What Did the Fed Really Say? Evidence from Global Equities

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Abstract

When the Federal Reserve surprises markets, what matters for international equity valuations is not the direction of the surprise but its *economic content*. We decompose 205 FOMC announcements (2000–2024) into Monetary Policy (MP) and Central Bank Information (CBI) shocks following Jarociński and Karadi (2020) and trace their transmission to equity markets in Germany, Brazil, Hong Kong, and India. Two results emerge. First, spillovers are sign-heterogeneous: contractionary MP shocks generate a trilemma-consistent hierarchy of negative responses, while CBI shocks produce opposite effects depending on whether recipient economies *complement or compete* with U.S. production. Commodity exporters respond positively to growth news, whereas economies competing for global capital respond negatively. Second, these patterns are remarkably stable across regimes, despite major changes in U.S. monetary policy. The findings imply that international transmission depends on the informational content of policy announcements and on structural economic linkages, rather than on the policy stance alone.

Keywords: Federal Reserve information shocks, Monetary policy spillovers, Central bank communication, International equity transmission, Complementarity versus substitution, Bayesian local projections, Cross-fitting inference

JEL Classification: C11, E52, E58, F31, F42, G15

1 Introduction

The Federal Reserve shapes financial conditions far beyond U.S. borders. For open economies, a Fed announcement changes not only expected interest rates but also expectations about global growth, risk appetite, commodity demand, and capital flows (Rey, 2015; Miranda-Agrippino and Rey, 2020). This distinction is central for equity markets: the same increase in U.S. rates can lower foreign stock prices when it signals tighter financial conditions, or raise them when it signals stronger future activity. Yet most of the existing spillover literature collapses this distinction—either by imposing sample splits around major global episodes (Bowman et al., 2015; Rogers et al., 2018) or by estimating average announcement effects without separating monetary-policy shocks from information shocks (Iacoviello and Navarro, 2019; Hausman and Wongswan, 2011; Canova, 2005). Economically, both approaches can blur the transmission mechanism: if one event tightens discount rates while another improves growth expectations, pooling them hides the true mapping between Fed news and foreign equity valuations.

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This paper asks two questions. First, do international equity spillovers depend on the *type* of news embedded in Fed communication—pure monetary-policy tightening versus a revelation of stronger fundamentals—as formalised by the decomposition of Jarociński and Karadi (2020)? Second, did those spillovers change as the Fed's conduction evolved from conventional rate targeting through the zero lower bound, large-scale asset purchases, and the post-pandemic tightening cycle (Swanson, 2021)? We address both questions by tracing 205 FOMC announcements (2000–2024) to equity markets in Germany, Brazil, Hong Kong, and India—four economies chosen because they span the two dimensions of heterogeneity that our theoretical approach identifies as determinative: *monetary-policy autonomy* and *productive-structure complementarity with the United States*.

The first dimension—monetary-policy autonomy—is well understood. The classical trilemma predicts that economies with less exchange-rate flexibility absorb larger discount-rate pass-through from foreign monetary shocks (Obstfeld et al., 2005). Hong Kong's currency board should import the full blow; India's managed float should buffer most of it; Germany and Brazil, with intermediate degrees of effective autonomy, should fall in between. We confirm this prediction with striking precision for pure monetary-policy (MP) shocks: the cross-country ranking of negative equity responses maps directly onto the degree of monetary autonomy each economy retains.

The second dimension—productive-structure complementarity—is the one the existing literature leaves largely unspecified, and it is the dimension that generates our most novel findings. When the Fed reveals unexpectedly strong fundamentals (a Central Bank Information, or CBI, shock), the equity-market consequences for a receiving economy depend on whether its output *complements* or *substitutes for* U.S. output in global markets. The intuition is rooted in the production-network logic recently formalised by Kalemli-Özcan et al. (2025): economies whose exports enter as inputs to U.S. production or consumption—commodity suppliers, intermediate-goods manufacturers—see their expected earnings rise when U.S. activity strengthens, generating a positive cash-flow spillover that can dominate the discount-rate cost of higher expected rates. By contrast, economies whose leading sectors compete with U.S. firms for the same global revenue pools and portfolio allocations face the opposite calculus: stronger U.S. fundamentals make U.S. assets relatively more attractive, prompting global portfolios to tilt toward U.S. assets at the expense of economies whose firms vie for the same investor base (Hau and Rey, 2002; Jotikasthira et al., 2012).

This complement-versus-substitute logic yields a sharp prediction that the conventional trilemma cannot generate: two economies with similar exchange-rate regimes and comparable levels of financial openness may respond to the *same* CBI shock with *opposite signs*, depending on their position in the global production chain. Our results bear this out. Brazil's IBOV—a commodity exporter whose earnings covary positively with U.S. growth expectations—responds to CBI shocks strongly and positively, consistent with a commodity-demand channel. India's SENSEX—whose IT-services and financial sectors compete with U.S. firms for global portfolio capital—responds *negatively* to the same nominally "good news," consistent with risk-rotation dynamics that redirect capital toward the source of the positive signal. Germany's DAX responds positively but moderately, reflecting export complementarity tempered by the ECB's partial insulation. Hong Kong's HSI, despite its maximal monetary pass-through, shows near-zero CBI sensitivity—the peg ensures full pass-through of the rate signal, yet the index's growing dependence on mainland Chinese revenue streams leaves the cash-flow channel largely disconnected from U.S. real-activity news.

The CBI ranking thus *overturns* the MP hierarchy entirely. This sign heterogeneity has a direct implication for how open-economy central banks should respond to Fed announcements: a hawkish surprise rooted in stronger U.S. fundamentals calls for a qualitatively different domestic response than one driven by inflation containment, even if both produce the same movement in U.S. interest-rate futures. For a commodity exporter like Brazil, confusing the two types of shock—mechanically tightening in response to any Fed hawkishness—risks amplifying the negative monetary-policy component while forfeiting the positive informational benefit that the commodity channel delivers. This extends the logic of Cavallino (2019) and Fanelli and Straub (2021) by adding a dimension they do not consider: what the shock *reveals* about the state of the world, not merely how large it is, should shape the domestic reaction.

Our second finding is that these heterogeneous propagation patterns have proved remarkably stable. Despite dramatic transformations in the Fed's operating work—and equally consequential changes in the sample countries themselves, from Brazil's sovereign-rating cycle to Hong Kong's progressive integration with mainland capital markets—the direction, ranking, and magnitude of both MP and CBI spillovers have remained essentially invariant over a quarter-century. Endogenous structural-break tests, implemented via a sup-Wald procedure with cross-fitting to prevent post-selection bias (Andrews, 1993; Chernozhukov et al., 2018), fail to reject parameter constancy at conventional significance levels across all four markets and both shock types. This time-invariance implies that the determinants of spillover heterogeneity are slow-moving institutional characteristics—exchange-rate architecture, the currency denomination of external debt, the depth of domestic capital markets, the composition of the export basket—not features of the current Fed policy regime.

The methodological architecture is designed to match the identification challenges these questions pose. We estimate Bayesian local projections with a first-order random-walk prior across impulse-response horizons and a skeptical shrinkage prior that centres post-regime responses on pre-regime responses, encoding resistance to finding structural breaks unless the data clearly demand them (Barnichon and Brownlees, 2019; Ferreira et al., 2023). Break dates are selected endogenously rather than imposed *ex ante*, and all estimation separates break selection from effect estimation through year-stratified cross-fitting, so that the break date chosen on training data is never used to estimate effects on the same observations. A latent factor captures residual cross-horizon comovement, and inference is summarised through highest posterior density intervals at both 68% and 90% levels.

Three broader implications follow from these results. First, the finding that a single Fed surprise generates opposite equity responses in complement and substitute economies means that the Fed *cannot* design communication that is uniformly benign across countries—the appropriate locus of policy adaptation is at the receiver, not the emitter. Second, the stability of propagation patterns over dramatically different policy regimes implies that durable insulation from external monetary shocks requires structural reform—unwinding corporate foreign-currency exposure (Du and Schreger, 2022), developing domestic-currency debt markets that reduce reliance on dollar intermediation (Bruno and Shin, 2015), and calibrating macroprudential tools to the specific channels through which external shocks propagate (Forbes and Warnock, 2012)—rather than cyclical fine-tuning calibrated to the prevailing Fed regime. Third, our evidence suggests a resolution to the debate between the trilemma and the "dilemma" of Rey (2015): for MP shocks, the classical trilemma holds; for CBI shocks, neither the trilemma nor the dilemma adequately describes the data, because the relevant organising principle is productive-structure complementarity rather than exchange-rate architecture or capital-account openness.

The remainder proceeds as follows. Section 2 develops the theoretical perspectives linking Fed announcements to international equity markets. Section 3 describes our data and empirical approach. Section 4 reports the main results. Section 5 conducts robustness exercises. Section 6 concludes with policy implications.

2 Theoretical perspectives on Fed announcements and their effects on international equity markets

The fundamental valuation identity—equity prices equal the present discounted value of expected future cash flows (Campbell and Shiller, 1988)—provides our organizing foundation. Fed policy shocks transmit to international equity markets through two primary channels. First, the discount rate channel operates directly: higher U.S. policy rates raise the global risk-free benchmark, compressing foreign equity valuations, and may increase equity risk premia through heightened macroeconomic uncertainty or flight-to-safety flows into dollar assets (Bernanke and Kuttner, 2005). Second, the cash flow channel operates through real economic linkages: contractionary U.S. policy dampens global aggregate demand—directly reducing expected earnings for firms with U.S. export exposure and indirectly affecting all firms through commodity prices, supply chains, and confidence effects.

Importantly, these channels need not move in tandem. A growth-driven rate hike may compress discount rates while simultaneously signaling stronger future cash flows, producing muted or even positive net spillovers. Conversely, an inflation-fighting hike tightens financial conditions without the offsetting growth signal. Similarly, propagation may vary across regimes as the relative strength of each channel shifts with changes in the Fed's reaction function, market expectations, or global financial integration (Jarociński and Karadi, 2020). Disentangling these scenarios empirically demands both sign-dependent identification and regime-aware estimation.

Implementing this distinction in practice requires addressing the endogeneity of policy decisions: the Fed responds to economic conditions that independently affect equity markets. High-frequency identification exploiting narrow windows around FOMC announcements isolates exogenous shifts in policy expectations by filtering out pre-existing information (Kuttner, 2001; Gürkaynak et al., 2005). Yet a subtler identification challenge arises from the dual nature of central bank communication. FOMC announcements convey not only policy actions but also the Committee's private assessment of economic fundamentals—the "Fed information effect" (Romer and Romer, 2000; Nakamura and Steinsson, 2018). A hawkish surprise may reflect either (i) the Fed tightening despite weak economic signals (a pure monetary shock) or (ii) the Fed revealing optimistic private information that justifies tightening (an information shock). These observationally similar events have opposite implications for the cash flow channel: the former depresses growth expectations while the latter lifts them, even as both compress discount rates through higher policy rates.

Jarociński and Karadi (2020) formalize this intuition through sign restrictions on high-frequency co-movements. A pure Monetary Policy (MP) shock is identified when interest rates and stock prices move in opposite directions within the announcement window, consistent with a surprise tightening that dominates any information content. A Central Bank Information (CBI) shock is identified when rates and prices move together, indicating that the information signal dominates. Crucially, these two shock types carry opposite predictions for international equity markets. A contractionary MP shock unambiguously tightens global financial conditions: it raises the discount rate, appreciates the dollar, and signals weaker future demand—all of which depress foreign equity valuations. By contrast, a CBI shock that raises rates while signaling economic strength may compress risk premia and boost expected earnings, partially or fully offsetting the mechanical discount rate effect (Cieslak and Schrimpf, 2019). Recent work by Jarociński and Karadi (2025) extends this decomposition by separating the Fed's endogenous response to publicly available news from its genuine private-information revelation, further refining the mapping between announcement content and asset-price responses. Meanwhile, Bauer and Swanson (2023) argue that much of the apparent domestic information effect reflects the Fed's systematic reaction to publicly observed data rather than private knowledge, a debate whose resolution has direct bearing on how strongly CBI shocks should propagate internationally: if CBI surprises merely confirm public signals, their cross-border pass-through should be weaker than if they reveal genuinely novel assessments.

The strength and *sign* of cash-flow spillovers, however, depend on a dimension that existing papers leave unspecified: the degree to which the receiving economy's productive structure *complements* or *substitutes for* U.S. output in global markets. Consider the CBI channel in isolation. When the Fed reveals unexpectedly strong fundamentals, this signals higher future U.S. demand for tradable goods and services. For economies whose output enters as an *input* to U.S. production or consumption—commodity suppliers, intermediate-goods manufacturers—stronger U.S. activity directly raises the expected value of their exports, generating a positive cash-flow spillover that may dominate the discount-rate effect (Frankel, 2014; Ready et al., 2017). By contrast, economies whose leading sectors—IT outsourcing, financial intermediation, generic pharmaceuticals—compete with U.S. firms for the same global revenue pools and portfolio allocations face a different calculus: stronger U.S. fundamentals make U.S. assets relatively more attractive, prompting global portfolios to tilt toward U.S. assets at the expense of economies whose firms vie for the same investor base(Hau and Rey, 2002; Jotikasthira et al., 2012). This distinction yields a sharp, testable prediction that the conventional trilemma cannot generate: two economies with identical exchange-rate regimes and similar levels of financial openness may respond to the same CBI shock with *opposite signs*.

This *complementarity-versus-substitution* logic builds on the production-network approach to international diffusion recently formalized by Kalemli-Özcan et al. (2025), who demonstrate that the macroeconomic impact of external shocks propagates through input-output linkages whose structure—whether upstream complements or horizontal substitutes—determines whether spillovers are amplified or attenuated. Applied to the equity-market setting, their work implies that an FOMC announcement simultaneously generates *positive-sum* spillovers for economies embedded as complements in U.S. supply chains and *zero-sum reallocations* for economies positioned as competitors. Engler et al. (2023) provide corroborating evidence from a different angle, showing that U.S. economic news—distinct from policy surprises per se—drives substantial heterogeneity in emerging-market financial responses, with the sign and magnitude depending on the nature of the bilateral economic linkage. We operationalize this prediction in Section 4 by mapping the MP–CBI decomposition onto our four-market sample.

The strength of MP spillovers, by contrast, is governed primarily by the institutional architecture of external constraints. Three factors govern the cross-country dispersion of responses (Aizenman et al., 2016): monetary policy autonomy (fixed vs. flexible exchange rate regimes determine pass-through of U.S. rate changes), financial market depth (shallow markets amplify portfolio rebalancing effects), and external balance sheet exposure (dollar liabilities create additional tightening channels through currency depreciation). For MP shocks, the conventional trilemma hierarchy should hold: economies with less monetary autonomy absorb larger discount-rate effects.

Monetary policy autonomy determines whether domestic authorities can offset imported tightening. Countries operating under fixed exchange rate regimes—such as Hong Kong's currency board since 1983—mechanically import U.S. monetary conditions, providing an upper bound for pass-through intensity (Shambaugh, 2004). At the other extreme, economies with floating rates and credible inflation targeting retain substantial room for countercyclical adjustment. Germany, operating within the Eurozone, and Brazil, with its inflation targeting regime since 1999, both possess policy flexibility—yet Curcuru et al. (2018) find that U.S. monetary surprises nonetheless move German bond yields significantly, while Kohlscheen (2014) documents that Brazilian inflation expectations exhibit greater exchange rate pass-through than advanced economy benchmarks. India's managed float combined with capital flow management occupies an intermediate position (Patnaik and Shah, 2012). Thus, even among economies with nominal policy independence, the degree of effective insulation varies considerably. Hoek et al. (2021) provide updated evidence confirming that both the nature of the shock and the receiver's macroeconomic vulnerabilities jointly determine transmission intensity—a finding that motivates our decomposition approach.

Financial market depth and integration shape the pace and amplitude of asset-price pass-through. Deep, liquid markets with sophisticated hedging instruments—characteristic of advanced economies—allow firms and investors to manage currency and interest rate exposure, potentially dampening the immediate equity market response (Ehrmann and Fratzscher, 2009). Yet this same integration creates tight arbitrage linkages: Ehrmann and Fratzscher (2005) show that German equity markets respond strongly to Fed announcements, particularly during periods of elevated uncertainty, suggesting that financial development facilitates rather than impedes propagation. For emerging markets, thinner liquidity and larger foreign-investor presence amplify price impact. Jotikasthira et al. (2012) document that global risk-sentiment shifts translate directly into emerging-market equity flows, creating a conduit for repricing.

External balance sheet exposure generates asymmetric vulnerabilities across economies. Dollar - denominated debt exposes firms to balance-sheet effects when the dollar appreciates alongside U.S. monetary tightening—a mechanism that is particularly acute in Brazil, where large firms are more likely to carry foreign-currency liabilities(Alfaro et al., 2019). Commodity exporters face an additional terms-of-trade channel as dollar strength typically coincides with commodity price declines (Obstfeld, 2022; Frankel, 2014). Kalemli-Özcan (2019) documents that capital flows directly affect emerging market credit spreads over and above domestic policy rates, since EME banking systems intermediate global liquidity and carry-trade reversals force domestic credit tightening. Advanced economies, while not immune to these channels, typically exhibit lower currency mismatch and less commodity dependence in their export baskets, attenuating—but not eliminating—balance-sheet pass-through.

These institutional factors interact with the nature of the shock itself, and the interaction is *asymmetric* in a way that maps directly onto the complementarity-substitution taxonomy. While Georgiadis (2016) found that generic trade linkages tend to mitigate standard U.S. monetary shocks—leaving financial integration and domestic rigidities as the primary amplifiers—we demonstrate that trade exposure responds asymmetrically when shocks are decomposed. Specifically, trade openness strongly amplifies the cash-flow channel during CBI shocks. For an export-oriented economy like Germany, this qualitative composition of trade rivals the financial propagation mechanism in importance. Yet trade exposure responds asymmetrically to MP versus CBI shocks. A contractionary MP shock signals both higher rates and weaker demand, reinforcing negative equity effects through both channels simultaneously. A positive CBI shock, by contrast, signals stronger U.S. growth alongside higher rates—potentially boosting export-oriented equities even as discount rates rise. Crucially, this positive cash-flow offset accrues disproportionately to economies whose exports *complement* U.S. demand (commodities, capital goods), while economies whose tradable sectors *compete* with U.S. firms may instead experience capital reallocation toward the now more attractive U.S. market (Forbes and Warnock, 2012; Kalemli-Özcan et al., 2025). The net CBI spillover therefore depends not on trade openness alone but on the *qualitative composition* of the bilateral economic relationship.

Taken together, the theoretical evidence generates a set of layered predictions. For MP shocks, the trilemma hierarchy should govern: the discount-rate channel dominates, and cross-country variation in negative equity responses should align with differences in monetary policy autonomy. For CBI shocks, a different ordering should emerge, driven by productive-structure complementarity rather than exchange-rate architecture. Economies whose output complements U.S. demand should display positive CBI responses (cash-flow gains dominate discount-rate costs), while economies whose leading sectors substitute for U.S. output should display negative or muted responses (capital-rotation losses dominate or offset any trade-channel benefit). The empirical design that follows is tailored to test precisely this pair of predictions.

Accordingly, our four-market configuration—DAX, IBOV, Hang Seng, and SENSEX—include both dimensions of this heterogeneity. The DAX (Germany), representing a highly trade-integrated economy with complementary manufacturing exports to the U.S. and substantial domestic policy flexibility, captures the dynamics of a mature, open economy. The IBOV (Brazil) combines commodity-export complementarity with the U.S. alongside significant exposure to U.S. dollar-denominated liabilities, reflecting the vulnerabilities of a resource-rich emerging market. The Hang Seng (Hong Kong) provides the polar case of zero monetary autonomy due to its currency board, but has a limited direct productive-structure linkage to U.S. demand, given its increasing orientation toward mainland Chinese earnings (Huo and Ahmed, 2017). Finally, the SENSEX (India) represents a managed float whose composition—heavily weighted in IT services and financials—places it in competitive substitution with U.S. firms (Lakdawala, 2021; Patnaik et al., 2016). This configuration allows us to examine how spillovers vary across both dimensions—monetary autonomy for monetary policy (MP) shocks, and productive complementarity for cross-border investment (CBI) shocks—rather than simply across geographic regions or income classifications.

3 Data and empirical approach

Our main explanatory variables are the Monetary Policy (MP) and Central Bank Information (CBI) shocks identified by Jarociński and Karadi (2020). Within a narrow window around each FOMC announcement, the co-movement between interest-rate futures and stock prices reveals whether markets are reacting to a policy surprise (rates up, stocks down $\Rightarrow$ MP) or to new information about fundamentals (rates up, stocks up $\Rightarrow$ CBI). We use the publicly updated series covering 205 scheduled FOMC announcements from January 2000 to January 2024[1].

Our dependent variables are daily equity returns for four indices chosen to span the key dimensions of heterogeneity discussed in Section 2: Germany's DAX, Brazil's IBOV, Hong Kong's Hang Seng, and India's SENSEX. Daily closing prices are from Refinitiv; the S&P 500 Total Return Index serves as a U.S. market control. All returns are percentage log-points. For each FOMC announcement date τ, we construct cumulative returns for market m over an event window that captures the initial repricing. Define:

- τ: index for FOMC announcement dates ($\tau = 1, \ldots, T$)
- m: market index ($m \in \{\text{DAX, IBOV, HSI, SENSEX}\}$)
- $t_m(\tau)$: the aligned trading day for market m, defined as the first available trading day on or after τ such that $|t_m(\tau) - \tau| \leq 7$ calendar days
- $r_{m,d}$: daily log return for market m on trading day d, in percentage points

The event-time cumulative outcome at horizon h is

$$y_{m,\tau}^{(h)} = \sum_{j=0}^{h} r_{m,\,t_m(\tau)+j}, \qquad h = 0, \ldots, 10, \tag{1}$$

where $j = 0$ captures the event-day return (or the first tradable repricing day for markets whose close precedes the announcement), and $j = 1, \ldots, h$ accumulates post-announcement drift. We focus on an event-study horizon of $h \in \{0, \ldots, 10\}$ trading days: short enough to remain close to high-frequency identification, but long enough to capture delayed international repricing through portfolio and balance-sheet channels (Kuttner, 2001; Gürkaynak et al., 2005; Jordà, 2005).

Event-time alignment follows market trading calendars. When announcement timing is observed, the impact window depends on whether the release occurs before or after local close; when timing is unobserved, we use conservative windows that guarantee inclusion of the first tradable repricing under each market clock. This choice prioritises identification validity over potential efficiency gains from narrower timing-sensitive windows (Fleming and Remolona, 1999; Hausman and Wongswan, 2011).

To ensure cross-market comparability despite heterogeneous unconditional volatility, we standardize all returns by each market's 10-day pre-event realized volatility. Standardizing by pre-event volatility produces a unit-free response metric and mitigates heteroskedasticity in pooled event-study inference, and means that all estimated coefficients are expressed in volatility-adjusted units.

[1] File `shocks_fed_jk_t.csv` from `marekjarocinski/jkshocks_update_fed_202401`, available at `https://github.com/marekjarocinski/jkshocks_update_fed_202401`.

Although the identification of Jarociński and Karadi (2020) rests on intraday co-movements, daily pre-announcement returns may exhibit conditional predictability—reflecting, for example, the pre-FOMC drift of Lucca and Moench (2015). We remove this predictable variation so that the shocks entering our regressions are orthogonal to the market's pre-event information set.

Each raw shock $\varepsilon \in \{\mathrm{MP}_\tau, \mathrm{CBI}_\tau\}$ is first standardised to unit variance on training-fold data, yielding $\tilde{\varepsilon}_{s,\tau}$. We then regress on a constant and four pre-event S&P 500 features that capture the market's pre-announcement information set:

$$\tilde{\varepsilon}_{s,\tau} = a_s + b_s' Z_\tau + \xi_{s,\tau}, \tag{2}$$

where Z_τ collects level, momentum, volatility, and tail-risk proxies constructed from pre-event S&P 500 returns (exact definitions in Appendix A.1). The residual $\xi_{s,\tau}$ is the orthogonalised shock used throughout. Under cross-fitting, all coefficients in (2) are estimated on training-fold data and applied to the held-out fold, preventing contamination of inference. For the pooled-panel regressions, an extended control vector X_τ augments Z_τ with three additional S&P 500 risk measures, yielding seven pre-event controls in total (see Appendix A.1 for the complete list and the formal argument that including Z_τ-overlapping variables in X_τ does not re-introduce the variation removed in (2)).

3.1 Break detection

A central contribution of this paper is to let the data determine whether and when transmission changed, rather than imposing a break date *ex ante*. We employ a sup-Wald procedure that searches endogenously over candidate break dates (Andrews, 1993; Hansen, 2000). We allow for gradual regime change through a logistic transition weight $w_\tau(t^*, \gamma) \in [0, 1]$, where t^* is the candidate break date and γ controls transition speed:

$$w_\tau(t^*, \gamma) = \frac{1}{1 + \exp\big[-\gamma(\tau - t^*)\big]}. \tag{3}$$

This nests sharp breaks as a limiting case ($\gamma \to \infty$). The transition speed γ is searched over a grid of half-lives spanning near-abrupt to gradual transitions; the parameterisation and grid values are detailed in Appendix A.2. For each candidate pair (t^*, γ), we estimate the pooled regression across all four markets at $h = 0$:

$$y^{(0)}_{m,\tau} = \alpha_m + \beta_s\, \xi_{s,\tau} + \delta_w\, w_\tau + \delta_s \big(\xi_{s,\tau} \cdot w_\tau\big) + \eta' X_\tau + u_{m,\tau}, \tag{4}$$

the distributional evidence in Table 1 motivates an important extension: because the Fed tightens gradually but eases abruptly, and because positive information revelations arrive as rare high-impact events, contractionary and expansionary surprises of the *same* shock type may propagate differently to international equity markets. To allow for this possibility without doubling the number of free parameters, we augment the break-selection regression with a single asymmetry term. Define the positive-tail interaction $\xi^{+,\mathrm{int}}_{s,\tau} = \xi_{s,\tau}\, 1(\xi_{s,\tau} > 0)$, which equals the shock when it is contractionary (MP) or optimistic (CBI). For each candidate pair (t^*, γ), the training-fold regression (4) is expanded to include both the linear shock $\xi_{s,\tau}$ and its positive-tail counterpart $\xi^{+,\mathrm{int}}_{s,\tau}$, and the break date is selected by maximising the *joint* Wald statistic over the two regressors. This design lets the data detect regime changes that manifest primarily in the heavy right tail—for instance, a shift in how large hawkish surprises transmit abroad—while preserving one-shock-at-a-time identification in the subsequent fold-specific estimation stage, where only the linear term enters.

The selected (t^*, γ) maximises the pooled mean of market-specific Wald statistics across the four equity indices (sup-Wald logic), and the joint null $H_0\colon \delta_w = \delta_s = 0$ is tested using cluster-robust standard errors at the calendar-year level. Because the supremum of the Wald statistic over candidate break dates follows a nonstandard distribution under H_0, p-values are computed via wild cluster bootstrap with Rademacher weights (Cameron et al., 2008). To reduce post-selection bias, break selection and effect estimation are separated by year-stratified cross-fitting with $K = 3$ folds (Chernozhukov et al., 2018). For each fold k, the candidate (t_k^*, γ_k) is selected using only the complementary training fold, and all subsequent quantities are estimated on the held-out test fold.

3.2 Bayesian local projections

With the break date selected, we estimate regime-dependent spillovers using a Bayesian local projection approach that navigates the bias–variance trade-off inherent in impulse-response estimation (Barnichon and Brownlees, 2019; Ferreira et al., 2023).

Stacking horizons $h = 0, \ldots, H$ ($H = 10$) into a vector $y_{m,\tau}$, the data-generating process *for each market m separately* is

$$y_{m,\tau} = \boldsymbol{\alpha}_m + \boldsymbol{\beta}_{\text{pre},m}\, \xi_{s,\tau}(1 - w_\tau) + \boldsymbol{\beta}_{\text{post},m}\, \xi_{s,\tau}\, w_\tau + \boldsymbol{\Gamma}_m X_\tau + \boldsymbol{\Lambda}_m f_{m,\tau} + \boldsymbol{\epsilon}_{m,\tau}, \tag{5}$$

where $\boldsymbol{\beta}_{\text{pre},m}$ and $\boldsymbol{\beta}_{\text{post},m}$ are $(H{+}1) \times 1$ vectors of market- and regime-specific impulse responses; $f_{m,\tau} \sim N(0, 1)$ is a market-specific scalar latent factor capturing residual cross-horizon comovement, with loadings $\boldsymbol{\Lambda}_m$ identified by constraining $\lambda_m^{(0)} > 0$; and $\boldsymbol{\epsilon}_{m,\tau} \sim N(0, \boldsymbol{\Psi}_m)$, $\boldsymbol{\Psi}_m = \text{diag}(\psi_{m,0}, \ldots, \psi_{m,H})$, is a horizon-specific residual orthogonal to $f_{m,\tau}$ by construction. The diagonal $\boldsymbol{\Psi}_m$ delegates all cross-horizon covariance to the latent factor while allowing idiosyncratic variances to differ freely across horizons, accommodating the mechanical increase in noise at longer cumulative horizons. Because the model is estimated independently for each market, cross-market heterogeneity is unrestricted; commonality across markets is tested at the reporting stage through the pooled panel specification (9).

Together, equation (5) and the Gaussian assumptions define a complete hierarchical Bayesian model with likelihood $p(Y \mid \boldsymbol{\Theta}, f)$ implied by the normal error structure and priors (see Appendix A.3). Estimation proceeds through Gibbs sampling, iterating over conditional posteriors.

The prior structure imposes two forms of regularisation. First, a first-order random walk across horizons penalises erratic horizon-to-horizon variation:

$$\beta^{(h)} \mid \beta^{(h-1)} \sim N\big(\beta^{(h-1)},\, \kappa^2\big), \tag{6}$$

where κ^2 controls smoothness. Second, a shrinkage prior centres the post-regime response on the pre-regime response:

$$\boldsymbol{\beta}_{\text{post}} \mid \boldsymbol{\beta}_{\text{pre}} \sim N\big(\boldsymbol{\beta}_{\text{pre}},\, \sigma_d^2\, I\big), \tag{7}$$

encoding skepticism toward regime change: a small σ_d^2 resists finding structural breaks unless the data clearly demand them. Both κ^2 and σ_d^2 receive conjugate inverse-gamma hyperpriors whose scales are anchored to observable sample quantities: $E[\kappa^2]^{1/2}$ is calibrated to approximately one-tenth of the cross-market median absolute event-day return, and $E[\sigma_d^2]^{1/2}$ to approximately one-half of the same benchmark (Gelman, 2006; Gabry et al., 2019). The complete prior table, economic calibration rationale, and prior-predictive diagnostics are reported in Appendix A.4 and A.5.

Factor loadings receive standard normal priors (with $\lambda^{(0)} > 0$ for sign identification); idiosyncratic variances follow conjugate inverse-gamma priors; market intercepts and control coefficients receive flat priors so that their posterior coincides with the conditional OLS distribution. The full specification is collected in Table 4 of the Appendix.

Our main estimand is the immediate regime difference:

$$\Delta\beta_m^{(0)} = \beta_{\text{post},m}^{(0)} - \beta_{\text{pre},m}^{(0)}, \tag{8}$$

complemented by $\text{AUC}_{0:3} = \sum_{h=0}^{3} \beta^{(h)}$ as a short-run propagation metric. Jointly, $(\Delta\beta_m^{(0)}, \text{AUC}_{0:3})$ separates immediate repricing from short-horizon accumulation. And to allow cross-market heterogeneity while maintaining a common break date, we also estimate a pooled specification at $h = 0$:

$$y_{m,\tau}^{(0)} = \alpha_m + \sum_{g\in\mathcal{G}} \beta_{s,g}\, \xi_{s,\tau} \cdot 1(m \in g) + \sum_{g\in\mathcal{G}} \delta_{s,g}\, \xi_{s,\tau} \cdot w_\tau \cdot 1(m \in g) + \eta' X_\tau + u_{m,\tau}, \tag{9}$$

where $\mathcal{G} = \{\text{DM}, \text{EME}\}$ with $\text{DM} = \{\text{DAX}\}$ and $\text{EME} = \{\text{IBOV}, \text{HSI}, \text{SENSEX}\}$. The test of regime change is the joint null $H_0 : \delta_{s,g} = 0\ \forall\, s, g$, with inference based on wild cluster bootstrap (Rademacher weights, clustered by event date).

We summarise posteriors by medians and highest posterior density intervals (HPDIs) at 90% and 68%. The 90% HPDI provides a conservative uncertainty envelope; the 68% HPDI is reported as a concentration band especially informative for sign and ranking comparisons under near-symmetric posteriors (Chen and Shao, 1999; Kruschke, 2015). Since estimation uses $K = 3$ cross-fitting folds, each yielding a fold-specific posterior, reported estimates aggregate these posteriors via a quality-weighted average that down-weights folds with noisy identification while retaining substantial influence from larger folds. The aggregation formula and the definition of fold-level identification quality scores are detailed in Appendix A.6.

4 Results and discussion

Table 1 reports descriptive statistics for sign-split shock components. Since shocks are standardized to unit variance prior to estimation, we focus on higher-order moments which remain informative about distributional shape.

Table 1: Descriptive statistics

	Mean	Skew	Kurtosis
MP ($s > 0$)	0.5576	2.2257	4.9859
MP ($s < 0$)	−0.4649	−4.7497	28.8742
CBI ($s > 0$)	0.4869	4.7346	31.0374
CBI ($s < 0$)	−0.5732	−2.3856	6.0001

The distributional properties of the shocks explain the *asymmetric nature of the Fed's own reaction function* and foreshadow the cross-country heterogeneity we document below. Since the shocks are standardised to unit variance prior to estimation, the mean is mechanically uninformative about scale; it is the higher-order moments that reveal the economic structure of the underlying policy events.

Consider first the asymmetry between the two tails of the MP distribution. Contractionary MP realisations display moderate right skewness (2.23) and excess kurtosis (4.99), indicating a distribution with a long right tail but well-behaved dispersion—consistent with the Fed's historical pattern of measured and incremental tightening (Goodfriend and King, 2005). Expansionary MP shocks, by contrast, exhibit extreme left skewness (−4.75) and kurtosis approaching 29. This is the distributional signature of *crisis-driven easing*: emergency rate cuts during the 2001 recession, the 2008 financial crisis, and the pandemic response of March 2020 generated outsized negative realisations that have no counterpart in normal-times tightening (Grasselli, 2022; English et al., 2021). The implication is institutional: the Fed tightens gradually but eases abruptly, and this institutional asymmetry is imprinted in the shock distribution. For international equity markets, this means that large negative MP surprises—the ones most likely to generate dramatic cross-border repricing—arrive as rare, concentrated events rather than as a continuous flow, a pattern that amplifies the importance of event-study identification relative to time-series approaches that smooth over these episodes.

The CBI distribution displays a mirror-image asymmetry that carries distinct economic content. Optimistic CBI realisations—events where the Fed reveals meaningfully stronger fundamentals than markets anticipated—show the most extreme departures from normality in our entire sample (skewness 4.73, kurtosis > 31). These are genuinely rare events: most FOMC communications confirm or modestly adjust the market's prior; only occasionally does the Committee reveal information sufficiently novel to generate a large positive co-movement of rates and equity prices. When such revelations do occur, however, they are *substantial*—the heavy right tail implies that positive information surprises arrive as discrete, high-impact episodes rather than as gradual updates. Pessimistic CBI realisations, by contrast, are more evenly spread (skewness −2.39, kurtosis 6.00), suggesting that negative information signals accumulate incrementally through successive communications rather than arriving in single large shocks.

4.1 MP transmission

Table 2 summarises the effects for the MP component across two distinct metrics: the impact response ($h = 0$) capturing immediate repricing on the announcement day and the cumulative response ($\mathrm{AUC}_{0:3}$) measuring shock persistence and potential feedback effects over the subsequent three days. Peak absolute responses across horizons, which capture changes in response amplitude, are reported in Appendix B. The central finding is a strict cross-country ordering in impact magnitudes: HSI (−0.33) > DAX (−0.26) > IBOV (−0.16) > SENSEX (−0.02). This is the prediction of the Mundell-Fleming trilemma (Mundell, 1963; Fleming, 1962) made visible in equity-market data. The ranking maps directly onto the degree of monetary policy autonomy each economy retains in the face of a U.S. rate change (Obstfeld et al., 2005; Shambaugh, 2004). Importantly, the level estimates underlying this ranking are themselves robust: for the majority of market–horizon pairs, highest posterior density intervals exclude zero, confirming that the cross-country pattern reflects genuine repricing rather than posterior noise.

The logic is causal and institutional. Hong Kong's currency board, operational since 1983, forces

Table 2: MP shock responses – impact and cumulative effects

Market	Estimand	Pre	Post	Diff	90% HPDI (Diff)	68% HPDI (Diff)
Panel A: Impact response (h=0, percentage log-points)						
HSI	$\hat{\beta}_{h=0}$	-0.33^{*}	-0.32^{*}	+0.01	[−0.07, 0.09]	[−0.04, 0.05]
DAX	$\hat{\beta}_{h=0}$	-0.26^{*}	-0.28^{*}	−0.02	[−0.10, 0.06]	[−0.07, 0.03]
IBOV	$\hat{\beta}_{h=0}$	-0.16^{*}	-0.16^{*}	−0.01	[−0.08, 0.07]	[−0.05, 0.04]
SENSEX	$\hat{\beta}_{h=0}$	−0.02	−0.03	0.00	[−0.09, 0.07]	[−0.05, 0.05]
Panel B: Cumulative response ($\mathrm{AUC}_{0:3}$, percentage log-points)						
HSI	$\sum_{j=0}^{3}\hat{\beta}_j$	-1.33^{*}	-1.31^{*}	+0.02	[−0.20, 0.24]	[−0.13, 0.14]
DAX	$\sum_{j=0}^{3}\hat{\beta}_j$	-1.03^{*}	-1.08^{*}	−0.06	[−0.30, 0.16]	[−0.18, 0.09]
IBOV	$\sum_{j=0}^{3}\hat{\beta}_j$	$-0.62^{\dagger}$	-0.65^{*}	−0.04	[−0.27, 0.18]	[−0.17, 0.10]
SENSEX	$\sum_{j=0}^{3}\hat{\beta}_j$	−0.09	−0.12	−0.03	[−0.27, 0.18]	[−0.16, 0.11]

Notes: Cross-fitted Bayesian local projections with stratified folds and hierarchical meta-draw aggregation (1,500 posterior draws). Fold-specific break dates are July 2006 ($\hat{\gamma} = 0.106$), November 2005 ($\hat{\gamma} = 0.137$), and July 2018 ($\hat{\gamma} = 0.085$). Corresponding wild-bootstrap sup-Wald p-values are 0.742, 0.677, and 0.937. All estimates are percentage log-points per one-standard-deviation MP shock. 90% and 68% highest posterior density intervals. In Pre/Post columns, * means the 90% HPDI excludes zero and † means only the 68% HPDI excludes zero. Peak absolute responses across horizons are reported in Appendix B.

the Hong Kong Monetary Authority to replicate Fed rate changes within hours. When the Fed tightens by surprise, Hong Kong's interbank rate adjusts mechanically, compressing equity valuations through the discount-rate channel with no domestic policy offset available (Hong Kong Monetary Authority, 2014; Park and Wyplosz, 2008). The estimated impact effect of −0.33 means that a one-standard-deviation MP shock at the FOMC lowers Hong Kong equity prices on impact by about 0.33 percentage points (in our volatility-adjusted event-study metric). Economically, this is what near-complete monetary pass-through looks like: because the currency board tightly imports U.S. monetary conditions, Hong Kong equities absorb almost the full discount-rate shock immediately, making this response the closest observable counterpart to a pure discount-rate experiment. The absence of any exchange-rate buffer means that the entirety of the shock transmits through the financial-conditions channel, making HSI the natural upper bound for MP spillovers in our sample.

Germany, operating within the Eurozone, possesses formal monetary independence via the European Central Bank but faces tight arbitrage linkages with U.S. financial markets. The −0.26 response reflects two reinforcing channels: first, the revaluation of future cash flows through the global risk-free rate (Bernanke and Kuttner, 2005); second, portfolio rebalancing by institutional investors who treat U.S. and European equities as partial substitutes (Ehrmann and Fratzscher, 2005; Dedola et al., 2017). The DAX response is smaller than the HSI because the ECB retains the option—though not always the inclination—to decouple euro-area financial conditions from the Fed's stance. That the gap between the two (0.07 pp at impact) is economically meaningful but modest confirms that financial integration can transmit shocks nearly as effectively as a hard peg, consistent with the "financial trilemma" argument of Schoenmaker (2011): deep capital-market integration creates a de facto monetary linkage even when de jure independence exists.

Within the emerging-market block, the orderly trilemma hierarchy gives way to a more nuanced pattern that requires looking beyond the currency arrangement alone. Brazil's IBOV shows an impact response of

-0.16, smaller than both HSI and DAX. The cumulative loss of approximately -0.6 pp over four trading days indicates that the shock propagates beyond the announcement window, consistent with a combination of two countervailing forces. Additionally, Table 2 indicates that the pre-response effects are statistically significant only at the 68% HPDI.

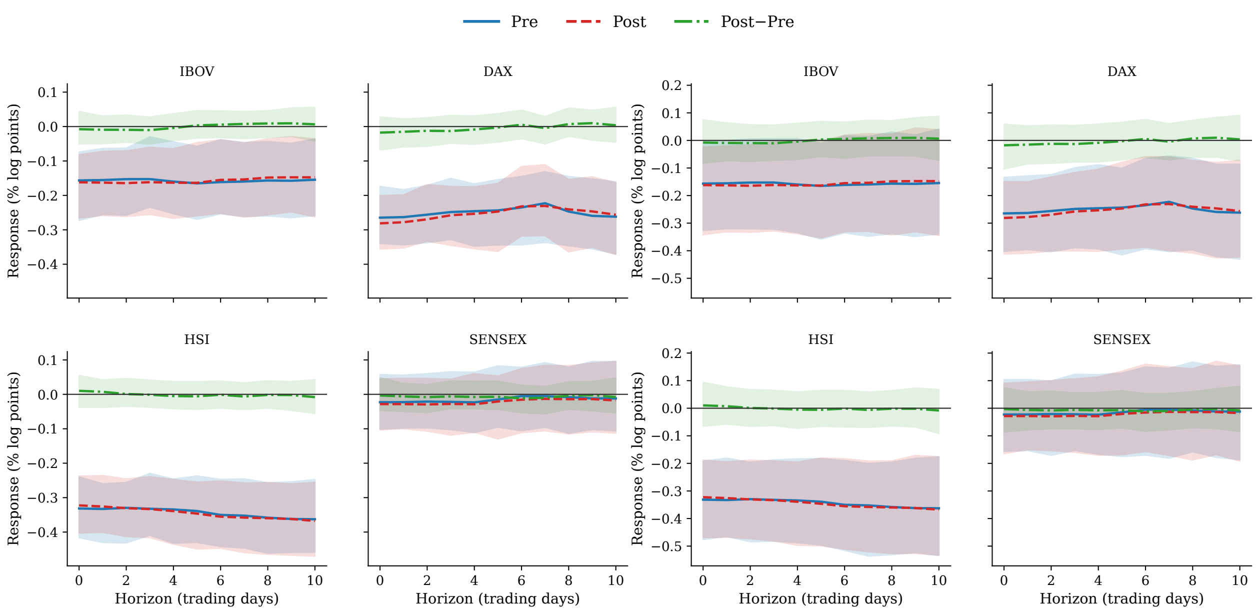
On the one hand, Brazil's floating exchange rate since 1999 provides a partial buffer: the real tends to depreciate under U.S. tightening, cushioning the blow to export competitiveness and giving the central bank more room to tailor policy to domestic conditions. On the other hand, this buffer is incomplete because large Brazilian firms carry significant foreign-currency liabilities(Alfaro et al., 2019). When the dollar strengthens alongside a U.S. rate hike, the real value of this debt rises, tightening corporate balance sheets and depressing investment—a valuation channel that operates independently of, and in addition to, the conventional discount-rate mechanism. The net effect is that Brazil absorbs roughly half the impact of a currency-board economy like Hong Kong: the exchange rate absorbs some of the shock, but the balance-sheet channel reintroduces vulnerability through the corporate sector. This finding resonates directly with Fernández et al. (2017), who show that world shocks account for the majority of business-cycle fluctuations in commodity-exporting emerging economies—our results suggest that the equity-market channel is one of the key conduits through which this external determination operates.

India's SENSEX response is statistically indistinguishable from zero. This near-zero central tendency (-0.02 pre; -0.03 post) reflects the institutional architecture of India's monetary regime. The Reserve Bank of India operates a managed float with active capital-flow management, giving it discretionary room to offset imported tightening—precisely the policy independence that the trilemma predicts for an economy that sacrifices some capital-account openness in exchange for monetary autonomy (Patnaik and Shah, 2012; Patra and Kapur, 2012). The 68% HPDIs concentrate posterior mass tightly around zero ($[-0.05, 0.05]$ at impact), lending modest support to a small-effect interpretation.

The most striking feature of Table 2 is not the cross-country ranking—which aligns with prior expectations—but the absence of any detectable change in that ranking over 24 years of dramatic institutional transformation. Every regime-difference estimate is centred near zero: the largest impact shift is -0.02 pp for the DAX, and both 90% and 68% highest posterior density intervals include zero for every market. The economic content of this non-rejection is substantial when one considers what *did* change between 2000 and 2024. The Fed moved from conventional rate targeting to the zero lower bound (2008), launched three rounds of large-scale asset purchases, experimented with calendar-based and state-contingent forward guidance, and executed the most aggressive tightening cycle in four decades (Swanson, 2021). During the same period, Brazil weathered a sovereign upgrade to investment grade and subsequent downgrade to speculative status, a deep political crisis, and a pandemic recession (Barbosa Filho, 2017; Mesquita and Torós, 2010); Hong Kong faced the progressive integration of mainland Chinese capital markets through the Stock Connect programs (Huo and Ahmed, 2017); Germany absorbed the European sovereign debt crisis (Lane, 2012); and India undertook major financial-sector reforms, including the 2016 demonetization (Chodorow-Reich et al., 2020). Through all of this, the *direction*, *ranking*, and *magnitude* of MP spillovers remained essentially invariant.

This stability implies that the determinants of spillover heterogeneity are *slow-moving institutional characteristics*—exchange-rate architecture, the currency denomination of external debt, the depth of domestic capital markets—not time-varying features of the Fed's reaction function or the prevailing policy instrument (Aizenman et al., 2016; Bernanke and Kuttner, 2005; Hoek et al., 2021). From the perspective of a policymaker in emerging countries, the practical corollary is clear: the exposure to U.S. monetary-policy shocks is a feature of the domestic financial architecture, not of the current phase of the Fed's policy cycle. Attenuating that exposure therefore demands institutional reform—lowering currency mismatch, broadening local-currency funding markets, reinforcing macroprudential safeguards—rather than tactical cycle-by-cycle policy calibration (Du and Schreger, 2022; Forbes and Warnock, 2012).

Figure 1 presents the cross-fitted Bayesian impulse responses to monetary-policy shocks. Panel (a) displays the 68% highest posterior density intervals and Panel (b) reports the corresponding 90% intervals. By providing both intervals, we can assess the signal strength: the tighter bands reveal the central tendency, while the wider bands provide a conservative test of statistical significance. The visual pattern confirms the economic narrative. The HSI and DAX impulse response paths remain clearly separated from zero across the full ten-day horizon in both panels, reflecting persistent negative repricing. The IBOV path is negative but approaches zero at intermediate horizons under the wider 90% bands—consistent with the partial exchange-rate buffering discussed above. The SENSEX path fluctuates around zero with credible bands that engulf the horizontal axis at all horizons: the posterior is genuinely diffuse, not merely imprecise around a hidden negative tendency.



(a) MP shock, 68% HPDI

(b) MP shock, 90% HPDI

Figure 1: Impulse responses to MP shocks by equity market

Note: Impulse responses to one-standard-deviation MP shocks across the four equity markets. Solid lines denote posterior medians; shaded regions denote highest posterior density intervals from cross-fitted Bayesian local projections with hierarchical meta-draw aggregation. Responses are cumulative equity log-returns in percentage log-points over horizons h = 0–10 trading days after FOMC announcements. Panel (a) displays the impulse response using the 68% HPDI, while panel (b) reports the same response using the 90% HPDI.

4.2 CBI transmission

Table 3 reports the corresponding estimates for CBI shocks and the results upend the MP hierarchy entirely. The cross-country ordering of CBI impact responses is: IBOV (+0.41) > DAX (+0.19) > HSI (0.00) > SENSEX (−0.17). This ranking is not merely different from the MP ordering—it is *sign-heterogeneous*. A positive CBI surprise, which by construction represents a favourable Fed information revelation about U.S. economic fundamentals (Romer and Romer, 2000; Jarociński and Karadi, 2020), simultaneously raises equity prices in some countries and lowers them in others. As with the MP results, level estimates are broadly well-identified: 68% HPDIs exclude zero for the markets that anchor both ends of the sign spectrum, indicating that the opposing responses are individually statistically credible and not merely an artefact of imprecise estimation.

Table 3: CBI shock responses – impact and cumulative effects

Market	**Estimand**	**Pre**	**Post**	**Diff**	**90% HPDI (Diff)**	**68% HPDI (Diff)**
Panel A: Impact response (h=0, percentage log-points)						
IBOV	$\hat{\beta}_{h=0}$	$+0.41^{*}$	$+0.41^{*}$	−0.01	[−0.09, 0.07]	[−0.05, 0.05]
DAX	$\hat{\beta}_{h=0}$	$+0.19^{*}$	$+0.18^{*}$	−0.02	[−0.09, 0.08]	[−0.06, 0.04]
HSI	$\hat{\beta}_{h=0}$	0.00	−0.04	−0.04	[−0.11, 0.05]	[−0.09, 0.01]
SENSEX	$\hat{\beta}_{h=0}$	-0.17^{*}	-0.18^{*}	−0.01	[−0.09, 0.07]	[−0.06, 0.04]
Panel B: Cumulative response ($\mathrm{AUC}_{0:3}$*, percentage log-points)*						
IBOV	$\sum_{j=0}^{3}\hat{\beta}_j$	$+1.67^{*}$	$+1.65^{*}$	−0.02	[−0.23, 0.23]	[−0.17, 0.10]
DAX	$\sum_{j=0}^{3}\hat{\beta}_j$	$+0.75^{*}$	$+0.71^{*}$	−0.04	[−0.27, 0.21]	[−0.19, 0.09]
HSI	$\sum_{j=0}^{3}\hat{\beta}_j$	−0.01	−0.14	−0.12	[−0.37, 0.10]	[−0.27, 0.00]
SENSEX	$\sum_{j=0}^{3}\hat{\beta}_j$	-0.69^{*}	-0.71^{*}	−0.02	[−0.26, 0.20]	[−0.16, 0.11]

Notes: Cross-fitted Bayesian local projections with stratified folds and hierarchical meta-draw aggregation (1,500 posterior draws). Fold-specific break dates are April 2009 ($\hat{\gamma}$ = 0.143), December 2005 ($\hat{\gamma}$ = 0.139), and July 2018 ($\hat{\gamma}$ = 0.048). Corresponding wild-bootstrap sup-Wald p-values are 0.885, 0.641, and 0.056. All estimates are percentage log-points per one-standard-deviation CBI shock. 90% and 68% highest posterior density intervals. In Pre/Post columns, * means the 90% HPDI excludes zero and † means only the 68% HPDI excludes zero. Peak absolute responses across horizons are reported in Appendix B.

This sign reversal is inconsistent with a single global discount-rate channel and reveals what we term an *informational trilemma*: the institutional features that determine a country's vulnerability to MP shocks (currency arrangement, monetary autonomy) are *different* from those that determine its sensitivity to CBI shocks (output composition, sectoral mix, position in global value chains). The conventional trilemma governs propagation of the first type; the informational trilemma governs the second. A country can be highly vulnerable to one and nearly immune to the other—as Hong Kong's pattern strikingly illustrates—or it can be exposed to both through different channels, as Brazil's case demonstrates.

The contrast between the MP and CBI rankings is immediately visible when comparing Figures 1 and 2: whereas the MP panels display a monotonically negative fan of impulse responses across all four markets, the CBI panels reveal trajectories of opposing sign, with the IBOV path rising sharply above zero and the SENSEX path falling below it—a divergence that survives even under the wider 90% bands.

Brazil's outsized positive response (+0.41 at impact; +1.67 pp cumulative over four days) is the single largest effect in our entire analysis. Its magnitude *exceeds* the corresponding MP cumulative effect (−0.62 pp) in absolute value, by a factor of nearly three. The economic mechanism is a commodity-price channel: when the Fed reveals that U.S. fundamentals are stronger than expected, this signals higher future global demand, which raises expected commodity prices and directly benefits Brazil's export-intensive equity market—where Petrobras, Vale, and agribusiness conglomerates dominate capitalization (Frankel, 2014; Kilian, 2009).

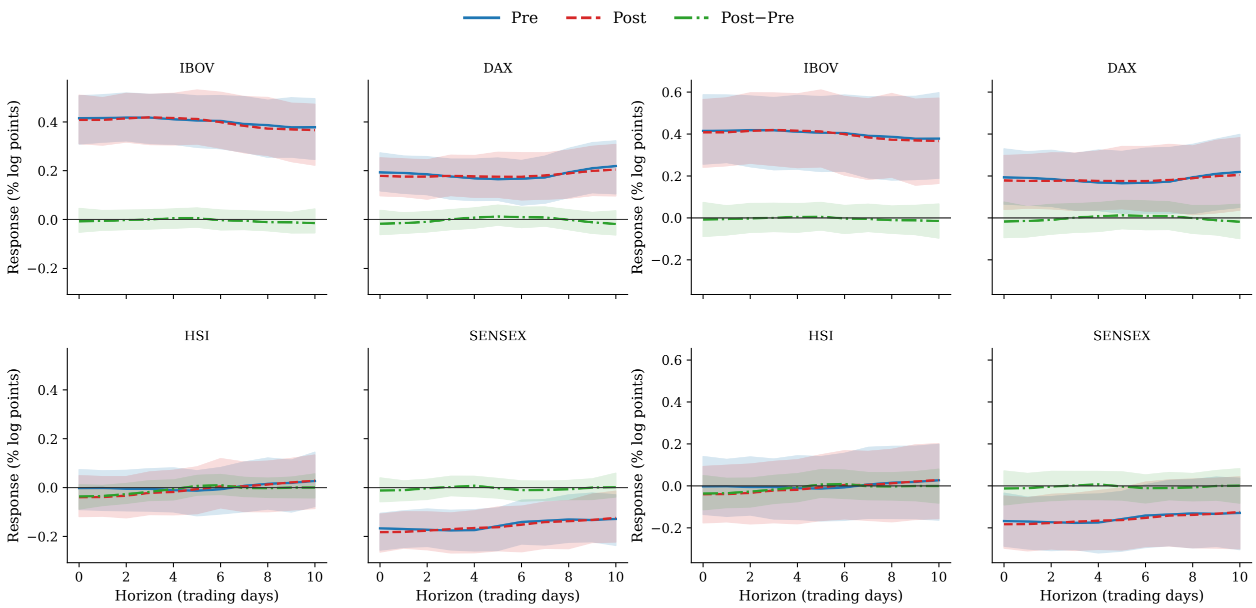
This finding connects to—and substantially extends—the work of Fernández et al. (2017), who show that world shocks explain the majority of business-cycle fluctuations in commodity-exporting emerging economies. Our results identify one specific channel through which this external determination operates: the informational content of Fed communication. Part of what their conduct attributes to "world commodity-price shocks" may in fact be transmitted through the CBI channel of FOMC announcements. More precisely, when the Fed reveals positive information about U.S. growth, the expected path of commodity demand shifts upward, and commodity-exporter equities reprice *before* commodity spot prices fully adjust—because equity markets aggregate forward-looking expectations faster than physical commodity markets clear.

The resulting *commodity-exporter paradox* is economically important. Brazil is *simultaneously* vulnerable to contractionary MP shocks (through the dollar-debt balance-sheet channel) and a primary beneficiary of positive CBI shocks (through the commodity-demand channel). These two shocks frequently coincide—a hawkish Fed surprise that is partly "justified" by stronger fundamentals contains both an MP and a CBI component. The net effect on the IBOV depends on the *composition* of the announcement, not merely its *direction*. A hawkish surprise that is 70% CBI and 30% MP has *opposite* implications for Brazilian equities compared to one that is 30% CBI and 70% MP, even if both produce the same movement in U.S. interest-rate futures.

This paradox has direct implications for the conduct of monetary policy by the Brazil's central bank. If the central bank responds to a Fed tightening by mechanically adjusting domestic rates upward to defend the exchange rate and limit capital outflows—as standard "fear of floating" prescriptions recommend (Calvo and Reinhart, 2002)—it risks amplifying the negative MP component while forfeiting the positive CBI benefit that the commodity channel delivers. A more efficient response would condition intervention on the *informational decomposition* of the Fed signal: when the tightening is CBI-dominated, Brazil can afford a more accommodative stance, allowing the commodity boost to support domestic activity; when it is MP-dominated, tighter conditions and reserve deployment may be appropriate. This logic extends the optimal-intervention approach of Cavallino (2019) and Fanelli and Straub (2021) by adding a dimension they do not consider: what the shock *reveals* about the state of the world, not merely how large it is, should shape the domestic reaction. The 68 and 90% HPDI on the cumulative IBOV response remains strictly bounded above zero from impact through the full ten-day horizon in Figure 2—Panel (a), confirming that this positive repricing is persistent and broadly based, not an artefact of a few extreme horizons.

India's negative response (-0.17 at impact; -0.69 pp cumulative) to what is nominally "good news" from the Fed is the most provocative individual result in our analysis. In the standard approach, positive information about U.S. fundamentals should benefit all trading partners through the global demand channel. The fact that India responds negatively implies that the propagation mechanism operates through a different economic logic.

We propose that the key distinction is between *economic complementarity* and *competitive substitution*.



(a) CBI shock, 68% HPDI

(b) CBI shock, 90% HPDI

Figure 2: Impulse responses to CBI shocks by equity market

Note: Impulse responses to one-standard-deviation CBI shocks across the four equity markets. Solid lines denote posterior medians; shaded regions denote highest posterior density intervals from cross-fitted Bayesian local projections with hierarchical meta-draw aggregation. Responses are cumulative equity log-returns in percentage log-points over horizons h = 0–10 trading days after FOMC announcements. Panel (a) displays the impulse response using the 68% HPDI, while panel (b) reports the same response using the 90% HPDI.

Countries whose export profiles are complementary to the U.S. economy—commodity exporters (Brazil), capital-goods manufacturers (Germany)—benefit from stronger U.S. growth because it directly increases demand for their output. Countries whose leading industries compete directly with U.S. sectors face a different calculus: stronger U.S. growth may redirect capital and demand *toward* the U.S. and *away from* the substitute economy.

India's equity market is dominated by IT services (Infosys, TCS, Wipro), financial services, and pharmaceuticals—sectors that compete directly with U.S. firms for global market share and, critically, for the allocation of global portfolio capital (Parmar, 2024). When the Fed signals stronger U.S. fundamentals, three reinforcing mechanisms work against Indian equities. First, capital repatriation: positive U.S. growth surprises trigger portfolio rebalancing from emerging markets toward U.S. assets, producing a "risk-rotation" dynamic distinct from a generalized risk-off episode (Hau and Rey, 2002; Jotikasthira et al., 2012). Jotikasthira et al. (2012) show that because foreign institutional investors account for a large fraction of trading activity in emerging equity markets, portfolio reallocations triggered by changes in global financial conditions or U.S. growth signals can translate quickly into capital flows and price movements in markets such as the SENSEX. Second, competitive reorientation: stronger U.S. growth steepens the expected path of U.S. wages and corporate profitability, making U.S. firms relatively more attractive as employers and investment targets in the same sectors where Indian firms compete. Third, the expected steepening of U.S. rates compresses risk premia on dollar-funded carry trades that benefit Indian assets, reducing the flow of yield-seeking capital (Lustig et al., 2019; Borio and Zhu, 2012). Under India's managed-float regime, the Reserve Bank of India's discretionary interventions buffer exchange-rate movements but cannot prevent the equity-market repricing that follows when global portfolio allocations shift (Prasad and Rajan, 2008).

Brazil and India are both large emerging markets, both receive substantial foreign portfolio investment, and both operate floating exchange rates—yet they respond to the *same* CBI shock with *opposite* signs. The difference is not captured by standard classifications (advanced versus emerging, fixed versus floating, open versus closed capital account); it is determined by whether the country's output composition complements or substitutes for U.S. output. This echoes the argument of Blanchard et al. (2013) that the macroeconomic impact of capital inflows depends on their type and on the financial structure through which they affect credit and exchange rates—our results show that the same logic applies to the *informational* spillovers of central-bank communication.

Despite being the most responsive market to monetary policy (MP) shocks, Hong Kong exhibits a CBI effect that is statistically negligible. This asymmetry reveals an underappreciated property of hard-peg regimes: the currency board is a *selective* propagation device, not a uniform amplifier. It mechanically imports U.S. interest-rate movements (Park and Wyplosz, 2008; Kang, 2016; Hong Kong Monetary Authority, 2014), but it does not import U.S. growth signals, because CBI shocks—which by construction are orthogonal to the policy-rate surprise—do not trigger the automatic pass-through that drives the HSI's extreme MP sensitivity.

The economic reason is that Hong Kong equity valuations are increasingly determined by mainland Chinese earnings rather than by U.S. real-activity conditions. The Hang Seng Index's progressive integration with mainland capital flows means that the cash-flow channel of CBI propagation—which runs through U.S. demand for the listed firms' output—is attenuated relative to the discount-rate channel of MP pass-through (Kang, 2016). In valuation terms: the discount rate is imported mechanically from the U.S. via the peg, but the numerator of the present-value calculation is driven by Chinese rather than American fundamentals. When the Fed reveals positive U.S. growth information, this shifts the denominator (via expected rates) but barely moves the numerator (because HSI earnings depend on mainland demand), producing a net effect near zero.

This finding quantifies an *underappreciated cost of hard pegs*: forfeiting monetary autonomy eliminates not only the ability to offset imported tightening but also the capacity to capture positive information spillovers that flexible-rate economies with complementary productive structures—like Brazil—naturally absorb. The currency board imports the costs of U.S. monetary tightening in full while transmitting almost none of the benefits of U.S. growth revelations to local equity markets. The cumulative horizon reveals a modest negative drift ($\text{AUC}_{0:3} = -0.14$ post-break, 68% HPDI of $[-0.27,\ 0.00]$), suggesting delayed portfolio-rebalancing effects as global investors rotate toward U.S. assets—a mechanism consistent with Jotikasthira et al. (2012)'s documentation of risk-sentiment-driven emerging-market flows. This incipient drift is visible in Figure 2, where either 68 and 90% bands span zero in all horizons.

Germany's moderate positive response (+0.19 at impact; +0.75 pp cumulative) completes the taxonomy. Germany's trade exposure to the U.S. activates a cash-flow channel through which positive CBI shocks boost expected earnings in export-intensive sectors—particularly automotive, machinery, and chemicals. The DAX response is positive, confirming that the cash-flow benefit of stronger U.S. demand dominates the discount-rate cost of higher expected rates—but it is smaller than Brazil's because Germany's export basket is less commoditized and because the ECB's independent monetary stance provides partial insulation from the discount-rate component.

Taken jointly, the MP and CBI results offer a resolution to one of the most contested debates in international macroeconomics: whether the Mundell-Fleming trilemma survives the era of global financial integration. Rey (2015) argues that a global financial cycle—driven primarily by U.S. monetary conditions and global risk appetite—reduces the trilemma to a "dilemma": monetary policy independence requires capital-account management regardless of the exchange-rate regime. Obstfeld et al. (2005) defend the trilemma's continued relevance, showing that exchange-rate flexibility still provides meaningful insulation from external monetary shocks. Our results suggest that *both are right, but for different types of shocks*.

For MP shocks, the classical trilemma holds with striking precision: the cross-country ordering maps directly onto exchange-rate flexibility, from Hong Kong's full pass-through to India's near-zero response. This validates the Obstfeld-Shambaugh-Taylor position. But for CBI shocks, neither the trilemma nor Rey's dilemma adequately describes the data. The CBI ranking is governed not by the exchange-rate framework or the degree of capital-account openness but by *real-economy complementarity with the United States economy*. Hong Kong's currency board—which should maximize pass-through under both the trilemma and the dilemma frameworks—produces a zero CBI response. Brazil's floating rate—which should provide insulation under the trilemma—produces the largest positive response in the sample. India's managed float—intermediate in the trilemma ranking—produces a *negative* response.

What emerges is a more nuanced architecture: the currency arrangement governs the propagation of *price signals* (interest rates, discount rates) but is largely irrelevant for the diffusion of *quantity signals* (expected output, commodity demand, earnings revisions). The former operates through the financial-conditions channel and respects the trilemma hierarchy. The latter runs through the real-economy channel and is governed by where a country sits in the global input-output network—whether it is a commodity complement, a manufacturing complement, or a competitive substitute to the U.S. economy. This interpretation extends Nakamura and Steinsson (2018)'s documentation of the domestic Fed information effect to the international arena, revealing that the international propagation of this effect is fundamentally *non-uniform*: the same piece of information about U.S. fundamentals generates positive-sum spillovers for some economies and zero-sum reallocations for others, depending entirely on the structure of the receiver.

As with the MP results, regime differences for CBI shocks are uniformly small relative to posterior uncertainty. Every impact and cumulative regime-shift estimate is centred near zero, and both 90% and 68% highest posterior density intervals include zero for all markets (Table 3, Panels A–B). Wild-bootstrap sup-Wald p-values of 0.885, 0.641, and 0.056 fail to reject parameter constancy at the 5% level across all folds, although fold 3's borderline p-value of 0.056 (break date: July 2018, $\hat{\gamma} = 0.048$) flags a possible late-sample instability that warrants monitoring as the post-pandemic sample grows.

The constancy of CBI propagation patterns is, if anything, *more* surprising than the stability of MP patterns. One might reasonably expect that 24 years of structural change—the rise of China, the deepening of commodity financialization, India's emergence as a global IT hub, shifts in global supply chains—would alter the channels through which Fed information propagates. Yet the cross-country pattern, sign structure, and magnitude of CBI spillovers are time-invariant. This suggests that the output-composition characteristics governing CBI diffusion—whether a country is a commodity exporter, a manufacturing complement, or a service-sector competitor—are *deeper* and more persistent than the institutional features that change with policy regimes. Brazil's commodity complementarity, Germany's export orientation, Hong Kong's intermediary role for Chinese earnings, and India's competitive substitution pattern all reflect entrenched positions in the world economy that shift over decades, not business cycles.

The joint reading of our MP and CBI results transforms the policy problem facing emerging-market central banks. The conventional prescription—monitor the Fed's interest-rate moves and adjust domestic conditions accordingly—is incomplete because it treats all Fed surprises as homogeneous. Our findings show that a one-standard-deviation hawkish surprise has an impact on the IBOV that ranges from -0.16 pp (if it is entirely MP) to +0.41 pp (if it is entirely CBI), a swing of 0.57 pp at impact and 2.29 pp cumulatively over four trading days. For a central bank calibrating its foreign-exchange intervention, reserve deployment, or domestic interest-rate response, confusing the two types of shock leads to a qualitatively misspecified policy response.

More broadly, these results challenge the premise underlying proposals for international monetary-policy coordination—namely, that the Fed should "internalize" its spillovers by moderating communication or adjusting the pace of tightening (Obstfeld, 2022). Our evidence shows that the Fed *cannot* design communication that is uniformly benign across countries, because the same informational content generates opposite equity-market effects in Brazil and India. The appropriate policy response is not at the source (the Fed) but at the receiver: emerging-market economies should build institutional capacity for real-time decomposition of Fed signals, develop communication-contingent intervention protocols, and—most importantly—pursue the foundational reforms that reduce exposure to both types of shock: lower currency mismatch in the corporate sector, deeper local-currency bond markets that reduce dependence on dollar funding, and macroprudential buffers calibrated to the specific channels through which external shocks propagate domestically.

5 Robustness check

A natural concern is whether the findings of Section 4 are artefacts of particular modelling choices. We address this through two complementary exercises applied to both shock types. The first exercise asks a *cross-market asymmetry* question: does the sign heterogeneity documented in Section 4 survive when we average each market's response across multiple specifications? Forest plots (Figures 3 and 5) display specification-averaged posterior medians for each market and regime, pooling over all six variants described below. The second exercise is a *specification curve* (Simonsohn et al., 2020; Steegen et al., 2016) that varies one modelling ingredient at a time and tracks the regime difference across variants (Figures 4 and 6). If a particular choice were driving the no-break conclusion, it would appear as an outlier in the curve.

The six specifications are:

- **(i)** **γ-spec (short):** replace the baseline logistic-transition half-life grid (5, 10, 14, 21) days with an alternative grid (3, 7, 14, 30) days, shifting the two shortest anchors downward and extending the upper bound, thereby increasing sensitivity to abrupt regime changes while still admitting slower transitions;

(ii) Prior (τ=0.05, σ_d=0.20): tighten the Bayesian smoothness prior from τ=0.06 to τ=0.05 and the regime-difference prior scale from σ_d=0.25 to σ_d=0.20, making the model *more skeptical* of breaks—if our no-break finding simply reflected loose priors, tighter ones would pull estimates further toward zero;

(iii) Baseline: the reference specification of Section 3 (K=3 folds, automatic orthogonalisation with gating thresholds, default priors τ=0.06 and σ_d=0.25, γ-grid (5, 10, 14, 21) days);

(iv) S&P 500 (removed): we drop all S&P 500 return controls from the event-window regression, testing whether our results depend on conditioning on the domestic U.S. market proxy;

(v) Orthogonalisation (none): we bypass the residualisation of monetary-policy shocks against pre-event S&P 500 returns and lagged market controls entirely, so that raw standardised shocks enter the local projection—a check on whether the pre-event conditioning creates or absorbs the signal;

(vi) Cross-fit (K=2): reduce the number of cross-fitting folds from K=3 to K=2, increasing the training-set share per fold while reducing the number of out-of-sample evaluation splits, altering both the train-test partition and the effective sample size per fold.

All six share the same 205-event sample and posterior-summary conventions (medians; 90% and 68% HPDIs from cross-fitted Bayesian local projections with hierarchical meta-draw aggregation). Importantly, the robustness grid adopts a deliberately more conservative estimation environment than Section 4. The endogenous-break search uses a weekly candidate grid with market-median pooling instead of a daily-step grid with pooled-mean aggregation; and the break-date refinement window is narrower (±7 vs. ±15 days). These choices are intentional: any signal that survives the robustness grid cannot be attributed to aggressive search or liberal gating.

5.1 MP robustness

Figure 3 displays the specification-averaged responses for monetary-policy shocks. The economic message is immediate: the trilemma hierarchy—HSI and the DAX absorbing the largest negative repricing, SENSEX intermediate, IBOV near zero and mildly positive—is preserved intact in both regimes, and the pre- and post-regime highest posterior density intervals overlap almost entirely for every market. Specification-averaged medians place the DAX at −0.244 (pre) and −0.234 (post), the HSI at −0.248 and −0.223, the SENSEX at −0.112 and −0.124, and the IBOV at +0.067 and +0.054—a ranking that maps cleanly onto the degree of monetary-policy autonomy each economy retains. The near-coincidence of pre- and post-regime point estimates across all four markets is precisely what one would expect if the channels of transmission are anchored in slow-moving institutional features—currency-board mechanics, dollar-debt exposure, capital-account architecture—rather than in the particular instrument the Fed happens to be using.

Figure 4 translates this stability into a specification-by-specification comparison. Each column shows the cross-market average regime difference under one variant. Across all six, the median sits between approximately −0.02 and +0.01 pp—economically negligible relative to specification-averaged impact magnitudes of −0.23 to −0.25 pp for the DAX and HSI. The only variant that widens uncertainty appreciably is K=2

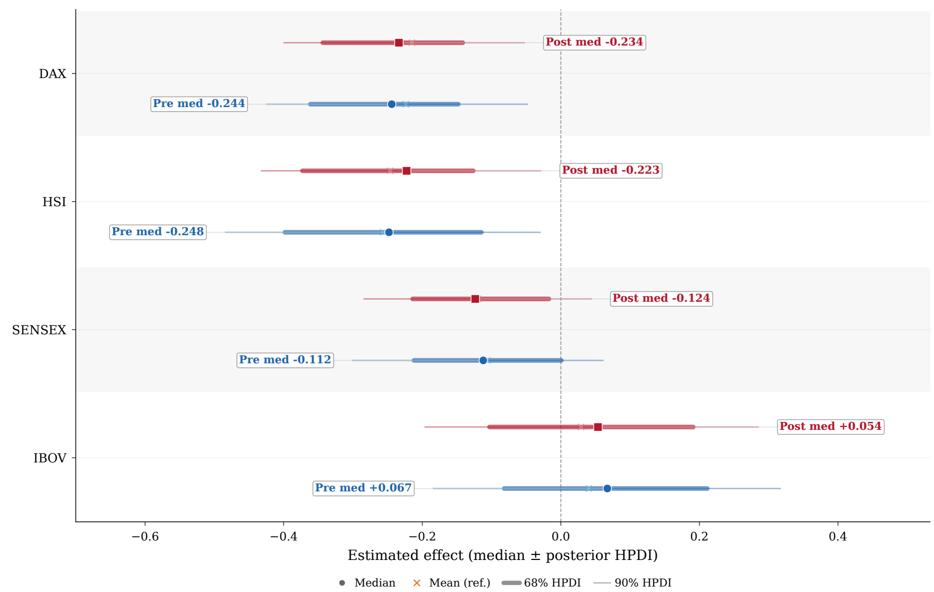


Figure 3: Forest illustration of MP impact responses by market and regime

Note: Pre-regime (blue circles) and post-regime (red squares) posterior medians of the impact response (h=0) to a one-standard-deviation MP shock for each equity market, averaged across six specification variants (see text). Thick bars denote 68% highest posterior density intervals; thin bars denote 90% HPDIs. The dashed vertical line marks zero. Responses are in percentage log-points.

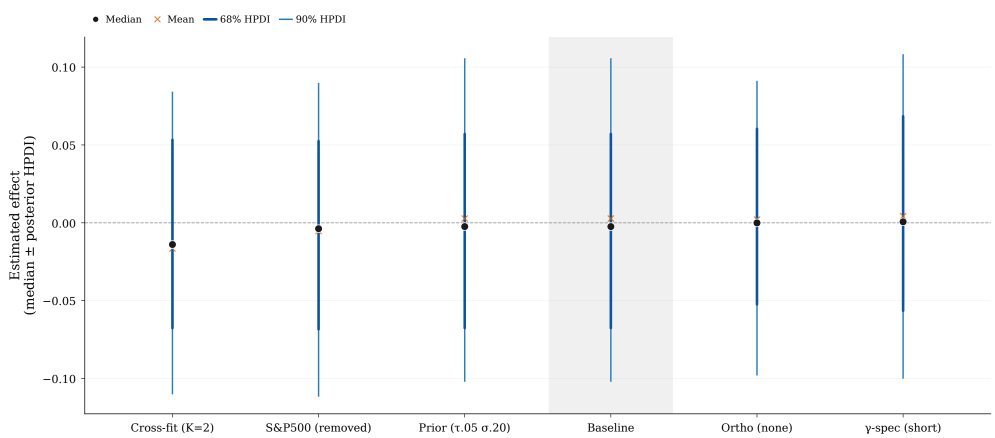


Figure 4: Specification curve for MP regime-difference estimates

Note: Each column corresponds to one specification variant. Black dots denote the posterior median of the regime difference averaged across four equity markets; grey diamonds show individual-market point estimates. Thick dark bars are 68% HPDIs; thin light bars are 90% HPDIs. The shaded column highlights the baseline specification. The dashed horizontal line marks zero. All estimates are percentage log-points per one-standard-deviation MP shock.

cross-fitting, which is expected: fewer folds mean less training data per split and noisier break selection, and the cross-market median drifts mildly negative (≈ -0.016). Even there, the 90% band comfortably spans zero. Neither removing S&P 500 controls—where a slight negative pull emerges for the SENSEX (-0.031) but remains well within posterior uncertainty—nor bypassing orthogonalisation, nor tightening priors shifts the conclusion. The four remaining specifications produce cross-market median regime differences clustered tightly between -0.005 and $+0.005$ pp, with 90% bands spanning zero in every case. Thus, the no-break finding is not an artefact of any single modelling choice.

5.2 CBI robustness

The CBI robustness exercise is the more demanding test. The key finding of Section 4 was not that CBI shocks move all markets in the same direction—as MP shocks do—but that they generate *opposite-sign* responses depending on whether the receiving economy complements or substitutes for U.S. output. The question here is whether that sign heterogeneity is a robust feature of the data or a by-product of a particular specification.

Figure 5 answers by displaying specification-averaged impact responses for each market. The cross-country asymmetry is striking and survives intact. Brazil stands alone on the positive side of the axis, with pre- and post-regime medians of +0.357 and +0.335—a large, persistent benefit consistent with the commodity-demand channel: when the Fed reveals stronger U.S. fundamentals, expected global commodity demand rises and the IBOV reprices accordingly. Germany posts moderate positive responses (+0.128 pre, +0.093 post), reflecting the cash-flow gains that accrue to an export-oriented manufacturing economy whose output enters U.S. production as a complement. These two cases confirm that economies positioned as *complements* in the global production network capture a positive-sum informational spillover from Fed good news.

On the opposite side of the axis, India's specification-averaged medians are negative in both regimes (−0.032 pre, −0.013 post). The sign is economically meaningful even though the magnitude is modest: it indicates that stronger U.S. fundamentals make U.S. assets relatively more attractive, triggering portfolio rotation *away from* an economy whose IT-services and financial sectors compete with U.S. firms for the same global revenue pools. Hong Kong occupies the intermediate position (+0.095 pre, +0.070 post)—mildly positive but close to zero, confirming that the currency board mechanically imports U.S. rate changes yet transmits almost none of the cash-flow content of CBI shocks, because Hang Seng earnings are increasingly driven by mainland Chinese rather than American demand.

Two features of the forest plot deserve emphasis. First, the ordering IBOV $\gg$ DAX > HSI ≈ 0 > SENSEX < 0 is the same in every specification variant that enters the average—it is not an artefact of the baseline alone. Second, within each market, pre- and post-regime estimates overlap substantially, reinforcing the time-invariance conclusion: the output-composition characteristics that govern CBI transmission—Brazil's commodity complementarity, India's sectoral substitutability—are embedded in the deep structure of the global production network and have not shifted detectably over a quarter-century.

Figure 6 provides the specification-curve counterpart, now tracking regime *differences* variant by variant. Four of the six specifications—γ-spec (short), Prior (τ=0.05, σ_d=0.20), Baseline, and S&P 500 (removed)—produce cross-market median regime differences clustered tightly between −0.04 and −0.03 pp, with 90% bands spanning zero in every case. The near-identity of these four columns confirms that neither the transition-speed grid, the prior tightness, nor the inclusion of the U.S. market control is responsible for the no-break finding.

The two remaining variants introduce instructive but contained perturbations. Bypassing orthogonalisation shifts the cross-market median toward zero (≈ -0.01) and modestly narrows credible sets, consistent with the orthogonalisation step absorbing pre-event predictability that would otherwise add noise. Reducing cross-fitting to K=2 folds produces the largest dispersion: the median drifts mildly positive ($\approx +0.014$) and

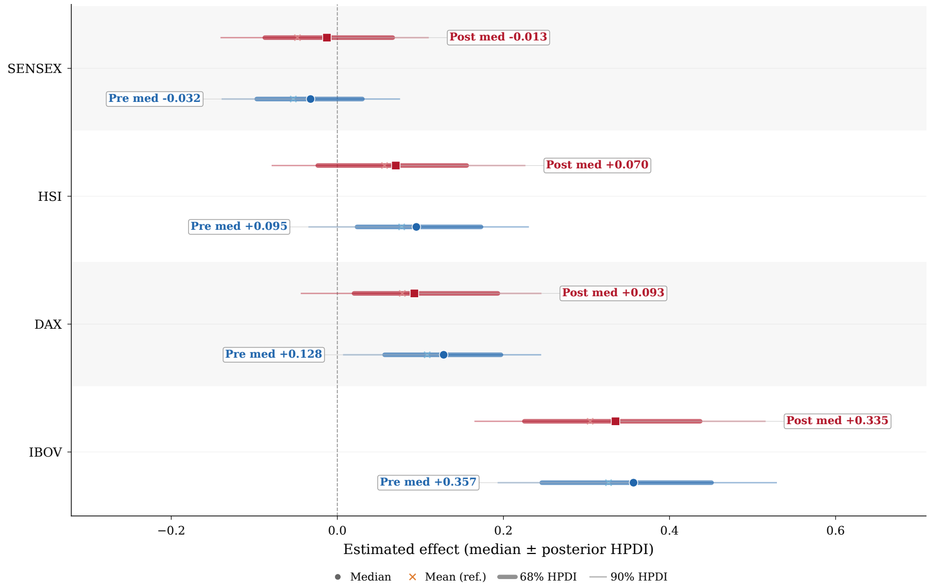


Figure 5: Forest illustration of CBI impact responses by market and regime

Note: Pre-regime (blue circles) and post-regime (red squares) posterior medians of the impact response (h=0) to a one-standard-deviation CBI shock for each equity market, averaged across six specification variants (see text). Thick bars denote 68% highest posterior density intervals; thin bars denote 90% HPDIs. The dashed vertical line marks zero. Responses are in percentage log-points.

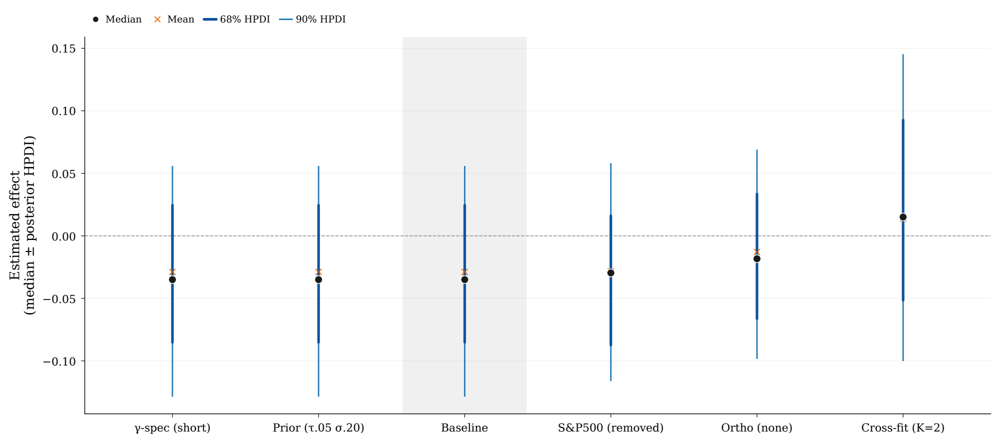


Figure 6: Specification curve for CBI regime-difference estimates

Note: Each column corresponds to one specification variant. Black dots denote the posterior median of the regime difference averaged across four equity markets; grey diamonds show individual-market point estimates. Thick dark bars are 68% HPDIs; thin light bars are 90% HPDIs. The shaded column highlights the baseline specification. The dashed horizontal line marks zero. All estimates are percentage log-points per one-standard-deviation CBI shock.

individual-market estimates fan out—most notably, the SENSEX point estimate shifts to +0.041 and the HSI to +0.027—reflecting the mechanical increase in estimation uncertainty when each fold contains fewer events. Even in this worst case, however, the 90% band includes zero and no individual market's point estimate departs qualitatively from the baseline ranking.

6 Conclusion

The evidence assembled here recasts how open economies should interpret Federal Reserve communication. A single hawkish FOMC surprise is not a single shock: it is a composite signal whose international equity-market consequences depend jointly on its informational anatomy and on the economic position of the receiving economy.

Three findings carry relevant implications. First, the taxonomy that best explains cross-country heterogeneity in Fed spillovers is not the conventional fixed-versus-floating or advanced-versus-emerging classification but the interaction between the *type* of shock—monetary-policy versus central-bank information—and the *nature* of the bilateral economic relationship with the United States. For pure monetary-policy shocks, the classical trilemma hierarchy holds with striking precision: currency-regime architecture governs the ranking of negative equity responses. For information shocks, a different organising principle emerges: whether an economy's output composition complements or substitutes for U.S. output determines both the sign and magnitude of the spillover, independently of the exchange-rate arrangement. This dual architecture implies that existing surveillance frameworks—which condition vulnerability assessments primarily on financial openness and exchange-rate flexibility—would benefit from incorporating a measure of *sectoral covariance* between domestic earnings and U.S. real activity.

Second, these heterogeneous propagation patterns have proved remarkably stable across a quarter-century that encompassed four distinct Federal Reserve operating regimes and multiple domestic structural transformations in our sample countries. The time-invariance suggests that spillover channels are embedded in deep-seated features of the global production network and financial architecture rather than in any particular policy configuration. For policymakers in open economies, the practical corollary is that durable insulation from external monetary shocks is more likely to come from institutional transformation—reducing balance-sheet currency mismatch, broadening local-currency capital markets, reinforcing macroprudential efforts—than from cyclical fine-tuning calibrated to the prevailing Fed regime.

Third, the impossibility of designing Fed communication that is simultaneously benign for all receivers—given that the same informational content generates opposite equity responses in complement and substitute economies—shifts the locus of appropriate policy adaptation from the emitter to the receiver. Open-economy central banks and fiscal authorities face a richer optimisation problem than standard "fear-of-floating" prescriptions acknowledge: the appropriate domestic response to an FOMC announcement depends on its informational decomposition, not merely on the direction or size of the interest-rate surprise.

Several limitations naturally circumscribe these conclusions. The four-country design privileges analytical clarity over cross-sectional breadth; scaling to a larger panel would permit estimation of spillover determinants as continuous functions of commodity-export share, dollar-debt ratio, and foreign-investor presence. The 205-event sample constrains our ability to estimate asymmetric responses to contractionary versus expansionary shocks separately, despite the pronounced distributional asymmetries documented in the shock series. The borderline sup-Wald statistic for CBI transmission in one cross-fitting fold ($p = 0.056$, break candidate July 2018) flags a possible late-sample instability whose resolution requires the accumulation of post-pandemic observations. Finally, embedding these reduced-form regularities within structural open-economy models would enable welfare quantification of communication-contingent policy strategies and provide a bridge between the empirical decomposition developed here and the normative design of optimal intervention rules.

Finally, the international diffusion of Fed communication is structured by the interplay between the informational content of the announcement and the output-composition position of the receiver—and that structure has proved invariant to a quarter-century of policy-regime upheaval, making it a durable foundation for both academic modelling and real-time policy design.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude Opus 4.6 in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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A Technical appendix

This appendix collects implementation details, closed-form derivations, and calibration diagnostics that underpin the estimation described in our empirical approach.

A.1 Orthogonalisation and control variables

The pre-event control vector Z_τ entering the orthogonalisation (2) consists of four S&P 500 features:

1. *Level factor*: cumulative 5-day pre-event log return, z-scored across the full event sample.
2. *Momentum factor*: difference between the 1-day pre-event return and the 5-day daily average, z-scored.
3. 10-day pre-event realised volatility (annualised, square root of the sum of squared daily returns).
4. 10-day pre-event minimum daily return (downside tail-risk proxy).

For the pooled-panel regressions, an extended vector X_τ augments Z_τ with three additional risk measures: z-scored 5-day cumulative absolute return, z-scored 20-day maximum drawdown, and the absolute S&P 500 event-window return. Since the orthogonalised shocks $\xi_{s,\tau}$ are already purged of the Z_τ components, the overlapping variables in X_τ serve only as a secondary hedge against residual confounding.

A.2 Break-detection implementation details

Logistic transition weight. The parameter γ in (3) is set to $\gamma = \ln(3)/\ell$, where the half-life ℓ ranges over $\{5, 10, 14, 21\}$ trading days. This grid spans near-abrupt transitions ($\ell = 5$: the weight moves from 0.25 to 0.75 in roughly two weeks) to moderate-speed regime evolution ($\ell = 21$: the same swing takes approximately two calendar months).

A.3 Full likelihood function

We recast the specification in Section 3.2 through its posterior kernel, which is the estimand targeted by our sampler. At the market level (with the index omitted for compactness), let $\boldsymbol{\Theta} = (\boldsymbol{\alpha}, \boldsymbol{\beta}_{\text{pre}}, \boldsymbol{\beta}_{\text{post}}, \boldsymbol{\Gamma}, \boldsymbol{\Lambda}, \boldsymbol{\Psi})$ denote the full parameter vector and Y the stacked horizon outcomes. The model is given by:

$$p(\boldsymbol{\Theta} \mid Y) \ \propto \ \underbrace{p(Y \mid \boldsymbol{\Theta})}_{\text{likelihood}} \cdot \ \underbrace{p(\boldsymbol{\beta}_{\text{post}} \mid \boldsymbol{\beta}_{\text{pre}}, \sigma_d^2)\ p(\boldsymbol{\beta}_{\text{pre}} \mid \kappa^2)\ p(\kappa^2)\ p(\sigma_d^2)\ p(\boldsymbol{\Psi})\ p(\boldsymbol{\Lambda})}_{\text{prior}}. \tag{10}$$

This posterior representation is the computational backbone of inference, integrating in a single object the cross-horizon smoothing discipline, skeptical shrinkage on post-break dynamics, and the latent-factor covariance structure that underpins the empirical design.

A.4 Prior specification

Table 4 collects all priors. The economic anchoring of scale parameters is discussed below.

Table 4: Complete prior specification

Parameter	Prior	Implied prior mean / scale
$\beta^{(0)}$ (impact)	$N(0,\ 1)$	Centre at zero; unit scale
$\beta^{(h)} \mid \beta^{(h-1)}$	$N(\beta^{(h-1)},\ \kappa^2)$	RW1 smoothness
κ^2	$\text{IG}(3,\ 2 \times 0.06^2)$	$E[\kappa]^{1/2} = 0.06 \approx \frac{1}{10}$ med. $\lvert y^{(0)} \rvert$
$\boldsymbol{\beta}_{\text{post}} \mid \boldsymbol{\beta}_{\text{pre}}$	$N(\boldsymbol{\beta}_{\text{pre}},\ \sigma_d^2 I)$	Skeptical shrinkage toward no break
σ_d^2	$\text{IG}(3,\ 2 \times 0.25^2)$	$E[\sigma_d]^{1/2} = 0.25 \approx \frac{1}{2}$ med. $\lvert y^{(0)} \rvert$
$\lambda^{(h)}$ (loadings)	$N(0,\ 1)$; $\lambda^{(0)} > 0$	Sign-identified factor
ψ_h	$\text{IG}(2,\ 0.25)$	$E[\psi_h] = 0.25$
$\alpha_m^{(h)},\ \gamma^{(h)}$	Flat (improper uniform)	OLS conditional posterior

Economic calibration of κ^2. Following the principle of anchoring hyperprior scales to observable sample quantities (Ferreira et al., 2023; Gabry et al., 2019), we set $E[\kappa^2]^{1/2} \approx 0.06$, approximately one-tenth of the cross-market median absolute event-day return (≈ 0.58). This implies that the prior concentrates adjacent-horizon impulse-response differences an order of magnitude below typical event-day returns while the $\text{IG}(3, \cdot)$ shape—which yields a finite second moment but substantial tail mass—allows the posterior to accommodate sharp horizon-to-horizon changes when warranted by the likelihood.

Economic calibration of σ_d^2. We set $E[\sigma_d^2]^{1/2} \approx 0.25$, roughly half a typical event-day return, implementing a "skeptical but not dogmatic" stance toward regime change in the spirit of Gelman (2006). Medium-sized structural breaks are *a priori* plausible, but the prior resists finding large shifts unless the data clearly demand them. We retain the inverse-gamma family for conjugacy with the Gibbs sampler; the shape parameter ($\nu = 3$) avoids the well-documented pathologies of near-improper $\mathrm{IG}(\epsilon, \epsilon)$ priors (Gelman, 2006) and the prior-predictive diagnostics in Table 5 confirm that the resulting distribution covers the empirically relevant range without excessive concentration (Gabry et al., 2019).

A.5 Prior-predictive calibration diagnostics

Following the Bayesian workflow of Gabry et al. (2019), we simulate from the joint prior *before* posterior estimation to verify that the hyperprior scales produce pre-data distributions consistent with the empirical scale of standardised event-window returns. Three target quantities are monitored:

$$q_1 = \beta^{(0)}, \qquad q_2 = \mathrm{AUC}_{0:3} = \textstyle\sum_{h=0}^{3} \beta^{(h)}, \qquad q_3 = \max_{0 \le h \le H} |\beta^{(h)}|. \tag{11}$$

Table 5: Prior-predictive calibration diagnostics (baseline priors)

Quantity (block)	5th pct	95th pct	Sample range
$\beta^{(0)}$ (pre)	−1.18	1.18	[−10.91, 13.36]
$\beta^{(0)}$ (post)	−1.18	1.19	[−10.91, 13.36]
$\beta^{(0)}$ (post−pre)	−0.22	0.22	[−10.91, 13.36]
$\mathrm{AUC}_{0:3}$ (pre)	−4.75	4.71	[−38.93, 30.42]
$\mathrm{AUC}_{0:3}$ (post)	−4.66	4.76	[−38.93, 30.42]
$\mathrm{AUC}_{0:3}$ (post−pre)	−0.66	0.66	[−38.93, 30.42]
$\max_h |\beta^{(h)}|$ (pre)	0.15	1.51	[0.61, 47.18]
$\max_h |\beta^{(h)}|$ (post)	0.15	1.52	[0.61, 47.18]
$\max_h |\beta^{(h)}|$ (post−pre)	0.10	0.32	[0.61, 47.18]

The pre- and post-regime blocks show that the prior-predictive 90% range for individual responses ($\approx \pm 1.2$ at impact) covers roughly one-sixth of the empirical sample range, concentrating prior mass in the economically relevant central region. The regime-difference block is substantially tighter (± 0.22 at impact), reflecting the skeptical shrinkage prior: shifts exceeding one full event-day return require strong likelihood support.

A.6 Aggregation implementation details

Fold aggregation. Fold-specific posterior realisations θ_k are aggregated via

$$\bar{\theta} = \frac{\sum_{k=1}^{K} \omega_k \, \theta_k}{\sum_{k=1}^{K} \omega_k}, \qquad \omega_k = \lambda \cdot q_k + (1 - \lambda) \cdot n_k, \tag{12}$$

where q_k is a fold-level identification quality score measuring the fraction of FOMC events in fold k for which the sign restriction cleanly separates MP from CBI shocks, n_k is fold k's sample share, and $\lambda = 0.45$. Formally, $q_k = |\mathcal{T}_k|^{-1} \sum_{\tau \in \mathcal{T}_k} 1\big(|\Delta i_\tau| > \bar{c} \text{ and } |\Delta s_\tau| > \bar{c}\big)$, with $\bar{c}$ set at the 25th percentile of the pooled absolute-surprise distribution. Sensitivity to λ over $\{0.30, \ldots, 0.60\}$ produces maximum changes of ± 0.01 pp in $\Delta\beta_m^{(0)}$ and ± 0.03 pp in $\text{AUC}_{0:3}$.

B Peak response amplitude as a robustness dimension

This appendix reports the peak absolute impulse response, $\max_{h\in\{0,\ldots,10\}} |\hat{\beta}^{(h)}|$, as a complementary robustness metric. Unlike impact responses ($h = 0$) or short-run cumulative effects ($\text{AUC}_{0:3}$), the peak captures the *largest* valuation displacement anywhere in the event window. Economically, this is a stress-type statistic: it represents the maximum repricing envelope that each market may face after an FOMC surprise, regardless of when that maximum occurs.

Because it is an order statistic, the peak is most useful for cross-market ranking and for comparing the relative importance of MP and CBI channels within each market. In this appendix, we therefore focus on the level ordering and on pre/post stability, using the peak metric as a consistency check for the main results rather than as a standalone identification device. In this sense, Table 6 shows a clear amplitude ordering for MP shocks: HSI and IBOV are highest (about 0.43–0.44), DAX is close (0.40), and SENSEX is substantially lower (0.22).

Table 6: MP shock – peak absolute response

Market	**Estimand**	**Pre**	**Post**	**Diff**	**90% HPDI (Diff)**	**68% HPDI (Diff)**
HSI	$\max_h \lvert\hat{\beta}_h\rvert$	0.43^*	0.43^*	0.13	[0.09, 0.18]	[0.10, 0.15]
DAX	$\max_h \lvert\hat{\beta}_h\rvert$	0.40^*	0.40^*	0.13	[0.09, 0.18]	[0.10, 0.16]
IBOV	$\max_h \lvert\hat{\beta}_h\rvert$	0.43^*	0.44^*	0.13	[0.09, 0.17]	[0.10, 0.15]
SENSEX	$\max_h \lvert\hat{\beta}_h\rvert$	0.22^*	0.22^*	0.13	[0.09, 0.18]	[0.10, 0.16]

Notes: Cross-fitted Bayesian local projections with hierarchical meta-draw aggregation (1,500 posterior draws). Estimates are percentage log-points per one-standard-deviation MP shock. 90% and 68% highest posterior density intervals for the regime difference.

Although the peak response for IBOV may appear contradictory given its moderate impact effect at $h = 0$, this discrepancy captures the conflict between Brazil's macroeconomic buffers and its corporate vulnerabilities. While the floating exchange rate partially cushions the immediate discount-rate blow, the accompanying U.S. dollar appreciation triggers a delayed but severe balance-sheet channel due to the corporate sector's substantial foreign-currency liabilities. Furthermore, as dollar strength typically coincides with commodity price declines, the terms-of-trade deterioration adds a second wave of repricing pressure for the resource-heavy index. Thus, an economy can exhibit moderate initial transmission yet still suffer high peak vulnerability as these structural exposures are priced in over the event window.

For CBI shocks, Table 7 displays a more stable and economically interpretable ranking. IBOV has the largest peak (0.55), DAX and SENSEX are intermediate (around 0.31–0.32), and HSI is lowest (0.21). This pattern matches the complementarity/substitution logic from Section 4: the strongest information-driven amplitude appears in Brazil, while Hong Kong remains comparatively less sensitive to the CBI channel.

Table 7: CBI shock – peak absolute response

Market	**Estimand**	**Pre**	**Post**	**Diff**	**90% HPDI (Diff)**	**68% HPDI (Diff)**
IBOV	$\max_h \lvert\hat{\beta}_h\rvert$	0.55^{*}	0.55^{*}	0.14	[0.09, 0.18]	[0.10, 0.16]
DAX	$\max_h \lvert\hat{\beta}_h\rvert$	0.32^{*}	0.31^{*}	0.15	[0.10, 0.21]	[0.11, 0.17]
HSI	$\max_h \lvert\hat{\beta}_h\rvert$	0.21^{*}	0.21^{*}	0.14	[0.09, 0.19]	[0.10, 0.16]
SENSEX	$\max_h \lvert\hat{\beta}_h\rvert$	0.32^{*}	0.31^{*}	0.14	[0.09, 0.19]	[0.11, 0.16]

Notes: Cross-fitted Bayesian local projections with hierarchical meta-draw aggregation (1,500 posterior draws). Estimates are percentage log-points per one-standard-deviation CBI shock. 90% and 68% highest posterior density intervals for the regime difference. As an order statistic, regime differences capture changes in response amplitude, not direction.