

Macro-Based Asset Allocation in India

Testing whether regime signals from growth, credit and financial vulnerability improve asset allocation in India



A collaborative research project by the International Finance Student Association (IFSA) chapters of Ramjas College and Lady Shri Ram College for Women, University of Delhi.

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An Empirical Analysis of Regime-Timing versus Static Diversification

IFSA Ramjas College and IFSA Lady Shri Ram College, University of Delhi

Abstract

Regime-based asset allocation aims to shift a portfolio toward the assets that historically perform best in each phase of the economic and financial cycle. We test whether it does so for India using seven indicators, following the framework of the European Investment Bank (2019). The indicators are GDP, the OECD composite leading indicator, a growth–inflation quadrant, private credit, the term spread between 10-year government bonds and 91-day Treasury bills, an external vulnerability index and a financial vulnerability index (FVI).

The FVI is estimated as a logit early-warning model on a panel of nine Asian economies. Each indicator is turned into Upturn and Downturn stages, and each stage into weights across Indian equity, government bonds, gold, commodities and cash. Every signal is built only from data available at the time: the FVI is re-estimated on an expanding window, and signals are lagged by their actual publication delays. Over 2013Q3–2025Q4, no regime strategy significantly outperforms a static 40/30/15/10/5 portfolio (Sharpe ratio 0.62). The term spread reaches the highest Sharpe ratio, 0.89, but the difference is not significant ($p = 0.28$), and its lead disappears when the sample starts in 2008 or the signal is lagged by a further quarter. Economic Climate reaches 0.57 ($p = 0.79$), the FVI 0.42, and two strategies are significantly worse than static. We conclude that, in real time, regime signals do not reliably improve on a simple diversified allocation for India.

Keywords: regime-based asset allocation; early-warning models; financial vulnerability; real-time data; India

Key findings

0.62	The static 40/30/15/10/5 portfolio's Sharpe ratio over 2013Q3–2025Q4; no regime strategy beats it significantly
0.89	The term spread has the highest Sharpe ratio, but the gap is not significant ($p = 0.28$) and does not survive an earlier start or a longer lag
2 of 7	Regime strategies are significantly worse than static at the 5% level: Credit and Growth/Inflation
0.42	The Financial Vulnerability Index strategy ranks below four passive benchmarks

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1 Introduction

Indian investors have lived through two severe equity crashes in twelve years. The NIFTY 50 fell 55% from its peak in December 2007 to its trough in November 2008, and 29% between December 2019 and March 2020. Over the same period, gold returned 14.6% a year in rupee terms, with a correlation of -0.26 with equity returns. An allocation rule that could recognise the phase of the economic and financial cycle in advance, and move between these assets accordingly, would benefit an Indian investor.

Regime-based asset allocation claims to do this. The framework of the European Investment Bank (2019) classifies each quarter into a stage of the cycle using macro-financial indicators, then holds the assets that have historically done best in that stage. That framework was built for European data and evaluated in-sample. A separate early-warning literature for emerging Asia predicts financial crises, but it does not ask whether an investor could trade on those predictions. No study we are aware of tests whether regime signals survive real-time construction for India.

This paper runs that test. We build seven regime indicators for India: real GDP, the OECD composite leading indicator (Economic Climate), a growth–inflation quadrant, private credit-to-GDP, the term spread between 10-year government bonds and 91-day Treasury bills, an External Vulnerability Index (EVI) and a Financial Vulnerability Index (FVI). The FVI is a logit early-warning model estimated on a nine-country Asian panel of equity-market crises, re-estimated every quarter on an expanding window. Every signal is lagged by its publication delay, every portfolio pays the same transaction costs, and strategies are compared with a formal test of Sharpe-ratio differences.

Over the common test window of 2013Q3–2025Q4 (50 quarters), the answer is largely negative. A static 40/30/15/10/5 portfolio has a Sharpe ratio of 0.62. None of the seven regime strategies is significantly better. The term spread comes closest, with a Sharpe ratio of 0.89 ($p = 0.28$), but its advantage disappears when the sample starts in 2008 or the signal is lagged by one more quarter. Economic Climate reaches 0.57 and the FVI 0.42, and two strategies, Credit ($p = 0.05$) and Growth/Inflation ($p = 0.04$), are significantly worse than static.

This paper makes three contributions. First, it builds a financial vulnerability index for India from an Asian early-warning panel, re-estimating it every quarter with only the crises that had ended by then. Second, it evaluates every signal with its actual publication lag, so the backtest reflects only what an investor could have traded. Third, it provides a like-for-like comparison against static portfolios that pay the same transaction costs, with formal tests of Sharpe-ratio differences.

Section 2 reviews the literature. Section 3 describes the data, and Section 4 sets out the methodology in pipeline order. Section 5 reports the main results and Section 6 the robustness checks. Section 7 discusses the findings and their limitations, and Section 8 concludes.

2 Literature review

Regime-based allocation. Ang and Bekaert (2002) show that regime shifts in international equity returns change optimal portfolio weights, and Kritzman, Page and Turkington (2012) argue that identifying regimes from economic variables can improve dynamic strategies. The European Investment Bank (2019) turns this idea into a practical rule: classify each quarter by the direction of an indicator, then hold the assets with the best average return in past quarters of the same stage. We take the stage definition and the percentile-cutoff weighting rule from this framework.

Early-warning models. Kaminsky and Reinhart (1999) established the signal approach to predicting crises, and Bussière and Fratzscher (2006) showed that a multinomial logit outperforms binary models once post-crisis periods are treated separately. Their point is that a model estimated on crisis and recovery quarters learns what a crisis looks like while it is happening, which is not a warning. We adopt their pre-crisis window labels and exclude crisis and recovery quarters from estimation.

Credit cycles. Borio and Lowe (2002) find that rapid credit growth combined with asset-price booms precedes financial distress. Drehmann, Borio and Tsatsaronis (2011) identify the credit-to-GDP gap as the best single indicator for setting the countercyclical capital buffer, and the Basel Committee on Banking Supervision (2010) standardised its computation. We follow that standard: a one-sided Hodrick and Prescott (1997) filter with $\lambda = 400,000$.

The yield curve. Estrella and Hardouvelis (1991) show that the spread between long and short government bond yields predicts real activity, and Estrella and Mishkin (1998) find it is among the most reliable leading indicators of recessions. A steep curve signals expected growth and a flat or inverted one signals tightening. We use the spread between the 10-year government bond and the 91-day Treasury bill as a market-based regime indicator that is available without a publication delay.

Table 1. Literature strands and what this paper takes from each

Strand	Key works	What this paper takes from it
Regime-based allocation	EIB Working Paper 2019/11; Ang & Bekaert (2002); Kritzman, Page & Turkington (2012)	Stage definition and the percentile-cutoff weighting rule
Early-warning models	Kaminsky & Reinhart (1999); Bussière & Fratzscher (2006)	Pre-crisis window labels and exclusion of crisis quarters (post-crisis bias)
Credit cycles	Borio & Lowe (2002); Drehmann, Borio & Tsatsaronis (2011); Basel Committee (2010)	Credit-to-GDP gap, one-sided HP filter with $\lambda = 400,000$
The yield curve	Estrella & Hardouvelis (1991); Estrella & Mishkin (1998)	The term spread as a leading, real-time regime indicator
Crisis dating	Laeven & Valencia (2018); Mishkin & White (2002)	Market-based dating, with the alternative discussed
Real-time data	Orphanides & van Norden (2002); Croushore (2011)	Why publication lags and one-sided filters matter
Performance testing	Jobson & Korkie (1981); Memmel (2003); Ledoit & Wolf (2008)	The Sharpe-difference test and its small-sample caveat

Real-time data. Orphanides and van Norden (2002) show that output-gap estimates change substantially once later data arrive, mainly because two-sided filters use the future. Croushore (2011) surveys the wider evidence that forecasting results often weaken when revised data are replaced by the data available at the time. These findings motivate our one-sided filters, expanding-window estimation and explicit publication lags.

Performance testing. Jobson and Korkie (1981) derive a test for the difference between two Sharpe ratios, and Memmel (2003) corrects its variance. Ledoit and Wolf (2008) propose a robust alternative and note that the asymptotic test can be unreliable in small samples. We use the Jobson–Korkie test with the Memmel correction and discuss its low power over 50 quarters.

India. The Reserve Bank of India monitors the credit-to-GDP gap and systemic risk in its Financial Stability Reports. Evidence on whether macro-financial signals can guide tactical allocation between Indian asset classes, under real-time conditions, remains limited. This paper places the question in that context.

Crisis dating. Laeven and Valencia (2018) date systemic banking crises from policy interventions, and their database is the usual reference. Their events are too few for a single emerging market and are recorded with a delay. Mishkin and White (2002) date stock-market crashes directly from price declines. We follow the market-based approach, which yields more events and dates them from data an investor could observe.

3 Data

3.1 Asset returns

The portfolio holds five Indian asset classes: equity (NIFTY 50 Total Return), government bonds (a G-Sec total return index), gold in rupees, a commodity index in rupees, and cash. Daily and monthly series are converted to quarterly returns. The cash return is the quarterly average of the call money rate rather than its quarter-end value, because the rate spikes at the end of March. The sample starts in 2006Q2, when the G-Sec series begins, and ends in 2025Q4, the last quarter of the NIFTY Total Return data. Table 2 lists all sources.

Table 2. Data sources and coverage

Series	Source	Frequency	Coverage used	Role
Equity indices, 9 Asian economies	Yahoo Finance (^NSEI, ^N225, ^HSI, ...)	Monthly	1985–2026 (India from 2007-09)	Crisis dating; 2-year equity growth
Credit to private non-financial sector, % GDP	BIS total credit (WS_TC)	Quarterly	Country-specific, to 2025Q3	Credit gap; 5-year credit growth; Credit index
NIFTY 50 Total Return	NSE	Daily → quarterly	2004–2025	Equity asset
Gold in INR	Own series	Quarterly	1973–2026	Gold asset
G-Sec total return index	Own series	Quarterly	2006Q2–2026Q2	Bond asset (binds the start)
Commodity index in INR	Own series	Quarterly	1996–2026	Commodity asset
Call money rate	FRED IRSTCI01INM156N	Monthly → quarterly mean	to 2025	Cash asset; risk-free rate
Real GDP	FRED NGDPRNSAXDCINQ	Quarterly	to 2025	GDP index; growth quadrant
CPI	FRED INDCPIALLMINMEI	Monthly	to 2025	Inflation quadrant
OECD CLI, India	OECD	Monthly	to 2025	Economic Climate index
USD/INR, Brent, VIX	FRED DEXINUS, DCOILBRENTU, VIXCLS	Daily → quarterly	to 2025	External Vulnerability Index
91-day T-bill and 10-year G-Sec yields	RBI DBIE (T-bill auction cut-off yields; month-end 10-year SGL yields)	Weekly and monthly → quarterly mean	1996Q2–2025Q4	Term spread index

Source: As listed.

Note: India's GDP series was rebased in 2015; the revised series is used throughout.

3.2 Macro and market indicators

The regime indicators draw on real GDP, CPI, the OECD composite leading indicator for India, BIS credit to the private non-financial sector, Reserve Bank of India yields on 91-day Treasury bills and 10-year government securities, the USD/INR exchange rate, the Brent oil price and the VIX. Monthly and daily series are aggregated to quarters. Each series enters the backtest with the publication lag described in Section 4.7.

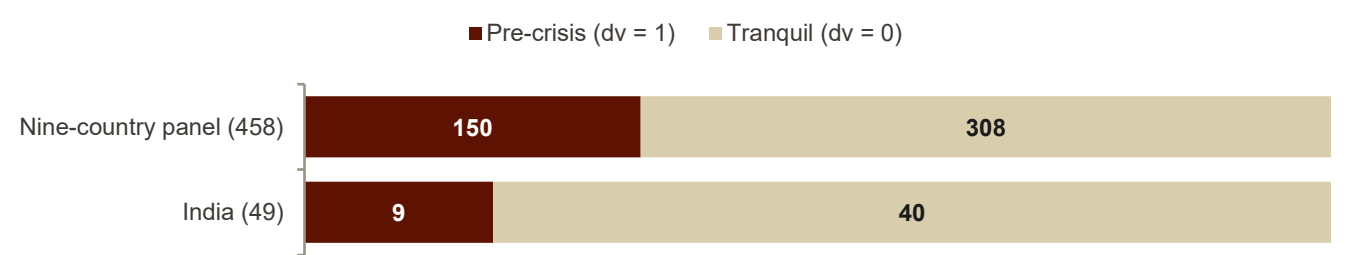
3.3 The Asian crisis panel

The early-warning model is estimated on nine Asian markets: Japan, Hong Kong, Singapore, Indonesia, Malaysia, Korea, Thailand, China and India. Equity indices date the crises and BIS credit series supply the credit regressors. After the labelling in Section 4.2, the panel contains 458 quarterly observations, of which 150 fall in a pre-crisis window. India contributes 49 quarters and 9 positives. The Thailand equity series has a gap from June 2023 to May 2026.

Figure 1 shows the balance of the panel. Pre-crisis quarters make up 33% of the nine-country panel but only 18% of India’s observations, so most of what the model learns about vulnerability comes from other Asian markets.

Figure 1. Pre-crisis and tranquil quarters in the estimation panel

Number of quarterly observations; 100% = all labelled quarters



Source: Yahoo Finance; BIS; authors’ calculations.
Note: Labels show the number of quarters in each group. Crisis and recovery quarters are excluded (Section 4.2).

3.4 Descriptive statistics

Table 3 summarises the five assets. Gold has the best risk-adjusted return, with a Sharpe ratio of 0.56. Equity earned 12.9% a year but with 21.0% volatility and a maximum drawdown of –51.3%. Commodities lost money in rupee terms (0.5% a year against 6.5% for cash) and fell 75.1% from peak to trough. G-Sec bonds had the smallest drawdown, –10.7%.

Figure 2 plots the same statistics. Gold is the only asset whose return exceeds equity’s with lower volatility, and commodities combine the highest volatility with the lowest return.

Table 4 reports correlations. Two negative pairs stand out: equity and gold (–0.26), and G-Sec bonds and commodities (–0.44). These negative correlations give a regime rule something to switch between. They also mean that a static mix of all five assets is already well diversified.

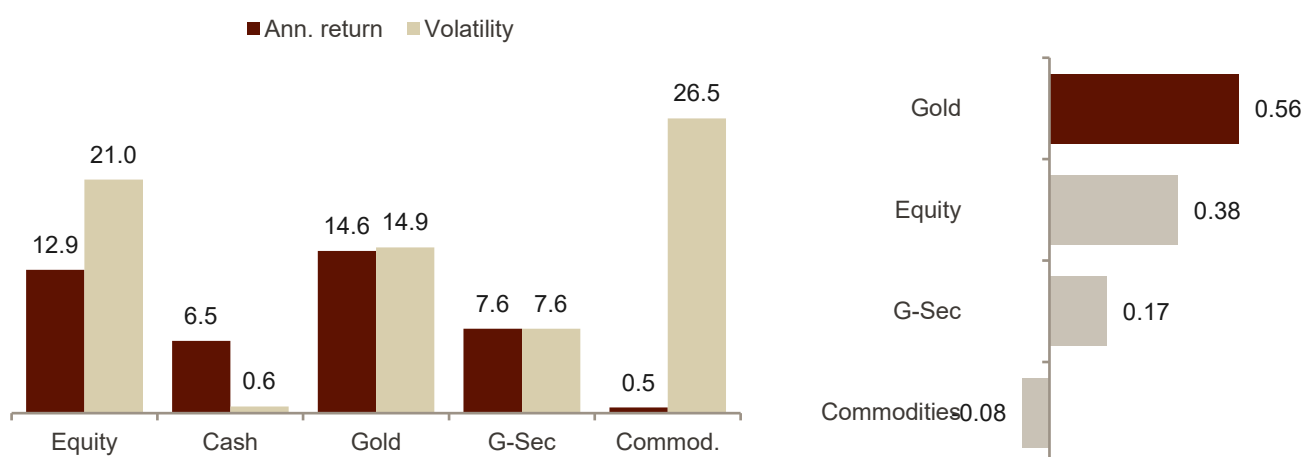
Table 3. Summary statistics of the five asset classes

2006Q3–2025Q4; quarterly data, annualised

Asset	Ann. return	Volatility	Sharpe	Max drawdown
Equity	12.9%	21.0%	0.38	–51.3%
Cash	6.5%	0.6%	–	–
Gold	14.6%	14.9%	0.56	–23.0%
G-Sec bonds	7.6%	7.6%	0.17	–10.7%
Commodities	0.5%	26.5%	–0.08	–75.1%

Source: NSE; FRED; authors' calculations.**Note:** Sharpe ratios are in excess of the call money rate (cash), so cash has none. Ann. return is the compound annual growth rate. Sharpe ratios use arithmetic quarterly excess returns over cash, annualised by $\sqrt{4}$, so they cannot be derived from the return and volatility columns.**Figure 2. Gold earned the best risk-adjusted return; commodities the worst**

Left: annualised return and volatility, %. Right: Sharpe ratio

**Source:** NSE; FRED; authors' calculations.**Note:** Cash is excluded from the Sharpe panel because it is the risk-free rate.**Table 4. Correlation of quarterly returns**

2006Q3–2025Q4

	Equity	Cash	Gold	G-Sec	Commodities
Equity	1	–0.04	–0.26	–0.13	+0.23
Cash	–0.04	1	–0.21	+0.07	–0.22
Gold	–0.26	–0.21	1	–0.13	+0.01
G-Sec	–0.13	+0.07	–0.13	1	–0.44
Commodities	+0.23	–0.22	+0.01	–0.44	1

Source: NSE; FRED; authors' calculations.**Note:** Shaded cells mark correlations of 0.20 or more in absolute value; maroon marks the negative ones, which are the pairs a switching rule can use.

4 Methodology

Figure 3 summarises the research design. Crises are dated from equity drawdowns (Section 4.1), quarters are labelled relative to those crises (4.2), seven indicators are built (4.3–4.4), each is turned into Upturn and Downturn stages (4.5), stages are mapped into portfolio weights (4.6), and the portfolios are backtested with lags, costs and a formal test (4.7).

Figure 3. Research design: from crisis dating to portfolio test

Five steps, each described in a subsection of this section

01	02	03	04	05
Date crises	Label quarters	Build indicators	Assign stages	Allocate and test
Equity drawdowns in nine Asian markets give 47 major events	dv = 1 from 12 to 4 quarters before a crisis peak	The FVI logit plus six macro and market indices	Smoothed direction gives an Upturn or Downturn	Stage-based weights, lags and costs, then the Sharpe test
Section 4.1	Section 4.2	Sections 4.3–4.4	Section 4.5	Sections 4.6–4.7

Source: Authors.

4.1 Dating crises from equity drawdowns

For each market i , the drawdown is the fall of the equity index from its running peak:

$$DD_{i,t} = \frac{P_{i,t}}{\max_{s \leq t} P_{i,s}} - 1 \quad (1)$$

An episode starts when the drawdown reaches 20%. It closes when the price recovers to 90% of the peak, or rises 50% above the trough. An episode is a major crisis if its depth is at least 25% and it has closed:

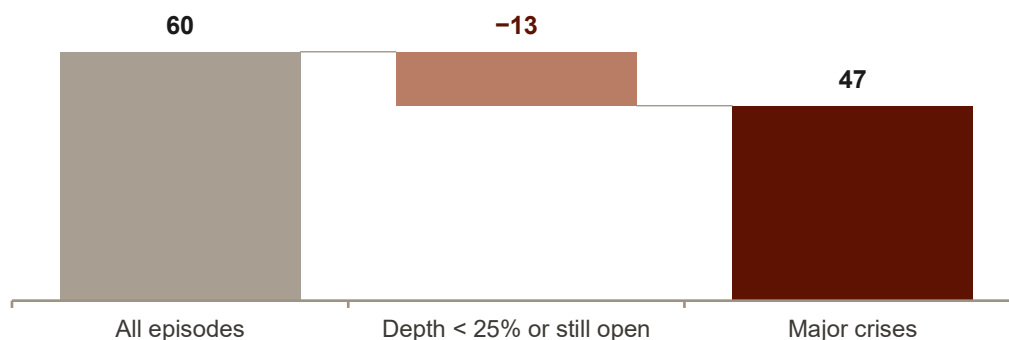
$$\begin{aligned} \text{start: } DD_{i,t} &\leq -0.20, & \text{major: } |DD^{\min}| &\geq 0.25 \\ \text{end: } P_{i,t} &\geq 0.9 P_i^{\text{peak}} \text{ or } P_{i,t} \geq 1.5 P_i^{\text{trough}} \end{aligned} \quad (2)$$

The rule finds 60 episodes across the nine markets, 47 of them major (Figure 4). It picks up the 1997 Asian crisis, the 2000 technology bust, 2008 and 2020 without any manual input. India has two major crises: December 2007 to November 2008 (–55%) and December 2019 to March 2020 (–29%).

Figure 4 shows how the 60 episodes reduce to the 47 major crises used as events: 13 episodes are excluded because they were shallower than 25% or had not closed. Figure 5 maps the 47 major crises by market and period; the full list is in Appendix B.

Figure 4. Of 60 drawdown episodes, 47 qualify as major crises

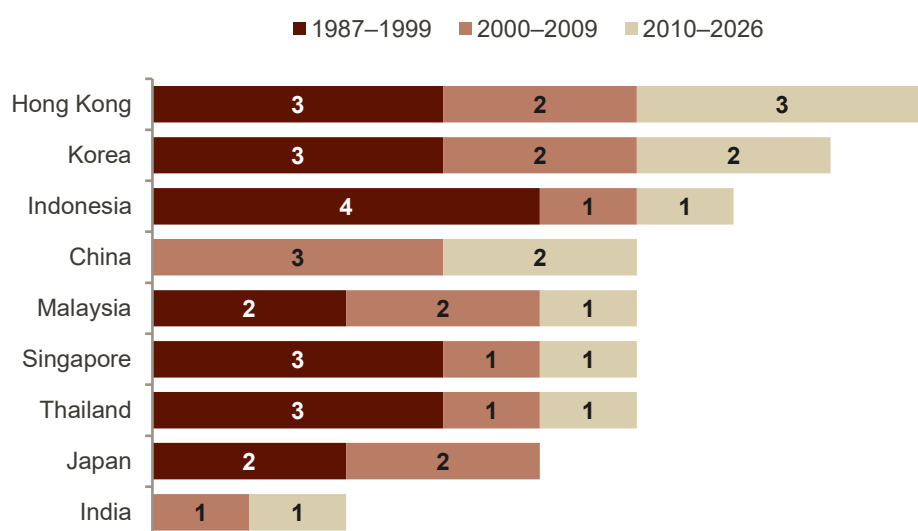
Number of episodes, nine Asian markets, 1987–2026



Source: Yahoo Finance; authors' calculations.

Figure 5. Major equity crises by market and period

Number of major crises (depth of at least 25%, closed), nine Asian markets

**47**

major crises across nine markets, 2 of them in India (2007–08 and 2019–20)

Source: Yahoo Finance; authors' calculations.

Note: Crises are assigned to a period by the date of the peak. The full list is in Appendix B.

4.2 Labelling pre-crisis quarters

A quarter is a positive observation if it lies 4 to 12 quarters before a crisis peak. Quarters from the peak to 8 quarters after the trough are dropped from estimation. All other quarters are tranquil:

$$dv_{i,t} = \begin{cases} 1 & \text{if } t \in [\tau_{i,k}^{\text{peak}} - 12, \tau_{i,k}^{\text{peak}} - 4] \text{ for some crisis } k \\ \text{dropped} & \text{if } t \in [\tau_{i,k}^{\text{peak}}, \tau_{i,k}^{\text{trough}} + 8] \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The exclusion window addresses the post-crisis bias identified by Bussière and Fratzscher (2006): without it, the model would learn what a crisis looks like while it is happening. Where windows from different crises overlap, the exclusion takes precedence. The FVI is still predicted for excluded quarters; they are only left out of estimation (Figure 6).

Figure 6. How each quarter is labelled around a crisis peak

Schematic; quarters relative to the equity peak and trough



Source: Authors.

Note: Quarters in the excluded block are dropped from estimation, but the FVI is still predicted for them.

4.3 The Financial Vulnerability Index (FVI)

The FVI has three regressors. The credit gap is the deviation of credit-to-GDP from its one-sided HP trend, where c is credit-to-GDP in percent and the trend at t uses data up to t only, starting after 20 quarters:

$$gap_{i,t} = c_{i,t} - \tau_{i,t|t}$$

$$\tau_{\cdot|t} = \arg \min_{\tau} \left\{ \sum_{s \leq t} (c_{i,s} - \tau_s)^2 + \lambda \sum_{s \leq t} (\Delta^2 \tau_s)^2 \right\}, \quad \lambda = 400,000 \quad (4)$$

Credit growth is the 5-year change in credit-to-GDP, and equity growth is the 8-quarter percentage change in the equity index. Each regressor is standardised with the mean and standard deviation of the estimation window, and the probability of a pre-crisis quarter is modelled as a logit:

$$\Pr(dv_{i,t} = 1) = \Lambda(\beta_0 + \beta_1 \widetilde{gap}_{i,t} + \beta_2 \widetilde{\Delta_{20}c_{i,t}} + \beta_3 \widetilde{g_{8,t}^E}), \quad \Lambda(z) = \frac{1}{1 + e^{-z}} \quad (5)$$

The key design choice is how the model is estimated. A label at quarter s is only known once 12 quarters have passed, because it depends on whether a crisis peak follows, and a crisis can only be used once it has ended. At each quarter t , the model is therefore re-estimated on the set of observations whose labels were known at t , and India's FVI is the fitted probability from that model:

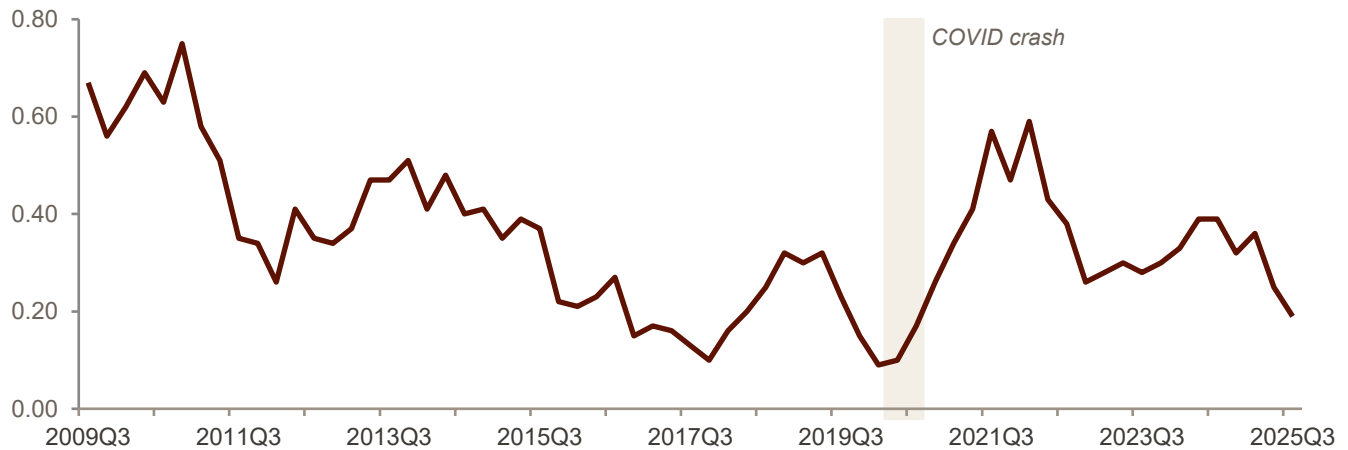
$$\widehat{\beta}^{(t)} = \arg \max_{\beta} \sum_{(i,s) \in \mathcal{W}_t} \ell(dv_{i,s}; \beta), \quad FVI_t = \Lambda(x'_{IN,t} \widehat{\beta}^{(t)}) \quad (6)$$

$$\mathcal{W}_t = \{(i, s) : s \leq t - 12, \text{ crisis of } (i, s) \text{ ended by } t\}$$

Figure 7 shows the resulting index. It rises through 2009–10, reaching 0.75 in 2010Q4, and again in 2021–22. It falls into the 2020 COVID crash, reaching 0.09 in 2020Q1, which is the first sign that the index does not anticipate India’s sharpest recent fall.

Figure 7. India’s FVI peaked in 2010 and fell into the 2020 crash

Predicted probability of a crisis in 1–3 years; expanding-window estimate, 2009Q3–2025Q3



Source: BIS; Yahoo Finance; authors' calculations.

Note: The shaded band marks the 2020 COVID crash. Each value uses only crises that had ended by that quarter. The FVI is first estimated in 2009Q3, when the panel first has enough pre-crisis observations. Its stages start in 2011Q1 after smoothing; with the three-quarter publication lag, and once each stage has been observed twice, the strategy first invests in 2012Q2.

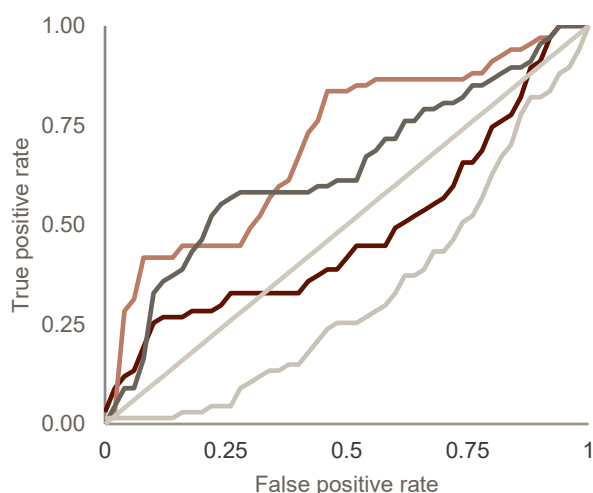
Figure 8 tests how well the FVI and its three inputs separate pre-crisis quarters from tranquil ones out of sample. Each signal is scored by the area under its ROC curve (AUC), where 0.5 is no better than chance. On the nine-country panel, the real-time FVI has an AUC of 0.48 (95% CI 0.40 to 0.58), so it does not beat chance. Five-year credit growth on its own does better, at 0.70, and the credit gap reaches 0.64, while two-year equity growth scores 0.33, below chance. For India the FVI's AUC is 0.06 (0.00 to 0.17), across 49 quarters with 9 pre-crisis observations: the index was lower before the 2020 crash than in tranquil quarters, the same pattern Figure 7 shows around 2020Q1.

Table 5 and Figure 9 report the coefficients from the last expanding-window fit. Five-year credit growth (+2.30) and two-year equity growth (+0.24) have the expected positive signs, the first strongly significant and the second borderline. The credit gap enters with a negative sign (−2.25), against theory. Because the gap and 5-year credit growth enter with opposite signs of almost equal size, the two are best read jointly; Section 7 returns to this.

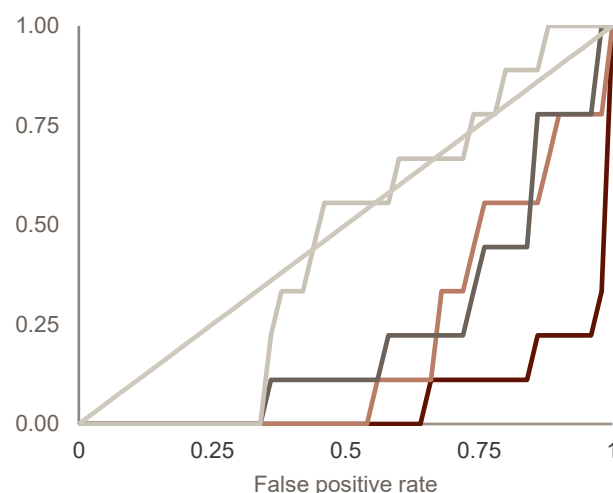
Figure 8. Out of sample, the FVI does no better than chance; credit growth alone does better

ROC curves of the real-time FVI and its three inputs; left: nine-country panel (2007Q2–2025Q3), right: India (2011Q1–2025Q3)

Nine-country panel n = 332, 67 pre-crisis



India n = 49, 9 pre-crisis



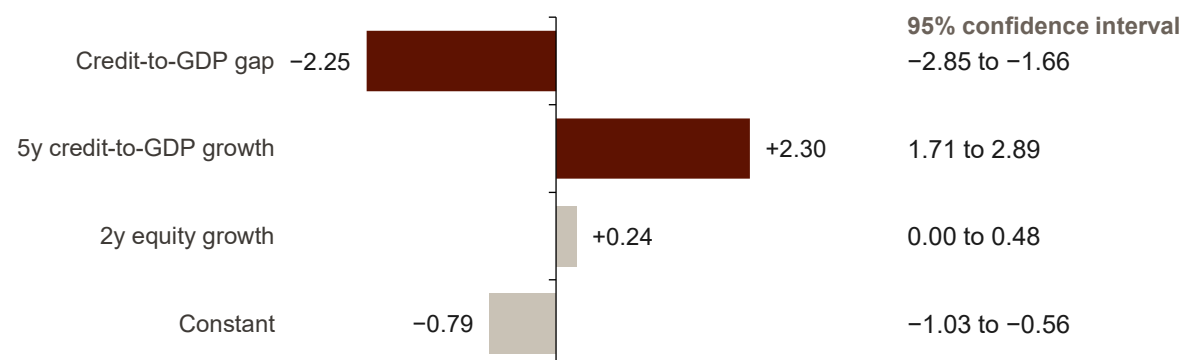
— FVI AUC 0.48	— 5y credit growth AUC 0.70	— FVI AUC 0.06	— 5y credit growth AUC 0.21
— Credit gap AUC 0.64	— 2y equity growth AUC 0.33	— Credit gap AUC 0.23	— 2y equity growth AUC 0.45

Source: BIS; Yahoo Finance; authors' calculations.

Note: The grey diagonal marks a signal with no predictive power (AUC = 0.50). 95% confidence intervals for the FVI: panel 0.40 to 0.58; India 0.00 to 0.17. Curves are scored on 332 out-of-sample predictions (2007Q2–2025Q3, 67 pre-crisis), each made with the model estimated on data available at that quarter.

Figure 9. Credit growth and the credit gap dominate the model, with opposite signs

Logit coefficients on standardised regressors; final expanding-window fit, nine-country panel



Source: Authors' calculations.

Note: Maroon bars mark the two credit terms, which are collinear.

4.4 The other six indicators

Three indicators are level series fed directly into the staging rule of Section 4.5: real GDP (GDP Index), the OECD composite leading indicator (Economic Climate) and credit-to-GDP (Credit Index). The growth–inflation indicator places each quarter in one of four quadrants by comparing year-on-year GDP growth and CPI inflation with their expanding means, using at least 8 quarters of history:

$$Q_t = ([g_t > \bar{g}_{1:t}], [\pi_t > \bar{\pi}_{1:t}]) \in \{G \uparrow I \uparrow, G \uparrow I \downarrow, G \downarrow I \uparrow, G \downarrow I \downarrow\} \quad (7)$$

Figure 10 shows how often India sat in each quadrant. The two mixed quadrants and the low-growth, low-inflation quadrant each account for 20 to 24 quarters; growth and inflation were both above their expanding means in only 9 quarters.

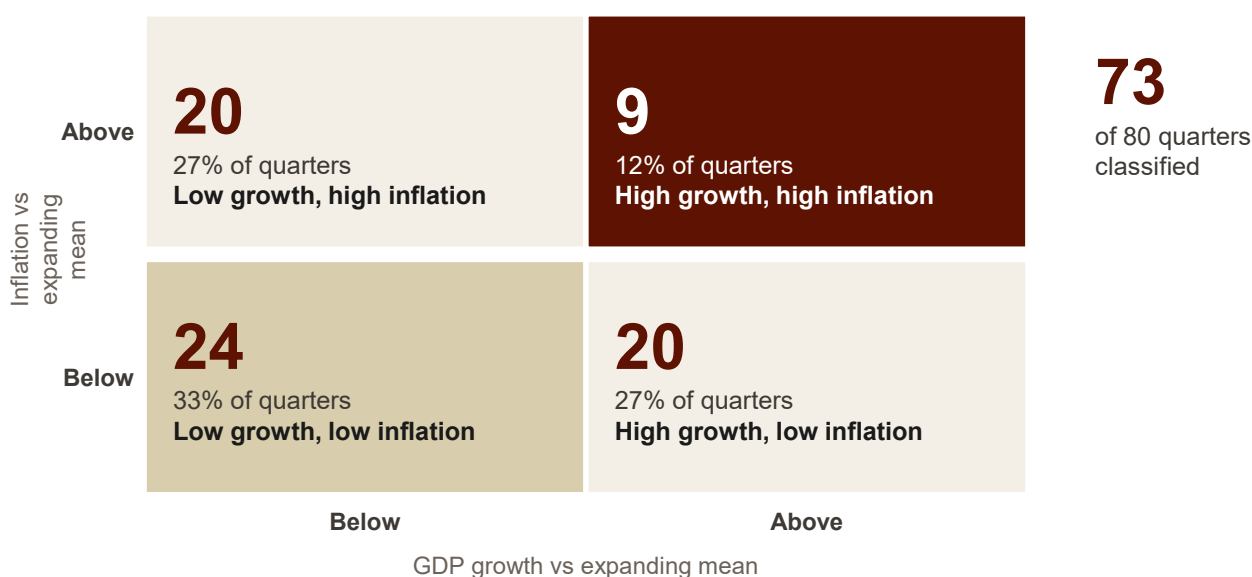
Table 5. FVI logit coefficients

Last expanding-window fit, standardised regressors

Term	Coefficient	95% CI	Reading
Constant	−0.791	−1.027 to −0.555	Baseline crisis-window probability ≈ 31%
Credit-to-GDP gap	−2.252	−2.845 to −1.660	Sign contrary to theory; collinear with 5-year credit growth
5-year credit growth	+2.300	1.713 to 2.887	Expected sign, strongly significant
2-year equity growth	+0.242	−0.0003 to 0.484	Expected sign, borderline

Source: Authors' calculations.**Note:** Panel of 9 Asian economies, 409 quarterly observations (1987Q1–2022Q3), 141 in the pre-crisis window. Estimated on data available at 2025Q3, using labels at least 12 quarters old.**Figure 10. India spent the fewest quarters with both growth and inflation above trend**

Quarters in each growth–inflation quadrant, 2005Q2–2025Q1

**Source:** FRED; authors' calculations.**Note:** The first 7 quarters have no quadrant because the expanding means need 8 quarters of data; 73 of 80 quarters are classified.

The External Vulnerability Index averages expanding z-scores of the change in the rupee exchange rate, the change in the Brent oil price, and the level of the VIX. The z-scores require at least 8 quarters and never use future data:

$$EVI_t = \frac{1}{3} (z_t(\% \Delta \text{INR/USD}) + z_t(\% \Delta \text{Brent}) + z_t(\text{VIX})), \quad z_t(x) = \frac{x_t - \bar{x}_{1:t}}{s_{1:t}(x)} \quad (8)$$

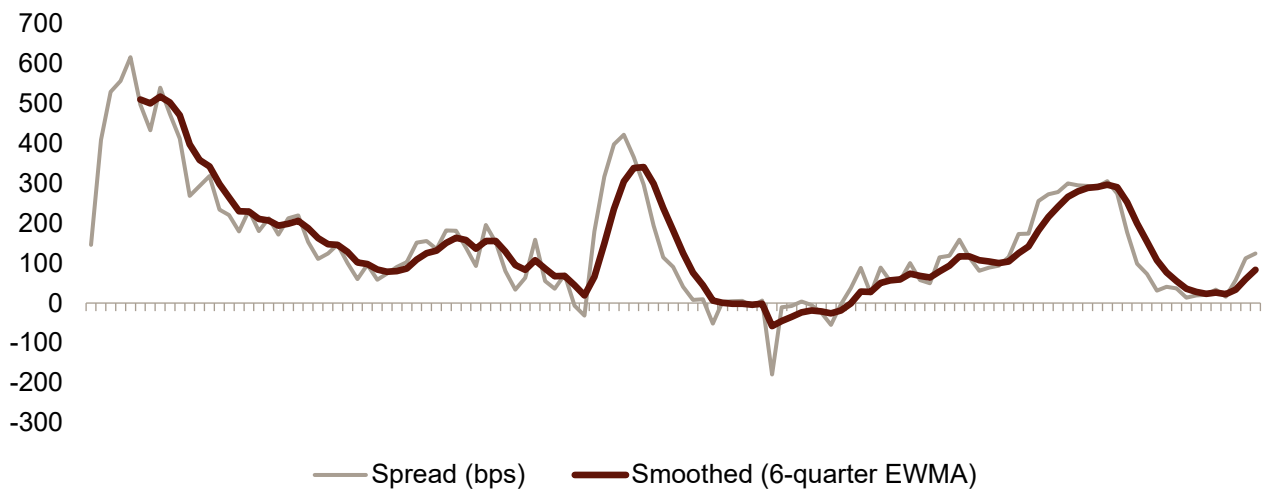
The term spread is the difference between the 10-year government bond yield and the 91-day Treasury bill yield, each averaged over the quarter, in basis points. A wide spread signals expected growth and a narrow or negative one signals tightening. Like the level indicators, it is fed into the staging rule of Section 4.5, so an Upturn is a steepening curve and a Downturn a flattening one. Both yields are market prices known at the end of the quarter, so the signal is traded with the same one-quarter lag as the EVI:

$$TS_t = y_t^{(10Y)} - y_t^{(91D)} \quad (9)$$

Figure 11 plots the series. The spread was wide in the late 1990s, turned negative in 2013–15 and widened again to about 300 basis points in 2021–22. It flattened through 2019, so the strategy entered the 2020 crash in its Downturn stage, which holds mainly gold. As a crisis signal, however, the spread is weak: a narrow spread does not identify India's pre-crisis quarters (AUC 0.42, 95% CI 0.31 to 0.52, over 96 quarters with 18 pre-crisis observations).

Figure 11. India's term spread narrowed into 2008 and flattened before 2020

10-year G-Sec minus 91-day T-bill, basis points, quarterly average, 1996Q2–2025Q4



Source: RBI DBIE; authors' calculations.

Note: The grey line is the quarterly spread and the maroon line its six-quarter exponentially weighted moving average (equation 10), whose direction sets the stage. The term spread AUC uses all India quarters with spread data (1996Q2–2025Q4, 96 quarters). On the FVI's 49 quarters (2011Q1–2025Q3) it is 0.17 (95% CI 0.06 to 0.31).

4.5 From indicator to regime: the staging rule

Each indicator except the growth–inflation quadrant is first smoothed with an exponentially weighted moving average over six quarters:

$$\tilde{x}_t = \sum_{k=0}^5 w_k x_{t-k}, \quad w_k = \frac{(1 - \alpha)^k}{\sum_{j=0}^5 (1 - \alpha)^j}, \quad \alpha = \frac{2}{6 + 1} \quad (10)$$

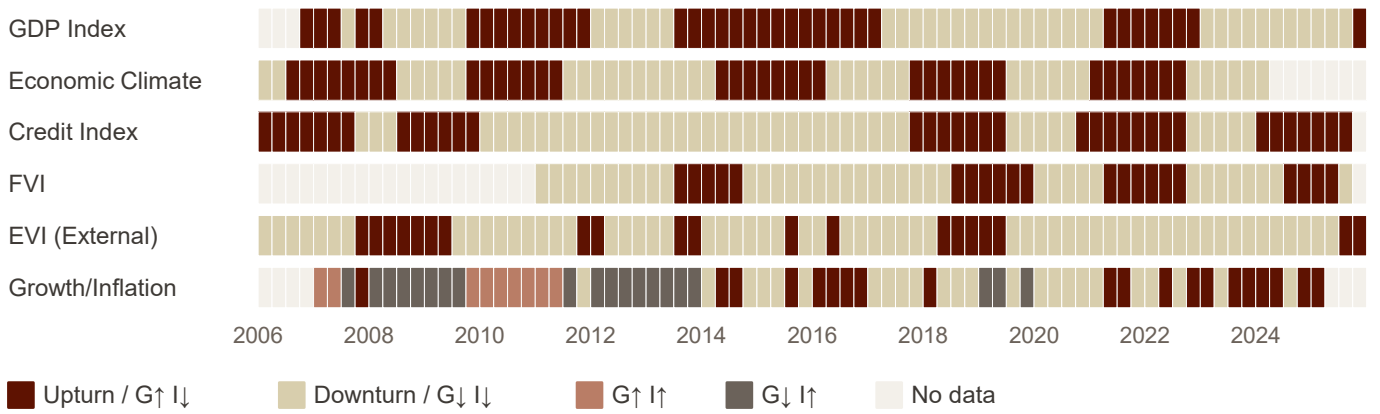
The raw stage is an Upturn when the smoothed series rises and a Downturn otherwise. To stop the portfolio from switching on noise, the final stage is the majority vote over the last five quarters, so a stage must persist before the portfolio changes:

$$s_t^{raw} = \begin{cases} \text{Upturn} & \tilde{x}_t - \tilde{x}_{t-1} > 0 \\ \text{Downturn} & \text{otherwise} \end{cases} \quad s_t = \text{mode}\{s_{t-4}^{raw}, \dots, s_t^{raw}\} \quad (11)$$

For the FVI, an Upturn means that vulnerability is rising. The allocation rule learns from history what to hold in each stage, so the label does not need to be good or bad. Figure 12 shows the stage of each indicator by quarter. The indicators rarely agree, which is one reason no single indicator dominates.

Figure 12. The seven indicators rarely agree on the stage

Stage of each indicator by quarter, 2006Q1–2025Q4



Source: Authors' calculations.

Note: For Growth/Inflation, the four colours are the four quadrants (G = growth, I = inflation, each above ↑ or below ↓ its expanding mean).

4.6 The allocation rule

At each quarter, the rule finds all past quarters that were in the same stage and computes each asset's mean return in those quarters. A cutoff is set at the p -th percentile of the five means. Only assets above the cutoff are held, in proportion to how far above it they are:

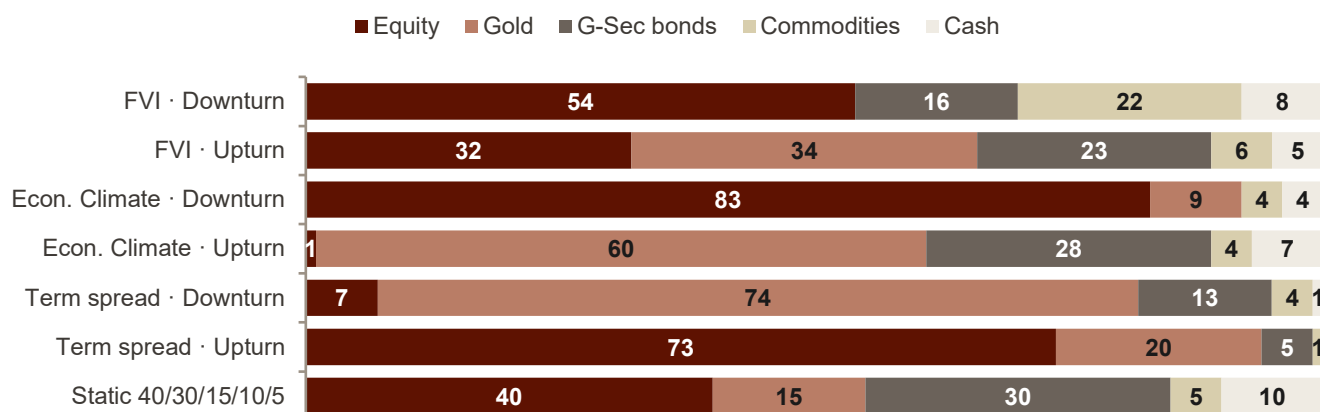
$$\bar{r}_{a,t} = \frac{1}{|\mathcal{S}_t|} \sum_{s \in \mathcal{S}_t} r_{a,s}, \quad \mathcal{S}_t = \{s < t : s_s = s_t\}; \quad c_t = \text{Pct}_p(\{\bar{r}_{a,t}\}_a) \quad (12)$$

$$w_{a,t} = \frac{\max(\bar{r}_{a,t} - c_t, 0)}{\sum_b \max(\bar{r}_{b,t} - c_t, 0)}$$

Setting $p = 40, 60$ or 80 gives the balanced, moderate and concentrated portfolios; with five assets these hold the top 3, 2 or 1 assets. The rule needs at least 8 quarters of history and at least 2 matching past quarters, and holds cash until then. Figure 13 shows the average weights by stage. Economic Climate is close to a switch between equity and gold. The term spread behaves the same way: it holds 73% equity on average when the curve steepens and 74% gold when it flattens.

Figure 13. Economic Climate switches between equity and gold

Average portfolio weight by stage, %; balanced portfolio after warm-up

**Source:** Authors' calculations.**Note:** Labels are percentage weights; weights below 1% are not labelled. Economic Climate's small upturn equity weight reflects rounding.

4.7 Backtest design, costs and statistical test

A signal for quarter t is used only once it would have been published. Market-based signals, the EVI and the term spread, are traded in quarter $t+1$. GDP, CLI and growth–inflation signals wait one further quarter and are traded in $t+2$. Credit and FVI signals, which depend on BIS data, are traded in $t+3$.

Figure 14 sets out these lags. The longer the lag, the later a stage change reaches the portfolio.

Figure 14. Publication lags: when each signal can be tradedQuarter in which the signal for quarter t enters the portfolio

	t	t+1	t+2	t+3	t+4
EVI, term spread (market data)	signal	trade			
GDP, CLI, Growth/Inflation	signal	wait	trade		
Credit, FVI (BIS)	signal	wait	wait	trade	

Source: Authors.**Note:** Signal = quarter measured; wait = data not yet published; trade = first quarter in which the signal is used.

Portfolio returns are net of a one-way transaction cost of $\kappa = 0.5\%$ on turnover, measured against the weights after the previous quarter's drift:

$$r_t^p = \sum_a w_{a,t} r_{a,t} - \kappa \cdot \frac{1}{2} \sum_a |w_{a,t} - w_{a,t-1}^{drift}|, \quad \kappa = 0.5\% \quad (13)$$

$$w_{a,t-1}^{drift} = \frac{w_{a,t-1}(1 + r_{a,t-1})}{\sum_b w_{b,t-1}(1 + r_{b,t-1})}$$

Static portfolios pay the same cost to rebalance back to their target weights, so benchmarks and regime strategies are treated identically. Strategies are compared by their annualised Sharpe ratios, and differences are tested with the Jobson and Korkie (1981) statistic with the Memmel (2003) correction:

$$SR_j = \frac{\sqrt{4(r_j - r_f)}}{\sigma(r_j - r_f)}, \quad z = \frac{\widehat{SR}_1 - \widehat{SR}_2}{\sqrt{\hat{\theta}}} \sim N(0, 1) \quad (14)$$

$$\hat{\theta} = \frac{1}{T} \left(2 - 2\hat{\rho} + \frac{1}{2} (\widehat{SR}_1^2 + \widehat{SR}_2^2) - \widehat{SR}_1 \widehat{SR}_2 \hat{\rho}^2 \right)$$

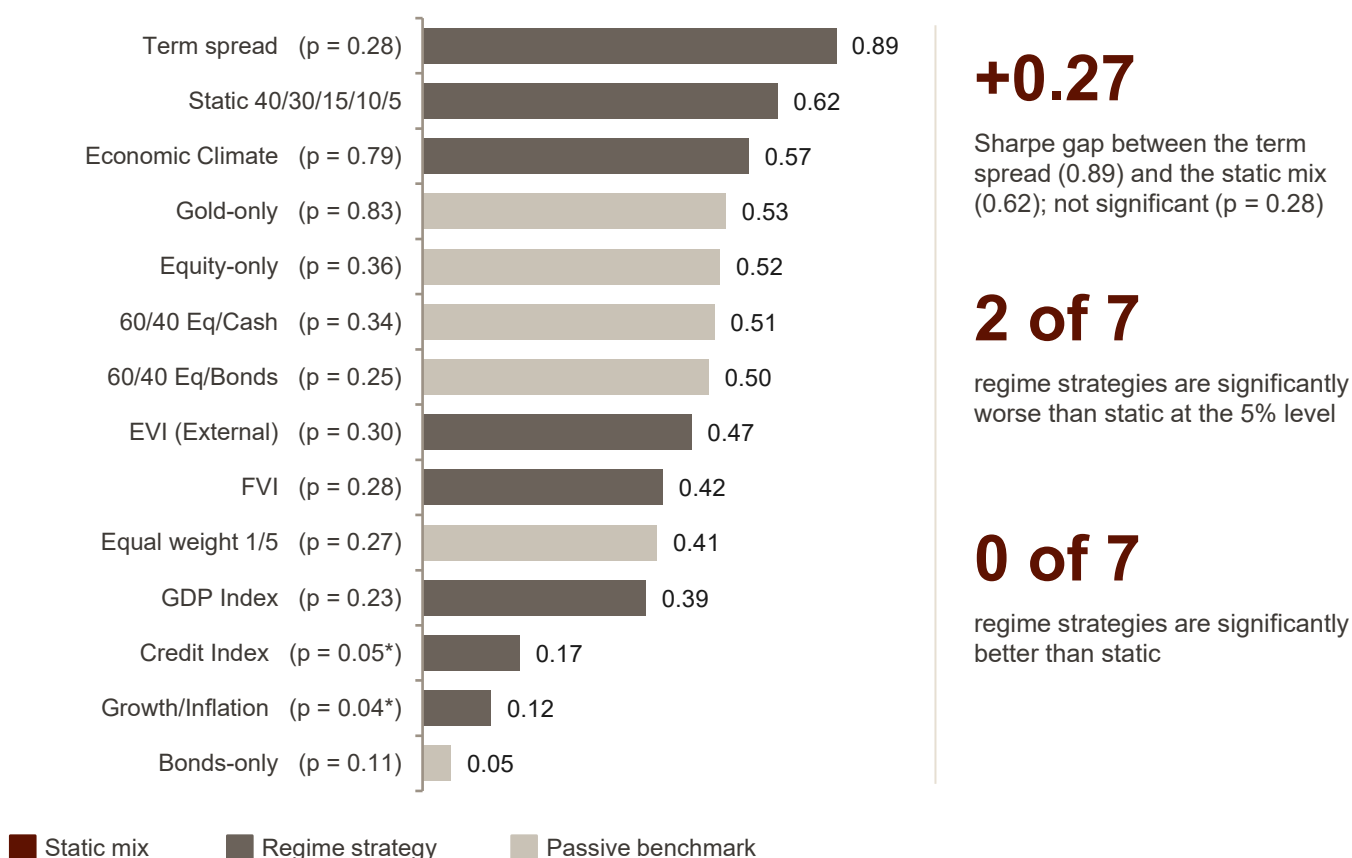
Here $\hat{\rho}$ is the correlation of the two excess-return series and T is the number of quarters; the Sharpe ratios inside $\hat{\theta}$ are quarterly, not annualised. Results are reported for two windows. The common window, 2013Q3–2025Q4 (50 quarters), is the headline because every strategy is live throughout. The full window, 2012Q2–2025Q4, starts once the last strategy leaves its warm-up.

5 Results

Table 6 reports performance over the common window. No regime strategy is significantly better than the static 40/30/15/10/5 portfolio, which has a Sharpe ratio of 0.62, the lowest volatility among invested strategies (7.1%) and a maximum drawdown of -10.1% . The term spread has the highest Sharpe ratio, 0.89, with an annual return of 16.7% , volatility of 10.8% and a maximum drawdown of -8.2% , but the difference from static is not significant ($p = 0.28$). Economic Climate reaches 0.57 ($p = 0.79$) and the FVI, the paper's main candidate, 0.42. Two strategies, Credit (0.17) and Growth/Inflation (0.12), underperform static at the 5% level. Section 6 shows that the term spread's lead depends on the sample start and on the one-quarter lag.

Figure 15. No regime strategy significantly beats the static mix

Sharpe ratio by strategy; balanced portfolio, common window 2013Q3–2025Q4, net of costs



Source: Authors' calculations.

Note: p is the two-sided Jobson–Korkie test with the Memmel correction against the static mix; * marks $p \leq 0.05$. Cash only is not shown.

A higher return is not the same as a better strategy. The term spread earns the most of any strategy, 16.7% a year, followed by Economic Climate at 14.2% . Economic Climate's return comes with twice the volatility of the static mix (14.2% against 7.1%) and a maximum drawdown of -26.4% against -10.1% . Figure 17 shows the wealth paths. Economic Climate and equity-only end with more wealth (₹5.26 and ₹5.20 per rupee invested, against ₹3.68 for static), but at roughly twice the volatility and with far deeper drawdowns. The term spread is the exception on this window: it ends with ₹6.86, the most of any strategy, with a smaller maximum drawdown than static (-8.2% against -10.1%), although its volatility is higher (10.8% against 7.1%).

Table 6. Main results: balanced portfolio

40th-percentile cutoff; common window 2013Q3–2025Q4, 50 quarters; net of 0.5% one-way costs

Strategy	Type	Ann. return	Volatility	Sharpe	Max drawdown	p vs static
Term spread	Regime	16.7%	10.8%	0.89	–8.2%	0.28
Static 40/30/15/10/5	Static	11.0%	7.1%	0.62	–10.1%	–
Economic Climate	Regime	14.2%	14.2%	0.57	–26.4%	0.79
Gold only	Benchmark	13.4%	13.6%	0.53	–15.6%	0.83
Equity only	Benchmark	14.1%	16.2%	0.52	–29.1%	0.36
60/40 Equity/Cash	Benchmark	11.3%	9.7%	0.51	–16.9%	0.34
60/40 Equity/Bonds	Benchmark	11.4%	10.1%	0.50	–15.7%	0.25
EVI (External)	Regime	11.3%	10.3%	0.47	–15.8%	0.30
FVI	Regime	10.8%	10.7%	0.42	–15.8%	0.28
Equal weight 1/5	Benchmark	9.4%	6.9%	0.41	–9.8%	0.27
GDP Index	Regime	9.9%	9.3%	0.39	–10.7%	0.23
Credit Index	Regime	7.9%	11.0%	0.17	–23.2%	0.05*
Growth/Inflation	Regime	7.2%	11.9%	0.12	–23.8%	0.04*
Bonds only	Benchmark	6.6%	5.2%	0.05	–2.6%	0.11
Cash only	Benchmark	6.5%	0.7%	–	–	–

Source: Authors' calculations.**Note:** p is the two-sided Jobson–Korkie test with the Memmel correction against the static 40/30/15/10/5 mix. * marks $p \leq 0.05$; both significant cases are regime strategies that are worse than static. No strategy is significantly better.

Figure 16 places every strategy on the same return–risk plane. The static mix earns more than every strategy of similar volatility; only the term spread lies above it, with a higher return at moderately higher volatility.

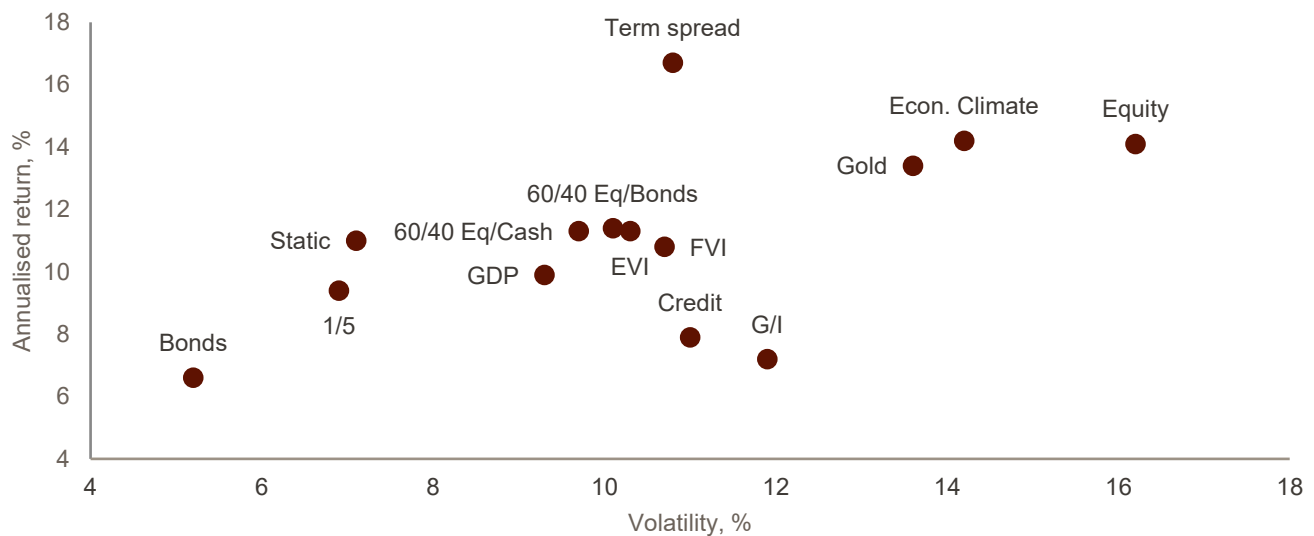
Figure 18 shows the same paths as year-end wealth with compound annual growth rates. From 2013Q4 to 2025Q4 the static mix compounded at 11.4% a year and Economic Climate at 14.1%. The extra growth of Economic Climate came with the volatility and drawdowns shown in Table 6 and Figure 19.

The 2020 crash illustrates this: India's equity market fell 29% between December 2019 and March 2020. The regime signals changed only after the fall, because the data they depend on arrived two or three quarters later. Figure 19 shows the result: Economic Climate's drawdown in 2020 is more than twice that of the static mix. The term spread is the one market-based signal that avoided the fall: the curve flattened through 2019, so the strategy entered 2020 in its Downturn stage, mostly in gold, and had no drawdown during the crash.

The allocation rule also concentrates the portfolio. In each stage it holds the assets with the best past average return, which in India means mainly equity or gold (Figure 13). The regime portfolios therefore carry high volatility and little diversification, while the static mix holds all five assets throughout. Moving to the moderate and concentrated cutoffs, which hold fewer assets, makes most regime strategies worse; the term spread, which already switches between equity and gold, is the exception (Section 6).

Figure 16. Higher returns mostly came with much higher volatility

Annualised return against volatility, %; common window, net of costs

**Source:** Authors' calculations.**Note:** Cash only is not shown.**Figure 17. Three strategies ended with more wealth than static**

Cumulative wealth of ₹1 invested in 2013Q3, net of costs

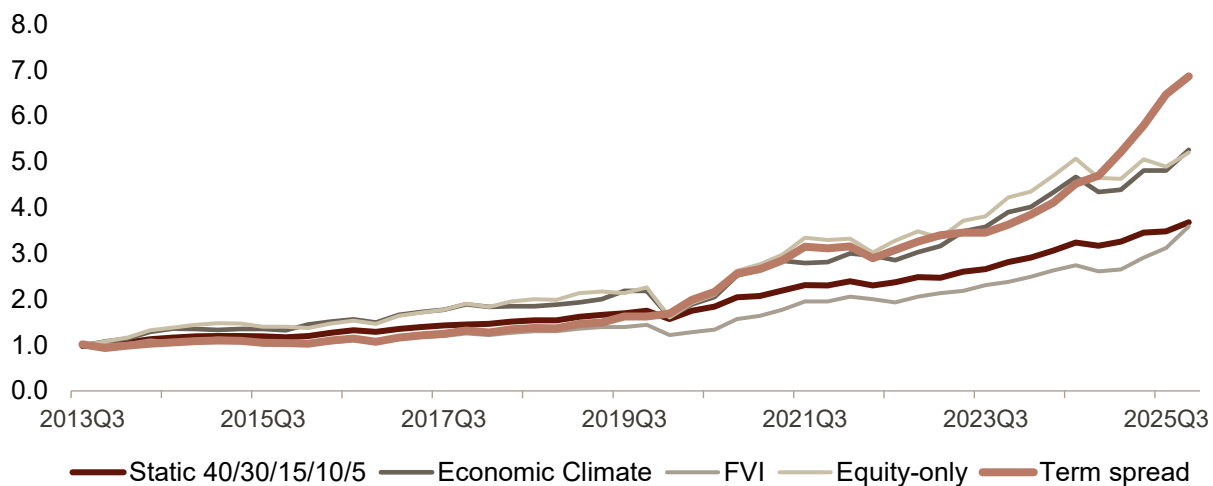
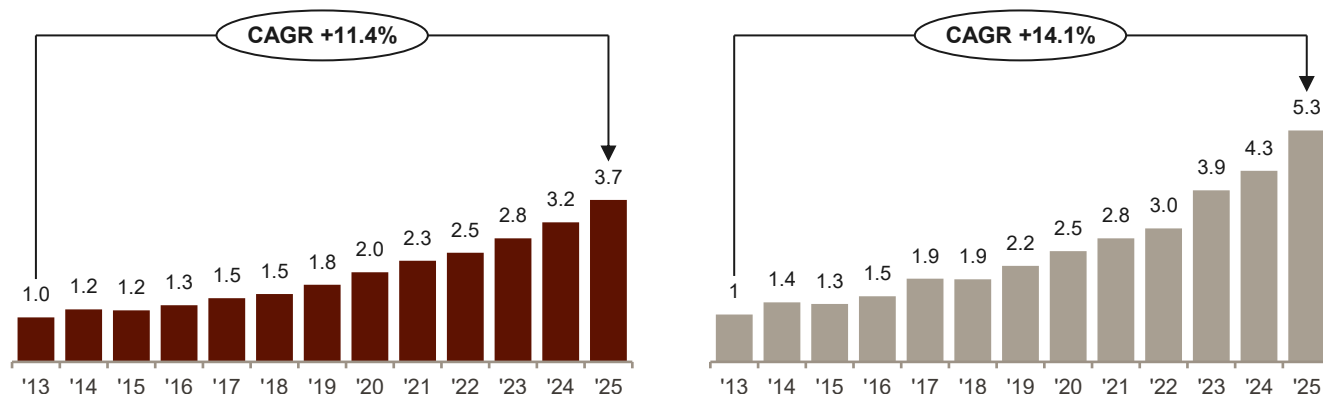
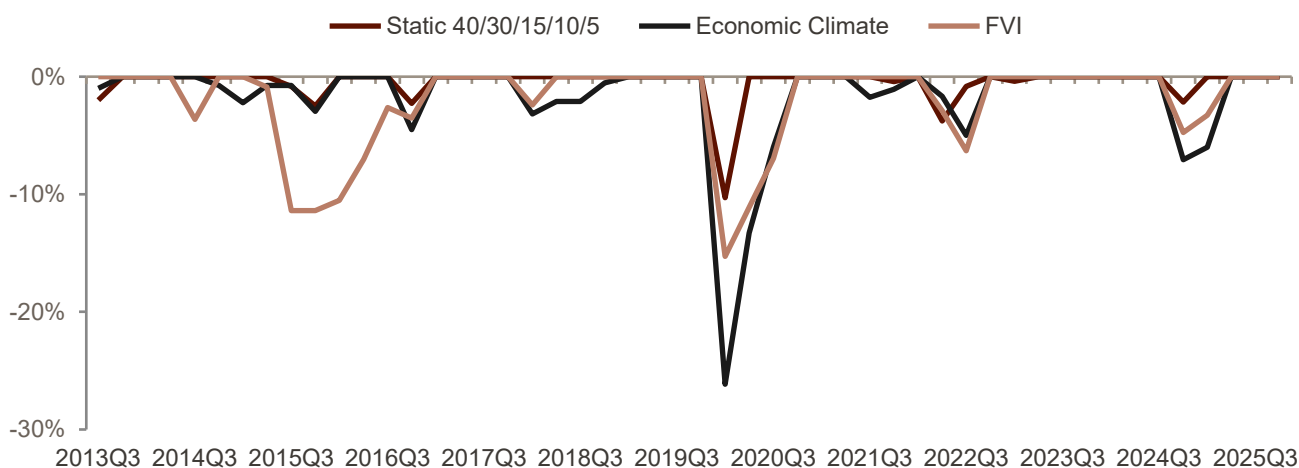
**Source:** Authors' calculations.**Note:** End values in 2025Q4: Economic Climate ₹5.26, equity only ₹5.20, static ₹3.68, FVI ₹3.59, term spread ₹6.86.

Figure 18. Year-end wealth and compound annual growth

Wealth of ₹1 invested in 2013Q3, at each year end (Q4)

Static 40/30/15/10/5**Economic Climate****Source:** Authors' calculations.**Note:** CAGR is the compound annual growth rate of year-end wealth from 2013Q4 to 2025Q4.**Figure 19. Economic Climate's 2020 drawdown was more than twice the static mix's**

Drawdown from the running peak, %; net of costs

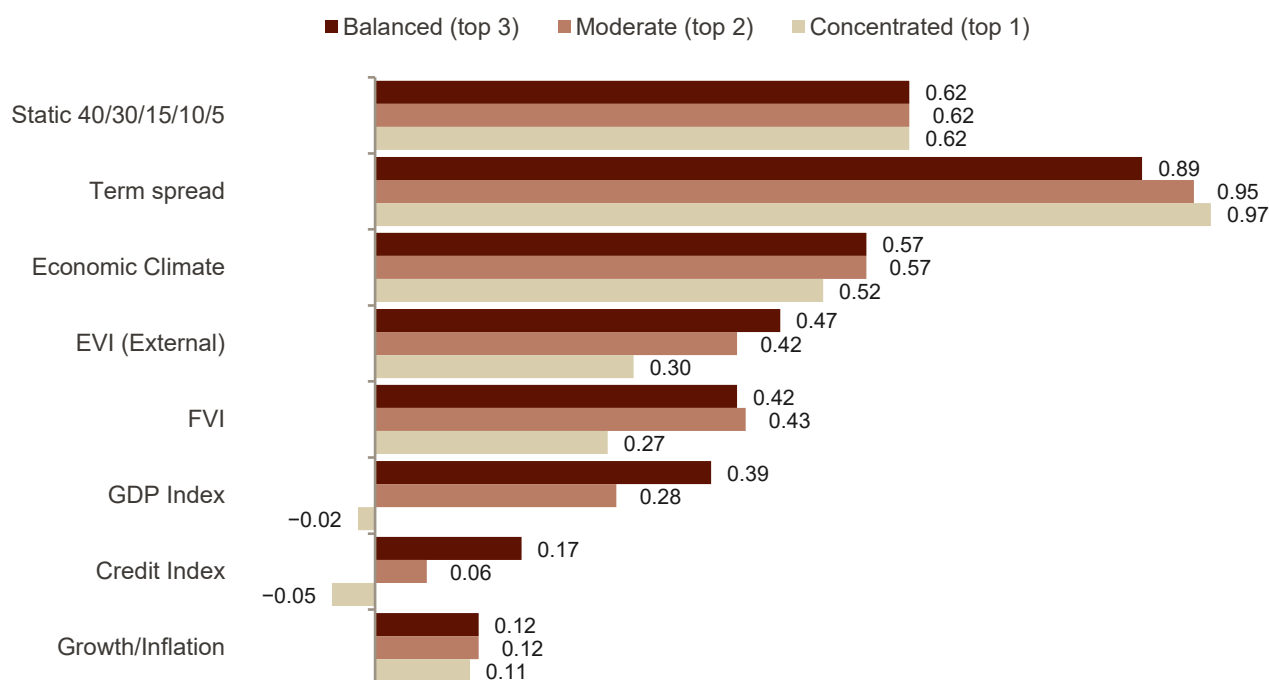
**Source:** Authors' calculations.**Note:** Drawdowns are computed from quarter-end wealth, so intra-quarter troughs are not captured and values can differ slightly from the maximum drawdowns in Table 6.

6 Robustness

Portfolio cutoff. Moving from the top 3 assets to the top 2 or top 1 lowers most regime Sharpe ratios (Figure 20). Under the concentrated cutoff, GDP falls to -0.02 and Credit to -0.05 . Apart from the term spread, no strategy at any cutoff reaches the static mix's 0.62. The term spread rises to 0.95 (moderate) and 0.97 (concentrated), because it already holds mostly one asset in each stage, but neither is significantly different from static ($p = 0.24$ and 0.26).

Figure 20. Concentrating the portfolio lowers most regime Sharpe ratios

Sharpe ratio by portfolio cutoff; common window, net of costs



Source: Authors' calculations.

Note: The static mix holds the same weights under every cutoff.

Credit-only FVI. Crises are dated from equity prices, and equity growth is one of the FVI regressors, which makes the model partly circular. Dropping equity growth gives a credit-only FVI with a Sharpe ratio of 0.39, against 0.42 for the main specification. The same sign pattern holds.

Additional Indian events. Adding the 2013 taper tantrum and the 2018 IL&FS episode to the Indian crisis list leaves every stage unchanged, so the backtest is unchanged.

Term spread: start date and lag. The term spread's advantage is concentrated in the common window. From its first invested quarter, 2008Q3, its Sharpe ratio is 0.43 against 0.55 for static ($p = 0.63$), so it trails static once 2008–12 is included. Its gains also depend on trading one quarter after the signal: with a two-quarter lag its Sharpe ratio falls to 0.51 ($p = 0.58$), below static. The lead is therefore not robust.

No transaction costs. Removing costs raises each regime strategy's Sharpe ratio by at most 0.06 (from 0.01 for GDP to 0.06 for Growth/Inflation); Economic Climate reaches 0.60. Costs do not drive the ranking.

Full window. Over 2012Q2–2025Q4 the term spread has a Sharpe ratio of 0.72 against 0.58 for the static mix, again not significant ($p = 0.53$), and the static mix ranks second (Appendix A, Table 9). Table 7 collects these results.

Figure 21 traces the FVI strategy through these checks. Costs reduce its Sharpe ratio by 0.03, and dropping equity growth reduces it by a further 0.03. At every step it remains well below the static mix.

Table 7. Robustness: Sharpe ratio of each regime strategy under alternative choices

Balanced portfolio

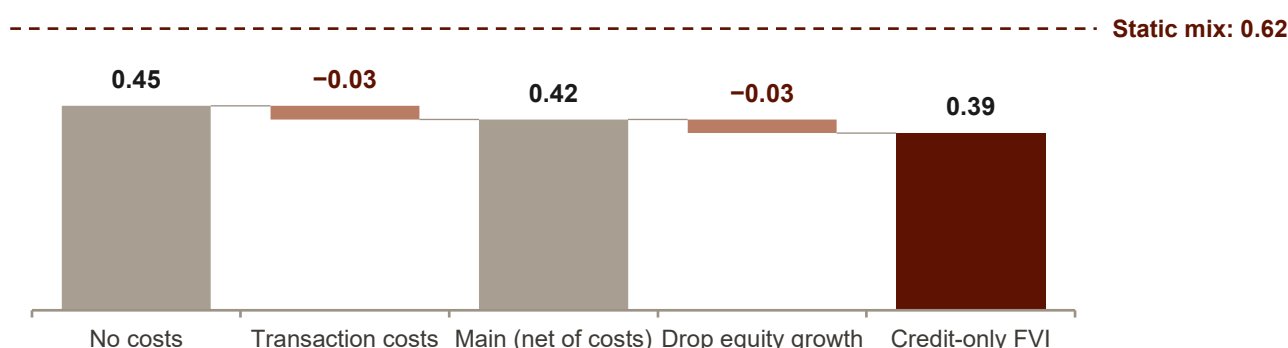
Strategy	Main	No costs	Credit-only FVI	Full window
Term spread	0.89	0.91	–	0.72
Economic Climate	0.57	0.60	–	0.53
EVI (External)	0.47	0.50	–	0.38
FVI	0.42	0.45	0.39	0.36
GDP Index	0.39	0.40	–	0.24
Credit Index	0.17	0.19	–	0.12
Growth/Inflation	0.12	0.18	–	0.07
Static 40/30/15/10/5	0.62	0.62	0.62	0.58

Source: Authors' calculations.

Note: Main, No costs and Credit-only FVI use the common window (2013Q3–2025Q4); Full window is 2012Q2–2025Q4. The term spread's Sharpe ratio is 0.43 from its own start in 2008Q3 and 0.51 with a two-quarter lag (common window).

Figure 21. Neither costs nor the equity regressor explain the FVI's shortfall

Sharpe ratio of the FVI strategy; common window



Source: Authors' calculations.

Note: The dashed line marks the static 40/30/15/10/5 mix.

7 Discussion and limitations

Three features of the Indian data explain the result. First, the signals arrive late relative to market moves. Both Indian crashes lasted between one and four quarters, while credit data arrive three quarters late; by the time a Credit or FVI stage changes, the fall is largely over. Second, there are few crises to learn from. India contributes two crises and 9 positive quarters to the panel, so the FVI is effectively an Asian model applied to India, and the crises it learns from differ in cause and structure. Third, diversification across Indian assets is already strong. With a correlation of -0.26 between gold and equity, a static mix captures much of the benefit a timing rule would seek, which raises the bar for any regime strategy.

The term spread is the only indicator with a higher Sharpe ratio than static, and the same features explain both its strength and its fragility. It is a market price, so it reaches the portfolio a quarter after it is measured, faster than any macro or credit series. Its gains come mainly from switching between equity and gold, and in particular from holding gold through the 2020 crash and the 2025 gold rally. A strategy that rests on a few well-timed switches over 50 quarters is easily overturned by a different start date or one more quarter of delay, which is what Section 6 finds. With seven indicators tested, one may also beat the benchmark by chance, so the term spread result should be read as suggestive rather than established.

Table 8. Limitations and how they bear on the result

Limitation	Detail
Credit-gap sign	It is -2.25 while 5-year credit growth is $+2.30$. The two are collinear, so read them jointly. A single credit variable, or ridge regularisation, is left to future work.
Circular equity signal	Crises are dated on equity, and equity growth is a regressor. The credit-only check (0.39) addresses this.
Short test sample	50 quarters means the test has low power. The FVI is live only from 2012Q2.
Term spread sensitivity	Its higher Sharpe ratio (0.89) is not significant, reverses from a 2008Q3 start (0.43 vs 0.55), and falls to 0.51 with a two-quarter lag.
Data vintages	Revised GDP (2015 rebase) is used, not real-time vintages. That makes the regime strategies look slightly better, which strengthens the negative result.
Coverage	$\wedge$ NSEI starts in 2007. There is a Thailand gap from 2023 to 2026, and house prices are not used.
Rule design	Percentile cutoffs mean holding the top 1–3 assets, and no volatility scaling or optimisation is tested.

Source: Authors.

The study has several limitations. The credit gap enters the FVI with a sign contrary to theory (-2.25) while 5-year credit growth enters at $+2.30$; the two are collinear and should be read jointly. A single credit variable, or ridge regularisation, would address this in future work. The equity-growth regressor is partly circular with equity-dated crises, which the credit-only check (0.39) addresses. The test sample of 50 quarters gives the Sharpe-difference test low power, so small gains cannot be ruled out, and the FVI is live only from 2012Q2. The term spread's advantage over static is not significant and depends on the sample start and the signal lag (Section 6).

The backtest uses revised GDP data (after the 2015 rebase) rather than real-time vintages. This makes the regime strategies look slightly better than they would have in practice, which strengthens the negative result. Coverage is also limited: the $\wedge$ NSEI equity series starts in 2007, the Thailand series has a gap from 2023 to 2026, and house prices are not used. Finally, the rule design is narrow. The percentile cutoffs always hold the top 1–3 assets, and no volatility scaling or portfolio optimisation is tested.

8 Conclusion

We asked whether macro-financial regime indicators can improve asset allocation for an Indian investor. Built with only the information available at the time, they do not do so reliably. None of seven regime strategies significantly beats a static, diversified 40/30/15/10/5 portfolio over 2013–2025, and this holds across portfolio cutoffs, without transaction costs and with a credit-only early-warning model. The term spread, a market signal published daily and used with a one-quarter lag, comes closest, with a Sharpe ratio of 0.89 against 0.62, but its lead is not significant and disappears with an earlier start or a longer lag. The practical lesson is that regime models for emerging markets should be judged on real-time construction, not on fitted history, and that fast market signals such as the term spread should be tested before slow macro series. Future work could test the term spread over a longer equity history, such as the BSE Sensex from 1997, combine it with other market signals, and use real-time GDP vintages.

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Appendix

A. Full-window results

Table 9 repeats the main comparison over the full window. The ranking is the same as in the common window: the term spread has the highest Sharpe ratio, not significantly different from static ($p = 0.53$), and the static mix is second.

Table 9. Main results on the full window

Balanced portfolio; 2012Q2–2025Q4, 55 quarters; net of 0.5% one-way costs

Strategy	Type	Ann. return	Volatility	Sharpe	Max drawdown	p vs static
Term spread	Regime	14.9%	10.9%	0.72	–15.5%	0.53
Static 40/30/15/10/5	Static	10.8%	6.8%	0.58	–10.1%	–
Economic Climate	Regime	13.6%	13.7%	0.53	–26.4%	0.76
60/40 Equity/Bonds	Benchmark	11.5%	9.8%	0.50	–15.7%	0.44
Equity only	Benchmark	13.7%	15.7%	0.49	–29.1%	0.42
60/40 Equity/Cash	Benchmark	11.2%	9.4%	0.49	–16.9%	0.41
Gold only	Benchmark	11.6%	13.6%	0.40	–23.0%	0.62
EVI (External)	Regime	10.4%	10.2%	0.38	–15.8%	0.15
Equal weight 1/5	Benchmark	9.1%	6.7%	0.36	–9.8%	0.20
FVI	Regime	10.2%	10.4%	0.35	–15.8%	0.21
GDP Index	Regime	8.7%	9.2%	0.24	–16.2%	0.07
Bonds only	Benchmark	7.4%	5.1%	0.15	–8.6%	0.21
Credit Index	Regime	7.4%	10.7%	0.12	–23.2%	0.03*
Growth/Inflation	Regime	6.8%	11.6%	0.07	–23.8%	0.02*
Cash only	Benchmark	6.7%	0.7%	–	–	–

Source: Authors' calculations.

Note: p is the two-sided Jobson–Korkie test with the Memmel correction against the static 40/30/15/10/5 mix. * marks $p \leq 0.05$.

B. Major crisis episodes

Table 10 lists the 47 major crises identified by the dating rule of Section 4.1.

Table 10. Major equity crises in nine Asian markets

Depth of at least 25%, closed episodes

Market	Peak	Trough	Depth	Market	Peak	Trough	Depth
China	Jun 2001	May 2005	–52%	Hong Kong	Mar 2000	Mar 2003	–50%
China	Oct 2007	Oct 2008	–71%	Hong Kong	Oct 2007	Feb 2009	–59%
China	Dec 2009	Jun 2010	–27%	Hong Kong	Apr 2011	Sep 2011	–26%
China	Oct 2010	Jun 2013	–34%	Hong Kong	Apr 2015	Feb 2016	–32%
China	May 2015	Dec 2018	–46%	Hong Kong	May 2021	Oct 2022	–50%
Hong Kong	Sep 1987	Nov 1987	–46%	India	Dec 2007	Nov 2008	–55%
Hong Kong	Dec 1993	Jan 1995	–38%	India	Dec 2019	Mar 2020	–29%
Hong Kong	Jul 1997	Aug 1998	–56%	Indonesia	Apr 1990	Oct 1991	–64%

Table 10 (continued). Major equity crises in nine Asian markets

Depth of at least 25%, closed episodes

Market	Peak	Trough	Depth	Market	Peak	Trough	Depth
Indonesia	Jan 1994	Apr 1995	-30%	Malaysia	Dec 1993	Jan 1995	-31%
Indonesia	Jun 1997	Sep 1998	-62%	Malaysia	Feb 1997	Aug 1998	-76%
Indonesia	Dec 1999	Apr 2001	-47%	Malaysia	Feb 2000	May 2001	-42%
Indonesia	Dec 2007	Nov 2008	-55%	Malaysia	Dec 2007	Oct 2008	-40%
Indonesia	Jan 2018	Mar 2020	-31%	Malaysia	Jun 2014	Mar 2020	-28%
Japan	Dec 1989	Jun 1995	-63%	Singapore	Mar 1990	Sep 1990	-30%
Japan	Jun 1997	Sep 1998	-35%	Singapore	Jan 1996	Aug 1998	-65%
Japan	Mar 2000	Apr 2003	-62%	Singapore	Dec 1999	Mar 2003	-49%
Japan	Jun 2007	Feb 2009	-58%	Singapore	Oct 2007	Feb 2009	-58%
Korea	May 1997	Dec 1997	-50%	Singapore	Apr 2018	Oct 2020	-33%
Korea	Jan 1998	Jun 1998	-48%	Thailand	Dec 1996	Aug 1998	-74%
Korea	Dec 1999	Sep 2001	-53%	Thailand	Jun 1999	Sep 1999	-25%
Korea	Mar 2002	Mar 2003	-40%	Thailand	Dec 1999	Dec 2000	-44%
Korea	Oct 2007	Feb 2009	-48%	Thailand	Oct 2007	Nov 2008	-56%
Korea	Jan 2018	Mar 2020	-32%	Thailand	Feb 2018	Mar 2020	-38%
Korea	Jun 2021	Sep 2022	-35%				

Source: Yahoo Finance; authors' calculations.