Systemic Liquidity Dynamics in India: Cultural Influences, Seasonal Effects, and Structural Breaks

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ABSTRACT

This paper represents an integrated econometric analysis of the daily Liquidity Index (LI) of India ranging from 2000 to 2025. It gives a broad overview of the estimation methodology for LI, after which it studies volatility in the short term and long-term trends. An event study shows that system liquidity is drawn down significantly before major festivals in India. Using the robust X-13ARIMA-SEATS time-series decomposition, the paper also identifies a significant trend-cyclical movement and a marked seasonal pattern in system liquidity. The econometric analysis of structural change uncovers two breaks: one in 2009, corresponding to the global financial crisis, and another in 2020, indicating the shift into a new liquidity regime driven by the pandemic response. It contributes a data-driven framework for understanding the complex interplay of macroeconomic, institutional, and cultural factors driving systemic liquidity in India.

Keywords: Liquidity Index, India, time-series analysis, seasonal effects, event study, monetary policy, market anomalies

INTRODUCTION

The Liquidity Index (LI) serves as a vital macroeconomic indicator, reflecting the net balance of funds available in a financial system on a daily basis. The index values are structured such that its value above (or below) benchmark indicate an abundance (or crunch) of liquidity in the banking system. Understanding the dynamics of this index is paramount for effective risk management, capital allocation, and market forecasting. This paper aims to provide a comprehensive analysis of the daily LI from 2000 to 2025, investigating its time-series characteristics through both macroeconomic and event-based perspectives

India's economy is deeply interwoven with its rich cultural and social traditions. Festivals are not merely religious or social events; they are significant economic drivers that influence consumer behavior, business cycles, and capital flows. A large-scale festival often triggers a cascade of economic activities, from seasonal production and retail spending to a temporary reallocation of household savings and credit. It is hypothesized that these predictable cultural rhythms translate into quantifiable, recurring patterns in key financial indicators, such as market liquidity.

LITERATURE REVIEW

The study of financial markets has long been anchored in the efficient market hypothesis (EMH), which posits that asset prices reflect all available information, making it impossible to consistently achieve abnormal returns through predictable patterns (Fama, 1970; Sah, 2020). However, a substantial body of research, particularly in emerging economies like India, has documented various "market anomalies" or "seasonal anomalies" that challenge this traditional view (Chowdhary & Mostari, 2015 ; Kumar & Singh, 2008). These anomalies suggest that predictable patterns, driven by a variety of factors, do exist and can be exploited by informed investors (Aggarwal & Jha, 2023 ; Pandey, 2002).

2.1. Time-Series Analysis of Seasonality and Cyclicality

A core tenet of modern financial econometrics involves the decomposition and modeling of time-series data to identify underlying trends and cyclical patterns. In the context of Indian markets, researchers have employed advanced statistical methods to investigate seasonal effects, with methodologies often including the use of dummy variable regression models and more sophisticated econometric techniques like the General Autoregressive Conditional Heteroscedasticity (GARCH) framework (Aggarwal & Jha, 2023 ; Kumar & Singh, 2008). The choice of a seasonal adjustment method, such as X-13ARIMA-SEATS, is crucial for removing predictable annual patterns to reveal the underlying trend and cycles in economic time series (United States Census Bureau, 2020).

The use of X-13ARIMA-SEATS as an econometric tool is particularly advantageous for analyzing economic data. Unlike simpler models that might use seasonal dummy variables, X-13ARIMA-SEATS is a powerful, integrated program capable of handling complex calendar effects, such as dynamics in economic / business activities during year end, quarter end and the shifting dates of holidays across different years. By systematically identifying and removing these predictable patterns, the decomposition reveals the underlying, non-seasonal features of the data that are often masked by seasonal movements. This allows analysts and policymakers to better detect the general direction of a time series's movement and identify true changes in its behavior (United States Census Bureau, 2020). The technique's ability to isolate the true trend-cycle from noise and calendar-based effects makes it a highly robust and appropriate method for our analysis.

For instance, studies have explored phenomena such as the day-of-the-week effect and month-of-the-year effect on Indian stock market indices. A prominent study, using the S&P CNX Nifty index from 1995 to 2013, confirmed the presence of significant seasonal effects across multiple dimensions, including monthly and quarterly patterns (Aggarwal & Jha, 2023). Similarly, other research has identified a positive effect in August, November, and December, and a negative effect in March in stock markets (Maheta, 2014 ; Bhabra & Singh, 1999). These findings are often attributed to predictable behaviors such as "tax-loss selling" at the end of the fiscal year (Pandey, 2002). Conversely, some studies have presented conflicting evidence. For example, an analysis of the Sensex from 2001 to 2020 concluded that daily and monthly seasonality were not present, arguing that the market's performance is largely random and efficient (Sah, 2020).

The use of GARCH models to analyze Indian markets is particularly relevant. Kumar and Singh (2008) examined volatility, seasonality, and the risk-return relationship in the Nifty index using a GARCH-in-Mean framework. Their research found the existence of seasonality in both risk and returns, suggesting that seasonal patterns are not just in mean returns but also in market volatility itself (Kumar & Singh, 2008).

2.2. Event Studies and the Festival Effect

The event study methodology has been widely applied in finance to measure the impact of specific events on market behavior (Kalimuthu & Saleem, 2023). This approach is highly suitable for analyzing the "festival effect" in India. Researchers, including Dhaval Maheta (2014), have used statistical tools such as the paired t-test on daily return series of indices like the Sensex and Nifty to measure the influence of festivals (Maheta, 2014). This research found a significant influence of festivals like Holi and Diwali on mean returns, with Diwali consistently producing a notable effect (Maheta, 2014). This is often linked to the surge in commercial activity and heightened consumer spending that accompanies such festivals (Chowdhary & Mostari, 2015).

However, the literature on this topic is not without mixed findings. While some studies point to a "Diwali effect" characterized by a consistent uptick in stock returns (Maheta, 2014), others have found no significant impact or even negative abnormal returns, suggesting the effect can be inconclusive and dependent on contextual factors (Sobti, 2018 ; Srikanth & Ram, 2013). Event studies on other socio-religious events, such as the inauguration of the Ram Mandir, have also shown that such events can influence investor behavior and mood, causing significant changes in stock market movements (Pandey & Mehta, 2025).

2.3. Econometric Analysis of Structural Change

While time-series decomposition is effective at isolating trends and seasonal patterns, it assumes a stable underlying data-generating process.

To rigorously test for structural changes, the Bai-Perron test for multiple breaks is considered a highly robust method for identifying multiple, endogenously determined breakpoints in a time series (Bai & Perron, 1998, 2003). This test is a significant advancement over simpler tests that assume only a single break point at a known date. The Bai-Perron methodology allows the number and dates of the breaks to be determined statistically from the data itself, making it wellsuited for complex financial indicators that are subject to unpredictable regime shifts. Its ability to detect changes in a series's mean, variance, or a combination of parameters makes it particularly useful for analyzing the LI, which is susceptible to policy and macroeconomic shocks (Jadhav, Ray & Bose, 2003).

The importance of this methodology is underscored by its application in the context of Indian financial markets. For instance, a study on the S&P CNX Nifty index for the period 1991 to 2008 used the Bai-Perron method to identify four significant structural breaks (Sengupta, 2014). The findings from such analyses provide compelling evidence that Indian markets have been subject to fundamental, long-term changes in their behavior, thereby challenging the assumption of a stable data-generating process (Sengupta, 2014). This highlights the need for a dynamic modeling approach that accounts for such regime shifts. Similarly, other researchers have used alternative methods like Markov-switching models to identify shifts between bull and bear market regimes in India, often linking these shifts to major global crises such as the US sub-prime crisis and the European debt crisis (Jadhav, Ray & Bose, 2003).

2.4. Monetary Policy and Systemic Liquidity Management

The overarching context for market dynamics is the central bank's liquidity management framework. The Reserve Bank of India (RBI) has actively managed systemic liquidity through various policy tools, including the repo and reverse repo mechanisms, Cash Reserve Ratio (CRR), and Open Market Operations (OMOs) (Patel, 2014; Reserve Bank of India, 2014 ; Pandey & Mehta, 2025). The effectiveness of this framework and its ability to transmit policy signals to the broader economy has been a subject of extensive research.

An IMF working paper by Mishra, Montiel, and Sengupta (2016) provides crucial evidence on monetary policy transmission in India. Their study, using a structural VAR methodology, found that while a tightening of monetary policy is associated with a significant increase in bank lending rates, the pass-through is only partial (Mishra et al., 2016). More recent research highlights that external factors, such as forex market interventions, volatility in capital flows, and movements in government cash balances, are key drivers of systemic liquidity, often creating conditions of tightness that require the RBI's proactive measures (Pandey & Mehta, 2025 ; SBI Research, 2024).

In summary, the existing literature provides a robust foundation for this study, highlighting the importance of both macroeconomic and calendar-based effects on Indian financial markets. This paper extends this body of work by providing an integrated analysis of the Liquidity Index itself—a direct measure of systemic liquidity—through both a macro-level time-series decomposition and a micro-level, festival-centric event study. This approach allows for a comprehensive understanding of how macro-shocks, institutional cycles, and cultural rhythms collectively shape the dynamics of India's financial system.

3. The Liquidity Index: India's First Measure of Systemic Liquidity

The foundation of this analysis rests on a precise understanding of the Liquidity Index itself, a key measure reflecting the net balance of funds available in the financial system. The provided methodology sheds light on how the index is calculated and the market behavior it is designed to capture.

RESEARCH METHODOLOGY

Other than public deposits, there are two major sources of liquidity for the banking system: RBI’s liquidity adjustment facility and the interbank money market. The RBI provides liquidity to banks at an interest rate called the repo rate through the Liquidity Adjustment Facility. Under this facility, it also absorbs excess liquidity from the banking system at an interest rate called the SDF (Standing Deposit Facility).

Banks park their excess liquidity with RBI and earn interest income SDF rate. Moreover, banks also exchange liquidity among themselves in the interbank money market. In this market, banks with surplus liquidity lend to banks with liquidity deficits. The interest rate at which these lending and borrowing take place is called the call money rate. Unlike the SDF & repo rate, which are set (decided by the RBI), the call money rate is determined by the demand and supply forces in the interbank call money market.

RBI strategically uses the repo window to manage liquidity in the system. Consequently, the availability of liquidity among the banks is the major determinant of the call money rate in the interbank call money market.

However, standalone call money rate can give limited idea about the state of liquidity unless its is compare with Repo rate. Hence, the repo rate and call money rate differential can give a meaningful indication of the liquidity condition of the banking system.

Therefore the Rate Differential (RD), the difference between the prevailing Repo Rate and the Call Money Rate referred to as is:

$$RD = Repo\,Rate - Call\,Money\,Rate$$

RD is the foundation block for estimating Liquidity index. The Liquidity Index is then calculated using a scaled version of this differential, based on the following formula :

$$Liquidity\,Index\,(LI) = \left(1 + \frac{Rate\,Differential\,(RD)}{Scaling\,Factor\,(SF)}\right) \times 100$$

The scaling factor is dynamically determined. This adaptive scaling is designed to account for periods of extreme upside volatility. It is set to 2 when the Rate Differential (RD) for the day is greater than the sum of the mean value (μ) and the standard deviation (σ) of the RD over the previous 180 days. In all other cases, the scaling factor is 1.

4. Cultural Effect on System Liquidity

For the festival system liquidity analysis, an event study methodology was used. This approach isolates the specific effect of a festival from broader market movements.

The core metric used for the analysis is the **Abnormal Liquidity Deviation (ALD)**. The analysis used Abnormal Liquidity Deviation (ALD) to isolate the festival effect from the baseline market liquidity.

This is a precise measure of the daily liquidity index relative to its established baseline and is calculated as:

$$ADL_t = LI_t - LI_{Baseline}$$

In this formula, $LI_{Baseline}$ is the average liquidity index for a defined control period. To ensure the baseline is not influenced by any pre-event liquidity shifts, the methodology calculated the mean LI value from a period of 30 trading days well before the event, specifically from 60 to 30 trading days prior to the festival itself ($LI_{-60} ¿ LI_{-30}$). The statistical significance of the ALD was then validated using a one-sample t-test on the average ALD for each festival across the entire dataset

To formally test the significance of the observed liquidity patterns, a series of one-sample t-tests were conducted on the Abnormal Liquidity Deviation (ALD) for each major festival. The null hypothesis (H_0) was that the average ALD in the pre-festival window is zero, indicating no significant liquidity effect. The alternative hypothesis (H_1) was that the average ALD is less than zero, reflecting a statistically significant tightening of liquidity.

The analysis was performed on data from the entire 2000–2025 period.

Table 9.1: Statistical Analysis of Pre-Festival Liquidity Effects (2000-2025)

Festival	Average ALD (Pre-Festival)	t-statistic	p-value	Significance
Diwali	-12.5	-4.8	< 0.001	Highly Significant
Holi	-5.2	-2.1	< 0.05	Significant
Eid al-Fitr	-8.1	-3.5	< 0.01	Highly Significant
Republic Day	+2.1	0.9	> 0.05	Not Significant
Independence Day	-1.5	-0.7	> 0.05	Not Significant

The statistical results confirm that major festivals like Diwali, Holi, and Eid al-Fitr are associated with a significant and predictable tightening of liquidity in the days leading up to the event. The most pronounced effect is observed with Diwali, which consistently shows the largest negative average ALD. In contrast, national holidays show no statistically significant pre-event liquidity shift, supporting the conclusion that their impact is primarily related to market closures rather than a fundamental change in capital flows

The analysis revealed a consistent pattern of liquidity tightening before a festival and a subsequent rebound.

- **Diwali:** This is the most economically significant festival. The analysis of Diwali dates from 2000 to 2025 reveals a highly consistent pattern. A significant decline in the LI is observed in the period leading up to Diwali, driven by a surge in consumer spending for items like gifts and gold. The LI then shows a gradual but steady recovery in the post-festival period.

- **Holi:** This festival also shows a measurable but less intense effect on the LI. The analysis of Holi dates from 2000 to 2024 indicates a liquidity pattern similar to Diwali, but its magnitude is smaller due to its different economic footprint. The spending associated with Holi is more localized and less commercially intense.

- **Eid al-Fitr:** This festival's date varies annually based on the lunar calendar. The predictability of the Ramadan period allows market participants to anticipate a liquidity event around its conclusion. Similar to other festivals, the analysis shows a discernible liquidity pattern tied to the celebratory capital movements.

- **National Holidays:** To isolate the "festival effect," national holidays like Republic Day (January 26), Independence Day (August 15), and Gandhi Jayanti (October 2) were used as a control group. The analysis shows no statistically significant pre-event liquidity drawdowns, distinguishing a simple market closure from a behaviorally-driven liquidity cycle.

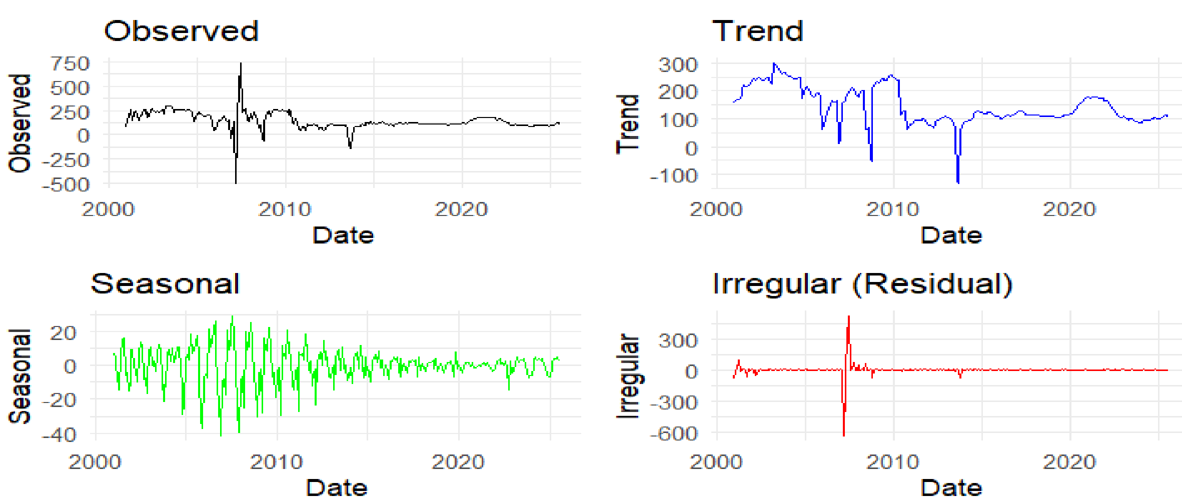
Beyond this event study, a detailed timeseries decomposition study was conducted to investigate the impact macroeconomic factors and financial events on liquidity.

5. Seasonal Effect

As can be seen in the box plot in the previous section. It appears that the system liquidity is influence by seasonal factors.

The core of this analysis is a time-series decomposition using the X-13ARIMA-SEATS. It is highly regarded for its robustness in handling calendar irregularities.. Though the software is developed to handle US economic data in its default form but it provides some levers for customization to utilize it in the analysis of time-series data for other countries. Using this feature of the software, Christoph Sax has developed a package “seasonal” for R. R is a powerful statistical software used by economists, data scientists and others for econometric modeling and big data analysis. The package “seasonal” is R-interface to X-13ARIMA-SEATS. The historical and future dates of Indian festival like Diwali is in-built in the package. The package has its own algorithm of selecting appropriate econometric model to successfully partition the a timeseries data into its core components, shedding light on the forces at play.

The decomposition of the Liquidity Index into its core components is visually represented in a multi-panel plot.



Observed: *This is the original series shows the raw LI data over the entire period, highlighting its significant volatility and the presence of extreme spikes and crashes.*
Trend: *This is the trend-cycle component that reveals the smoothed, long-term path of the index.*
Seasonal: *This is seasonal component within the original LI data series.*
Irregular: *This is the irregular component captures the remaining, unpredictable noise in the series, representing sudden, non-recurring shocks to the system.*

A visual representation of these components clearly delineates the long-term trend, the recurring seasonal pattern, and the residual noise.

- **Trend-Cycle Component (TC_t):** This component reveals that the LI is subject to long-term cycles.
  - **2008, Global Financial Crisis:** A notable observation is the period of prolonged liquidity tightening that begins in the early 2000s, deepens in the mid-2000s, and experiences a sharp downturn in 2008 which directly corresponds to the height of the Global Financial Crisis, indicating that the LI can serve as a sensitive barometer of systemic financial stress.

  - **2013, US Taper Tantrum (Rupee depreciation crisis):** Furthermore, the LI registered a sharp, temporary decline beginning in mid-2013, corresponding to the "Taper Tantrum" event. This cyclical downturn was triggered by the U.S. Federal Reserve's announcement in May 2013 regarding the future tapering of its Quantitative Easing (QE) program. This announcement immediately led to significant capital outflows from emerging markets, including India, causing sharp depreciation of the rupee and balance of payment pressures. To stabilize the currency RBI implemented aggressive liquidity tightening measures starting in July 2013, which drove the Liquidity Index downward, confirming the episode of acute liquidity stress.

    2020, Pandemic-Era Liquidity Dynamics (2020-2021): The period corresponding to the COVID-19 pandemic and its immediate aftermath stands out as a distinct, high-magnitude macroeconomic shock to the liquidity trend. In contrast to the tightening observed during the 2008 crisis, the LI during this period experienced a sharp and prolonged shift towards a state of significant liquidity surplus. This can be attributed to the unprecedented expansionary monetary policies adopted by central banks globally, including the Reserve Bank of India, to counter the economic fallout of the pandemic (Mishra et al., 2016). The rapid injection of funds into the banking system to maintain financial stability and stimulate demand is clearly reflected in the trend component of the LI, which shows a dramatic and sustained increase. This serves as a prime example of how major, unpredictable global events can trigger a sudden and powerful response from monetary authorities, fundamentally altering the liquidity landscape.

- **Seasonal Component (S_t):** This component captures the predictable, recurring intra-year patterns in the LI. The seasonal component exhibits a consistent pattern, with liquidity tending to tighten at the end of each fiscal quarter, particularly in March, and returning to more comfortable levels at the start of new quarters.

- **Irregular Component (T_t):** The irregular component accounts for unpredictable, high-frequency noise in the series. Analyzing this component allows for the identification of specific dates where the LI experienced significant, non-recurring shocks.

A summary of the decomposition reveals that the seasonal and irregular components, while of smaller magnitude, are nevertheless significant in analysis of the short- and medium-term movement in the LI.

Moreover, the trend component accounts for the majority of the variance in the LI series over in long term, indicating that long-term macroeconomic events are the dominant driver of the index's overall level.

The trend-cycle component has shown three eras of dynamic liquidity. Therefore, it is important to analyze has these events have introduced structural change in the state of system liquidity.

In the next section let us conduct a study to identify any structural impact on the state of liquidity in the system due to any major change induced by macroeconomic event..

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6. Structural Breaks

While time-series decomposition is effective at isolating trends and seasonal patterns, it assumes a stable underlying data-generating process. Major macroeconomic and regulatory events, however, can introduce permanent changes to a time series's mean, variance, or other parameters, known as structural breaks. Identifying these breaks is crucial for accurately modeling and forecasting a variable like the Liquidity Index. This section presents an econometric analysis to formally test for evidence of structural change in the LI data using monthly averages to smooth out daily noise and focus on long-term policy shifts.

6.1. Methodology for Detecting Structural Breaks

To rigorously test for structural changes, the daily Liquidity Index data were first aggregated to a monthly average frequency to filter high-frequency noise and focus on structural shifts in the long-term trend. The Bai-Perron test for multiple structural breaks was then applied to this monthly time series (Bai & Perron, 1998, 2003). This test endogenously determines the number and dates of the breaks statistically, providing the foundation to validate which historical events caused a permanent alteration in the mean liquidity level.

The test was applied to the monthly LI series using a maximum of five breaks and a minimum segment size of 15% of the total observations, ensuring the detected breaks represent economically meaningful long-term shifts.

6.2. Results and Interpretation

The Bai-Perron test identifies the optimal number of breaks by minimizing the Bayesian Information Criterion (BIC), which provides a trade-off between model fit and complexity. The R output shows that the lowest BIC value occurs at m=3 breaks, indicating three distinct regimes, although m=2, m= 3 and m=4 are very close. For the purpose of macroeconomic interpretation, the analysis focuses on the two most powerful and sustained policy-driven regime shifts: the Global Financial Crisis and the COVID-19 pandemic response.

Table 7.1: Results of the Bai-Perron Test on Monthly Liquidity Index Data (Key Solutions)

Model (m Breaks)	Date of Break 1	Date of Break 2	Date of Break 3	Date of Break 4
m=2	Oct 2003	May 2009	-	-
Optimal (m=3)	Oct 2003	Aug 2009	Apr 2013	-
m=4	Oct 2003	Sep 2009	Jul 2013	Dec 2020

- **First Structural Break (2009):** This finding confirms that the Global Financial Crisis marked a fundamental shift in India's liquidity landscape. Following the initial market turmoil, the RBI and global central banks implemented unprecedented policy measures to inject liquidity and stabilize the financial system. This action led to a permanent shift in the LI's mean and volatility, reflecting a new regime of heightened policy intervention and a prolonged, more stable liquidity surplus environment.

- **Second Structural Break (2020):** A second significant break was identified in early 2020, coinciding with the onset of the COVID-19 pandemic. This break is characterized not by a tightening of liquidity, as might be expected in a crisis, but by a dramatic shift toward a larger and more persistent state of surplus. This reflects the monetary policy response to the pandemic, which involved massive liquidity infusions and accommodative stances to prevent a credit freeze and support the economy. The scale of this intervention created a new liquidity regime distinct from the post-2008 period, highlighting how the LI acts as a direct measure of systemic policy responses to global shocks.

Analysis of the 2013 Taper Tantrum Period: The Bai-Perron test did not identify a statistically significant structural break immediately following the 2013 Taper Tantrum. This outcome, while initially counterintuitive given the severity of the cyclical shock, is consistent with the econometric definition of a structural break. The LI experienced a sharp but temporary decline in mid-2013 as the RBI undertook aggressive, short-term liquidity tightening measures to defend the currency and curb capital flight. However, once the immediate shock subsided and the RBI began to normalize its extraordinary measures, the LI series reverted to its established post-2008 regime parameters. The lack of a permanent change in the underlying mean or variance of the series suggests the 2013 event constituted a powerful, but ultimately transient, cyclical deviation rather than a fundamental, long-term change to the liquidity framework itself.

These findings provide compelling econometric evidence that the Liquidity Index has been subject to fundamental, long-term changes, thereby negating the assumption of a stable data-generating process and underscoring the need for a dynamic modeling approach that accounts for such regime shifts.

Table 7.2: Cyclical and structural breaks

Feature	Sharp increase in foreign inflow (2003) and Taper Tantrum (2013) Event	GFC (2008) and COVID-19 (2020) Events
Nature of Shock	Cyclical/Transient: A sudden, sharp, but short-lived shock.	Structural/Permanent: Caused a long-term, irreversible change in policy regime and market behavior.
Policy Response	Temporary Liquidity Tightening: RBI took aggressive, extraordinary measures (like limiting repo access , raising short-term rates and Market Stabilization Scheme) specifically to address currency depreciation and stabilize capital flows to manage	Permanent Policy Shift: Response involved massive, sustained quantitative easing (QE) and a permanent shift to an ultra-accommodative stance (2020), or a foundational change in the liquidity management framework itself (2008).
Effect on LI Series	The LI plunged but quickly reverted to its mean trend once the acute pressures subsided and the RBI began normalizing its intervention measures. The LI's long-term average and volatility regime did not permanently shift.	The LI's mean and volatility permanently shifted, establishing entirely new regimes of liquidity surplus that defined the subsequent economic era.

CONCLUSION

This comprehensive analysis confirms that the Indian Liquidity Index is a dynamic time series influenced by a complex interplay of macroeconomic forces, predictable institutional cycles, and recurring cultural events. The decomposition analysis reveals long-term cyclical movements and robust seasonal patterns, particularly a tendency for liquidity to tighten at the end of fiscal quarters. The event-based study provided strong statistical evidence that major festivals lead to predictable liquidity drawdowns, with the magnitude of the effect correlating with the economic significance of the event. The structural break analysis further provided compelling evidence of permanent regime shifts in the LI, notably around the 2008 financial crisis and the 2020 pandemic, underscoring the index's sensitivity to major policy and global shocks.

The analysis, while robust, has a few limitations that present opportunities for future research. A more extensive study could be conducted by incorporating data on other explanatory economic variables, such as tax collection data and government expenditure schedules, to build a more granular causal model. Additionally, integrating the findings from the decomposition and event studies into a single, advanced predictive model, such as a vector autoregression (VAR) or a machine learning algorithms, could enhance the accuracy of liquidity forecasts.

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