# Too Big to Co-Move:
# Concentration and Sector Connectedness Around the World

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**Abstract**

The ten largest firms rose from 24% to 41% of S&P 500 market capitalization between 2018 and 2025, and by August 2026 connectedness among the eleven GICS sectors had reached its lowest level in the sample. This paper asks whether concentration explains the disconnection, using daily returns of the Select Sector SPDR funds from October 2018 to August 2026, an uncapped constituent panel with point-in-time membership, a filtered TVP-VAR, and constituent panels for ten other major markets. Concentrated sectors co-move less with the rest of the market. On uncapped U.S. returns, a one-point rise in a sector's top-three share lowers its monthly $R^2$ against the other ten sectors by 0.75 points, and the result holds when concentration paths are randomly reassigned across sectors ($p = 0.04$). The mechanism is granular: in every market studied, a sector's three largest firms co-move less with the market than the rest of the sector, in 78% of 933 sector-years. The link between concentration and co-movement reappears in Japan, Canada and, more weakly, the United Kingdom, but not in the other seven markets; across markets it is strongest where sectors are deep and concentration rose. Everywhere, the shift in weight toward the largest firms is small in aggregate, and sector co-movement fell after 2025 in eight of eleven markets, including several where concentration fell. Net directional connectedness, the usual way to read such results, depends on how the variance decomposition is normalized and overstates the link. Concentration explains which sectors are least connected, not why markets disconnected.

**Keywords:** connectedness, market concentration, granularity, normalization, randomization inference, TVP-VAR
**JEL:** C12, C23, C32, G12, L11

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# 1 Introduction

U.S. equity market concentration is at its highest level in decades. In our constituent panel the ten largest firms held 24% of S&P 500 market capitalization at the end of 2018 and 41% at the end of 2025. Within sectors it is higher still: by August 2026 the three largest firms held 82% of Communication Services and 54% of Information Technology, against 18% of Industrials.

Over the same years the eleven sectors of the index drifted apart. Total connectedness among them, in the sense of Diebold and Yilmaz (2012), peaked in the COVID-19 crash and reached the lowest value of our sample in August 2026. A common reading of concentration is that it makes the market more fragile, because a shock to one giant firm moves everything. The sector-level data suggest something closer to the opposite. A literature following Gabaix (2011) argues that when a few firms are large relative to their aggregate, their idiosyncratic shocks no longer diversify away. Applied one level down, the argument predicts that a sector whose return is driven by two or three firms will look idiosyncratic to the other sectors, and that a market of concentrated sectors will look disconnected. The connectedness and granularity literatures have not met, and this paper tests both predictions.

The sample covers the eleven GICS sectors from October 2018 to August 2026, a window that contains the late-2018 sell-off, the COVID-19 crash, the 2022 rate shock, the March 2023 regional bank failures, and the April 2025 tariff shock. Sector returns come from the Select Sector SPDR funds, which track the full GICS sectors with point-in-time membership. Concentration comes from a separate constituent panel that uses point-in-time index membership, historical share counts, and the March 2023 GICS reclassification. Time variation comes from a TVP-VAR estimated by a forgetting-factor Kalman filter (Koop and Korobilis, 2013; Antonakakis et al., 2020), so each daily estimate uses only data available that day. A firm-level decomposition splits every sector's return into the return on its three largest firms and the return on the rest of the sector. The same constituent design is then applied to ten other markets, which together with the United States cover eight of the ten largest economies.

The answer comes in three parts.

First, concentrated sectors do co-move less. On uncapped constituent returns, a one-point rise in a sector's lagged top-three share lowers its monthly $R^2$ against the other ten sectors by 0.75 points, with sector and month fixed effects. The estimate survives inference built for slow-moving regressors, including a permutation test that reassigns concentration paths across sectors. The firm-level decomposition shows the mechanism: the largest firms co-move less with the market than the rest of their sector in 91 of 99 U.S. sector-years, and in 78% of 933 sector-years across all eleven markets. The concentration effect itself travels less far. It reappears in Japan and Canada and more weakly in the United Kingdom, but not in the other seven markets, and across markets it is strongest where sectors are deep and concentration rose. Korea runs the other way: there, technology grew to more than half of the market, and its giants' shocks became the market's.

Second, concentration does not explain why markets disconnected. Holding each sector's top-three weight at its 2018 level changes the U.S. system's average squared correlation over the last

twelve months by less than one point, against a fall of 28 points since 2018, and the composition effect is no larger than 2.1 points in any market. The decline is broad. Average pairwise correlation among the U.S. funds fell from 0.58 in 2025 to 0.21 in the first eight months of 2026, and sector co-movement fell in eight of the eleven markets, including China, Germany, and Australia, where concentration fell or held steady. In the United States the largest firms instead form a cluster that crosses three GICS sectors, so sector returns increasingly mix that cluster with firms unrelated to it.

Third, the standard way of reading connectedness overstates the link. Connectedness among daily sector returns is contemporaneous: Granger links found by classical tests vanish under heteroskedasticity-robust inference, and lagged cross-sector returns have negative out-of-sample $R^2$ for every sector (Appendix A). The directional measures are therefore a transformation of the correlation matrix, and the transformation depends on how the variance decomposition is normalized. Under the usual row normalization, concentrated sectors look like net receivers of shocks; under the scalar normalization of Caloia et al. (2019), the effect on net connectedness disappears. Panel regressions of filtered connectedness on concentration also produce large $t$-statistics that random pairings of sectors match. These cautions apply to any connectedness study built on daily equity returns.

The rest of the paper is organized as follows. Section 2 places the paper in the literature, Section 3 describes the data, and Section 4 sets out the econometrics. Section 5 reports results for the United States and the ten other markets, and Section 6 discusses the results that run against intuition. Appendix A reports the lead-lag tests and Appendix B the summary statistics and static connectedness.

## 2 Related literature

**Concentration and granularity.** Gabaix (2011) shows that when the firm-size distribution is fat-tailed, idiosyncratic shocks to large firms generate aggregate fluctuations. Grullon et al. (2019) and Kwon et al. (2024) document rising concentration across U.S. industries. Campbell et al. (2001) show that idiosyncratic volatility is a large and time-varying part of stock risk. To our knowledge, no study relates within-sector concentration to a sector's position in the connectedness network.

**Connectedness.** Diebold and Yilmaz (2009) measure spillovers with forecast-error variance decompositions from a VAR; Diebold and Yilmaz (2012) replace the Cholesky decomposition with the order-invariant generalized decomposition of Koop et al. (1996) and Pesaran and Shin (1998), which also yields directional measures; Diebold and Yilmaz (2014) link the measures to network degree. Antonakakis et al. (2020) replace the rolling window with a TVP-VAR estimated by the forgetting-factor Kalman filter of Koop and Korobilis (2013), and Baruník and Křehlík (2018) decompose connectedness by frequency. Billio et al. (2012) measure system-wide linkages among financial institutions with principal components and Granger networks. Two papers question how the generalized decomposition is normalized. Caloia et al. (2019) show that row normalization can

produce net spillovers of the wrong sign and rank, and recommend dividing by the largest row sum. Lastrapes and Wiesen (2021) propose a joint spillover index and find, on U.S. industry returns, that it can differ substantially from the generalized one.

**Inference with persistent regressors.** Ferson et al. (2003) show that regressions involving persistent financial series produce spurious significance even in large samples. With few clusters, Cameron et al. (2008) and Webb (2023) recommend the wild cluster bootstrap, and Young (2019) shows how often randomization tests overturn conventional significance.

# 3 Data

## 3.1 Sector returns and volatility

Sector returns are daily log returns, in percent, of the eleven Select Sector SPDR funds (XLC, XLY, XLP, XLE, XLF, XLV, XLI, XLK, XLB, XLRE, XLU), adjusted for distributions. The sample runs from 1 October 2018 to 31 August 2026, 1,989 trading days. The start date follows the September 2018 GICS reorganization that created Communication Services. The funds cover every member of each sector, their membership is point-in-time, and they are investable. Their disadvantage is weight capping, which limits single-name weights and therefore understates concentration where it is highest. We address this with a second return series built from constituents without caps (Section 3.2).

Volatility is the Parkinson (1980) range estimator, $\hat{\sigma}_t^2 = (\ln H_t - \ln L_t)^2/(4 \ln 2)$, annualized and in logs, $v_t = \ln(100\sqrt{252\,\hat{\sigma}_t^2})$. Table B1 in Appendix B reports summary statistics.

## 3.2 Constituents, market capitalization, and concentration

Index membership is point-in-time: current members enter on their S&P 500 addition date, and firms removed during the sample enter and leave on their actual dates. Removed firms are kept when price and share data remain available, which recovers 78 firms; firms that were acquired and delisted cannot be recovered. A removed ticker whose price path duplicates a current ticker is treated as a rename rather than a second firm. The panel covers 428 firms on the first day and 497 on the last.

Market capitalization is the daily closing price times historical shares outstanding, with both series on the same split basis and a five-day rolling median applied to the vendor share series to remove recording spikes. Firms with two listed share classes are counted once. Firms are assigned to GICS sectors with the March 2023 reclassification applied on its effective date: payment processors are in Information Technology before 17 March 2023 and in Financials after, and Target, Dollar General, and Dollar Tree move from Consumer Discretionary to Consumer Staples on the same date.

For sector $s$ on day $t$, with market-capitalization weights $w_{i,t}$ inside the sector, the two concentration measures are the Herfindahl index $\mathrm{HHI}_{s,t} = \sum_i w_{i,t}^2$ and the top-three share, the sum of the three largest weights. Both use total rather than float-adjusted market capitalization, which is the

economically relevant size for the granular argument. The index-level top-ten share computed this way is 24.1% at the end of 2018, 33.0% at the end of 2023, and 40.8% at the end of 2025, within one to three points of published float-adjusted figures.

Figure 1 shows the top-three share by sector. Concentration rose most in Communication Services (62% to 82%), Consumer Discretionary (48% to 65%), Information Technology (45% to 55%), and Consumer Staples (38% to 49%), and fell slightly in Industrials, Financials, and Energy.

A second, uncapped return series weights each constituent's daily return by its previous-day market capitalization inside its sector. Its daily correlation with the corresponding fund is between 0.986 and 0.999 for ten sectors and 0.926 for Communication Services, where fund caps bind hardest.

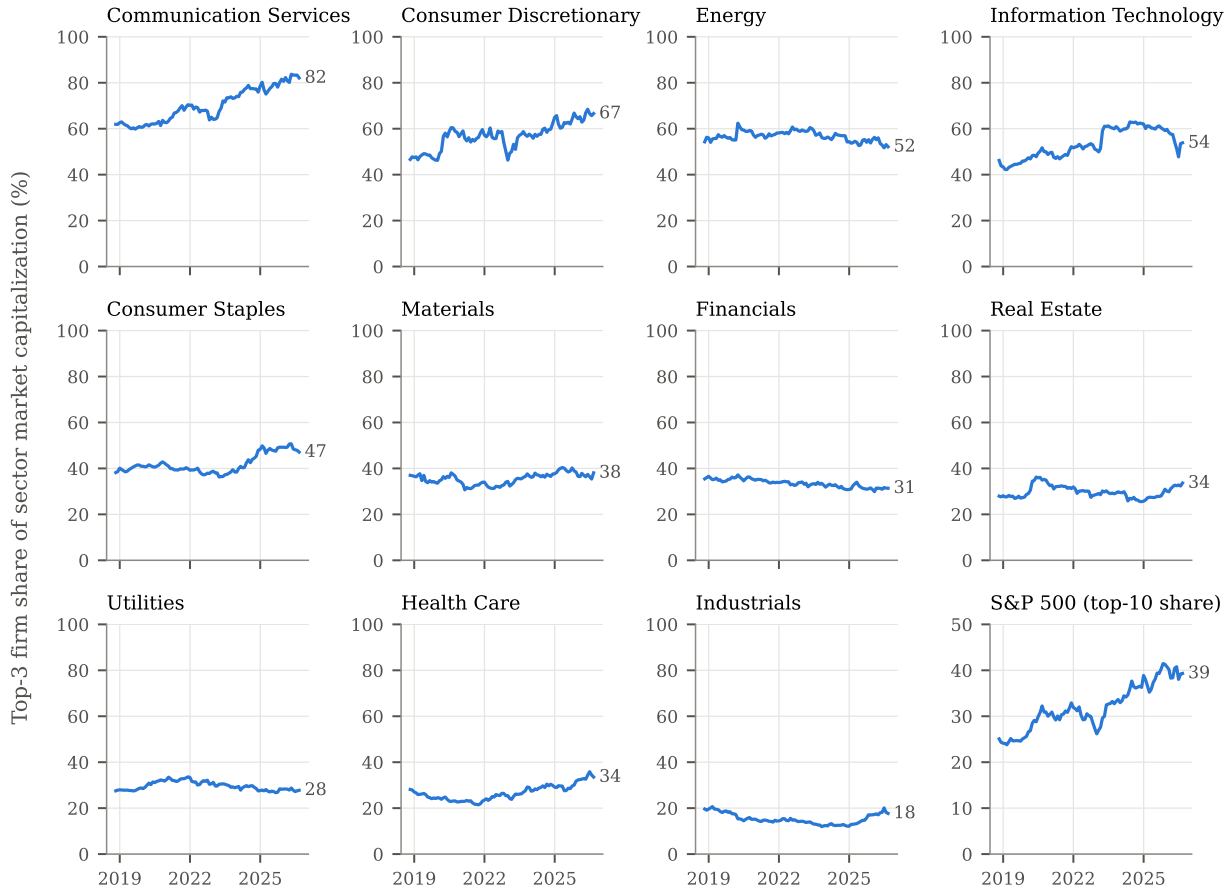



Figure 1: Share of sector market capitalization held by the three largest firms, month-end, October 2018 to August 2026. The last panel is the top-ten share of the whole index. Values at the right edge are August 2026.

### 3.3 The three largest firms

For the firm-level decomposition we collect the same price and share data for 121 firms that could hold a top-three position in some sector during the sample, between 9 and 15 per sector. On every day after 6 November 2018 the top-three share computed from these candidates equals the share

from the full panel in nine sectors and is within two points in Industrials and Materials. Before that date Praxair, which left the index in the Linde merger and is not among the candidates, was one of the three largest Materials firms; the decomposition's base period therefore starts on 6 November 2018.

### 3.4 Ten other markets

The same constituent panel is built for ten other markets: Japan (TOPIX 500, from the exchange's constituent file), China (CSI 300), the United Kingdom (FTSE 350, excluding closed-end investment companies), Canada (S&P/TSX Composite), Korea (KOSPI 200), Australia (S&P/ASX 200), India (NIFTY 50 and NIFTY Next 50), Germany (DAX and MDAX), Hong Kong (Hang Seng), and Brazil (Ibovespa). Firms are assigned to the eleven GICS sectors from a single vendor classification, so sector definitions are identical across markets, and a sector enters a market's panel when it has a median of at least five firms. Market capitalization, weights, sector returns, concentration, and the top-three decomposition are computed exactly as for the United States, in local currency. Vendor share series outside the United States contain occasional unit errors, which we detect against each firm's current share count and repair, and daily returns beyond 40% are dropped as bad ticks. Each rebuilt market tracks its benchmark closely: the daily correlation between the cap-weighted universe return and the index lies between 0.945 for Japan, measured against the price-weighted Nikkei 225, and 0.998 for Canada.

These universes use current index membership, because point-in-time constituent histories are not freely available outside the United States. Two checks bound the consequences. Applied to today's S&P 500 members with the same vendor classification, the design gives a concentration coefficient of $-0.70$ for monthly $R^2$, against $-0.75$ with point-in-time membership. Second, a firm that lists during the sample enters a current-membership universe on its listing date and lowers concentration mechanically, so we also measure concentration among the firms already trading in October 2018.

## 4 Methodology

### 4.1 Generalized connectedness and its normalization

Let $y_t$ be the $k = 11$ vector of sector returns (or log volatilities), with VAR($p$) representation $y_t = c + \sum_{l=1}^{p} B_l y_{t-l} + u_t$, $u_t \sim (0, \Sigma)$, and moving-average coefficients $\Phi_h$. The generalized forecast-error variance decomposition of Pesaran and Shin (1998) at horizon $H$ is

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} e_i' \Phi_h \Sigma \Phi_h' e_i}, \qquad \tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_j \theta_{ij}(H)}, \tag{1}$$

the share of sector $i$'s $H$-step forecast-error variance attributable to shocks in sector $j$. Following Diebold and Yilmaz (2012), in percent,

$$\text{FROM}_i = \sum_{j \neq i} \tilde{\theta}_{ij}, \quad \text{TO}_j = \sum_{i \neq j} \tilde{\theta}_{ij}, \quad \text{NET}_i = \text{TO}_i - \text{FROM}_i, \quad \text{TCI} = \frac{1}{k} \sum_{i \neq j} \tilde{\theta}_{ij}. \tag{2}$$

We set $H = 10$ and choose $p$ by BIC. For daily returns BIC selects no lags and we use $p = 1$; for log volatility it selects $p = 1$.

The row normalization $\tilde{\theta}$ divides each row by its own sum, so FROM is bounded by 100 while TO is not. Caloia et al. (2019) instead divide every element of $\theta$ by the largest row sum, a single scalar that preserves magnitudes across rows; we report both. A useful benchmark is the case with no lag dynamics. When $\Phi_h = 0$ for $h \geq 1$, $\theta_{ij} = \rho_{ij}^2$, the squared correlation between the two sectors' innovations. The row-normalized measures are then functions of the correlation matrix alone,

$$\text{FROM}_i = 100 \left(1 - \frac{1}{S_i}\right), \qquad \text{TO}_j = 100 \sum_{i \neq j} \frac{\rho_{ij}^2}{S_i}, \qquad S_i = \sum_k \rho_{ik}^2, \tag{3}$$

and under the scalar normalization the matrix is symmetric, so TO equals FROM and NET is zero for every sector. We compute this covariance-only version, with $H = 1$, alongside the full model.

### 4.2 Time-varying parameter VAR

The TVP-VAR is $y_t = Z_t \beta_t + u_t$ with $Z_t = I_k \otimes (1, y_{t-1}')$, $\beta_t = \beta_{t-1} + \xi_t$, and $u_t \sim (0, \Sigma_t)$. Following Koop and Korobilis (2013) and Antonakakis et al. (2020), the state covariance is inflated by a forgetting factor rather than estimated, $P_{t|t-1} = P_{t-1|t-1}/\kappa_1$, and the measurement covariance is an exponentially weighted average of prediction errors, $\Sigma_t = \kappa_2 \Sigma_{t-1} + (1-\kappa_2)\hat{u}_t \hat{u}_t'$, with $\kappa_1 = \kappa_2 = 0.99$. The intercept is included because log volatility has a large mean. The filter starts on 20 June 2018 with $\beta_0 = 0$ and $P_0 = 0.1I$, and estimates before 1 October 2018 are discarded as burn-in. We use filtered, not smoothed, estimates, so the measure on day $t$ uses only data through day $t$. At each date the measures in (2) are computed from $(\beta_{t|t}, \Sigma_t)$ under both normalizations, and from $\Sigma_t$ alone.

### 4.3 Concentration and co-movement

The panel regression is

$$C_{s,m} = \alpha_s + \delta_m + \gamma \, \text{Conc}_{s,m-1} + \phi_1 \ln(\text{share}_{s,m-1}) + \phi_2 \bar{v}_{s,m} + \varepsilon_{s,m}, \tag{4}$$

where Conc is the top-three share or the HHI in percentage points, share is the sector's weight in the index, and $\bar{v}$ is the sector's average log volatility in the period. Sector fixed effects remove permanent differences between sectors, and period fixed effects remove anything common to all sectors, including the level of system connectedness and market volatility. The monthly panel has 11 sectors and 94 months, November 2018 to August 2026.

We use two kinds of outcome $C$. The first is measured afresh in each period from that period's daily returns only: the $R^2$ of the sector's return on the equal-weighted return of the other ten sectors, and the average squared correlation with each of the other ten, $\bar{\rho}_s^2$. We compute both monthly (1,034 observations) and quarterly (341). The second is the monthly average of daily TVP-VAR FROM, TO, and NET, under each normalization.

The two kinds of outcome call for different care. Monthly averages of the filtered measures inherit the filter's memory, an effective window of about 100 trading days. Concentration is also persistent: its within-sector first-order autocorrelation is 0.94, and sector-specific linear trends absorb 59% of its within-sector variation after the fixed effects. Regressing one slow-moving series on another can yield large $t$-statistics without any relationship (Ferson et al., 2003). We therefore report three kinds of inference for $\gamma$: Driscoll and Kraay (1998) standard errors with three lags; sector-clustered standard errors with $p$-values from the wild cluster restricted bootstrap with the six-point weights of Webb (2023), 4,999 draws; and a permutation test. The permutation test reassigns each sector's concentration path to another sector, keeping the controls with their own sector, and recomputes the Driscoll-Kraay $t$-statistic over 2,000 random permutations. It asks whether the observed pairing of concentration and outcome is unusual among all pairings, which is the relevant question when both series trend. Finally, we compare long differences across the eleven sectors: the change in each variable from the first twelve months of the sample to the last twelve.

### 4.4 Granular decomposition

Let $W_{s,t-1}$ be the combined weight of sector $s$'s three largest firms at the close of day $t-1$, with the three chosen on that day's weights. The uncapped sector return splits exactly into

$$r_{s,t} = W_{s,t-1}\, r_{s,t}^{\text{top}} + (1 - W_{s,t-1})\, r_{s,t}^{\text{rest}}, \tag{5}$$

where $r^{\text{top}}$ is the weighted return of the three firms and $r^{\text{rest}}$ follows from the identity. We measure each component's co-movement with the equal-weighted return of the other ten sectors. The counterfactual return holds the weight at its average from 6 November to 31 December 2018, $r_{s,t}^{\text{cf}} = \bar{W}_s\, r_{s,t}^{\text{top}} + (1 - \bar{W}_s)\, r_{s,t}^{\text{rest}}$. The comparison is accounting, not regression. It keeps the component returns as they were, so it measures how much the shift in weight alone changed co-movement.

## 5 Results

### 5.1 How connected the sectors are

Over the full sample the total connectedness index is 79.5% for returns and 77.7% for volatility (Table B2). The return index barely moves with the VAR specification: across lag orders 1, 2, and 5 and horizons 5, 10, and 20 it ranges from 79.4% to 79.5%, and the covariance matrix alone gives 79.7%. Return connectedness is almost entirely contemporaneous correlation. Appendix A

confirms this directly. Classical Granger tests find 90 of 110 directed links after false-discovery-rate control, heteroskedasticity-robust tests find none, and the classical rejections come from February to June 2020, when every sector reversed with the market from one day to the next. Out of sample, lagged sector returns fail to beat the historical mean for every sector.

Figure 2 plots the filtered TCI. Return connectedness averages 75.4%. It rises through the fourth quarter of 2018, jumps to its sample maximum of 88.9% on 16 March 2020, decays through 2021, rises again during the 2022 rate shock, and jumps by roughly 15 points in the first days of April 2025. From late 2025 it falls steadily, to 53.7% on 26 August 2026, the lowest value in the sample. Volatility connectedness follows the same path, peaking at 86.9% on 25 March 2020 and reaching its low of 55.5% on 24 August 2026.

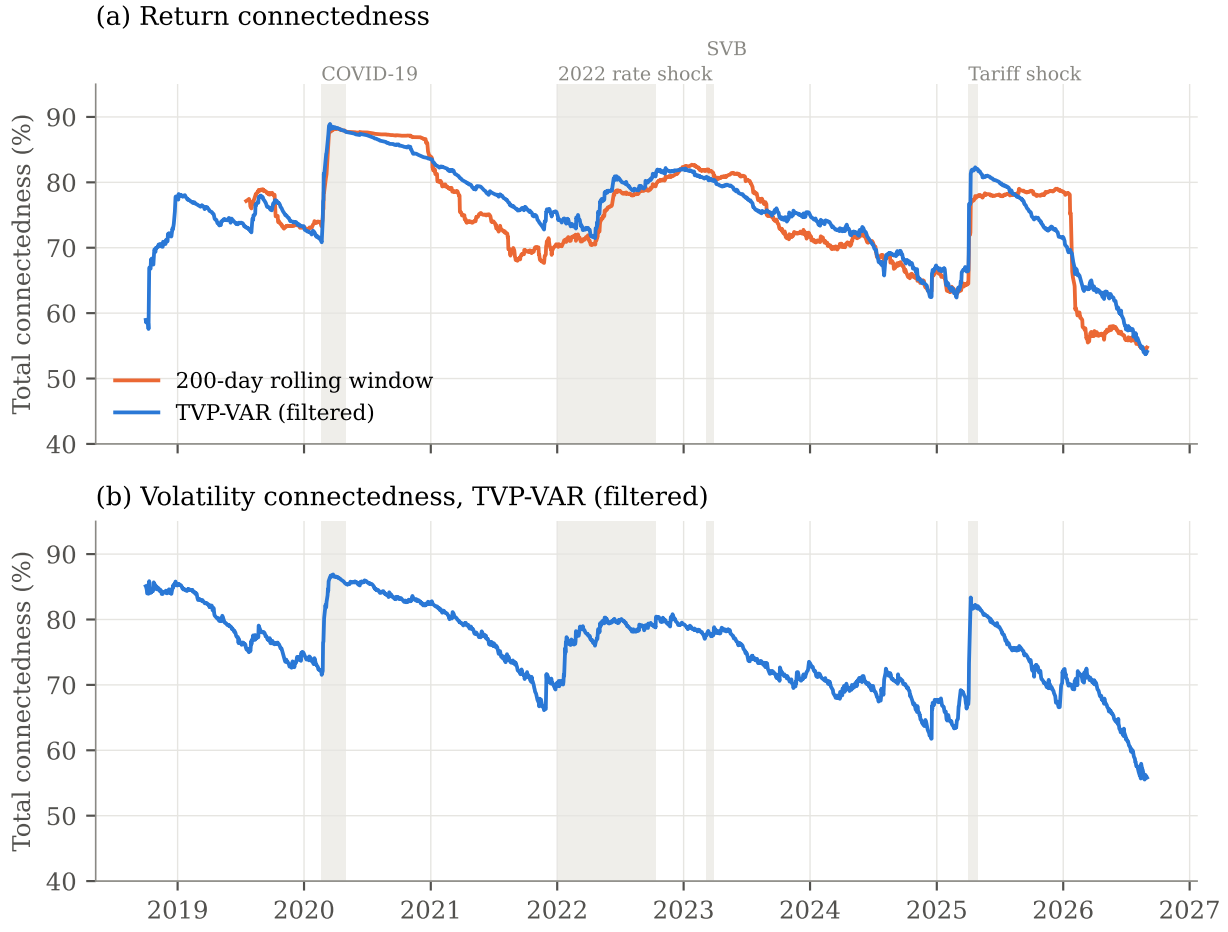



Figure 2: Total connectedness index, daily. Panel (a): returns, filtered TVP-VAR and a 200-day rolling VAR. Panel (b): log range volatility, filtered TVP-VAR. Shaded: COVID-19 crash, 2022 rate shock, March 2023 bank failures, April 2025 tariff shock.

The 2026 decline is not confined to one sector. The average pairwise correlation of daily fund returns is 0.58 in 2025 and 0.21 from January to August 2026. From May to August 2026 it is 0.14, or 0.20 without Information Technology, whose correlation with the equal-weighted return

of the other ten sectors over those four months is $-0.16$. Lagged cross-correlations stay near zero throughout, so the decline is not an artifact of misaligned dates.

The 200-day rolling index in panel (a) shows why the filter matters. After the April 2025 shock the rolling estimate rises to about 77%, five points below the filtered estimate, stays there until early 2026, and then drops by more than 20 points within a few days. That drop is the tariff shock leaving the window, not a change in the market on those days. The filtered return index is insensitive to the forgetting factors: its correlation with the baseline is 0.999 or higher for $\kappa_1 \in \{0.98, 0.995\}$ and 0.79 when the covariance forgetting factor is lowered to 0.96, which makes $\Sigma_t$ noisier. Its correlation with the same estimate on uncapped constituent returns is 0.993.

### 5.2 Concentrated sectors co-move less

Table 1 reports regression (4) for both kinds of outcome. Panel A, co-movement measured afresh each period, carries the paper's conclusions; Panel B, the filtered connectedness measures, is discussed in Section 5.5.

The Panel A outcomes have within-sector autocorrelation between 0.31 and 0.43, low enough for conventional inference to be informative. On uncapped constituent returns, a one-point rise in the top-three share lowers the monthly $R^2$ against the rest of the market by 0.75 points and the average squared correlation with the other sectors by 0.26 points. All four constituent outcomes, monthly and quarterly, reject in the permutation test at 5% and in the wild cluster bootstrap at 1%. The $R^2$ coefficient is the same with three, six, or twelve Driscoll-Kraay lags, is $-0.89$ for the Herfindahl index ($t = -2.7$), and ranges from $-0.67$ to $-0.83$ when sectors are dropped one at a time. On fund returns the coefficients are smaller and the permutation $p$-values lie between 0.10 and 0.18, consistent with weight caps muting concentration exactly where it is highest.

Table 1: Concentration and co-movement: inference that allows for persistent regressors

| Returns | Outcome | Coef. | $t_{DK}$ | $t_{CL}$ | $p_{\text{wild}}$ | $p_{\text{perm}}$ | AR(1) |
|---|---|---|---|---|---|---|---|
| *Panel A: co-movement measured afresh each period* | | | | | | | |
| Constituents | $R^2$, monthly | −0.75 | −4.6 | −5.1 | 0.001 | 0.04 | 0.35 |
| | $\bar{\rho}^2$, monthly | −0.26 | −4.0 | −3.4 | 0.006 | 0.03 | 0.42 |
| | $R^2$, quarterly | −0.76 | −4.7 | −5.2 | 0.002 | 0.02 | 0.43 |
| | $\bar{\rho}^2$, quarterly | −0.29 | −3.4 | −3.7 | 0.003 | 0.04 | 0.38 |
| Funds | $R^2$, monthly | −0.56 | −3.3 | −2.8 | 0.008 | 0.10 | 0.31 |
| | $\bar{\rho}^2$, monthly | −0.17 | −2.5 | −1.9 | 0.066 | 0.16 | 0.40 |
| | $R^2$, quarterly | −0.51 | −2.5 | −2.2 | 0.051 | 0.14 | 0.41 |
| | $\bar{\rho}^2$, quarterly | −0.18 | −1.9 | −1.9 | 0.093 | 0.18 | 0.36 |
| *Panel B: monthly means of daily filtered TVP-VAR measures* | | | | | | | |
| Constituents | NET, row | −0.66 | −4.8 | −5.2 | 0.001 | 0.19 | 0.95 |
| | TO, scalar | −0.61 | −3.8 | −4.3 | 0.009 | 0.22 | 0.94 |
| | FROM, scalar | −0.60 | −4.0 | −4.3 | 0.006 | 0.22 | 0.94 |
| Funds | NET, row | −0.47 | −3.6 | −2.9 | 0.003 | 0.30 | 0.94 |
| | TO, scalar | −0.33 | −2.1 | −1.9 | 0.098 | 0.49 | 0.93 |
| | FROM, scalar | −0.31 | −2.2 | −1.8 | 0.124 | 0.49 | 0.93 |

Coefficient on the lagged top-three share (percentage points) in regression (4) with sector and period fixed effects. $t_{DK}$: Driscoll-Kraay, three lags. $t_{CL}$: clustered by sector. $p_{\text{wild}}$: wild cluster restricted bootstrap, Webb weights, 4,999 draws. $p_{\text{perm}}$: share of 2,000 random reassignments of concentration paths across sectors with $|t_{DK}|$ at least as large as observed. AR(1): mean within-sector first-order autocorrelation of the outcome. $R^2$ and $\bar{\rho}^2$ in percent. Monthly panels have 1,034 observations, quarterly 341.

The long differences point the same way. Across the eleven sectors, the change in the top-three share from the first to the last twelve months of the sample has a correlation of −0.60 with the change in constituent $R^2$ (permutation $p = 0.05$; Figure 3(a)) and −0.35 with the change in $\bar{\rho}^2$ ($p = 0.30$). Figure 3(b) shows the within-sector relationship behind the monthly $R^2$ estimate. It runs across the bins rather than through a few extreme observations.

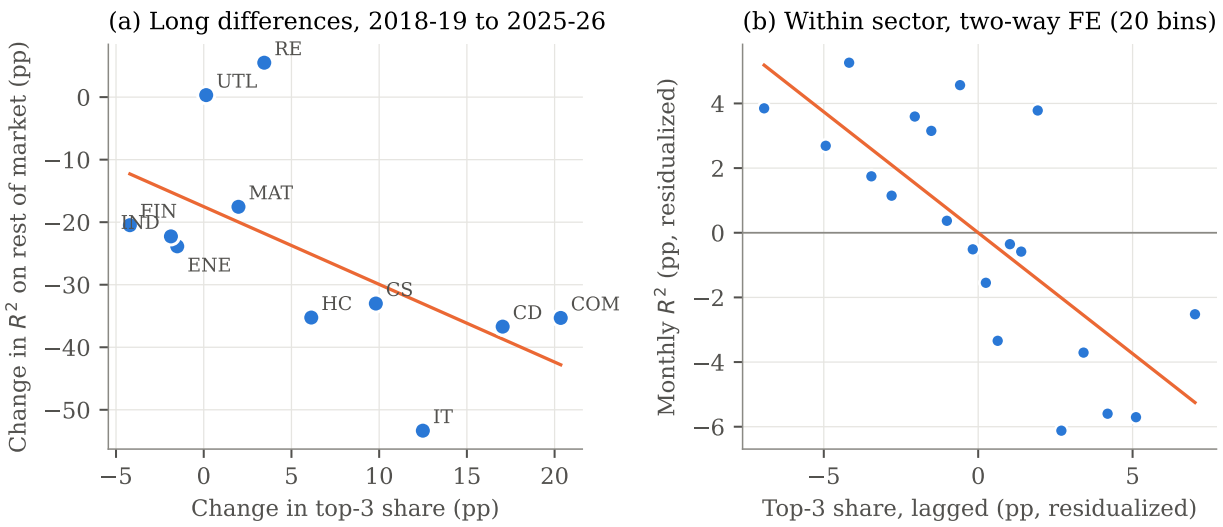



Figure 3: Top-three share and co-movement with the rest of the market, uncapped constituent returns. Panel (a): change from October 2018 to September 2019 to the twelve months ending August 2026. Panel (b): binned scatter of lagged top-three share and monthly $R^2$ after removing sector and month fixed effects, log index share, and own volatility; 20 equal-count bins; line is the OLS fit on all observations.

### 5.3 The largest firms carry their own news

Figure 4(a) splits each sector's return into its three largest firms and the rest. In 91 of 99 sector-years the top-three component has a lower $R^2$ against the rest of the market than the rest of its own sector. The gap is widest in Consumer Discretionary (41% against 70%, averaged over years), Health Care (26% against 54%), and Industrials (53% against 75%). The top-three component is also the more volatile of the two in 69 of 99 sector-years.

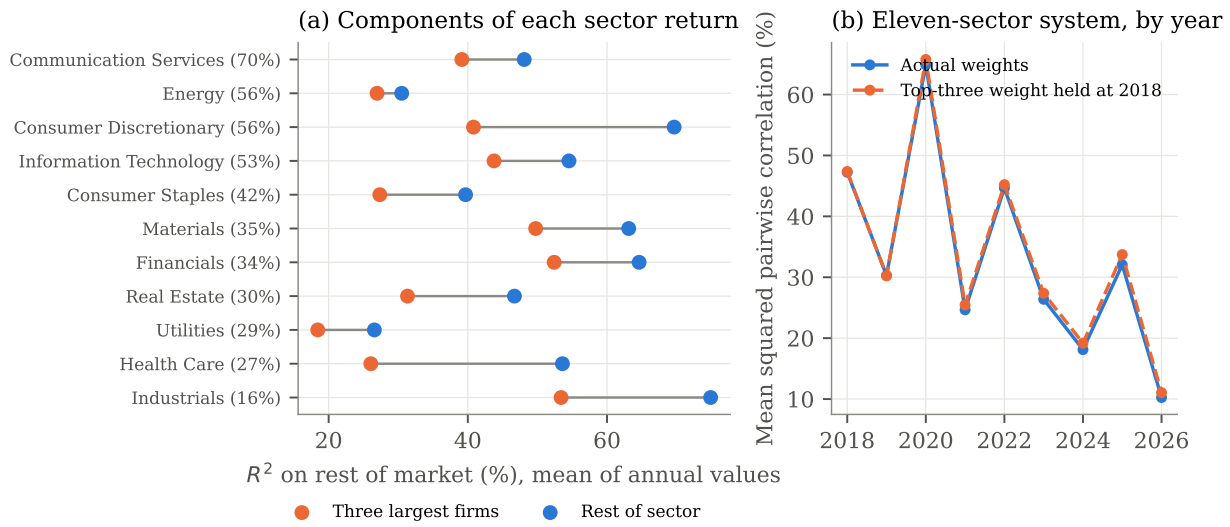



Figure 4: Granular decomposition, uncapped constituent returns. Panel (a): mean of annual $R^2$ of each component on the equal-weighted return of the other ten sectors; the average top-three weight is in parentheses. Panel (b): mean squared pairwise correlation among the eleven sector returns by calendar year, with actual weights and with each sector's top-three weight held at its 6 November to 31 December 2018 average.

Table 2 measures how much this matters. With each sector's top-three weight held at its late-2018 level, the last-twelve-month $R^2$ of Consumer Discretionary would have been 37.1% rather than 31.0%, and the gaps for Materials, Real Estate, and Health Care are between 2.9 and 3.5 points. Those differences are real but small against the fall in co-movement over the sample: Consumer Discretionary's $R^2$ was 77.4% in the first twelve months. Information Technology runs the other way, because by 2026 its three largest firms co-moved with the market more than the rest of the sector did. For the system, the frozen weights raise average squared correlation over the last twelve months from 10.1% to 11.0% and the covariance-based TCI from 48.2% to 50.0%; over the first twelve months they leave it at 38.2%. The composition effect has grown with concentration, from nothing in 2018 and 2019 to between 0.5 and 1.7 points a year from 2020 on (Figure 4(b)).

Table 2: Counterfactual co-movement with top-three weights held at late-2018 levels

| | Top-3 weight (%) | | $R^2$ on rest of market (%) | | | |
|---|---|---|---|---|---|---|
| Sector | Late 2018 | Last 12m | First 12m | Last 12m | Counterfactual | Difference |
| Communication Services | 61.9 | 81.6 | 64.4 | 17.0 | 18.9 | −1.9 |
| Consumer Discretionary | 47.3 | 65.1 | 77.4 | 31.0 | 37.1 | −6.1 |
| Consumer Staples | 38.8 | 49.2 | 50.2 | 4.0 | 5.6 | −1.7 |
| Energy | 55.7 | 54.3 | 51.9 | 3.1 | 2.7 | 0.4 |
| Financials | 36.0 | 31.0 | 66.6 | 30.3 | 31.3 | −1.0 |
| Health Care | 27.9 | 32.4 | 68.0 | 15.8 | 18.8 | −2.9 |
| Industrials | 19.1 | 17.4 | 79.8 | 42.7 | 43.5 | −0.8 |
| Information Technology | 44.1 | 56.5 | 75.2 | 5.5 | 4.0 | 1.5 |
| Materials | 36.4 | 37.7 | 65.6 | 38.3 | 41.8 | −3.5 |
| Real Estate | 27.8 | 31.0 | 27.8 | 26.9 | 30.3 | −3.4 |
| Utilities | 27.8 | 27.9 | 8.7 | 9.4 | 10.5 | −1.1 |

Late 2018 is 6 November to 31 December 2018. First 12m is October 2018 to September 2019; last 12m is September 2025 to August 2026. $R^2$ of the uncapped sector return on the equal-weighted return of the other ten sectors. The counterfactual holds the top-three weight at its late-2018 value in every sector and keeps component returns as observed. Difference is actual minus counterfactual.

### 5.4 Ten other markets

Table 3 repeats the analysis of Sections 5.2 and 5.3 market by market. Own volatility is the log of realized volatility in the month, since range data for sector aggregates are not available outside the fund series, and the U.S. row uses the same current-membership design so that the rows are comparable.

The granular pattern holds everywhere. In every market the top-three component has a lower $R^2$ against the market's other sectors than the rest of its sector in most sector-years, from 52% in Germany to 92% in Korea, and in 78% of the 933 sector-years pooled across markets (Figure 5(a)).

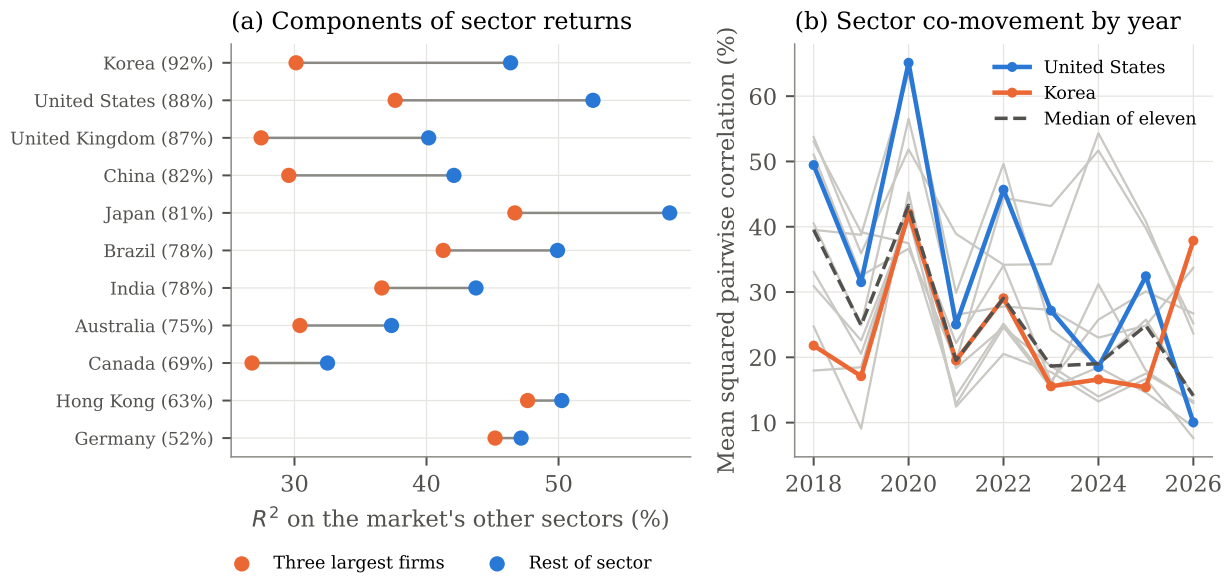



Figure 5: Granular pattern and sector co-movement in eleven markets, current-membership constituent panels. Panel (a): mean of annual $R^2$ of each component on the equal-weighted return of the market's other sectors; the share of sector-years in which the top-three component has the lower $R^2$ is in parentheses. Panel (b): mean squared pairwise correlation among sector returns by calendar year (2018 is October to December, 2026 is January to August); grey lines are the other nine markets.

The concentration effect is narrower. Under current membership the coefficient on monthly $R^2$ is negative in eight of the ten other markets, and the permutation test rejects in Japan ($-0.55$, $p = 0.05$) and Canada ($-0.40$, $p = 0.02$). The United Kingdom is weaker for $R^2$ ($p = 0.17$) and closer for the average squared correlation ($-0.22$, $p = 0.06$). With concentration measured among the firms trading in October 2018, the same three markets keep their estimates, the estimates for China, Korea, Australia, and Brazil turn small and positive, and India's stays positive; none of these is significant by permutation. Pooled across the ten other markets, with market-by-sector and market-by-month fixed effects and permutations within each market, the coefficient is $-0.14$ ($p = 0.10$) under current membership and $-0.03$ ($p = 0.75$) under fixed membership. Outside the United States the evidence rests on Japan, Canada, and the United Kingdom (Figure 6(a)).

Two market characteristics line up with where the effect appears. Across the eleven markets, the estimated coefficient has a correlation of $-0.72$ with the median number of firms per sector (Figure 6(b)) and $-0.89$ with the change in the average top-three share. Developed markets average $-0.33$ and the three emerging markets $+0.11$. With eleven markets these correlations are descriptive.

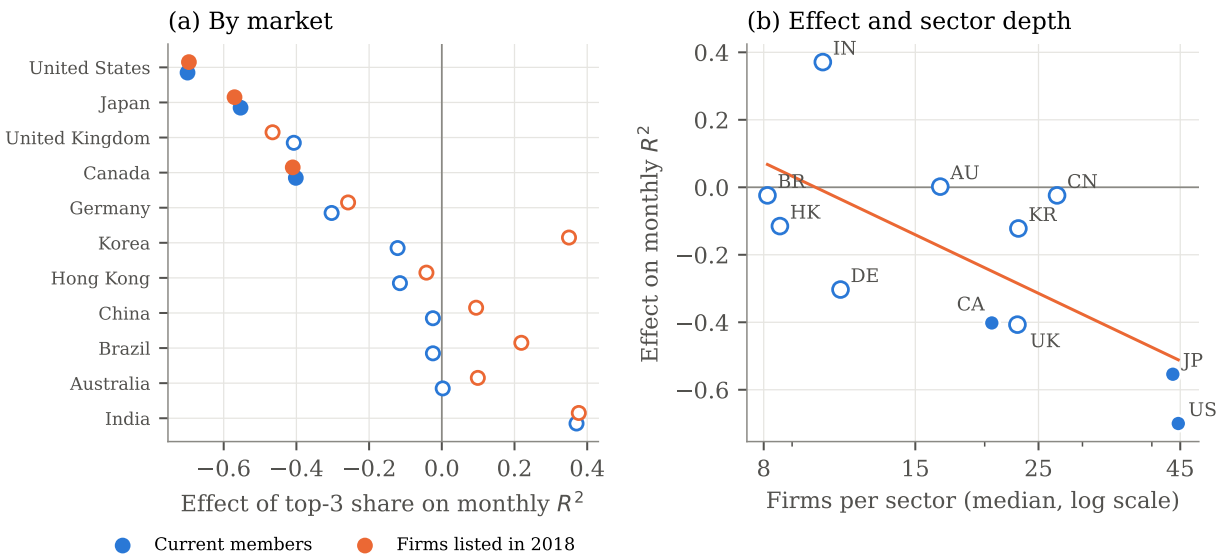



Figure 6: Effect of the lagged top-three share on monthly $R^2$, by market. Panel (a): concentration among current members and among firms trading in October 2018; filled markers have permutation $p$-values below 0.10. Panel (b): current-membership estimates against the median number of firms per sector; the line is a least-squares fit on log firms per sector across the eleven markets.

The decline in co-movement is not confined to the United States. Average squared correlation among sector returns fell by more than two points from the first to the last twelve months of the sample in eight markets, including China, Germany, and Australia, where concentration fell or held steady. It held in India and Brazil and rose in Korea (Figure 5(b)). Holding top-three weights at their late-2018 levels changes the last-twelve-month value by at most 2.1 points in any market.

Table 3: Concentration and co-movement in eleven markets

| | | Firms per | Top-3 share (%) | | Effect on monthly $R^2$ | | Top 3 | $\bar{\rho}^2$ (%) | |
|---|---|---|---|---|---|---|---|---|---|
| Market | Universe | sector | First | Last | Current | Fixed | below | First | Last |
| United States | S&P 500 | 44.6 | 35.9 | 43.6 | −0.70 (0.03) | −0.70 (0.03) | 88 | 39.9 | 10.0 |
| Japan | TOPIX 500 | 43.6 | 41.7 | 47.3 | −0.55 (0.05) | −0.57 (0.07) | 81 | 44.1 | 24.0 |
| United Kingdom | FTSE 350 | 22.9 | 63.3 | 62.6 | −0.41 (0.17) | −0.47 (0.10) | 87 | 16.8 | 11.7 |
| Canada | S&P/TSX | 20.6 | 58.1 | 55.9 | −0.40 (0.02) | −0.41 (0.02) | 69 | 15.7 | 7.6 |
| Germany | DAX, MDAX | 11.0 | 74.5 | 74.3 | −0.30 (0.38) | −0.26 (0.45) | 52 | 39.8 | 13.2 |
| Korea | KOSPI 200 | 23.0 | 58.0 | 60.3 | −0.12 (0.59) | 0.35 (0.22) | 92 | 18.7 | 33.8 |
| Hong Kong | Hang Seng | 8.6 | 71.0 | 67.3 | −0.12 (0.54) | −0.04 (0.89) | 63 | 38.5 | 26.5 |
| China | CSI 300 | 27.0 | 53.9 | 51.0 | −0.02 (0.94) | 0.09 (0.79) | 82 | 45.1 | 11.8 |
| Brazil | Ibovespa | 8.1 | 80.0 | 73.2 | −0.02 (0.93) | 0.22 (0.45) | 78 | 30.0 | 30.6 |
| Australia | S&P/ASX 200 | 16.6 | 68.5 | 63.8 | 0.00 (0.99) | 0.10 (0.61) | 75 | 21.3 | 9.0 |
| India | NIFTY 100 | 10.2 | 67.6 | 57.2 | 0.37 (0.30) | 0.38 (0.28) | 78 | 25.4 | 25.3 |
| Pooled, ten other markets | | | | | −0.14 (0.10) | −0.03 (0.75) | | | |
| Pooled, all eleven markets | | | | | −0.19 (0.02) | −0.11 (0.25) | 78 | | |

Current-membership constituent panels, sectors with a median of at least five firms. Firms per sector: median, averaged over included sectors. First and last: October 2018 to September 2019 and September 2025 to August 2026. Effect: coefficient on the lagged top-three share in regression (4) with sector and month fixed effects, controls for log sector share and log realized volatility, and the permutation $p$-value (1,000 reassignments within the market; 500 for fixed membership) in parentheses. Current: concentration among current members; Fixed: among firms trading in October 2018. Pooled rows use market-by-sector and market-by-month fixed effects. Top 3 below: share of sector-years in which the top-three component has the lower $R^2$ against the market's other sectors. $\bar{\rho}^2$: mean squared pairwise correlation among sector returns.

### 5.5 What the standard measures would have said

Because lags carry almost no information, the directional measures are in effect a transformation of the correlation matrix. Figure 7(a) compares monthly NET from the TVP-VAR with NET computed from the filtered covariance matrix alone; the correlation is 0.99.

The transformation is not neutral. Under row normalization, FROM is $100(1 - 1/S_i)$, and for these sectors $S_i$ lies between 3.5 and 6.2, so FROM is confined to a narrow band, 71.2 to 83.8 in Table B2. TO sums ten entries that are each divided by a different row sum, and it ranges from 46.0 to 103.6. If one sector's correlations with all others fall by the same proportion, its TO falls 4.5 times as much as its FROM (the median across sectors; the range is 2.1 to 6.8), and its NET falls with it. A sector that becomes less correlated with everyone is labeled a net receiver, whatever the direction of any shock. Under the scalar normalization of Caloia et al. (2019), the full-model NET is close to zero for every sector and has a correlation of 0.11 with the row-normalized NET (Figure 7(b)).

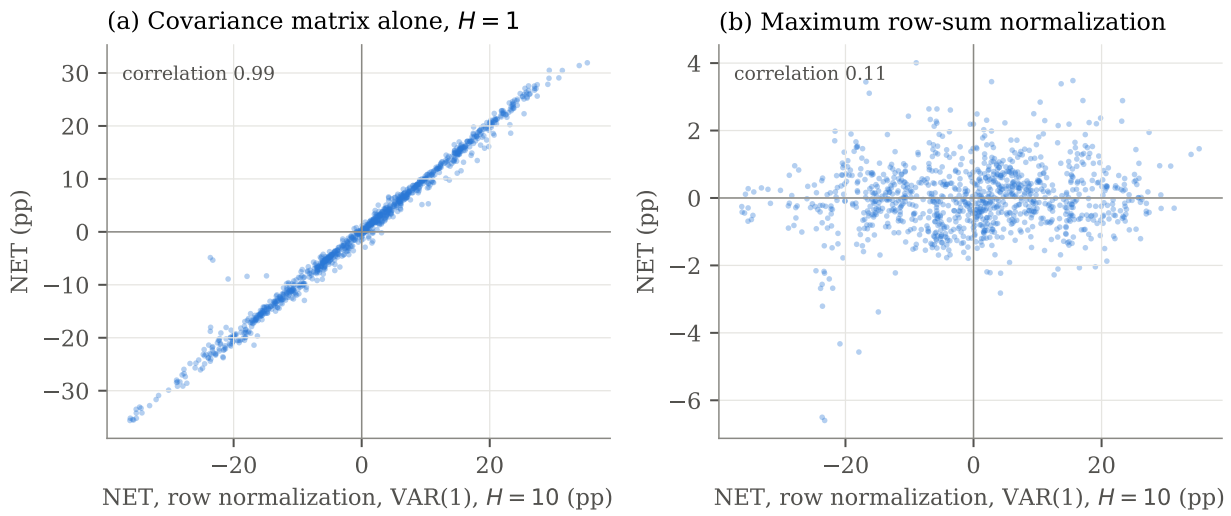



Figure 7: Net directional return connectedness, monthly means of daily filtered estimates, 11 sectors by 94 months. Horizontal axis: TVP-VAR(1), $H = 10$, row normalization. Panel (a): row normalization of the filtered covariance matrix alone. Panel (b): the full model under the maximum row-sum normalization of Caloia et al. (2019).

Table 4 shows what this does to the effect of concentration. Under row normalization, the top-three share lowers TO and NET but barely moves FROM, the pattern the arithmetic above predicts for a fall in correlation, and the covariance-only measures give the same coefficients. Under the scalar normalization, the effect on NET disappears ($-0.02$, $t = -0.7$, on fund returns), while TO and FROM fall by similar amounts. Concentrated sectors are not net receivers in any meaningful sense. They are less connected in both directions, which is the result of Section 5.2 in another form.

Table 4: Top-three share and connectedness under three versions of the decomposition

| Returns | Decomposition | FROM | TO | NET |
|---|---|---|---|---|
| Funds | VAR(1), $H = 10$, row normalization | $-0.04$ (0.08) | $-0.50$ (0.20) | $-0.47$ (0.13) |
| | Covariance only, row normalization | 0.00 (0.10) | $-0.50$ (0.20) | $-0.50$ (0.11) |
| | VAR(1), $H = 10$, scalar normalization | $-0.31$ (0.15) | $-0.33$ (0.16) | $-0.02$ (0.02) |
| Constituents, uncapped | VAR(1), $H = 10$, row normalization | $-0.17$ (0.08) | $-0.83$ (0.21) | $-0.66$ (0.14) |
| | Covariance only, row normalization | $-0.14$ (0.10) | $-0.82$ (0.21) | $-0.68$ (0.12) |
| | VAR(1), $H = 10$, scalar normalization | $-0.60$ (0.15) | $-0.61$ (0.16) | $-0.01$ (0.02) |

Coefficient on the lagged top-three share in regression (4), with log index share and own log volatility as controls, sector and month fixed effects, and Driscoll-Kraay standard errors (three lags) in parentheses. 11 sectors, 94 months. Dependent variables are monthly means of daily filtered TVP-VAR measures, in percentage points.

The inference is the second problem. The filtered measures in Panel B of Table 1 have monthly first-order autocorrelation between 0.93 and 0.95. For them, Driscoll-Kraay and the wild cluster bootstrap mostly reject, but the permutation test does not. Randomly reassigned concentration paths produce Driscoll-Kraay $t$-statistics beyond $\pm 6.1$ to $\pm 7.2$ in one permutation in twenty, and the observed statistics are exceeded in 19% to 49% of permutations. A filtered panel cannot tell the

actual pairing of concentration and connectedness from a random pairing of two trending series, which is why the conclusions of this paper rest on Panel A.

## 6 Reading the results that run against intuition

**Record concentration, record-low connectedness.** The time series invites a simple story: the index concentrated, the sectors drifted apart, so concentration pulled them apart. The decomposition rejects that version of the story. The weight shift toward the largest firms accounts for about one point of a 28-point fall in average squared correlation, and most of the decline happened inside both components. Sector co-movement also fell in markets whose concentration fell, which makes concentration an unlikely common cause. A more promising explanation runs through the firms themselves. Over the last twelve months the top-three components of Communication Services, Consumer Discretionary, and Information Technology have an average pairwise correlation of 0.49, against 0.16 for the rest of those sectors. The same top-three components have an average correlation of 0.08 with the other eight sectors. The market's leading names form a cluster that crosses three GICS sectors, and each of those sector returns mixes the cluster with firms that have little to do with it. The sector partition is losing its grip on how returns actually group, and a connectedness measure built on that partition records the loss as disconnection. Whether index options priced the same shift, through implied correlation, is a natural next test.

**Why concentrated sectors co-move less.** Two channels predict it. The first is diversification arithmetic. If firm returns are $r_i = \beta_i f + \varepsilon_i$ with similar idiosyncratic variances $\sigma_\varepsilon^2$, a sector's idiosyncratic variance is close to $\mathrm{HHI} \cdot \sigma_\varepsilon^2$, so its $R^2$ on the common factor falls as the Herfindahl index rises. This is the argument of Gabaix (2011) applied one level down, and it is strengthened here because the largest firms are also the more volatile and less market-correlated part of the sector. The second channel runs in reverse. Firms become dominant through large returns of their own, so the months in which a sector concentrates are, almost by construction, months of firm-specific news. The counterfactual in Table 2 isolates the first channel and finds it modest: Communication Services gained 20 points of top-three weight and lost 1.9 points of $R^2$ to it. The panel coefficient, 0.75 points of $R^2$ per point of top-three share, is several times larger, which is what the second channel would produce.

**Why the link travels only partway.** Three features of a market seem to matter. The first is depth. With eight to eleven firms in a sector, as in Hong Kong, Brazil, India, and Germany, the three largest firms are most of the sector, and a change in their combined share is a reshuffling among a few names rather than a shift between a few giants and a diversified remainder. The granular argument needs the remainder. The second is how concentration changes. In the United States and Japan the top-three share rose as incumbents pulled away from the rest of their sectors, the setting of the second channel above. Where concentration fell, as in India even among firms trading in 2018, or fell only because new firms listed, as in China and Hong Kong, changes in the share carry no such information. The third is scale. In Korea, technology rose from 36% to 56%

of the market's capitalization, and its three largest firms hold 92% of the sector. The $R^2$ of that top-three component against Korea's other sectors rose from 25% in 2024 to 37% in 2026, and Korea is the only market whose sector co-movement rose. When a few firms are half of a market, their shocks are the market's shocks: the aggregate version of the granular argument in Gabaix (2011), not its sector-level version.

**Receivers that are really isolates.** Energy and Utilities are the largest net receivers in Table B2, and Information Technology moves from a NET of +11.4 in 2019 to −13.8 in 2024. With no lag dynamics, a net receiver is simply a sector weakly correlated with the rest. Energy's daily variance is dominated by oil-specific news, and Utilities trade on rates and regulation. Information Technology's $R^2$ against the rest of the market fell from 71% in 2019 to 24% in 2024 and 3% in 2026 on constituent returns. Leading the market's returns is not the same as sharing its shocks.

**Sectors that reversed together.** In February to June 2020 every sector's lagged return predicted every other sector's with nearly the same negative coefficient as its own (Appendix A). That is the footprint of liquidity, not transmission. Price moves driven by liquidity demand reverse (Campbell et al., 1993), and the returns to supplying liquidity rise steeply with the VIX (Nagel, 2012), which averaged 39.5 in that window and peaked at 82.7 on 16 March 2020. Sector funds are index products, whose growth Baltussen et al. (2019) link to negative daily autocorrelation in index returns.

**Implications.** For portfolio construction, a book diversified across GICS sectors in 2026 holds the same cluster of firms through three sector funds, so diversification measured across sectors overstates diversification across the firms that carry the weight. For connectedness research, three practices follow from this paper: report the covariance-only benchmark next to the full model, report net measures under a scalar normalization, and use randomization inference when regressing filtered connectedness on slow-moving variables.

Two limitations matter most. First, membership. The U.S. constituent panel covers 85% of index members at the start of the sample, because firms acquired and delisted before 2026 cannot be recovered, and the other markets use current membership; the U.S. comparison of the two designs suggests this changes the main estimate little. Second, with eleven sectors per market the evidence is an association with limited power. It is clear on uncapped U.S. returns, weaker on fund returns and in most other markets, and it is not a causal estimate.

# 7 Conclusion

Sectors of the S&P 500 share shocks within the day but do not forecast each other from one day to the next, so their connectedness is a reading of the correlation matrix. Read that way, the evidence is consistent. Sectors dominated by a few firms co-move less with the rest of the market, because their largest firms carry more news of their own, and the same is true of the largest firms in ten other markets. Whether rising concentration then lowers a sector's co-movement depends on the market: it does where sectors are deep and incumbents pulled away, as in the United States and Japan, and

it reverses where a few firms become the market, as in Korea. The weight shift toward those firms is too small, though, to explain why the eleven U.S. sectors reached their lowest connectedness of the sample in 2026, a decline shared by most of the markets studied. That decline points to a market whose main lines of co-movement no longer follow sector boundaries, and measuring connectedness on clusters of firms rather than GICS labels is the obvious next step.

**Data availability.** Fund prices, index constituents and share counts are from public sources: Yahoo Finance for prices, share counts and the VIX; Wikipedia's list of S&P 500 companies for current GICS classifications and addition dates; a publicly maintained file of historical S&P 500 membership for removals; and, for the other markets, the Japan Exchange Group's TOPIX constituent file, B3's Ibovespa portfolio, and published index constituent lists. The processed data and code that reproduce every table and figure are available from the author on request.

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# A Lead-lag relationships

A lead-lag literature argues that information diffuses slowly across economically linked industries: Hou (2007) finds that large firms lead small firms within industries, Menzly and Ozbas (2010) document cross-predictability along supply chains at monthly frequency, Hong et al. (2007) report that some industries lead the aggregate market, and Rapach et al. (2019) find out-of-sample industry predictability at monthly frequency. Vilasuso (2001) shows that causality tests are unreliable under conditional heteroskedasticity. This appendix asks the daily question for the eleven sectors.

**Tests.** For each ordered pair $(j, i)$ we test whether lags of $y_j$ enter the equation for $y_i$. The system version conditions on the lags of all eleven sectors; the bivariate version conditions only on lags of $y_i$. Test statistics are Wald statistics with the HC3 covariance estimator, which is valid under conditional heteroskedasticity of unknown form. For comparison we also report classical F statistics. Across the 110 ordered pairs, $p$-values are adjusted with the Benjamini and Hochberg (1995) false-discovery-rate procedure and with Bonferroni. Out of sample, we forecast each sector's next-day return from the current returns of all eleven sectors, re-estimating by OLS on an expanding window that starts with the first quarter of the sample, so the evaluation period begins on 23 September 2020. We also report the equal-weighted combination of eleven single-predictor forecasts. The benchmark is the prevailing historical mean. We report $R^2_{OS} = 1 - \sum(r - \hat{r})^2 / \sum(r - \bar{r})^2$ (Campbell and Thompson, 2008) and the Clark and West (2007) test with Newey-West variance.

**Granger results.** Table A1 reports the tests. Rows (1) to (4) use classical statistics. Taking the minimum $p$-value over lags one to five for each pair, a procedure that is common in applied work, gives 94 raw rejections and 90 after FDR control. Fixing the lag at five reduces this to 77, fixing it at one to 48, and conditioning on the full system to 20. Rows (5) to (7) use HC3 Wald statistics. No link survives FDR control, in the bivariate or system form, at lag one or five, in the full sample or either half.

Table A1: Granger causality among 110 ordered sector pairs, daily returns

| | Test | Raw $p < 0.05$ | FDR | Bonferroni |
|---|---|---|---|---|
| *Full sample, classical statistics* | | | | |
| (1) | Bivariate F, minimum $p$ over lags 1 to 5 | 94 | 90 | |
| (2) | Bivariate F, lag 5 | 80 | 77 | |
| (3) | Bivariate F, lag 1 | 65 | 48 | |
| (4) | System VAR(1), Wald | 40 | 20 | |
| *Full sample, HC3 Wald* | | | | |
| (5) | Bivariate, lag 1 | 20 | 0 | 0 |
| (6) | Bivariate, lag 5 | 20 | 0 | 0 |
| (7) | System VAR(1) | 6 | 0 | 0 |
| *Subsamples* | | | | |
| (8) | System VAR(1), HC3, Oct 2018 to Aug 2022 | 15 | 0 | 0 |
| (9) | System VAR(1), HC3, Sep 2022 to Aug 2026 | 4 | 0 | 0 |
| (10) | As (1), excluding 20 Feb to 30 Jun 2020 | 22 | 0 | |
| (11) | As (1), 2021 to 2026 | 12 | 0 | |
| (12) | As (1), calendar 2020 only | 89 | 87 | |

About 5.5 raw rejections are expected by chance at the 5% level. FDR is Benjamini and Hochberg (1995) at 5%.

A Monte Carlo experiment explains the gap. We simulate returns from a one-factor model in which the factor and each sector's residual follow GARCH(1,1) processes with Student-$t$ innovations, all estimated on the fund returns, and in which no sector's lag predicts any other sector. The factor process is highly persistent ($\hat{\alpha} = 0.159$, $\hat{\beta} = 0.815$, $\hat{\nu} = 7.1$). With 1,989 observations and 1,000 replications, the classical F-test at lag five rejects a true null 21.0% of the time at a nominal 5%, and the minimum-over-lags procedure rejects 30.7% of the time. HC3 tests reject 5.2% (lag one) and 4.1% (lag five). Over 100 replications of the full 110-pair procedure, the classical minimum-over-lags approach produces 5.3 false FDR survivors on average, with 16.5 at the 90th percentile; HC3 produces 0.09.

The simulation produces far fewer false survivors than the 90 found in the data, so heteroskedasticity inflates the classical test but does not by itself account for the count. Rows (10) to (12) of Table A1 locate the rest. Excluding 20 February to 30 June 2020, 4.6% of trading days, removes every classical FDR survivor, while calendar 2020 alone produces 87. That window contains 97.6% of the lag-one cross-covariance between sectors over the whole sample. Inside it, the average lag-one correlation between one sector's return and another's is $-0.29$, almost equal to the average own-lag correlation of $-0.28$. Each sector's lagged return predicts the others only because all sectors reversed together from one day to the next, and even within the window no link survives HC3 testing with FDR control.

**Out-of-sample results.** The lagged returns of other sectors carry no usable information (Table A2). $R^2_{OS}$ is negative for all eleven sectors, between $-4.0\%$ and $-8.8\%$ for the unrestricted regression and between $-0.1\%$ and $-1.9\%$ for the combination forecast. One of 22 Clark-West tests rejects at 5% and none after FDR control.

Table A2: Out-of-sample predictability of next-day sector returns, 23 September 2020 to 31 August 2026

| | All 11 lagged returns | | Combination of 11 forecasts | |
|---|---|---|---|---|
| Sector | $R^2_{OS}$ (%) | CW $p$ | $R^2_{OS}$ (%) | CW $p$ |
| Communication Services | −5.63 | 0.42 | −0.95 | 0.33 |
| Consumer Discretionary | −5.23 | 0.55 | −0.59 | 0.37 |
| Consumer Staples | −5.78 | 0.60 | −1.87 | 0.76 |
| Energy | −4.02 | 0.03 | −0.14 | 0.21 |
| Financials | −8.83 | 0.13 | −1.65 | 0.65 |
| Health Care | −7.53 | 0.47 | −1.48 | 0.79 |
| Industrials | −8.09 | 0.45 | −0.81 | 0.44 |
| Information Technology | −4.99 | 0.23 | −0.72 | 0.11 |
| Materials | −6.19 | 0.32 | −0.75 | 0.42 |
| Real Estate | −6.97 | 0.44 | −1.38 | 0.73 |
| Utilities | −7.79 | 0.93 | −1.19 | 0.71 |

Expanding-window OLS; benchmark is the prevailing mean. CW is the one-sided Clark and West (2007) test.

These results bear on how connectedness should be read. The directional measures describe how contemporaneous shocks are shared, identified through the generalized decomposition. They do not describe one sector's returns forecasting another's, and they should not be used to motivate daily sector-rotation rules.

# B Summary statistics and static connectedness

Every sector has negative skewness and excess kurtosis between 7 and 17 (Table B1). Log volatility is persistent, with first-order autocorrelation between 0.50 and 0.63. Table B2 reports full-sample connectedness. Industrials has the largest NET in both systems, followed by Materials and Financials for returns; Energy has the most negative NET for returns and Utilities for volatility. Volatility connectedness, where lagged dynamics matter, ranges from 72.6% to 77.7% across lag orders and horizons, and the return index on the uncapped constituent series from 78.6% to 78.7%.

Table B1: Summary statistics, 1 October 2018 to 31 August 2026 (1,989 days)

| | Daily log return | | | | Log range volatility | | Top-3 share (%) | |
|---|---|---|---|---|---|---|---|---|
| Sector | Mean | Vol. | Skew | Ex. kurt. | Mean | AR(1) | 2018Q4 | 2026 |
| Communication Services | 11.4 | 22.4 | −0.47 | 7.1 | 2.54 | 0.57 | 62.1 | 82.3 |
| Consumer Discretionary | 9.6 | 24.3 | −0.51 | 7.3 | 2.61 | 0.63 | 47.7 | 65.4 |
| Consumer Staples | 8.4 | 15.8 | −0.42 | 14.3 | 2.29 | 0.53 | 38.3 | 49.2 |
| Energy | 11.0 | 32.4 | −0.95 | 14.9 | 2.92 | 0.58 | 54.7 | 54.0 |
| Financials | 11.2 | 23.6 | −0.58 | 15.5 | 2.53 | 0.58 | 35.8 | 31.0 |
| Health Care | 9.1 | 17.7 | −0.33 | 9.5 | 2.40 | 0.50 | 27.7 | 33.4 |
| Industrials | 11.8 | 21.6 | −0.48 | 12.6 | 2.49 | 0.58 | 19.4 | 17.9 |
| Information Technology | 21.2 | 27.2 | −0.26 | 7.5 | 2.69 | 0.55 | 44.7 | 54.8 |
| Materials | 9.6 | 22.2 | −0.40 | 9.3 | 2.55 | 0.55 | 36.6 | 36.9 |
| Real Estate | 7.1 | 22.2 | −1.04 | 17.4 | 2.59 | 0.51 | 27.5 | 32.0 |
| Utilities | 9.0 | 20.6 | −0.25 | 15.0 | 2.59 | 0.50 | 27.6 | 27.9 |

Mean and volatility of returns are annualized, in percent. Log range volatility is the log of the annualized Parkinson volatility in percent. The top-three share is the average of daily values over October to December 2018 and over January to August 2026.

Table B2: Static connectedness, full sample

| | Returns | | | | Log range volatility | | | |
|---|---|---|---|---|---|---|---|---|
| Sector | Own | FROM | TO | NET | Own | FROM | TO | NET |
| Communication Services | 20.2 | 79.8 | 76.5 | −3.3 | 20.8 | 79.2 | 85.7 | 6.5 |
| Consumer Discretionary | 18.6 | 81.4 | 84.7 | 3.3 | 21.9 | 78.1 | 90.6 | 12.4 |
| Consumer Staples | 22.0 | 78.0 | 72.1 | −5.9 | 21.7 | 78.3 | 77.5 | −0.8 |
| Energy | 28.8 | 71.2 | 46.0 | −25.2 | 26.8 | 73.2 | 52.6 | −20.6 |
| Financials | 17.3 | 82.7 | 97.2 | 14.5 | 20.6 | 79.4 | 86.7 | 7.3 |
| Health Care | 20.2 | 79.8 | 80.5 | 0.6 | 22.8 | 77.2 | 67.7 | −9.5 |
| Industrials | 16.2 | 83.8 | 103.6 | 19.8 | 19.4 | 80.6 | 99.5 | 18.9 |
| Information Technology | 20.6 | 79.4 | 73.1 | −6.3 | 21.4 | 78.6 | 83.0 | 4.5 |
| Materials | 17.0 | 83.0 | 97.5 | 14.5 | 19.8 | 80.2 | 94.7 | 14.5 |
| Real Estate | 19.4 | 80.6 | 83.4 | 2.8 | 24.7 | 75.3 | 63.4 | −11.8 |
| Utilities | 24.8 | 75.2 | 60.3 | −15.0 | 25.4 | 74.6 | 53.2 | −21.4 |
| TCI | | | | 79.5 | | | | 77.7 |

Generalized variance decomposition at $H = 10$ from a VAR(1), row normalization, in percent. Own is the diagonal share. The covariance-only NET values have a correlation of 0.998 with these and never differ from them by more than 1.3 points.