant.

A.4. EFG: robustness checks

Table AI presents robustness checks for the EFG. The results show that ETF demand has a greater effect after 2013, when ETFs become a larger share of the market, as seen from columns 1–2 and 4–5.

A potential concern is that maybe the EFG arises due to price pressure in the VIX options market after 2009, and ETF demand just happens to be correlated with this pressure. To address this concern, I add the hedging pressure from the options market as a control in the EFG regressions (columns 3 and 6 in Table AI). I measure the pressure in terms of delta-hedging. For each day, I calculate the delta-hedging demand as $-\sum_{j=1}^{M} \Delta_{t,j} OI_{t,j} F_{t,T_i}$, where M is the total number of options on the futures expiring at T_i, $\Delta_{t,j}$ is the Black-Scholes delta of option j, and $OI_{t,j}$ is the total open interest for option j. I also calculate gamma-hedging demand to account for second-order effects.[17] The estimates show that the positive and statistically significant effects of ETF demand are robust to including the measures of hedging pressure from the options market. They are also robust to the Fama-French five factors and momentum.

Another concern is that, even though ETF demand does not directly influence the VIX options market, prices of options could be disrupted if investors hedge the futures exposure with options. However, the results from Table III show that this is not the case since ETF demand has no impact on the more fundamental, synthetic futures contract.

Anecdotal evidence from my discussions with several hedge fund traders suggests that hedge funds are replicating the VIX futures with a portfolio of options and trading the difference between the two, thereby extracting the EFG. Empirically, ETFs are usually net buyers of futures contracts, whereas managed money (usually hedge funds) takes the opposite side of the trade. Figure A1 shows the weekly positions of different types of investors in VIX and gas markets. The graphs show that leveraged money (mostly hedge funds) is consistently short VIX futures after 2009, whereas asset managers and dealers are mostly net long. Table AII shows that a 100% increase in the EFG is correlated with a $33 million decrease in hedge funds' positions.

[17] Ni et al. (2021) show that hedge rebalancing by option market makers, determined by delta and gamma, affects stock prices.

Table AI

Robustness

The table presents robustness tests. Columns 1–2 and 4–5 show the impact of ETF demand by splitting the main period on two sub-periods: February 2009 – December 2012 and January 2013 – February 2018. Columns 3 and 6 present the results of a regression with the Fama–French five factors, momentum, and hedging pressure from the VIX options market (Delta$_{t,i}$ and Gamma$_{t,i}$). Delta$_{t,i}$ is the negative sum of all Black-Scholes deltas multiplied with the open interest and the futures price for all options on the first-month or second-month futures. The negative sum captures the idea that if the total delta in the options market is positive, the hedging demand would be negative (agents would sell the underlying to hedge the positive-delta option position). Gamma$_{t,i}$ is the negative sum of all Black-Scholes gammas multiplied with the open interest and the squared price for all options on the first-month or second-month futures. Columns 7–8 show the results for the period before ETFs. $D^{\$,all}_{t,i}$ is scaled by market capitalization. $R_{M,t} - R_{f,t}$, HML$_t$, SMB$_t$, CMA$_t$, RMW$_t$, Mom$_t$ are the Fama–French five factors and momentum. Daily frequency, February 2009 – February 2018.

Dependent variables	EFG$_{t,1}$		EFG$_{t,1}$	EFG$_{t,2}$		EFG$_{t,2}$	EFG$_{t,1}$	EFG$_{t,2}$
	bef 2013	aft 2013		bef 2013	aft 2013		bef 2009	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D^{\$,all}_{t,i}$	0.35**	0.62*	0.51*	0.42*	1.66**	1.01**		
	(0.17)	(0.36)	(0.31)	(0.23)	(0.70)	(0.43)		
$\sigma^2_{bmk,t}$	-0.14	0.47	0.26	-0.38*	0.04	-0.10	-0.79***	0.48
	(0.16)	(0.40)	(0.30)	(0.22)	(0.51)	(0.38)	(0.30)	(0.51)
OI$_{t,i}$	0.73*	-0.26	-0.11	-0.21	-0.27	-0.71***	0.23	-0.27
	(0.43)	(0.30)	(0.27)	(0.17)	(0.39)	(0.23)	(0.23)	(0.29)
S$_t$	0.31	-0.14	-0.20	-0.47	-0.003	0.08	-1.33**	-0.42
	(0.33)	(0.46)	(0.30)	(0.35)	(0.41)	(0.39)	(0.58)	(0.55)
Liq$_{t,i}$	-0.14	0.06	-0.06	-0.21	0.07	-0.04	0.16	0.63*
	(0.23)	(0.20)	(0.16)	(0.30)	(0.20)	(0.17)	(0.20)	(0.36)
TED$_t$	-0.34	0.37**	0.32	0.22	-0.24*	-0.08	-0.18	-0.06
	(0.39)	(0.17)	(0.21)	(0.37)	(0.14)	(0.18)	(0.53)	(0.50)
EFG$_{t-1,1}$	0.56***	0.35***	0.41***	0.66***	0.59***	0.68***	0.65***	0.51***
	(0.08)	(0.06)	(0.06)	(0.05)	(0.08)	(0.05)	(0.04)	(0.05)
α_t	-0.64*	-0.78**	-0.68***	0.07	0.48**	0.46***	-0.23	1.11**
	(0.37)	(0.35)	(0.24)	(0.17)	(0.22)	(0.13)	(0.27)	(0.40)
$R_{M,t}$-$R_{f,t}$			-0.21			-0.27		
			(0.23)			(0.22)		
Mom$_t$			0.10			-0.19		
			(0.15)			(0.15)		
SMB$_t$			0.24			0.42		
			(0.34)			(0.31)		
HML$_t$			0.004			0.01		
			(0.30)			(0.24)		
RMW$_t$			0.15			-0.27		
			(0.35)			(0.36)		
CMA$_t$			-0.52			0.30		
			(0.51)			(0.39)		
Delta$_{t,i}$			-0.53*			-0.09		
			(0.31)			(0.10)		
Gamma$_{t,i}$			-0.21			-0.14		
			(0.35)			(0.15)		
Observations	608	1,190	1,797	608	1,190	1,797	506	518
R^2	0.34	0.23	0.24	0.49	0.45	0.53	0.52	0.31

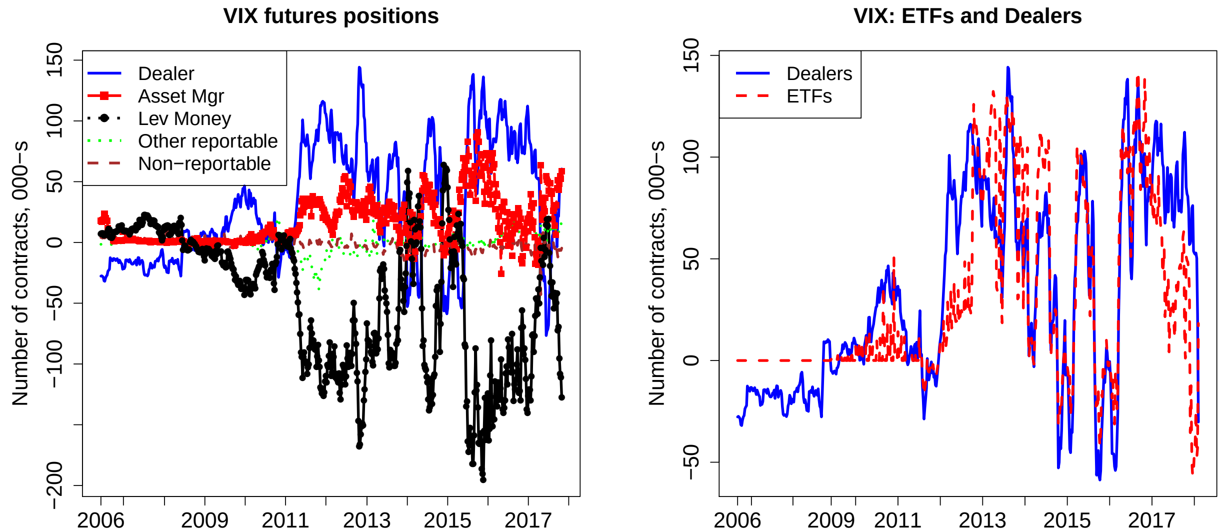

Figure A1. Positions of traders. The figure shows net futures positions of different types of traders in the VIX market. The data are from the Traders in Financial Futures (TFF) reports by the CFTC. The right panel shows weekly net ETF positions and net Dealer/Swap positions. The names of the different groups of traders are the same as in the TFF classification. "Asset Mgr" are asset managers (mostly pension funds, endowments, insurance companies and mutual funds), "Lev Money" are mostly hedge funds and other proprietary traders.

Table AII

Positions of leveraged money in VIX futures

The table presents weekly regressions of the positions of leveraged money (mostly hedge funds) on the ETF futures gap. $b_{t,1}$ and $b_{t,2}$ are absolute basis and spread. Column 3 is with raw variables, the rest with standardized ones. Weekly frequency, September 2006 – December 2017 (some data are missing).

Dependent variables	Weekly Hedge Funds' net positions, million USD				
	(1)	(2)	(3)	(4)	(5)
EFG_t	**-8.75*****	**-9.12*****	**-33.05*****		
	(2.12)	(2.56)	(8.92)		
ETF positions$_t$	-38.11***	-38.45***	-0.80***	-44.69***	-32.88***
	(4.15)	(4.16)	(0.07)	(3.06)	(4.57)
$\sigma^2_{bmk,t}$		-12.42**	-28.35	-4.68	-8.55
		(5.43)	(20.12)	(3.64)	(7.17)
$b_{t,1}$	-1.35	-2.41	-1.75	-0.47	-3.48
	(2.35)	(2.91)	(1.89)	(2.13)	(2.53)
$b_{t,2}$	-12.66**	-12.83**	-6.12***	-12.11***	-12.40**
	(5.14)	(5.67)	(2.20)	(3.79)	(5.35)
S_t	4.62	2.12	1.43	0.21	-1.63
	(4.44)	(2.27)	(1.33)	(4.33)	(5.59)
Observations	416	416	416	452	452
R^2	0.62	0.64	0.64	0.72	0.55

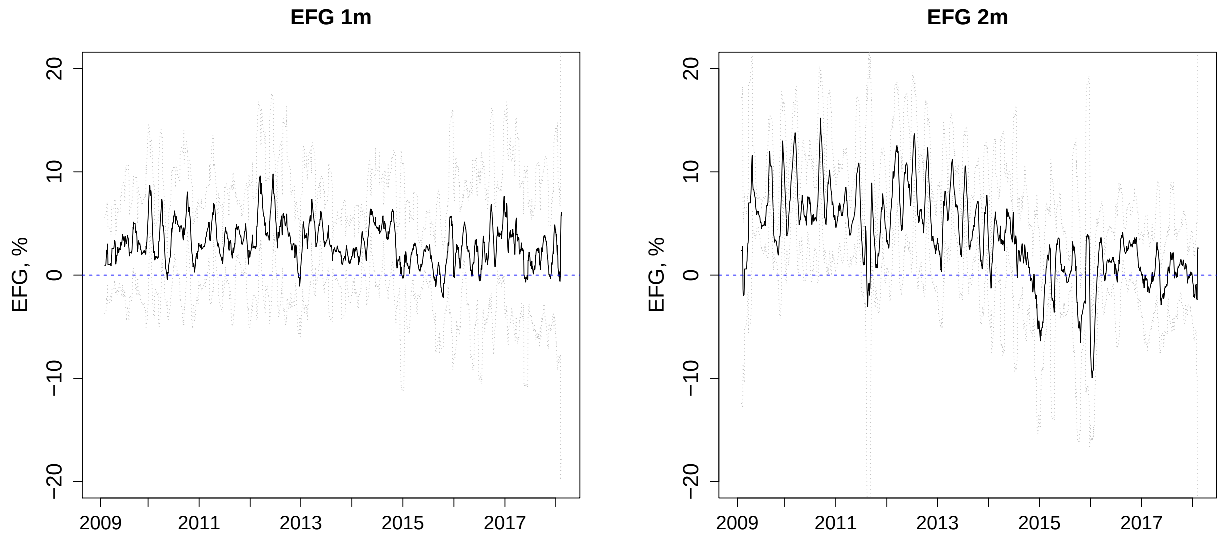

Figure A2. ETF futures gap: monthly averages as share of the futures price. The figure shows the dynamics of the ETF futures gap (EFG) for one and two months maturities after the introduction of the first VIX ETF (29 January 2009). The grey dotted lines indicate two standard deviations. EFG is scaled by the same-maturity futures price.

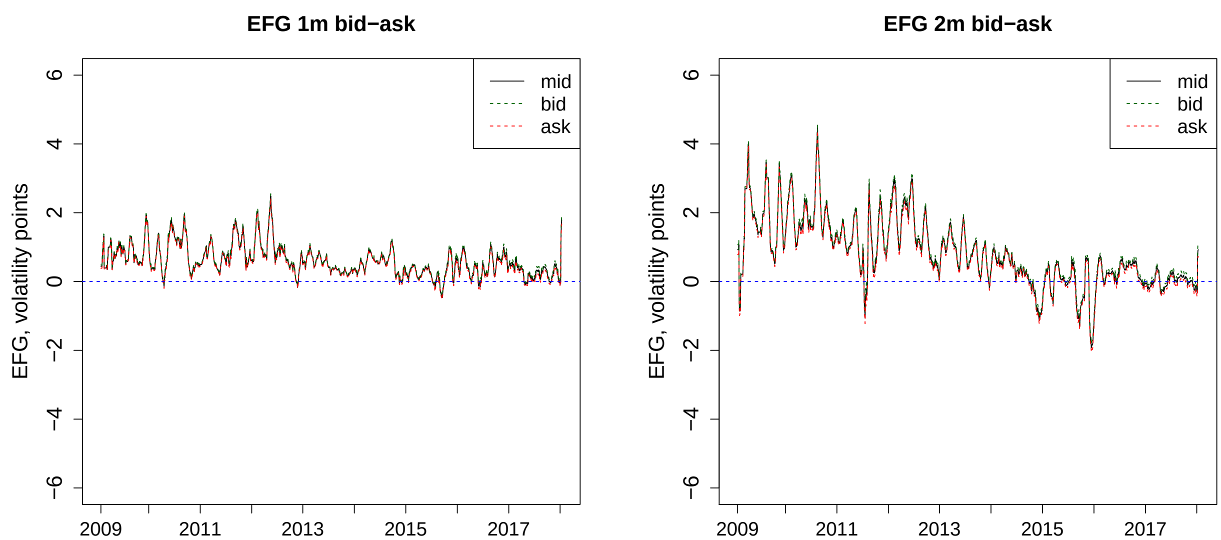

Figure A3. ETF futures gap: bid-ask. The figure shows the dynamics of the ETF futures gap (EFG) for one and two months maturities using bid/ask prices of options.

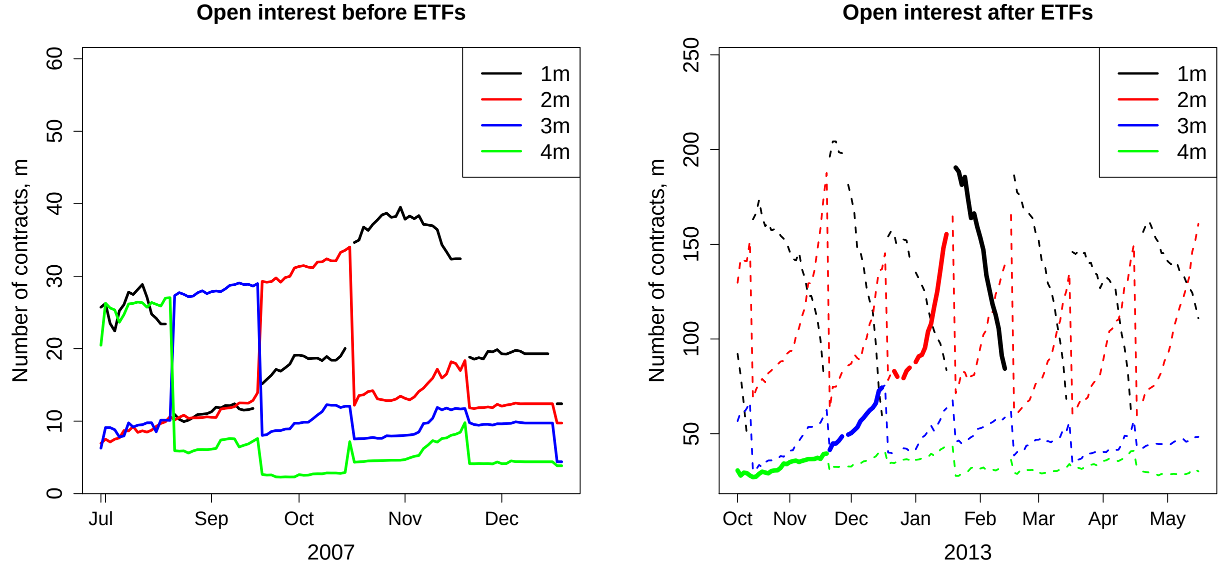

Figure A4. Open interest dynamics before and after ETF introduction. The left panel shows typical dynamics of open interest for futures maturities at one, two, three and four months for the period before ETFs were introduced. The right panel illustrates typical dynamics after the introduction of ETFs. The emphasized straight lines show the usual cycle of open interest. The graphs show a representative sample (July 2007 – December 2007 and October 2012 – May 2013) to illustrate the typical pattern. To understand the pattern, consider, for example, the four-month VIX futures in November 2012. Open interest spikes as soon as it becomes a two-months futures contract in January 2013 and ETFs start to buy it. When it becomes a one-month futures contract in February 2013, ETFs start to sell it and open interest declines. The increase in the number of contracts for the two-months futures is roughly equal to the decrease in the number of contracts for the one-month futures.

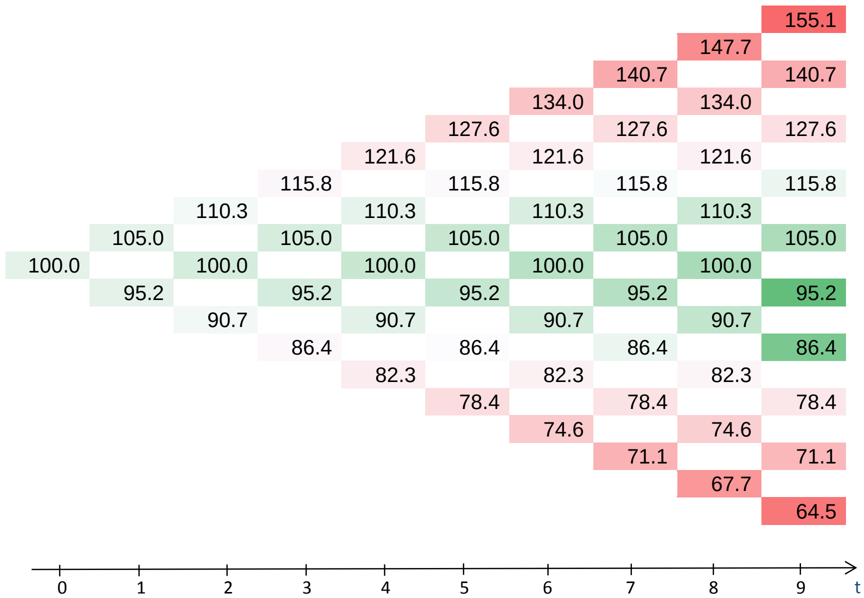

Figure A5. Trading against opposite ETFs. The figure shows the profit dynamics of liquidity provision to opposite ETFs using a binomial tree example. The graph illustrates the dynamics of the ETF benchmark and the corresponding profits for an arbitrageur who sells short a pair of opposite ETFs ($L = 2$ and $L = -2$). For each period, the parameters of the tree are $u = 1.05$ and $ud = 1$. Red areas indicate nodes where the arbitrageur loses money, and green ones show where the arbitrageur makes profit. More color-intense nodes indicate larger losses or profits. By trading against the leverage rebalancing of ETFs, arbitrageurs acquire a short position if the price increases, and a long position if the price decreases. If the price drifts steadily up, arbitrageurs lose money since they sell the asset and the price keeps increasing. If the price reverts back to the initial value, they make a profit since they sell the asset and the price decreases.

Table AIII

Predictive regressions of futures returns on EFG

Columns 1 and 2 show the results of monthly predictive regressions of the realized futures returns on the EFG. For one-month futures contract, I use returns from 21 days before maturity, to expiration, since this is one of the most frequent maturities. Similarly, for two-months futures contract, I use returns calculated from 47 days before maturity, to expiration. $r^{F_i}_{t,T_i} = \frac{F_{T_i,T_i} - F_{t,T_i}}{F_{t,T_i}}$. Columns 3 and 4 present daily predictive regressions. Return on futures is already excess return because the collateral earns the risk-free rate of interest: all futures positions are fully collateralized, with the collateral invested in three-month Treasury bills. $R_{M,t} - R_{f,t}$, HML_t, SMB_t, CMA_t, RMW_t, Mom_t are the Fama–French five factors and momentum. The data sample is February 2009 – February 2018. Refer to Table II and Table III for definitions of other variables.

Dependent variables	$r^{F_1}_{t,T_1}$ (1)	$r^{F_2}_{t,T_2}$ (2)	$r^{F_1}_{t}$ (3)	$r^{F_2}_{t}$ (4)
$\text{EFG}_{t,i}$	-1.66***	-1.59***	-0.01*	-0.02***
	(0.52)	(0.41)	(0.01)	(0.01)
$\sigma^2_{bmk,t}$	0.01	0.01	0.01***	0.01***
	(0.02)	(0.02)	(0.00)	(0.00)
$\text{OI}_{t,i}$	-0.06**	-0.07**	0.00	-0.01*
	(0.03)	(0.03)	(0.00)	0.00)
S_t	-0.05	-0.05	0.001	-0.0003
	(0.03)	(0.05)	(0.002)	(0.0005)
$\text{Liq}_{t,i}$	0.01	0.07***	0.00	0.00
	(0.03)	(0.03)	(0.00)	(0.00)
TED_t	-0.02	-0.04*	-0.00	-0.01***
	(0.02)	(0.02)	(0.00)	(0.00)
α_t	0.05***	-0.02	0.00	-0.00
	(0.01)	(0.02)	(0.00)	(0.00)
$R_{M,t} - R_{f,t}$	-0.05***	0.01	-0.00	0.00
	(0.01)	(0.02)	(0.00)	(0.00)
HML_t	0.08*	0.03	-0.00	0.00
	(0.05)	(0.07)	(0.0)	(0.00)
SMB_t	0.001	-0.04	0.00	-0.00
	(0.03)	(0.04)	(0.00)	(0.00)
CMA_t	-0.11**	-0.15**	-0.00	-0.00
	(0.05)	(0.07)	(0.00)	(0.00)
RMW_t	-0.01	0.07	-0.00	0.00
	(0.03)	(0.07)	(0.00)	(0.00)
Mom_t	0.01	0.08***	-0.00	0.00
	(0.02)	(0.02)	(0.00)	(0.00)
Observations	94	90	1,847	1,805
R^2	0.20	0.48	0.11	0.06

Internet Appendix

IA.1. Details on the synthetic VIX futures calculation

$VIX^2_{t\to T_1}$, and $VIX^2_{t\to T_2}$ are calculated using the exact same procedure as outlined in the CBOE VIX White Paper. The correlation between the calculated VIX and the CBOE-quoted one for a maturity of one month is 99.8%.

Empirically, sometimes no S&P 500 Index options expire at the exact same time as VIX futures. VIX futures typically expire in the morning of the Wednesday before the third Friday of the month (the settlement value is calculated using special opening quote values). There are always options expiring 30 days after, since these are used to calculate the settlement price of VIX. S&P 500 Index options (weeklys) also cease trading on Wednesday, but are p.m.-settled and expire at 4:00 p.m. I deal with this issue in several ways. First, I compute $\mathrm{E}^{\mathrm{Q}}_t(VIX^2_{T_1\to T_2})$ using the evening quotes for options. Second, I interpolate in the volatility space to get prices of options expiring in the morning, and compute $\mathrm{E}^{\mathrm{Q}}_t(VIX^2_{T_1\to T_2})$ using these prices. With both approaches, the estimates for the EFG shared similar patterns as in Figure 2. Sometimes, especially before weeklys were introduced, there were no S&P 500 Index options expiring at the same time as VIX futures. For those, I interpolate $VIX^2_{t\to T_1}$ using the nearest (usually within 1–2 days) expiring option contracts.

For the computation of $\mathrm{Var}^{\mathrm{Q}}_t(VIX_{T_1\to T_2})$, I need the futures price F_{t,T_1}. I tested three different ways to estimate it. First, by finding the strike for which put and call prices are closest (analogous to the calculation of VIX). Second, by implementing an iterative procedure to find $F_{t,T_1} = \mathrm{E}^{\mathrm{Q}}_t(VIX_{T_1\to T_2})$ that makes Eq. (3) hold. Third, by using the traded VIX futures price. The main results were similar with each of the three estimates.

A potential concern for the computation of $VIX^2_{T_1\to T_2}$ is the existence of discretization errors. As a robustness check, similar to Aït-Sahalia et al. (2018), I calculated forward VIX by interpolating the volatility surface and finding option prices for all strikes following the methodology of Carr and Wu (2009). The EFG was less volatile and smaller in magnitude, on average, but the main results of the paper were unchanged. As another robustness test, I calculated the EFG using minimum price instead of mid-point price for each option in Eq. (5)

similar to Kadan and Tang (2020). The main results of the paper were unchanged but the EFG was underestimated even more using this approach.

Another concern is that the specific rules used by the CBOE for selecting options to calculate VIX could lead to instabilities in the intra-day value of the index, especially during extreme market movements as noted by Andersen et al. (2011). However, I use the CBOE methodology to compute forward VIX on a daily basis. These instabilities should be less severe than on an intra-day basis (e.g., Aït-Sahalia et al., 2018).

IA.2. Evidence on ETF rebalancing

There are several pieces of evidence that ETFs (irrespective of their legal structure as a fund or note) follow their benchmarks and rebalance in the way described in section IV. First, anecdotal evidence from my discussions with several ETF managers and authorized participants suggests that ETFs have no incentive to deviate from the benchmark,[18] as their performance is evaluated based on the tracking error. The compensation for ETF sponsors arises from fees but not from over-performance or under-performance. Second, some of the ETFs make their daily holdings publicly observable. The change in holdings actually seen matches the one predicted by the rebalancing from Eq. (10) and Eq. (11). Third, the implied weekly net positions of ETFs closely follow the reports from the CFTC, as seen in Figure A1, although the match is not perfect because the CFTC data are weekly, and the holdings are aggregated for ETFs and other dealers. Eraker and Wu (2017) also conclude that VIX ETFs track their benchmark indices fairly well at a daily frequency.

IA.3. Mid-term VIX ETFs

Table IA.1 shows the results of regression (1) for mid-term VIX ETFs. These ETFs invest one third of their AUM in the fifth-month futures contract, one third in the sixth-month one, and roll one third from the fourth-month to the seventh-month futures contract on a daily basis. The results from Table IA.1 illustrate that ETF demand has an impact only on the fifth-month spread and the sixth-month spread, mainly due to leverage rebalancing

[18]Except in extreme situations, e.g., negative spot prices as in the oil market in 2020.

and flows. The effects of calendar rebalancing are less pronounced, probably because mid-term VIX ETFs constitute a lower fraction of open interest compared to short-term VIX ETFs. One standard deviation rise in leverage rebalancing increases the fifth-month spread by 0.25%, and the sixth-month spread by 0.33%.

Table IA.1

Mid-term VIX ETFs

The table presents the results of regression (1) for mid-term VIX ETFs. Columns 1–4 correspond to the relative spread of 4–7 months futures. Panel B shows the estimates for ETF demand components. All independent variables are standardized. Refer to Table II for variable definitions. Daily data, February 2009 – December 2017.

Panel A: Total effect				
Dependent variables	$b_{t,4}$, rel (1)	$b_{t,5}$, rel (2)	$b_{t,6}$, rel (3)	$b_{t,7}$, rel (4)
$D^{\$,all}_{t,i}$	-0.17	0.13**	0.12*	0.01
	(0.11)	(0.06)	(0.06)	(0.02)
$b^H_{t,i}$	4.21***	4.35***	4.98***	5.30***
	(1.00)	(0.94)	(0.97)	(1.44)
$r_{bmk,t}$	-0.06	-0.02	-0.02	-0.06*
	(0.05)	(0.06)	(0.07)	(0.03)
$\sigma^2_{bmk,t}$	-0.18*	-0.15***	-0.12	-0.01
	(0.10)	(0.03)	(0.09)	(0.08)
$OI_{t,i}$	0.15	0.78***	0.82***	0.45***
	(0.21)	(0.23)	(0.18)	(0.10)
S_t	-2.47***	-1.61***	-0.96***	-0.75***
	(0.27)	(0.30)	(0.28)	(0.18)
$Liq_{t,i}$	-0.48**	-0.10***	-0.70*	-0.91***
	(0.24)	(0.02)	(0.41)	(0.16)
α_t	-0.18**	-0.03	0.07	0.10
	(0.08)	(0.07)	(0.07)	(0.06)
Observations	1,732	1,720	1,724	1,731
R^2	0.50	0.38	0.38	0.27

Panel B: Split on components				
Dependent variables	$b_{t,4}$, rel (1)	$b_{t,5}$, rel (2)	$b_{t,6}$, rel (3)	$b_{t,7}$, rel (4)
Calendar $reb_{t,i}$	-1.58*			0.26
	(0.84)			(0.81)
$Remainder_{t,i}$	1.40			-0.24
	(1.38)			(0.27)
Leverage $reb_{t,i}$	-0.25	0.25**	0.33**	0.17
	(0.31)	(0.12)	(0.13)	(0.28)
Flow $reb_{t,i}$	-0.30**	0.10*	0.15	-0.81
	(0.12)	(0.06)	(0.151)	(0.63)
Observations	1,697	1,685	1,694	1,692
R^2	0.58	0.41	0.35	0.30

IA.4. Commodity markets-specifics

In the regressions for commodity markets, I use relative basis as the dependent variable, instead of the difference between the ETF-influenced futures price and that of the control contract, due to the concern that some systematic factors have changed the pricing across US and European markets in the post-ETF period. In particular, gas prices in the US have fallen substantially after the increase in shale gas drilling from 2010, and the difference with prices in Europe has widened. US crude oil prices have also diverged from Brent during the period 2010–2013 due to local supply factors.[19] Thus, using absolute levels of futures prices of the control asset to isolate the impact of ETFs could capture other changes in cross-market factors. However, using relative basis and assuming that storage costs have changed in a similar way for both the ETF-influenced and the control contracts (which is a within-market factor) is a more realistic assumption, as anecdotal evidence suggests. To account for the above-mentioned changes in cross-market factors, I control for the difference in spot prices between US and Europe in the respective basis and spread regressions. This difference captures the systematic change across the two markets, which is not influenced by ETFs as ETFs trade in the futures contract.

[19] After 2010, increased volumes of crude oil from North Dakota and Canada flowed into Cushing (where WTI US crude oil is delivered). These inflows led to a build-up in inventories and decreased the price of US crude oil, widening the spread with Brent.

IA.5. Additional figures and tables

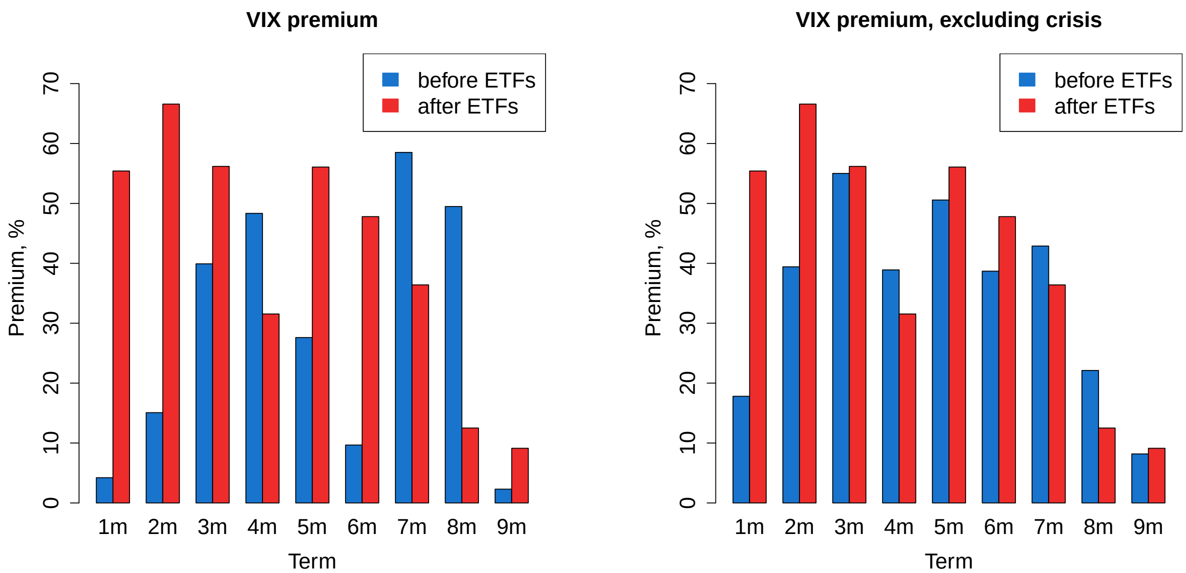

Figure IA.1. Realized VIX futures premium before and after ETFs. The left chart shows the average size of the VIX futures premium for different maturities before ETFs (June 2004 – January 2009) and after ETFs (February 2009 – February 2018). The right one presents the same premium but the "before ETFs" period excludes the 2008 crisis episode: the time frame is June 2004 – September 2008. The premium is calculated as the annualized net return of a short-seller of a VIX futures $\frac{F_{t,T}-F_{T,T}}{F_{t,T}}$, where T (Term) is maturity in months. If the increase in premium after ETFs was driven by a general rise in the price of variance risk, one would expect a more uniform increase in the premium for all maturities. Instead, the graphs show a large rise for the most ETF-dominated maturities of one and two months, and a little change or even a decrease in premiums for other maturities.

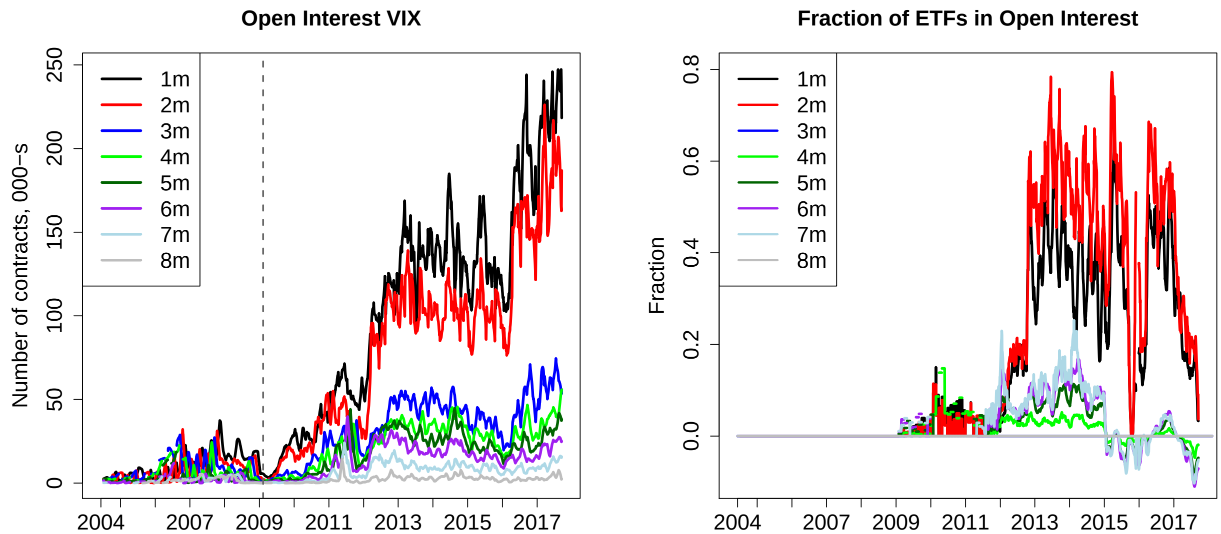

Figure IA.2. Open interest dynamics. The left panel shows the dynamics of open interest (monthly averages) in the VIX market for futures with maturities at 1–8 months. The dotted vertical line indicates the date when the first ETF was introduced. The right panel shows the fraction of ETFs in open interest (monthly averages) for futures with maturities at 1–8 months.

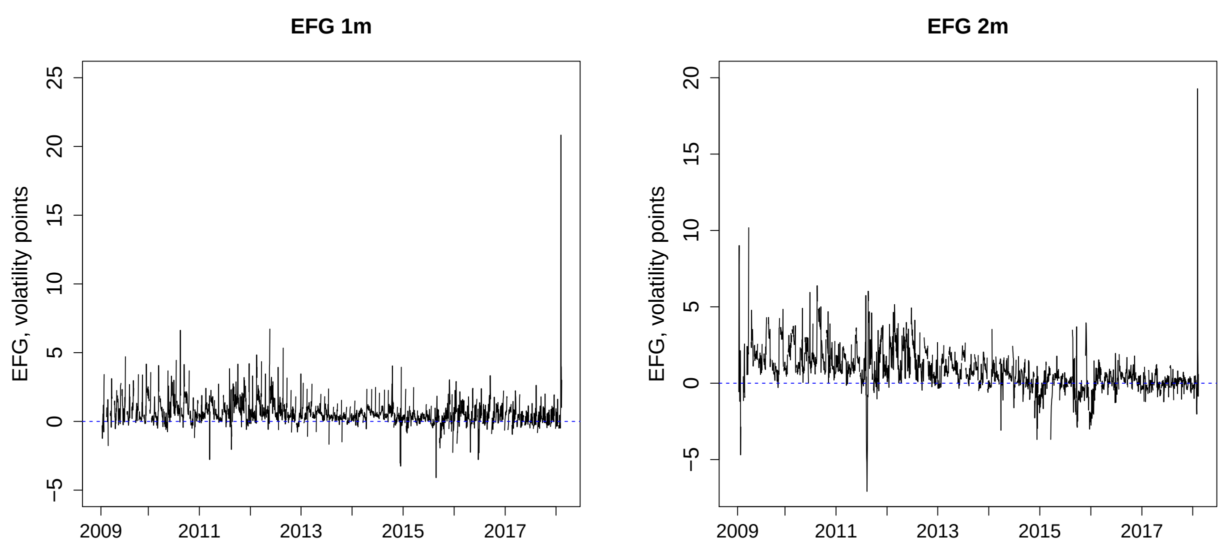

Figure IA.3. ETF futures gap: daily plots. The figure shows the dynamics of the ETF futures gap (EFG) for one and two months maturities after the introduction of the first VIX ETF (29 January 2009). EFG is in volatility points, daily frequency.

Previous volumes in this series

951 July 2021	Distrust or speculation? The socioeconomic drivers of US cryptocurrency investments	Raphael Auer and David Tercero-Lucas
950 June 2021	Fiscal regimes and the exchange rate	Enrique Alberola, Carlos Cantú, Paolo Cavallino and Nikola Mirkov
949 June 2021	The natural interest rate in China	Sun Guofeng and Daniel M Rees
948 June 2021	Central bank digital currency: the quest for minimally invasive technology	Raphael Auer and Rainer Böhme
947 June 2021	Money, technology and banking: what lessons can China teach the rest of the world?	Michael Chui
946 June 2021	The pricing of carbon risk in syndicated loans: which risks are priced and why?	Torsten Ehlers, Frank Packer and Kathrin de Greiff
945 May 2021	US monetary policy and the financial channel of the exchange rate: evidence from India	Shesadri Banerjee and M S Mohanty
944 May 2021	Income inequality, financial intermediation, and small firms	Sebastian Doerr, Thomas Drechsel and Donggyu Lee
943 May 2021	Income inequality and the depth of economic downturns	Emanuel Kohlscheen, Marco Lombardi and Egon Zakrajšek
942 May 2021	FX policy when financial markets are imperfect	Matteo Maggiori
941 May 2021	The digitalisation of money	Markus K Brunnermeier, Harold James and Jean-Pierre Landau
940 May 2021	Monetary-fiscal crosswinds in the European Monetary Union	Lucrezia Reichlin, Giovanni Ricco and Matthieu Tarbé
939 May 2021	The constraint on public debt when $r < g$ but $g < m$	Ricardo Reis
938 May 2021	CCP Auction Design	Wenqian Huang and Haoxiang Zhu

All volumes are available on our website www.bis.org.