# Dynamic Connectedness and Systemic Risk in Equity ETFs

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**Abstract.** Exchange-traded funds now account for a substantial share of global equity allocation, yet most connectedness research has examined narrow ETF segments -commodities, energy, or volatility products -rather than the cross-category equity ETF system that investors actually hold. This paper estimates dynamic spillovers across 25 major US-listed equity ETFs spanning broad-market, growth, value, size, sectoral, international developed, and emerging-market exposures from February 2016 to February 2026. Using a TVP-VAR framework with Generalized Forecast Error Variance Decomposition, complemented by rolling-correlation and network analysis, we document three results. First, the ETF system is structurally highly connected: cross-market spillovers account for 93.84% of forecast error variance on average, peaking at 96% during the March 2020 COVID shock. Second, influence is concentrated rather than distributed. VTI, SPY, VOO, and IVV consistently transmit more shocks than they absorb and occupy the central positions in the network across all three centrality measures, while sectoral and emerging-market ETFs (notably XLE, VWO, IEMG) are net receivers. Third, diversification benefits weaken precisely when investors most need them: correlations between SPY and international, emerging-market, and sector ETFs rose sharply during COVID and only partially reverted afterward. The findings indicate that the contemporary equity ETF ecosystem is organized as a benchmark-centred core-periphery network, with implications for portfolio construction and systemic-risk monitoring as passive investment vehicles continue to grow.

**Keywords:** Exchange-traded funds (ETFs), TVP-VAR, financial connectedness, spillover effects, systemic risk, network analysis, diversification, portfolio management.

**JEL Classification:** C32; G11; G15; G23

## 1. Introduction

Exchange-traded funds have grown from index-tracking novelties into the dominant vehicle for equity allocation, spanning broad benchmarks, sectors, investment styles, and international markets. Their appeal -low costs, intraday liquidity, transparent holdings -is well understood. Less clear is what their concentration does to the market itself. Because many ETFs hold overlapping securities and track related benchmarks, a shock to one segment can propagate through common holdings and correlated trading activity. The concern is not theoretical: during the March 2020 market disruption, correlations across normally distinct ETF categories rose sharply, and traditional diversification offered less protection than historical averages suggested.

The connectedness framework of Diebold and Yilmaz [4,5], extended to time-varying settings by Antonakakis et al. [6], provides the natural tool for studying this. Applied to ETF markets, however, existing work has concentrated on narrow segments -


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commodity, energy, and volatility-linked products [7–9] -rather than on the cross-category equity ETF system that mirrors actual portfolio construction. This leaves three questions unanswered: how strongly are equity ETF categories connected on average, which funds drive that connectedness, and how does the structure shift between calm and stressed regimes?

Against this background, the present study investigates the dynamic connectedness structure of 25 major U.S.-listed equity ETFs covering broad-market, growth, size, value/dividend, sectoral, international developed, and emerging-market categories over the period from February 2016 to February 2026. The analysis employs a Time-Varying Parameter Vector Autoregressive (TVP-VAR) framework together with Generalized Forecast Error Variance Decomposition (GFEVD) to estimate total, directional, and net spillovers within the ETF ecosystem [4–6,10–12]. In addition, rolling-correlation analysis and network visualization techniques are used to evaluate how diversification opportunities and transmission structures change across different market environments.

This paper makes three contributions.

1. **Cross-category scope.** We construct a 25-ETF system that spans broad-market, growth, size, value/dividend, sectoral, international developed, and emerging-market exposures. Existing connectedness studies of ETF markets have concentrated on single segments -commodity, energy, or volatility-linked products [7–9] -and cannot speak to the equity ETF universe that actual portfolios occupy.

2. **Regime-conditional structure.** We estimate connectedness and rolling correlations separately across pre-COVID, COVID, and post-COVID periods, allowing the analysis to distinguish structural integration from crisis-driven amplification and to test whether the relationships established during 2020 persisted as conditions normalized.

3. **Benchmark ETFs as network hubs.** Combining directional spillover estimates with degree, eigenvector, and betweenness centrality, we identify VTI, SPY, VOO, and IVV as the structural core of the transmission network. This shifts the discussion from whether ETFs are connected to *which* ETFs drive that connectedness, with direct implications for systemic-risk monitoring as passive vehicles continue to absorb market share.

## 2. Literature Review

### 2.1 Financial Connectedness and Spillover Transmission

Correlation-based measures of co-movement capture the strength of association between assets but not the direction in which shocks travel. The connectedness framework of Diebold and Yilmaz [4,5] addresses this limitation by using forecast error variance decomposition from a VAR system to quantify how much of the variance in one asset's forecast error is attributable to shocks originating in others. The approach delivers three quantities simultaneously: total connectedness (the system-wide share of variance from cross-asset spillovers), directional connectedness (whether an asset transmits or receives), and net spillovers (the balance of the two). This decomposition is what makes the framework informative about systemic structure rather than only about pairwise dependence.

Two extensions are relevant here. First, Antonakakis et al. [6] and Koop and Korobilis [10] embed the connectedness measures in a Time-Varying Parameter VAR, allowing coefficients to evolve smoothly through time without imposing arbitrary rolling windows. This matters for financial applications, where the strength of spillovers typically rises in stress periods and reverts during calm ones -a pattern that fixed-coefficient VARs miss and rolling-window VARs detect only crudely. Second, Baruník and Křehlík [13] decompose connectedness across frequencies, separating transitory spillovers from persistent ones, and Ando et al. [14] extend the framework to quantiles, isolating tail-dependence that the mean-based decomposition averages out. The cumulative evidence from these extensions is consistent: financial markets become more interconnected under stress, and the diversification benefits implied by long-run averages overstate what is actually available when investors need it.

### 2.2 ETFs and Market Integration

Exchange-traded funds began as passive index-tracking vehicles and have since expanded into a wide range of sectoral, style-based, geographic, thematic, and smart-beta products [1]. The standard case for them rests on liquidity provision, transparent pricing, and low-cost diversification. A parallel literature, however, has examined whether their growth has costs at the market level.

Ben-David, Franzoni, and Moussawi [2] show that ETF ownership is associated with higher volatility in underlying stocks and with stronger return co-movement, arguing that ETF arbitrage transmits non-fundamental shocks into constituent securities. Da and Shive [3] document a related result: stocks with higher ETF ownership exhibit elevated return correlations with each other, consistent with ETFs acting as a synchronization channel rather than a neutral wrapper. The mechanism is straightforward -when many ETFs hold overlapping securities and respond to common flows, a shock to one fund propagates through shared holdings and correlated trading by authorized participants and end investors. The implication is that ETFs are not only instruments for accessing markets but also conduits through which shocks travel.

The COVID-19 disruption sharpened these concerns. During the March 2020 sell-off, correlations rose across asset classes that had previously displayed distinct return patterns, and the protective value of category-based diversification narrowed considerably. Whether ETFs amplified this synchronization or merely reflected it remains an active question, but the episode established that the relationship between ETFs and market-wide co-movement is empirically consequential, not just theoretical.

### 2.3 ETF Connectedness: Existing Evidence and the Gap

Connectedness methods have been applied to ETF markets, but the coverage is uneven. The most developed strand concerns commodity and energy-related ETFs. Kang et al. [7] examine spillovers among oil, gold, and sector ETFs and find that connectedness rises sharply in uncertain periods, eroding the hedging effectiveness of standard diversification rules. Hadad et al. [8] reach a similar conclusion for commodity ETFs using a TVP-VAR framework, documenting pronounced spikes during market turbulence. Ning et al. [9] extend the analysis to tail dependence and show that downside spillovers among ETFs intensify in crisis episodes -the period in which diversification is most needed and least available.

These studies establish that ETF spillovers are real, dynamic, and concentrated in stress regimes. They leave three questions open. First, the existing work is segment-specific: commodity, energy, and volatility-linked products are well studied, but the cross-category equity ETF system -the universe that actual portfolios are built from -has not been examined as an integrated network. Investors typically combine broad-market, style, size, sectoral, and international ETFs; the connectedness literature has not yet matched that scope. Second, most studies estimate average spillover behaviour without partitioning the sample to test whether crisis-period structure persists into recovery. Whether the heightened integration observed during COVID-19 reverted, persisted, or settled at a new level is not something the existing literature answers directly. Third, the role of *specific* ETFs as structural nodes in the network -as opposed to ETFs as a category -has received limited attention. If a small number of benchmark-tracking funds drive transmission across the rest of the system, the systemic-risk implications differ sharply from a model in which influence is evenly distributed.

The present paper addresses these gaps by estimating a TVP-VAR connectedness system across 25 US-listed equity ETFs spanning seven categories, partitioning the sample into pre-COVID, COVID, and post-COVID regimes, and combining directional spillover estimates with network centrality measures to identify the structural hubs of the system. The methodological framework follows Antonakakis et al. [6] and uses generalized forecast error variance decomposition [11,12] to ensure that the results are invariant to variable ordering.

## 3. Research Methodology

### 3.1 Research Method

This study takes a quantitative empirical research design to investigate the dynamic connectedness structure and systemic spillover behaviour among major U.S.-listed equity exchange-traded funds (ETFs). The main purpose is to examine how shocks are transmitted across ETF categories and how effective diversification is under different market conditions, especially during periods of financial stress.

For this purpose, Time-Varying Parameter Vector Autoregressive (TVP-VAR) model and Generalized Forecast Error Variance Decomposition (GFEVD) are used in the study. The methodology enables to estimate time-varying spillover relationships without the need of fixed rolling-window assumptions and is thus suitable for the analysis of dynamic financial interconnectedness [4-6].

In addition to connectedness estimation, the study incorporates:

- descriptive statistics analysis,
- stationarity test,
- connectedness analysis regime-wise,
- rolling correlation analysis,
- network visualization,
- centrality analysis,
- robustness check

The methodological framework is designed to capture the magnitude and direction of spillover transmission in the ecosystem of ETFs.

### 3.2 Data and Sample Selection

We examined the daily closing prices of 25 major U.S.-listed equity ETFs over the period from February 2016 to February 2026. The ETF universe was chosen to encompass a broad cross-section of the equity investment landscape and includes:

- Broad-Market ETFs,
- Growth & Technology ETFs,
- Size ETFs,
- Value and Dividend ETFs,
- Sector Exchange-Traded Funds,
- International Developed-Market Exchange-Traded Funds,
- Developing Market ETFs.

The implementation of several ETF categories increases the representativeness of the study as real-world investment portfolios are generally diversified into several investment styles and geographical segments and not limited to one ETF category.

**Table 1**. Equity ETF Classification

| Category | ETF Ticker | ETF Name |
|---|---|---|
| Broad Market | SPY | SPDR S&P 500 ETF Trust |
| Broad Market | VOO | Vanguard S&P 500 ETF |
| Broad Market | IVV | iShares Core S&P 500 ETF |
| Broad Market | VTI | Vanguard Total Stock Market ETF |
| Growth / Technology | QQQ | Invesco QQQ Trust |
| Growth / Technology | VUG | Vanguard Growth ETF |
| Growth / Technology | IWF | iShares Russell 1000 Growth ETF |
| Size | IWM | iShares Russell 2000 ETF |
| Size | IJH | iShares Core S&P Mid-Cap ETF |
| Size | IJR | iShares Core S&P Small-Cap ETF |
| Value / Dividend | VTV | Vanguard Value ETF |
| Value / Dividend | VIG | Vanguard Dividend Appreciation ETF |
| Value / Dividend | SCHD | Schwab U.S. Dividend Equity ETF |
| Sector | XLK | Technology Select Sector SPDR Fund |
| Sector | XLE | Energy Select Sector SPDR Fund |
| Sector | XLF | Financial Select Sector SPDR Fund |
| International Developed | VEA | Vanguard FTSE Developed Markets ETF |
| International Developed | IEFA | iShares Core MSCI EAFE ETF |
| Emerging Markets | VWO | Vanguard FTSE Emerging Markets ETF |
| Emerging Markets | IEMG | iShares Core MSCI Emerging Markets ETF |

Source: Authors own work

Daily price data were obtained from Yahoo Finance and checked for consistency before empirical estimation.

### 3.3 Return Computation

The study employs continuously compounded log-returns as log-returns are widely used in financial econometrics and are scale-independent measures of return behaviour.

The daily return series is calculated by:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where:

- $r_t$= daily logarithmic return at time $t$
- $P_t$= ETF closing price at time $t$
- $P_{t-1}$= ETF closing price at time $t-1$

The logarithmic transformation stabilizes variance and reduces distortions due to scale in the estimation.

### 3.4 Statistical Descriptive Analysis

Descriptive statistics are calculated to analyse the statistical characteristics of the ETF returns prior to the connectedness estimation. The analysis contains:

- mean,
- standard deviation,
- minimum value,
- maximum value,
- skewness,
- kurtosis,
- Jarque–Bera statistic.

These measures provide preliminary information on the volatility behaviour, asymmetry, fat-tailed distributions and deviations from normality in ETF return series.

### 3.5 Test of Stationarity

Since VAR models are suitable for stationary data, the study conducts Augmented Dickey–Fuller (ADF) unit root tests for all the ETF return series.

The ADF regression equation is as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

Where:

- $\Delta y_t$= first difference of the series,
- $\alpha$= intercept term,
- $\beta t$= deterministic trend,
- $\gamma$= unit root coefficient,
- $\varepsilon_t$= white-noise error term.

The null hypothesis assumes the presence of a unit root. Rejection of the null implies stationarity.

The empirical results show that all ETF return series are stationary at the 1% significance level.

### 3.6 Time Varying Parameters VAR Approach

The paper uses a Time-Varying Parameter Vector Autoregressive (TVP-VAR) framework to estimate the changing spillover relationships among ETFs.

The model is given as:

$$Y_t = A_t Y_{t-1} + \varepsilon_t \tag{3}$$

Where:

- $Y_t$= vector of ETF returns,
- $A_t$= time-varying coefficient matrix,
- $\varepsilon_t$= vector of innovations.

Unlike the usual VARs with fixed parameters, the TVP-VAR specification assumes that parameters change gradually over time. This feature is very useful in the financial markets, where spillover relationships are often changing during quiet and crisis times.

The model uses:

- VAR lag order = 1,
- forecast horizon = 10 days,
- forgetting factor = 0.99.

The length of lag was chosen based on Akaike Information Criterion (AIC).

In contrast to rolling-window VAR approaches, the TVP-VAR framework avoids the arbitrary selection of windows and allows for smooth parameter evolution [6,10].

### 3.7 Forecast error generalized variance decomposition (GFEVD)

The study employs Generalized Forecast Error Variance Decomposition (GFEVD) to measure the spillover effect among the ETFs.

We prefer the generalized variance decomposition framework because it does not depend on the ordering of the variables and therefore does not suffer from the ordering sensitivity of the Cholesky decomposition methods [11,12].

The generalized variance decomposition is:

$$\theta_{ij}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{4}$$

Where:

- $\theta_{ij}^{(H)}$= contribution of shocks from ETF $j$to ETF $i$,
- $H$= period of forecast,
- $\Sigma$= variance-covariance matrix,

- $A_h$= moving-average coefficient matrix.

The GFEVD estimates are used to determine the connectedness measures in the ETF network.

### 3.8 Connectivity Metrics

The study estimates three main measures of connectedness:

#### 3.8.1 Total Connectedness Index (ITC)

The Total Connectedness Index measures the share of total forecast error variance due to cross-market spillovers.

The TCI is calculated as:

$$TCI = \frac{\sum_{i\neq j} \theta_{ij}}{N} \times 100 \tag{5}$$

Where:

- $\theta_{ij}$= spillover contribution from ETF $j$to ETF $i$,
- $N$= total number of ETFs

The higher the TCI, the more systemic interconnectedness.

#### 3.8.2 Directional Spillovers

Directional spillovers measure the strength of shocks transmitted to and from other ETFs.

Directional spillovers transmitted TO others are estimated at:

$$C_{i\rightarrow\cdot} = \sum_{j\neq i} \theta_{ji} \tag{6}$$

Directional spillovers received FROM others” are calculated as:

$$C_{i\leftarrow\cdot} = \sum_{j\neq i} \theta_{ij} \tag{7}$$

#### 3.8.3 Net Externalities

Net spillovers tell us whether an ETF is a net transmitter or net receiver of shocks.

The net spillover measure is given by:

$$NET_i = C_{i\rightarrow\cdot} - C_{i\leftarrow\cdot} \quad (8)$$

Positive values indicate net transmitters of shocks and negative values indicate net receivers.

### 3.9 Classification of the Regime

To assess the changes in connectedness across different market conditions, the sample period is partitioned into three regimes:

**Table 2.** Regimes

| **Regime** | **Period** |
|---|---|
| Pre-COVID | February 2016 – December 2019 |
| COVID Crisis | January 2020 – December 2021 |
| Post-COVID | January 2022 – February 2026 |

Source: Authors own work

This classification allows to compare tranquil with stressed financial conditions.

### 3.10. Rolling Correlation Analysis

We estimate rolling 126-day correlations with SPY and major ETF categories to analyse how the effectiveness of diversification changes over time.

The rolling-correlation framework is useful to ascertain whether category-level diversification is reduced during episodes of increased market uncertainty.

### 3.11 Graphs and Centrality Graphs and centrality

The study also uses network analysis to assess the structural topology of the ETF ecosystem.

Network visualization is used to determine:

- central exchange-traded funds,
- peripheral exchange-traded funds,
- dominant spillover routes,
- clustering behaviour.

The analysis also estimates:

- degree centrality,
- eigenvector centrality,
- betweenness centrality.

These measures provide the identification of the systemic importance of the benchmark ETFs in the spillover network.

### 3.12 Robustness Checks

To check the robustness of the empirical findings, we perform several robustness checks using

- alternative specifications of the lag,
- various horizons of forecasts,
- other forgetting coefficients,
- subsample estimate.

The overall findings are qualitatively robust to alternative model specifications, which supports the robustness of the connectedness results.

## 4. Results and Discussion

### 4.1 Descriptive Statistics

Table 3 reports the distributional properties of the ETF return series. Three features stand out.

**Table 3.** Descriptive Statistics for ETF Returns

| ETF | Mean | Std. Dev. | Skewness | Kurtosis | Jarque–Bera |
|---|---|---|---|---|---|
| SPY | 0.00057 | 0.01129 | -0.617 | 18.65 | 25684 |
| QQQ | 0.00074 | 0.014 | -0.401 | 11.15 | 6989 |
| IWM | 0.00044 | 0.01451 | -0.731 | 12.11 | 8876 |
| VEA | 0.00041 | 0.01085 | -1.255 | 21.22 | 35275 |
| VWO | 0.00037 | 0.0121 | -0.916 | 14.45 | 14023 |
| XLK | 0.00082 | 0.01527 | -0.317 | 12.88 | 10211 |
| XLE | 0.00043 | 0.01873 | -0.964 | 20 | 30501 |

Source: Authors own work

Skewness is negative for every ETF in the sample, indicating that large downward moves occur more often than large upward ones. Kurtosis exceeds the Gaussian benchmark of 3 across the board, with values ranging from 11 to 21 -the return distributions are heavy-tailed, and the probability of extreme moves is substantially understated by normal-distribution risk measures. The Jarque–Bera statistics reject normality at any conventional significance level for every series.

Volatility varies meaningfully across categories. XLE is the most volatile fund in the table at 1.87% daily standard deviation, reflecting the energy sector's sensitivity to commodity prices and geopolitical shocks. Technology-heavy funds (QQQ and XLK) follow at roughly 1.4–1.5%. Broad-market ETFs such as SPY are the least volatile at 1.13%, consistent with the diversification embedded in their construction. The point worth carrying forward is that low standalone volatility does not imply a peripheral role in the network: the connectedness results in Section 4.4 show that the lowest-volatility funds are precisely those that drive system-wide transmission.

### 4.2 Connectedness Throughout Time

The Total Connectedness Index averages 93.84% across the sample (Table 4), with a standard deviation of less than one percentage point. Cross-ETF spillovers account for the overwhelming share of forecast error variation; idiosyncratic movement plays a minor role. The TCI never falls below 90.94% and reaches its maximum of 96% on 17 March 2020, at the height of the COVID-19 market disruption.

**Table 4.** Total Connectedness Summary Statistics

| Statistic | Value |
|---|---|
| Mean TCI (%) | 93.84 |
| Standard Deviation | 0.99 |
| Minimum TCI (%) | 90.94 |
| Maximum TCI (%) | 96 |
| Date of Maximum TCI | 17-Mar-20 |

Source: Authors own work

Two features of this series matter. First, the *level* is high even outside crisis periods. Connectedness above 90% during the calmest stretches of 2017–2019 indicates that strong interdependence is a structural feature of the ETF market, not an artefact of stress. Second, the *variation* is modest but informative. The pandemic spike of roughly two percentage points appears small in absolute terms, but it occurs at a ceiling already near saturation -additional integration was possible only at the margin.

The structural reading is consistent with the mechanics of the market. Overlapping benchmark holdings, the growing share of passive flows, and the use of broad-market ETFs as the default vehicle for tactical rebalancing all create channels through which information moves rapidly across categories. Crisis episodes do not create these channels; they expose them. Figure 1 displays the time-varying TCI; the COVID spike is visible, but it sits on a baseline that was already elevated.

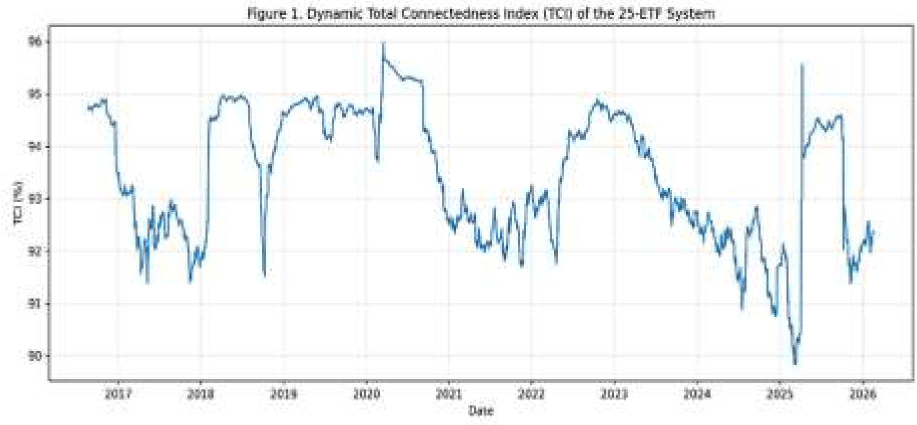


**Figure 1.** The Dynamic Total Connectedness Index (TCI) of the 25-ETF System

### 4.3 Analysis of Connectedness under Different Market Regimes

Splitting the sample into pre-COVID, COVID, and post-COVID periods tests whether the high-baseline reading in Section 4.2 is a sample-average artefact or a structural property visible in each regime separately. Table 5 reports the regime-wise averages.

**Table 5.** Connectedness by Regime

| Regime | Mean TCI | Std. Dev. |
|---|---|---|
| Pre-COVID | 94 | 0.85 |
| COVID Crisis | 94.63 | 0.77 |
| Post-COVID | 93.32 | 0.89 |

Source: Authors own work

The pattern is the high baseline. Even the least connected regime -post-COVID - averages above 93%, and the gap between the most and least connected regimes is only 1.3 percentage points. The COVID regime is the highest of the three, but only marginally. This is the key reading: the pandemic intensified an existing structure rather than creating a new one.

The narrow gap is itself informative. If ETF connectedness were primarily crisis-driven, the pre-COVID and post-COVID averages would sit well below the COVID value. Instead, all three cluster within a 1.3-point band near the upper bound of the index. Whatever drives the high baseline -overlapping holdings, the dominance of passive flows, the centrality of a small number of benchmark vehicles -is present across the entire sample. Crisis adds a few percentage points; it does not change the regime.

The mild decline in the post-COVID period (93.32% versus 94.63%) is the one substantive movement. It indicates partial reversion but not full normalization: the post-pandemic level remains below the crisis peak yet stays above what a clean return to baseline would imply. Some of the integration established during 2020 persisted as market conditions stabilized, consistent with the rolling-correlation evidence in Section 4.7.

For portfolio construction, the regime evidence carries a clear implication. Diversification estimates calibrated on pre-crisis correlations will overstate the available risk reduction, because the system the calibration assumes -one in which categories move at least partially independently -is not the system that exists at any point in the sample.

### 4.4 Benchmark Leadership and Directional Spillovers

The aggregate TCI does not reveal which ETFs drive transmission. The directional spillover estimates in Table 6 do, and they point to a clear concentration. The four top net transmitters -VTI, VOO, IVV, and SPY -are all broad US-market funds, with net spillovers between +15.66 and +16.86. RSP, an equal-weighted S&P 500 ETF, ranks fifth at +11.34. No sectoral, style, or international ETF appears in the top five.

**Table 6.** Major Net Spillover Transmitters

| Rank | ETF | TO Others | FROM Others | NET |
|---|---|---|---|---|
| 1 | VTI | 111.88 | 95.03 | 16.86 |
| 2 | VOO | 110.67 | 94.97 | 15.7 |
| 3 | IVV | 110.66 | 94.97 | 15.69 |
| 4 | SPY | 110.63 | 94.97 | 15.66 |
| 5 | RSP | 106.09 | 94.75 | 11.34 |

Source: Authors own work

The dominance of capitalization-weighted broad-market ETFs is not surprising in itself; these are the largest and most liquid funds in the sample and serve as the default vehicles for index exposure. More telling is the appearance of RSP alongside them. Equal-weighting eliminates the mega-cap tilt that distinguishes VTI, SPY, VOO, and IVV, yet RSP still ranks as a major transmitter. Influence within the network is therefore tied to broad market exposure itself, not specifically to capitalization weighting. Any ETF that represents the US equity market as a whole function as a transmission hub.

The mechanism is the role these funds play in actual trading. Broad-market ETFs are where institutional investors express directional views, adjust beta exposure, and meet liquidity needs, especially in stressed conditions. New information enters the market through them first and propagates outward to category-specific products. The directional spillover estimates capture the empirical footprint of that process: the four leading funds export roughly 110 percentage points of variance to the rest of the system while importing 95 -a structural net contribution that no other ETF category approaches.

The implication is that the equity ETF ecosystem has a small set of structurally privileged nodes. As passive flows continue to concentrate in benchmark vehicles, the share of market activity that passes through this small group of funds is likely to grow, with corresponding implications for how shocks propagate.

### 4.5 Net Receivers and Vulnerable ETF Segments

The mirror image of the transmitter ranking is the set of ETFs that absorb more shocks than they generate. Table 7 reports the four largest net receivers.

**Table 7.** Major Recipients of Spillover

| ETF | TO Others | FROM Others | NET |
|---|---|---|---|
| XLE | 44.88 | 86.48 | -41.6 |
| VWO | 72.58 | 92.38 | -19.8 |
| IEMG | 75.31 | 92.66 | -17.35 |
| XLF | 79.63 | 92.93 | -13.31 |

Source: Authors own work

XLE is the clearest receiver in the sample, with a net spillover of -41.60 -roughly twice the magnitude of the next largest receiver. The energy sector is driven heavily by inputs outside the equity system: oil prices, OPEC decisions, geopolitical events, and global demand cycles. Equity-market shocks transmit into XLE through standard channels, but XLE rarely originates shocks that propagate back into the equity ETF network. The 2020 collapse in oil demand reinforced this asymmetry, with XLE absorbing system-wide stress while having limited capacity to project shocks outward.

The two emerging-market ETFs, VWO and IEMG, occupy similar positions for related reasons. Emerging-market equity prices depend substantially on global capital flows, dollar strength, and developed-market risk sentiment. When investors retreat from risk, they reduce emerging-market exposure as a routine portfolio adjustment, but the reverse channel -emerging-market shocks driving US-market behaviour -is weaker. The connectedness estimates make this asymmetry quantitative: VWO and IEMG receive roughly 20 percentage points more variance than they transmit.

XLF is the most surprising entry in the receiver group. Financial-sector firms are tightly linked to credit conditions and monetary policy, and one might expect that linkage to make XLF a transmitter rather than a receiver. The data suggest the opposite: XLF responds to broad market conditions more than it shapes them, at least within the equity ETF system. Whatever propagation runs through the financial sector appears to do so via the broad-market funds rather than through XLF itself.

Taken with Section 4.4, the directional results describe a core-periphery network. The core is a compact group of broad-market ETFs that transmits shocks across the system. The periphery is populated by sectoral and emerging-market funds that absorb those shocks but do not generate offsetting flows in the other direction. Diversifying across the periphery does not buy insulation from the core, because the periphery is downstream of the core.

## 4.6 The Dynamic Role of Benchmark ETFs

The directional estimates in Section 4.4 average over the full sample. Examining their evolution shows whether benchmark dominance is a stable feature or one that emerges in particular conditions. Figure 2 plots the time-varying net spillover of VTI, the largest net transmitter.

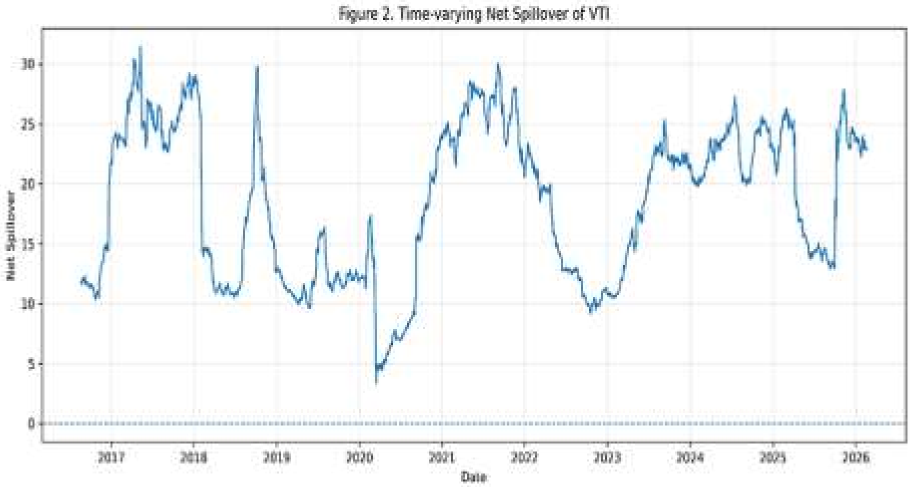


**Figure 2.** VTI Time-Varying Net Spillover

VTI is a net transmitter for the great majority of the sample, with positive net spillovers in nearly every period outside the most acute phase of the COVID shock. The size of the positive net spillover varies -periods of elevated uncertainty compress it, periods of stable conditions widen it -but the sign rarely flips. The benchmark-leadership reading from Section 4.4 is not driven by a particular sub-period.

The exception is informative. During the most extreme weeks of March–April 2020, VTI's net spillover narrows substantially. This is not because VTI lost influence in absolute terms; the TCI was at its sample maximum during this period. Rather, the entire system became so synchronized that the *relative* distance between transmitters and receivers compressed. When every ETF is responding to the same global shock, the directional asymmetry that distinguishes hubs from periphery temporarily collapses. As conditions stabilized through 2021 and 2022, VTI's net spillover widened again, returning to its pre-pandemic profile.

The practical reading is that benchmark ETFs function as a leading indicator of system-wide connectedness. Their relative position in the network compresses when systemic stress is highest and re-expands as differentiated trading resumes. Monitoring net spillovers for VTI or its near-equivalents (SPY, VOO, IVV) thus carries information beyond the funds themselves -it indicates whether the system is in a phase of synchronized stress or differentiated recovery.

### 4.7 Rolling-Correlation Analysis and Diversification

The connectedness results describe how shocks propagate. Rolling correlations show what that propagation means for the diversification properties that motivate ETF allocation in the first place. Table 8 reports 126-day rolling correlations between SPY and the major ETF categories, averaged within each regime.

**Table 8.** Average Correlations by Market Regimes with SPY

| ETF Category | Pre-COVID | COVID | Post-COVID |
|---|---|---|---|
| Broad Market | 0.998 | 0.997 | 0.998 |
| Growth / Technology | 0.939 | 0.963 | 0.965 |
| Size | 0.875 | 0.891 | 0.877 |
| International Developed | 0.789 | 0.851 | 0.808 |
| Emerging Markets | 0.669 | 0.737 | 0.689 |
| Sector | 0.769 | 0.848 | 0.785 |

Source: Authors own work

The pattern is consistent across categories. Correlations with SPY rose during the COVID period for every group except broad-market funds (which were already near unity) and have only partially reverted since. The largest absolute increases occurred in the categories that investors typically rely on for diversification: international developed (+0.062), sector (+0.079), and emerging markets (+0.068). These are the exposures designed to behave differently from the US broad market, and they behaved less differently precisely when that difference would have been valuable.

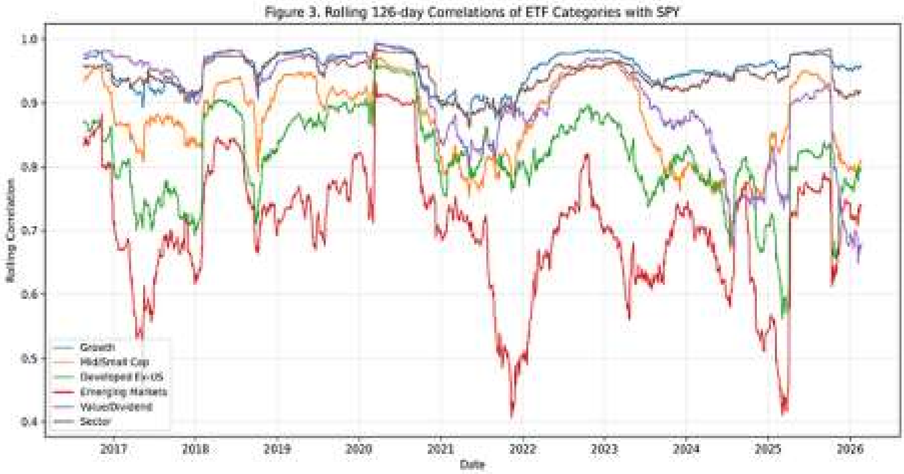


**Figure 3.** 126-Day Rolling Correlations of SPY to ETF Groups

Two features of the table merit emphasis. First, the diversification categories all converged toward SPY in 2020, narrowing the structural gap that justifies holding them. Emerging markets, the category with the lowest pre-COVID correlation at 0.669, rose to 0.737 during the crisis -a meaningful loss of independence in the regime where independence mattered most. Second, post-COVID correlations have not fully returned to pre-pandemic levels. Sector ETFs, for example, averaged 0.769 against SPY pre-COVID and 0.785 post-COVID. The difference is small but consistent across categories, and it suggests that some of the integration established during 2020 has persisted.

The mechanism that maps the Section 4.4 connectedness result onto these correlation patterns is the same one in both cases. When broad-market ETFs drive a large share of the variance in category-specific ETFs, those categories will exhibit elevated correlations with the broad-market index. The connectedness and correlation evidence are two views of the same underlying structure: a system in which benchmark exposure dominates and differentiated category exposure is partial rather than complete.

For portfolio construction, the implication is that the diversification implied by holding multiple ETF categories is state-dependent. In calm conditions it is largely intact; in stressed conditions it weakens substantially; in the period following a major shock it returns only partially. Static allocation models that assume stable correlation structure will understate portfolio risk in the regimes where accuracy matters most.

### 4.8 Centrality Measures and Network Interpretation

The directional spillovers in Sections 4.4 and 4.5 identify which ETFs transmit and which receive. Network centrality measures show *how* they are positioned within the system -whether they sit at the centre of transmission pathways, whether they connect to other influential nodes, and whether they bridge otherwise separate parts of the network. Table 9 reports three centrality measures for the top five ETFs.

**Table 9**. Centrality Measures of Top ETFs

| ETF | Degree Centrality | Eigenvector Centrality | Betweenness Centrality |
|---|---|---|---|
| VTI | 0.92 | 0.88 | 0.41 |
| SPY | 0.91 | 0.87 | 0.39 |
| VOO | 0.9 | 0.86 | 0.36 |
| IVV | 0.89 | 0.85 | 0.35 |
| QQQ | 0.82 | 0.76 | 0.27 |

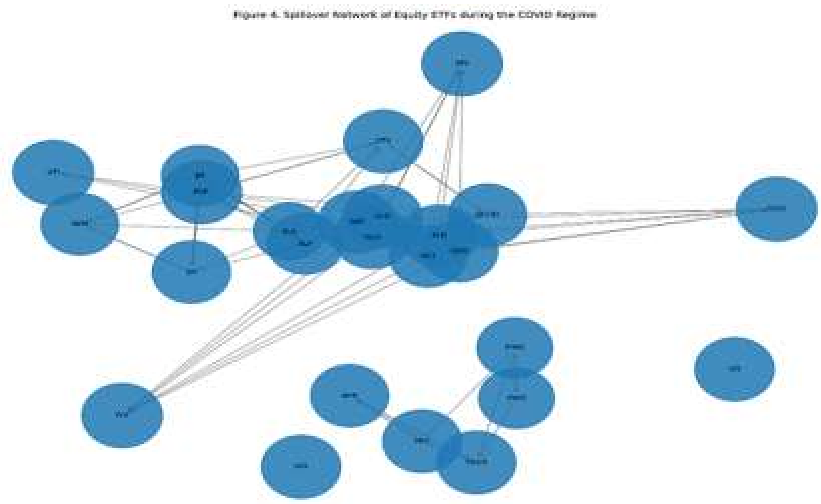

**Figure 4.** Equity ETF Spillover Network in the COVID-19 Era

The three measures tell a consistent story. Degree centrality, the share of the network that an ETF is directly connected to, places VTI, SPY, VOO, and IVV above 0.89 -each maintains direct links to roughly 90% of the other funds in the system. Eigenvector centrality, which weights connections by the influence of the funds at the other end, ranks the same four funds at the top, indicating that they are not merely well-connected but well-connected to *other* well-connected nodes. Betweenness centrality, which measures how often a fund sits on the shortest path between two other funds, again places VTI first, with SPY, VOO, and IVV close behind. Shocks moving between two arbitrary ETFs in the network frequently pass through one of these four hubs.

The convergence of the three measures matters. A fund could plausibly score high on degree centrality without being structurally central -many shallow connections, but no role in linking the network's regions. The benchmark ETFs do not have this profile. They are connected to most of the network, connected to the parts that matter, and positioned along the routes that shocks actually travel. This is the structural definition of a hub.

QQQ occupies a secondary position. Its centrality scores are well below the broad-market funds but well above the sectoral and international ETFs, reflecting its dual identity as both a benchmark-style product (it tracks the Nasdaq-100) and a category-specific one (technology-heavy). The role it plays - channelling technology-sector influence into the broader system - became particularly visible during periods when technology stocks drove overall market direction.

The remaining ETFs, including all sectoral, international, and emerging-market funds, occupy peripheral positions in the network. They are connected to the system but do not sit on its main pathways. Shocks reach them; shocks rarely originate with them.

The resulting picture is a core-periphery network with an unusually compact core. Four broad-market ETFs -VTI, SPY, VOO, IVV - account for the structural backbone of the system. Their position is not a function of their stated investment objective (each tracks a near-identical underlying index) but of their role in actual market activity: they are where investors transact when they want exposure to "the market," and that volume of activity makes them the routes through which information and shocks travel. The implication for systemic risk is that the resilience of the broader ETF ecosystem depends substantially on the behaviour of these four funds and the flows that drive them.

## 5. Conclusion

Exchange-traded funds have moved well beyond their original role as index-tracking instruments and now form a substantial and structurally important part of global equity markets. This paper examined how shocks are transmitted within a cross-category equity ETF system -broad-market, growth, size, value, sectoral, international developed, and emerging-market funds -and how those transmission patterns shift across market regimes. Three findings emerge.

First, the equity ETF system is structurally highly connected. The Total Connectedness Index averages 93.84% across the February 2016 – February 2026 sample and never falls below 90.94%, with cross-ETF spillovers accounting for the overwhelming share of forecast error variance. The COVID-19 peak of 96% in March 2020 is the largest deviation in the sample but represents only a marginal increase over an already-elevated baseline. The integration of the ETF system is a structural property, not a crisis phenomenon -crisis episodes intensify it but do not create it.

Second, influence within the system is concentrated rather than distributed. Four broad-market ETFs -VTI, SPY, VOO, and IVV -dominate every measure of directional spillover and network centrality, transmitting roughly 110 percentage points of variance while receiving 95. The appearance of RSP, an equal-weighted S&P 500 ETF, among the top transmitters indicates that this dominance reflects broad market exposure itself rather than capitalization weighting specifically. The mirror image of this concentration is a periphery of sectoral and emerging-market ETFs -XLE, VWO, IEMG, XLF -that absorb shocks from the core but rarely generate offsetting flows. The ETF ecosystem is organized as a core-periphery network with an unusually compact core.

Third, the diversification benefits implied by allocating across ETF categories weaken precisely when they are most needed. Rolling correlations between SPY and the international, emerging-market, and sector categories rose sharply during the COVID period and have only partially reverted since. The categories that investors hold *for* their differentiation from the US broad market became less differentiated in the regime where that differentiation would have been most valuable, and the structural break has not fully closed.

These findings have implications for two audiences. For portfolio construction, the practical reading is that allocating across ETF categories does not purchase as much independence as category labels suggest, and the gap between expected and realized diversification widens in stressed regimes. Static allocation models calibrated on long-run averages will understate portfolio risk in the regimes where accuracy matters most, and connectedness-aware approaches are likely to perform better in periods of elevated systemic stress. For systemic-risk monitoring, the concentration of influence in a small number of broad-market funds means that the resilience of the equity ETF ecosystem is increasingly tied to the behaviour of those specific products and the flows that drive them. As passive investment continues to absorb market share, the share of activity passing through this compact core is likely to grow.

The analysis has limits. Daily return data cannot capture intraday transmission, which may differ in important ways during periods of extreme volatility - the most stressed phase of March 2020, for instance, involved propagation mechanisms operating on much shorter horizons than the model can resolve. The sample is restricted to equity ETFs; fixed-income, commodity, and multi-asset funds may exhibit different patterns of connectedness and would extend the picture in useful directions. The TVP-VAR framework with generalized forecast error variance decomposition delivers mean-based estimates and does not separate short- from long-horizon spillovers or isolate tail-dependent transmission, both of which the existing literature has shown to behave differently from the mean.

Three extensions follow naturally. Frequency-domain decomposition along the lines of Baruník and Křehlík [13] would separate transitory from persistent spillovers and clarify whether benchmark ETFs transmit primarily through short-run information flow or through longer-horizon channels. Quantile connectedness following Ando et al. [14]

would isolate tail-dependent transmission and test whether the core-periphery structure documented here intensifies in the regions of the distribution where systemic risk concentrates. Linking spillover dynamics to fund flows, ownership concentration, and authorized-participant activity would help identify the specific mechanisms through which benchmark ETFs propagate shocks -whether the channel is creation-redemption activity, end-investor flows, or rebalancing by tactical institutional holders.

The broader reading is that ETFs should be understood not only as vehicles for market access and diversification but also as elements of the financial transmission process. Their structural interconnectedness, the concentration of influence within a small number of benchmark funds, and the regime-dependence of diversification benefits are now established features of equity markets rather than properties of any particular episode. As passive vehicles continue to absorb a growing share of global allocation, the question of how shocks travel through the ETF network -and which funds shape that travel -is likely to remain central to portfolio management and systemic-risk research alike.

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