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Can effects of weather variation predict future economic downturn? Evidence from systemic risk in Indian financial markets

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Keywords: Weather, Systemic risk, Forecast, Generalized additive models, India

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1. Introduction

The heavy rains in August 2018 in a south Indian state, Kerala, provided considerable threat of non-performing loans to the Federal Bank which has 47% of its branches located in affected region[1]. During the period from July to September, the Indian stock market observed a drop of $\approx$ 23% in stock returns for the bank and an increase in the systemic risk conditional on Federal Bank alone by $\approx$ 7%[2]. The systemic risk is the possibility that instability in a single institution could ripple out and upset the whole financial system. This weather event in Kerala shows the possibility of a localized weather event influencing the systemic risk in the entire stock market. While the Kerala floods represent an extreme case, the underlying mechanism may also broadly apply to variations in temperature and precipitation. Early studies for Europe (Tzouvanas et al., 2019), China (Song and Fang, 2023; X. Wu et al., 2023) and the USA (Curcio et al., 2023) also demonstrate that variations in temperature and precipitation (extreme or moderate) increase the systemic risk in the stock markets. However, these limited studies do not account for the differential impact of expected weather vis-à-vis weather anomaly (defined as decomposed weather variables)[3]. Furthermore, to our knowledge, no research has yet examined this relationship in India—an emerging economy experiencing an annual stock market capitalization growth of approximately 6% in the last two decades. Accordingly, the current study examines the differential impact of weather variations on systemic risk in the Indian stock market.

While examining the impact of weather variations on systemic risk, we shed light on three important aspects not explored in previous literature. Firstly, we highlight the advantages of using decomposed weather variables over aggregate ones while estimating systemic risk in Indian stock markets. Secondly, we capture the *asymmetric effect* on systemic risk in stock markets given expected weather vis-à-vis weather anomaly. Finally, we explore the *heterogeneous impact* of weather on systemic risk across different seasons and all seven broad clusters (consumer, manufacturing, health care, energy, technology, finance, and others).

The focus is on systemic risk as it has taken particular importance in predicting economic downturns because of the economic recession that succeeded the global financial crisis of 2007–2009. Various systemic risk measures have been developed and are established as good proxies for early signalling for future economic downturns (Allen et al., 2012; Chen et al., 2020; Giglio et al.,

[1] https://www.forbesindia.com/article/leaderboard/flood-impact-federal-bank-raises-red-flag/51113/1

[2] Author's computation

[3] Stock market reaction to anticipated and unanticipated news has been studied for monetary policy (Bernanke & Kuttner, 2005), government policy (Pastor & Veronesi, 2012), unemployment news (Gonzalo & Taamouti, 2017), and company announcements (Purda, 2007).

2016; Li et al., 2024). With the growing literature on the significant effect of weather variations on macroeconomic outcomes (Burke et al., 2015; Damania et al., 2020; Dell et al., 2012; Kotz et al., 2022), having early signals of the effect of weather variations on future economic activities can prove helpful. Consequently, this study also examines whether systemic risk from weather variations in financial markets can predict future economic downturns.

We consider a systemic risk measure, ΔCoVaR, as proposed by Adrian and Brunnermeier (2016) and compute monthly ΔCoVaR for 898 firms listed on Indian stock exchanges. We also compute the 1995-year economic activity weighted temperature and precipitation variables from grid-level monthly data obtained from Harris et al. (2020). Further, given that markets may react differently to expected as compared to unexpected fluctuations, we decompose weather variables into expected and anomaly components using ensemble empirical mode decomposition (Z. Wu and Huang, 2009). Finally, we estimate the impacts of weather variations on systemic risk—for January 2005 to November 2022—by employing a Generalized Additive Model (GAM), a semi-parametric econometric tool, differing from the parametric techniques.

The GAM estimates for both models—aggregate or decomposed weather—indicate the significance of weather variations in explaining the systemic risk in Indian financial markets. However, crucial differences in estimates exist in the interpretation and magnitude of these weather effects. We demonstrate that aggregate weather GAM misestimates the positive effect on systemic risk through precipitation fluctuation and no effect from temperature fluctuation. Contrary to this, the decomposed weather GAM demonstrate that a positive temperature variation increases systemic risk, whereas a positive precipitation variation decreases it. In addition, the aggregate weather model fails to capture the interplay between temperature and precipitation like the decomposed one. These findings point to the potential erroneous estimation due to aggregate weather.

Our findings also reveal that a rise in the systemic risk of a 0.1°C rise in expected temperature (0.01 percentage points or pp) is significantly lower than a rise in temperature anomaly (0.20 pp). Similarly, a fall in the systemic risk for a 10 mm increase to expected precipitation (0.01 pp) is significantly lower than one to precipitation anomaly (0.03 pp). These results indicate the asymmetric effect of weather variations. Furthermore, these asymmetric effects vary across seasons and broad industry clusters. We observe that the asymmetric effect is mainly driven by the monsoon season. While decomposed temperature variation has a homogeneous asymmetric effect across broad industry clusters, heterogeneity is observed for the decomposed precipitation variation, especially for the energy, finance, technology, and healthcare clusters.

We explain these results by examining two potential channels through which weather variations impact firms' future cashflows and investor decision-making—changes in economic conditions and uncertainty. Specifically, we analyze the impact of decomposed weather variations on macroeconomic time series data of power demand growth, year-on-year inflation, and credit supply growth using an autoregressive model with generalized autoregressive conditional heteroskedasticity terms. Our findings indicate that both expected and anomaly weather fluctuations affect the mean power demand growth and credit supply growth, suggesting a potential impact on firms' future cashflows. Additionally, we observe that weather variations influence the volatility of wholesale inflation rates and credit supply growth, which may, in turn, affect investor decision-making.

In our final part, we illustrate the significance of these weather-induced systemic risks in predicting future economic activity, proxied by the mean industrial production index. This analysis reveals that weather-induced systemic risk demonstrates a weak to negligible short-term forecasting power (months from 1 to 6) but a more significant potential to foresee economic downturns in the medium to long run (months from 7 to 12). Systemic risk in Pre-monsoon and Winter seasons predicts short- to medium-run future economic downturns but has no predictive capacity during Monsoon and Post-monsoon seasons. In the case of cluster-wise analysis, while we observe medium to longer horizon forecasting ability for most clusters, the weather-induced systemic risk from the healthcare cluster can forecast from shorter to longer horizons. In contrast, the weather-induced systemic risk from the energy cluster can only forecast longer periods.

1.1. Contribution to existing literature

With the above mentioned findings, we contribute to the existing literature in the following ways. First, this study contributes to the limited literature on the impact of weather variations on systemic risk in financial markets by considering the Indian financial market as its case study. We find that only expected temperature fluctuation demonstrates an inverted-U-shaped relation with systemic risk, unlike Tzouvanas et al. (2019), which has shown this relation with aggregate temperature in the case of the European region. We also show an asymmetric effect between expected and anomaly weather variation, which was considered in isolation by Curcio et al. (2023), Song and Fang (2023), Tzouvanas et al. (2019), and X. Wu et al. (2023). We have also considered the interactive effect between temperature and precipitation, which is only considered in the case of China by X. Wu et al. (2023). Finally, we introduce a unique but flexible semiparametric econometric technique of generalized additive model deviating from the parametric assumption considered in previous studies.

Second, our paper highlights climate risk pricing in Indian financial markets and thus touches upon existing climate finance literature. Venturini (2022) discusses the financial consequences of weather variations for asset pricing. Using asset pricing models, Balvers et al. (2017) and Gregory (2024) note that temperature shock raises the cost of equity for US firms and has a negative factor loading on risk premiums. Huynh et al. (2020) find that in the case of Chinese firms, firms afflicted by drought pay higher equity capital costs. Our findings of the asymmetric effect of expected vis-á-vis anomaly weather across seasons and broad industry clusters add to climate pricing understanding.

Third, Cao and Wei (2004), Kamstra et al. (2003), Kang et al. (2010), Kathiravan et al. (2021), and Saunders (1993) show that weather variations like changes in temperature, cloud-cover, seasonal affective disorder, or extreme weather affect investor's mood, which influences stock returns. However, as pointed out by Venturini (2022) and demonstrated by Jacobsen and Marquering (2008) and Yan et al. (2022), weather variations alter investor mood and economic conditions to influence stock returns. Our mechanism analysis provides evidence of this conundrum by indicating that weather variations affect the mean and volatility of power demand growth, inflation, and credit supply growth.

Finally, we provide a new perspective to understand the impact of weather variations on economic outcomes. Existing global (Burke et al., 2015; Dell et al., 2012; Kalkuhl and Wenz, 2020) and regional studies (Kumar and Maiti, 2024b; Mendelsohn, 2014) conclude that temperature shocks hinder economic growth due to negative effects on investment, labour productivity, human health, and agricultural and industrial output. A precipitation shock significantly affects the overall economic growth in agriculture (Damania et al., 2020; Kotz et al., 2022). Indian studies also show that temperature shocks reduce economic growth (Jain et al., 2020; Kumar and Maiti, 2024a; Sandhani et al., 2023), total factor productivity (Kumar and Maiti, 2024a), agricultural yield (Birthal et al., 2021; Pattanayak et al., 2021; Taraz, 2018), labour productivity (Colmer, 2021; Somanathan et al., 2021), and increases suicides (Carleton, 2017). On the other hand, a positive precipitation shock is favourable for agricultural output (Auffhammer et al., 2006; Birthal et al., 2021; Mitra, 2014), but increasing precipitation volatility has a detrimental effect on Indian agriculture (Pattanayak et al., 2021). While these studies demonstrate a direct impact of weather shocks on economic outcomes, our forecasting analysis points out indirect impact channels through financial markets. Our results indicate that weather variations create financial instability, which affects Indian economic conditions.

The rest of the paper proceeds as follows. Section 2 summarises the data and computation of systemic risk and weather decomposition. Section 3 performs a preliminary analysis and develops the hypotheses of the study. Section 4 tests these hypotheses and provides results for the mechanism analysis. The results on forecasting ability are presented in Section 5, and Section 6 concludes the paper.

2. Data and variable construction

The firm data needed to calculate systemic risk and weather-related data are all detailed in this section.

2.1. Computation of Systemic risk ($\Delta CoVaR$)

We use the Datastream database to retrieve the monthly share prices (S_{it}) for 1596 firms denoted by 'i' and month-year by 't'. These firms are listed on the Bombay Stock Exchange and National Stock Exchange (major stock exchanges in India). For each firm, the monthly returns are computed as $r_{it} = ln\left(\frac{S_{it}}{S_{it-1}}\right)$. Firms are filtered out to ensure that every firm has 90% observations to compute systemic risk. We, therefore, have a dataset covering 898 firms from February 1999 to July 2023. The descriptive statistics of these firms in various sectors are provided in Table A1 of Appendix A1.

We follow the three-step empirical method of ΔCoVaR (Adrian & Brunnermeier, 2016) to compute the systemic risk. Using the quantile regression, the Value at Risk (VaR) and Conditional Value at Risk (CoVaR) for the firm and the system, respectively, is calculated as follows:

$$\begin{aligned} X_t^i &= \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i \\ X_t^{\text{System}|i} &= \alpha_q^{\text{System}|i} + \gamma_q^{\text{System}|i} M_{t-1} + \beta_q^{\text{System}|i} X_t^i + \varepsilon_{q,t}^{\text{System}|i} \end{aligned} \tag{1}$$

where M_{t-1} refers to lagged monthly state variables representing a vector of seven macroeconomic state variables, as considered by Verma et al. (2019). It includes short-term liquidity (the difference between the 3-month MIBOR and the 3-month treasury bill rate), changes in the 3-month treasury bill rate, yield changes (the difference between the 10-year government bond rate and the 3-month treasury bill rate), credit spread (the difference between the commercial paper rate and the 3-month treasury bill rate), prime lending rate, monthly market returns, and volatility. Panels (a)–(j) of Figure 1 illustrate the state variables retrieved from the CEIC database. We define the loss of firm ($X_t^i = -r_{it}$) and market ($X_t^{\text{System}|i} = -r_{mkt,t}$) and compute VaR and CoVaR at q = 99% as the predicted value of Equation (1), as shown below:

$$\begin{aligned} \text{VaR}^i_{q,t} &= \hat{\alpha}^i_q + \hat{\gamma}^i_q M_{t-1} \\ \text{CoVaR}^i_{q,t} &= \hat{\alpha}^{\text{System}|i}_q + \hat{\gamma}^{\text{System}|i}_q M_{t-1} + \hat{\beta}^{\text{System}|i}_q VaR^i_{q,t} \end{aligned} \tag{2}$$

where, $\text{VaR}^i_{q,t}$ and $\text{CoVaR}^i_{q,t}$ are the predicted VaR and CoVaR values, respectively. $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ represent the quantile regression coefficient estimates from Equation (1). Finally, we compute the systemic risk ($\Delta\text{CoVaR}^i_{q,t}$) conditional on the failure of a firm using Equation (3).

$$\Delta\text{CoVaR}^i_{q,t} = \text{CoVaR}^i_{q,t} - \text{CoVaR}^i_{50,t} = \hat{\beta}^{\text{System}|i}_q \left(\text{VaR}^i_{q,t} - \text{VaR}^i_{50,t}\right) \tag{3}$$

Panels (h)–(k) of Figure 1 show the mean and standard deviation of VaR and ΔCoVaR for the period. Panel (j) of Figure 1 shows three noticeable upward spikes and one downward spike. The initial upward rise in 2008-09 corresponded to the start of the global financial crisis period. It is followed by a downward spike in 2010, signalling that Indian financial markets have recovered from the global financial crisis. The second upward spike in 2019 reflects the Indian financial crisis, which was triggered by high-profile defaults by non-banking financial companies, mainly Infrastructure Leasing and Financial Services and Dewan Housing Finance Ltd. The third upward spike highlights the stock market's systemic risk following India's first COVID-19 lockdown. Accordingly, we conclude that the systemic risk computed for Indian financial markets using the ΔCoVaR method fairly represents a risk in Indian financial markets.

2.2. Weather variables

We obtained grid-level monthly temperature and precipitation from version 4.08 of the database given by Harris et al. (2020) from October 1994 to July 2023. While average monthly weather data for India can be analyzed, we use economic activity-weighted monthly total temperature and precipitation data for India in our calculations. With this weighting, we aim to capture the dispersion of firms and investors across India who are the agents of stock markets.

Furthermore, weather shocks may have varying impacts across regions in India (Jain et al., 2020; Kumar and Maiti, 2024a; Sandhani et al., 2023), which can be accounted for by weighting the weather by the region's economic activity. Accordingly, we use district-level economic activity data from Nordhaus (2006) of the year 1995 to avoid endogeneity and generate 1995-year economic activity weighted monthly temperature (T_t) and precipitation (P_t) data.

Several reasons, such as seasonal variations, anomalies, extreme weather, and forecasted weather,

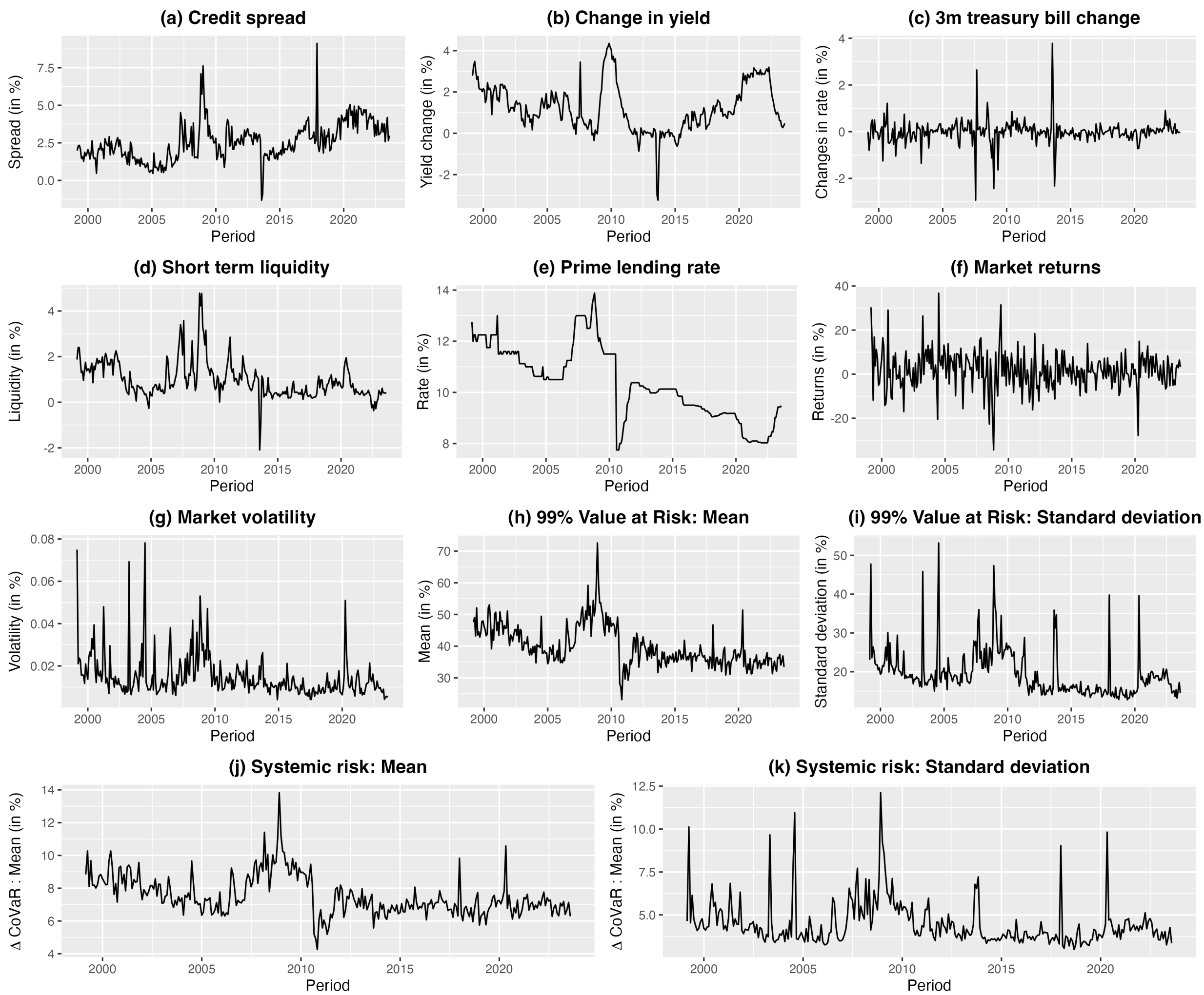

Figure 1: **Summary statistics of systemic risk variables:** Macroeconomic state variables, Value at Risk (VaR) and systemic risk (ΔCoVaR) are plotted against monthly time series. Plots (a)–(g) portray the macreconomic state variables as suggested by Verma et al. (2019). Plot (h)–(k) are computed accordingly to Equation (3).

cause weather changes. The knowledge about weather changes is complex due to the range of short- and long-term effects of various factors. To determine the differential impact of each expected and anomaly weather change, we break down the weighted monthly temperature (T_t) and precipitation (P_t) into three categories: trend, seasonal, and anomaly. We make use of ensemble empirical mode decomposition (Z. Wu and Huang, 2009) and bifurcate the weather variables as follows:

$$\begin{aligned} \underbrace{T_t}_{\text{Aggregate temperature}} &= \underbrace{T_{\text{trend},t} + T_{\text{seasonal},t}}_{\text{Expected temperature}} + \underbrace{T_{\text{anomaly},t}}_{\text{Anomaly temperature}} \\ \underbrace{P_t}_{\text{Aggregate precipitation}} &= \underbrace{P_{\text{trend},t} + P_{\text{seasonal},t}}_{\text{Expected precipitation}} + \underbrace{P_{\text{anomaly},t}}_{\text{Anomaly precipitation}} \end{aligned} \tag{4}$$

where trend ($T_{\text{trend},t}$ and $P_{\text{trend},t}$) and seasonal ($T_{\text{seasonal},t}$ and $P_{\text{seasonal},t}$) component of weather are summed up to denote the expected weather ($T_{\text{expected},t}$ and $P_{\text{expected},t}$) whereas the anomaly part ($T_{anomaly,t}$ and $P_{anomaly,t}$) denote the unexpected weather[4]. The aggregate weather (T_t and P_t), expected weather, and anomalous weather time series are plotted for reference in Figure 2.

3. Preliminary analysis and hypothesis development

This section explores the variation of systemic risk by season in Indian financial markets. For this, we evaluate the computed systemic risk from January 2005 to November 2022 and extract the monthly cyclical patterns using the Generalized additive model (GAM)[5]. Unlike the month-fixed effect in parametric forms, GAM supports cyclical smoothers known as cyclic cubic splines, which assume no discontinuity in January or December. This smoother enables us to extract the seasonal pattern of systemic risk throughout the year. Therefore, we define the GAM specification as follows:

$$\begin{aligned} \Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y \\ + s(\text{month, bs = ``cc'', k=12}) + \eta^i_t \end{aligned} \tag{5}$$

[4]The residual series, represented by the trend term, may show patterns brought on by climate change or El Nino. In IPCC reports, global surface temperature rise calculation treats the trend as an anomaly. Given the growing knowledge of climate change, this study assumes that companies and investors anticipate weather changes. As a result, we consider trend terms as expected weather variables.

[5]This data period was chosen based on available economic data for mechanism analysis. Section 4.4 provides a detailed description of these variables. Section 4.5 details our robustness check utilizing extended data from February 1999 to July 2023.

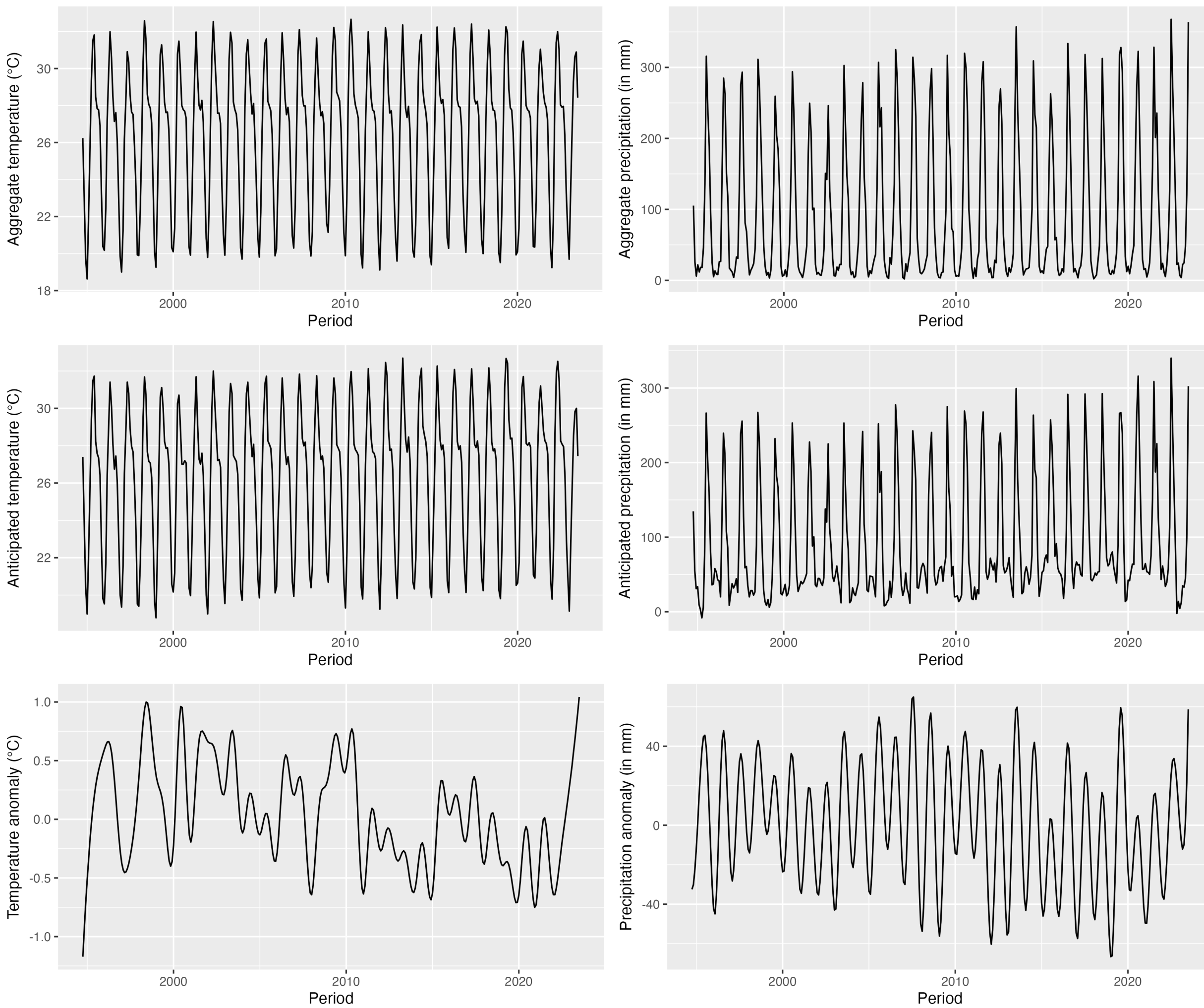

Figure 2: **Decomposition of temperature and precipitation variables:** The expected and anomaly parts of weather variables are bifurcated using the ensemble empirical mode decomposition method. The plot uses 1995-year economic activity weighted aggregate temperature and precipitation for decomposition.

where $\Delta\text{CoVaR}^i_{q,t}$ is the systemic risk computed in Section 2.1. We consider three lags of dependent variable to capture short-term memory of systemic risk. We control for the log of the firm's size based on market capitalization [$\log(\text{size})^i_t$], as per Tzouvanas et al. (2019). To account for the heterogeneity of systemic risk, our model adds firm- and year-fixed effects. We assume that the error term (η^i_t) is identically and independently distributed and follows the Scaled-t distribution. The Scaled-t distribution captures the fat-tail distribution of error terms, which is often the case with stock returns distribution.

The smooth term—s(month, bs = "cc", k=12)—captures seasonal patterns across months. The basis function (bs = "cc") defines the smoothing estimator as a cyclic cubic spline, and we consider knots (k) to be 12 defined based on the number of months in a year. We consider the double-penalty technique to avoid over-fitting while balancing fit and smoothness (Marra and Wood, 2011)[6].

The effective degrees of freedom for month cubic spline, estimates for parametric terms, and additional statistical metrics such as adjusted R^2, Akaike information criterion (AIC), and fast residual maximum likelihood (fREML) score are reported in Appendix A3. We plot the estimated cyclical systemic risk over months in Figure 3. The dashed blue line depicts the confidence interval derived from GAM estimates to determine significance. Based on the Indian Meteorological Department's (IMD) classification of seasons, we consider four seasons: pre-monsoon (March to May), Monsoon (June to September), post-monsoon (October to December), and winter (January and February), which are separated by dotted red vertical lines.

We observe that the expected systemic risk shows variations across different seasons. While the winter season shows systemic returns (negative risk), the same can not be seen for other seasons. However, we do find that as we advance into the pre-monsoon season, the systemic risk rises gradually. Furthermore, while systemic risk begins to decline after July and is lowest in August—high rainfall months in monsoon season—we also observe positive systemic risk during the same season. However, these observations can be driven by other economic factors, and further analysis is required to determine the true impact of weather variations on the systemic risk. Accordingly, we propose the following hypothesis:

Hypothesis 1: Variation in weather impacts the systemic risk in Indian financial markets.

Stock prices, profits, and losses react differently to weather anomalies (unexpected) than to trends

[6]We have discussed the GAM estimation strategy in Appendix A2.

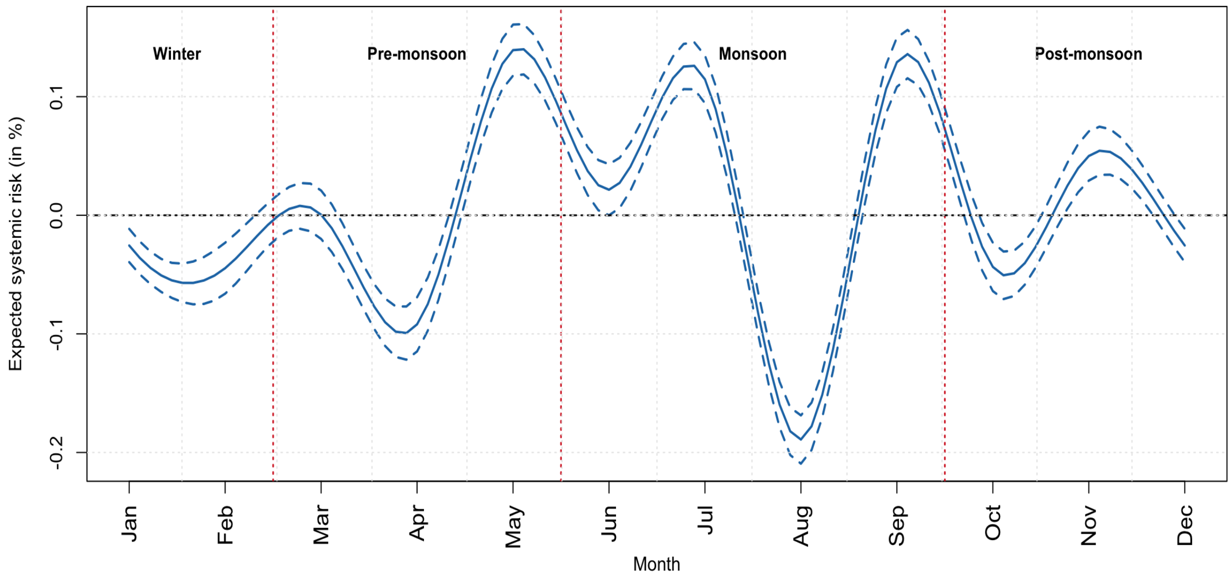

Figure 3: **Monthly cyclical pattern of the Indian systemic risk:** The figure plots the smooth term in Equation (5) obtained from GAM estimation. The dependent variable is systemic risk, as obtained from Section 2.1. The specification controls for three lags of systemic risk variable, size of the firm, firm and year fixed effects. The error term follows the Scaled-t distribution.

or seasonality (expected) if weather information is considered an important pricing determinant for stocks. Thus, there are several benefits to splitting weather into expected and anomalous components. First, considering the decomposed weather in the analysis gives us further data on the impact on systemic risk that we might otherwise lose via aggregation (Orcutt et al., 1968). Second, compared to aggregated information, disaggregated information in aggregate models yields superior forecasting estimates (Hendry and Hubrich, 2011). Finally, segregation aids in determining the asymmetric effect of changes in expected vis-à-vis anomaly weather on systemic risk. It offers some evidence of how weather risk is absorbed in systemic risk. As a result, we put forth our hypotheses that follows:

Hypothesis 2: There is a significant advantage to using decomposed weather variables instead of aggregate ones in estimating the impact of weather variations on systemic risk

Studies at the global level (Acevedo et al., 2020; Burke et al., 2015; Damania et al., 2020; Kalkuhl and Wenz, 2020; Kotz et al., 2022) conclude that temperature and precipitation variations have a non-linear impact on economic growth. In the case of India, studies indicate that temperature and precipitation variations have a heterogeneous impact on India's economic outcomes. Weather variations may benefit in certain seasons but have an adverse effect during some seasons (Auffhammer et al., 2006; Kumar and Maiti, 2024a). The impact of weather variations on economic output also varies across regions with different climatic zones (Gilmont et al., 2018; Jain et al., 2020; Mitra, 2014; Sandhani et al., 2023). Sector-level analysis have shown differential impact on agriculture (Birthal et al., 2021; Carleton, 2017; Pattanayak et al., 2021), manufacturing (Colmer, 2021; Somanathan et al., 2021) and energy sector (Basu and Chakraborty, 2019; Dunning et al., 2015; Kumar and Maiti, 2024a). Regarding the impact of systemic risk, Tzouvanas et al. (2019) find an inverted-U-shaped association between temperature shocks and systemic risk in the case of European economies. Given the current literature, we propose the following:

Hypothesis 3: The effect of weather variations on systemic risk varies across seasons and sectors.

4. Hypothesis testing

We continue implementing the Generalized Additive Model (GAM) to test the hypotheses mentioned in Section 3. We define two broad classes of GAMs. The first class (or the aggregate class) of GAMs considers aggregate weather variables (T_t and P_t) for estimation and the second class (or the decomposed class) uses decomposed weather components, that is, expected weather ($T_{\text{expected},t}$ and $P_{\text{expected},t}$) and weather anomaly ($T_{\text{anomaly},t}$ and $P_{\text{anomaly},t}$).

We alter Equation (5) by replacing the cyclic smooth term for months with the thin plate spline smooth terms of economic and weather variables. This change distinguishes the impact of economic and weather variables on systemic risk. Both classes of GAM include smooth terms of seven contemporaneous macroeconomic state variables (used in systemic risk computation). The aggregate class of GAM accounts for smooth terms of contemporaneous, one-month lagged, and interaction of aggregate weather variables. On the other hand, the decomposed class of GAM accounts for smooth terms of contemporaneous, one-month lagged, and interaction of decomposed weather variables. Accordingly, we have 16 monthly time series variables for the aggregate class and 39 for the decomposed class of GAM (Refer Appendix A4). However, using too many smooth terms will result in a high pairwise concurvity issue, that is, the possibility of a smooth term being a non-linear function of another smooth term, making it redundant for the model. The presence of high concurvity increases the risk of type 1 error (Ramsay et al., 2003) and results in instable estimates (Buja et al., 1989).

As a result, we must determine the factors that explain most of the systemic risk while ensuring that the variables considered have minimal concurrency. The minimal redundancy maximum relevance (mRMR) feature selection technique is especially appealing since its algorithm for identifying relevant and complementary features is relatively simple to compute (Peng and Ding, 2005). Hence, we proceed with the following technique to select the best-fit model while maintaining minimal concurvity, avoiding overfitting, and balancing goodness-of-fit with model complexity.

1. Using the Augmented Dickey fuller (ADF) test, we ensure the stationarity of predictor variables by considering the first difference of variables in the case of unit roots. The results are presented in the Appendix A4;

2. Using the mRMR algorithm, we rank the predictor variables (macroeconomic and weather variables), ensuring maximum correlation with systemic risk variables and minimum correlation with other predictor variables;

3. We then perform step-wise GAM specification selection to the following base model of Equation (5) without month cyclic smooth term:

$$\Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ \zeta^i_t$$

   where D_q denotes the quarterly disclosure dummies for the listed firms. We progressively incorporate the smooth terms of predictor variables derived in Step 2, adding them one at a time based on their rank. Following each addition, we evaluate pairwise concurvity in the revised specification. If the pairwise concurvity stays less than 0.50, the base model preserves the variable and inserts the next ranking variable. However, if introducing a new variable increases pairwise concurvity above 0.50, it is excluded, and we move on to the next ranking variable. This progressive selection process continues until all variables have been addressed. Similar to Equation (5), we use double-penalty estimation to reduce overfitting, assume knots of smooth terms to be ten, and a scaled-t distribution for error terms;

4. Of the selected specifications in step 3, we select the best-fit model based on the AIC and fREML scores. In case of discrepancies between AIC and fREML, we use the Analysis of Variance (ANOVA) test to determine the final model.

The above strategy provides a list of predictor variables that significantly explain the systemic risk in Indian financial markets. Step 3 indicates that 7 (out of 16) specifications for the aggregate class of GAMs and 10 (out of 39) specifications for the decomposed class of GAMs contain low pairwise concurvity between its smooth terms. The list of all the specifications selected based on concurvity is presented in Appendix A4 for reference.

4.1. Hypothesis 1: Impact of weather variation on Indian systemic risk

Based on step 4 of the specification-selection strategy in the previous section, we obtain the following *optimal* specifications for Aggregate class [Equation (6)] and decomposed class [Equation (7)] of GAMs:

$$\begin{aligned}\Delta\text{CoVaR}^{i}_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}^{i}_{q,t-j} + \beta_4 \log(\text{size})^{i}_{t} + \gamma_i + \delta_y \\ + \; D_{Jan} \; + \; D_{April} \; + \; D_{July} \; + \; D_{Oct} \\ + \; s_1(\text{Vol}_t) \; + \; s_2(\Delta\text{PLR}_t) \; + \; s_3(\Delta\text{Yield}_t) \\ + \; w_1(\Delta T_t) \; + \; w_2(\Delta T_{t-1}) \; + \; w_3(\Delta P_t) \; + \; w_4(\Delta P_{t-1}) + \zeta^{i}_{t}\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta\text{CoVaR}^{i}_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}^{i}_{q,t-j} + \beta_4 \log(\text{size})^{i}_{t} + \gamma_i + \delta_y \\ + \; D_{Jan} \; + \; D_{April} \; + \; D_{July} \; + \; D_{Oct} \; + \; s_1(\text{Vol}_t) \; + \; s_2(\Delta\text{PLR}_t) \\ + \; s_3(\text{CTB3}_t) \; + \; s_4(\text{Mret}_t) \; + \; s_5(\text{Credit}_t) \\ + \; w_1(T_{\text{expected},t} \times P_{\text{anomaly},t-1}) \; + \; w_2(\Delta T_{\text{anomaly},t-1} \times P_{\text{anomaly},t-1}) \\ + \; w_3(\Delta P_{\text{expected},t-1} \times \Delta T_{\text{anomaly},t}) \; + \; w_4(\Delta T_{\text{anomaly},t-1}) \\ + \; w_5(T_{\text{expected},t}) + \zeta^{i}_{t}\end{aligned} \tag{7}$$

where, Vol_t represents market returns volatility; ΔPLR_t represents first difference of prime lending rate; ΔYield_t represents first difference of yield changes; CTB3_t represents change in three-month treasury bill rate; Mret_t represents market returns; and Credit_t represents credit spread. These are selected economic variables influencing the systemic risk. The smooth terms for these economic variables are presented by $s(.)$ terms.

The smooth terms for these weather variables are presented by $w(.)$ terms. For selected weather variables, the aggregate class of GAM includes the first difference of contemporaneous (ΔT_t and ΔP_t) and lagged (ΔT_{t-1} and ΔP_{t-1}) weather variables. In contrast, decomposed class of GAM includes contemporaneous expected temperature ($T_{\text{expected},t}$), first difference of contemporaneous ($\Delta T_{\text{anomaly},t}$) and lagged ($\Delta T_{\text{anomaly},t-1}$) temperature anomaly, first difference of lagged expected precipitation ($\Delta P_{\text{expected},t-1}$), and lagged precipitation anomaly ($P_{\text{anomaly},t-1}$). The first difference of selected weather variables represents the presence of long memory property (Takalo, 2022).

To illustrate the complexity of smooth terms [$s(.)$s and $w(.)$s] for the aforementioned *optimal* GAM specifications, Table 1 displays the Effective Degrees of Freedom (EDF) for GAM estimation. The EDF greater than one indicates that the smooth term is non-linear. However, EDF merely shows the complexity of the relationship between these variables and systemic risk but provides no information regarding the direction or magnitude of the impact. The significance of EDF for each smooth term indicates the relevance of a given variable while predicting the systemic risk.

The *optimal* GAM specifications of Equations (6) and (7) highlight the economic and weather variables that best explain the Indian systemic risk. Furthermore, Table 1 shows that the selected variables significantly affect systemic risk. Specifically speaking, we notice that the EDF of the smooth term of all weather variables is greater than 7.00 irrespective of the aggregate class [Column (1)] or decomposed class [Column (2)] of GAM. These EDF values—considerably greater than one—indicate that the relationship between weather variables and systemic risk is highly non-linear and complex. Hence, our findings confirm that weather variables, regardless of GAM classes, play a significant influence in determining systemic risk, supporting hypothesis 1.

4.2. Hypothesis 2: Aggregate vs decomposed weather variables

The fREML score and AIC in Table 1 are lower for the decomposed class of GAM than the aggregate class, making it a better fit for in-sample performance and complexity. Furthermore, adjusted R^2 is higher for the decomposed class than for the aggregate class. We perform ANOVA test and confirm that incorporating decomposed components of weather variables significantly improves model performance.

The superiority of the decomposed class of GAM over the aggregate one highlights the possibility of certain information not being considered in the aggregate class. Aggregate class of GAM [Equation (6) and Column (1) of Table 1] indicate that market volatility (Vol_t), prime lending rate (ΔPLR_t), and yield changes (ΔYield_t) are important economic variables that explain monthly cycle of systemic risk. On the other hand, for decomposed class [Equation (7) and Column (2) of Table 1], additional economic variables like changes in treasury bill rate (CTB3_t), credit spread (Credit_t), and market returns (Mret_t) are more important economic variables than yield changes as considered in aggregate class.

Notably, we do not observe the interaction between temperature and precipitation variables for the aggregate class, unlike the decomposed class of GAM. This interaction demonstrates the joint effect of temperature and precipitation on the systemic risk, which is not considered in the existing literature (Song and Fang, 2023; Tzouvanas et al., 2019). Furthermore, the aggregate class of GAM assumes that the impact of weather variation on systemic risk is homogeneous across expected or

Table 1: **Effective degrees of freedom**

	(1) Aggregate class	(2) Decomposed class
Weather variables:		
Equation (6)		
$w_1(\Delta T_t)$	8.925***	
$w_2(\Delta T_{t-1})$	8.761***	
$w_3(\Delta P_t)$	8.900***	
$w_4(\Delta P_{t-1})$	8.326***	
Equation (7)		
$w_1(T_{\text{expected},t} \times P_{\text{anomaly},t-1})$		14.446***
$w_2(\Delta T_{\text{anomaly},t-1} \times P_{\text{anomaly},t-1})$		14.288***
$w_3(\Delta P_{\text{expected},t-1} \times \Delta T_{\text{anomaly},t})$		15.757***
$w_4(\Delta T_{\text{anomaly},t-1})$		7.825***
$w_5(T_{\text{expected},t})$		7.848***
Economic variables:		
Equation (6)		
$s_1(\text{Vol}_t)$	8.916***	
$s_2(\Delta\text{PLR}_t)$	7.967***	
$s_3(\Delta\text{Yield}_t)$	8.938***	
Equation (7)		
$s_1(\text{Vol}_t)$		8.833***
$s_2(\Delta\text{PLR}_t)$		8.922***
$s_3(\text{CTB3}_t)$		8.943***
$s_4(\text{Mret}_t)$		8.336***
$s_5(\text{Credit}_t)$		8.584***
Fixed effects	firm, year	firm, year
Controls	Quarterly dummies, 3 lags of $\Delta\text{CoVaR}^i_{q,t}$, firm size	
Adj R^2	0.744	0.750
AIC	766,591.70	761,593.30
fREML score	340,233.10	339,925.60

This table includes the Effective Degrees of Freedom (EDF) for each smooth term in the *optimal* GAMs and post-diagnostic tests. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta\text{CoVaR}^i_{q,t}$ framework. The smooth term of predictor variables is selected based on a 4-step specification selection strategy.

The F-test determines the significance of the EDF values for the smooth terms. EDF values demonstrate the complex relation between predictor and outcome variables. The Akaike information criterion (AIC) and fast residual maximum likelihood (fREML) scores evaluate model fit using in-sample performance and complexity.

Columns (1) and (2) represent the optimal aggregate and decomposed class of GAM from Equation (6) and (7), respectively. All models have firm-fixed effects and year-fixed effects. The other control variables include quarterly disclosure dummies, three lags of dependent variables, and a log of firm size. Standard errors are in the parenthesis. Error term follows the Scaled-t distribution. Significance levels: * 10%, ** 5%, and *** 1%.

anomaly rises in weather variables. The decomposed class of GAM relaxes this constraint, allowing us to study the asymmetry behaviour to increases in expected vs anomalous weather. We utilize a simple epsilon difference approach[7] to determine the average derivative of systemic risk concerning each weather variable. The cumulative average marginal effect of aggregate, expected, and anomaly weather variation on the systemic risk are presented in Table 2.

Table 2: **Cumulative marginal effect of change in weather**

	(1) **Aggregate class**	**(2)** **Decomposed class**
For 0.1°C temperature rise		
Aggregate (ΔT)	-0.0003	
	(0.0008)	
Expected ($T_{expected}$)		0.0125***
		(0.0009)
Anomaly ($\Delta T_{anomaly}$)		0.1951***
		(0.0147)
For 10mm precipitation rise		
Aggregate (ΔP)	0.0118***	
	(0.0027)	
Expected ($\Delta P_{expected}$)		-0.0139***
		(0.0015)
Anomaly ($P_{anomaly}$)		-0.0268***
		(0.0040)

This table includes the cumulative average slopes of weather variations on systemic risk obtained from a simple epsilon difference approach for the aggregate and decomposed class of GAM. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta\text{CoVaR}^{i}_{q,t}$ framework.
Column (1) represents the cumulative average marginal effect of aggregate temperature and precipitation from the aggregate class of GAM [Equation (6)]. Column (2) presents the cumulative average marginal effect of expected and anomaly temperature and precipitation from the decomposed class of GAM [Equation (7)].
All models have firm-fixed effects and year-fixed effects. The other control variables include quarterly disclosure dummies, three lags of dependent variables, and a log of firm size. Error term follows the Scaled-t distribution. Standard errors are in the parenthesis. Significance levels: * 10%, ** 5%, and *** 1%.

The average marginal effect on systemic risk due to a rise of 0.1°C in temperature and a 10 mm rise in precipitation are reported in Table 2. Column (1) indicates an insignificant effect of an aggregate temperature (ΔT) rise but a significant positive effect (0.01 pp per 10 mm) of an aggregate precipitation (ΔP) rise on the systemic risk. On the other hand, the decomposed class of GAM [Column

[7] $\frac{dy}{dx} = \frac{f(x+\xi/2)-f(x-\xi/2)}{\xi}$ where, here $f(.)$ is the predicted value of smooth term under consideration, and ξ is the step size to use when calculating numerical derivatives.

(2)] provides a different picture. It is observed that decomposed temperature variation increases systemic risk, whereas decomposed precipitation variation decreases systemic risk. Furthermore, the magnitude of the effect of positive expected weather variation (0.01 pp per 0.1°C and -0.01 pp per 10 mm) is significantly lower than that due to positive anomaly weather variation (0.20 pp per 0.1°C and -0.03 pp per 10 mm). These findings indicate the asymmetric effect of fluctuations to expected vis-á-vis anomaly on Indian systemic risk, which is ignored when aggregate weather variables are used.

Accordingly, aggregating the weather variables fails to identify relevant economic variables, accurate estimates of weather variations, and asymmetric effect of expected vis-á-vis anomaly weather variation, providing evidence for hypothesis 2.

4.3. Hypothesis 3: Heterogeneous effect

To further evaluate the differential impact of weather variation on systemic risk across seasons and clusters, we augment the GAM model in Equation (7) by interacting the dummy variable of seasons or clusters with smooth terms related to weather variables and obtain the following specification:

$$
\begin{aligned}
\Delta\text{CoVaR}^i_{q,t} = \beta_0 &+ \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y \\
&+ D_{Jan} + D_{April} + D_{July} + D_{Oct} + s_1(\text{Vol}_t) + s_2(\Delta\text{PLR}_t) \\
&+ s_3(\text{CTB3}_t) + s_4(\text{Mret}_t) + s_5(\text{Credit}_t) \\
&+ \sum_l w_{l,1}(T_{\text{expected},t} \times P_{\text{anomaly},t-1}) \times D_l \\
&+ \sum_l w_{l,2}(\Delta T_{\text{anomaly},t-1} \times P_{\text{anomaly},t-1}) \times D_l \\
&+ \sum_l w_{l,3}(\Delta P_{\text{expected},t-1} \times \Delta T_{\text{anomaly},t}) \times D_l \\
&+ \sum_l w_{l,4}(\Delta T_{\text{anomaly},t-1}) \times D_l + \sum_l w_{l,5}(T_{\text{expected},t}) \times D_l + \zeta^i_t
\end{aligned}
\tag{8}
$$

where D_l indicates the dummy variable for season or broad clusters. In case of season-wise analysis, $l = \{\text{Winter, Pre-monsoon, Monsoon, Post-monsoon}\}$ which are seasons of the year as defined by IMD. Similarly, in case of cluster-wise analysis, $l = \{\text{Consumer, Manufacturing, Technology, Energy, Finance, Health Care, Others}\}$ as bifurcated in Table. Equation (8) is termed as Varying Coefficient Generalized Additive Models (VC-GAM), which was introduced by T. Hastie and Tibshirani (1993). These models estimate $w(.)s$ for each season or cluster separately, helping us estimate the differential effect of weather variation on the systemic risk.

4.3.1. Season-wise analysis

We derive the group average marginal effect of 0.1°C temperature variation and 10 mm precipitation variation on systemic risk across seasons from the season-wise VC-GAM estimates and present it in Table 3. The positive impact of temperature rise in overall systemic risk [Refer to Column (2) of Table 2] is driven by a temperature rise in monsoon season—Column (3) of Table 3. Interestingly, there is a negative marginal effect of expected temperature rise on systemic risk during other seasons with no significant effect of anomaly temperature variation [Columns (1), (2), and (4)]. These findings confirm an inverted U-shaped relation between expected temperature and systemic risk, corresponding to the relation suggested for aggregate temperature by Tzouvanas et al. (2019).

Table 3: **Cumulative marginal effect across different seasons of a year**

	(1) Winter	**(2) Pre-monsoon**	**(3) Monsoon**	**(4) Post-monsoon**
For 0.1°C temperature rise				
Expected ($T_{expected}$)	-0.0655***	-0.0260***	0.1275***	-0.0603***
	(0.0137)	(0.0061)	(0.0103)	(0.0085)
Anomaly ($\Delta T_{anomaly}$)	0.8970*	-0.2430	1.5190***	0.2710
	(0.5253)	(0.5121)	(0.1286)	(0.3384)
For 10 mm precipitation rise				
Expected ($\Delta P_{expected}$)	-0.1200*	-0.0131	-0.2484***	-0.0436***
	(0.0693)	(0.0293)	(0.0179)	(0.0119)
Anomaly ($P_{anomaly}$)	-0.4730***	-0.0814**	-0.1082***	-0.3478***
	(0.0616)	(0.0370)	(0.0406)	(0.0463)

This table includes the cumulative average slopes of decomposed weather variables on systemic risk obtained from a simple epsilon difference approach using season-wise varying coefficient GAM [Equation (8)]. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta \text{CoVaR}^i_{q,t}$ framework.

Column (1) represents the cumulative average marginal effect of decomposed weather variables for the winter season. Column (2) presents results for pre-monsoon season. Column (3) for monsoon season and Column (4) for post-monsoon season.

Season-wise varying coefficient GAM has firm-fixed effects and year-fixed effects. The other control variables include quarterly disclosure dummies, three lags of dependent variables, and a log of firm size. Error term follows the Scaled-t distribution. Standard errors are in the parenthesis. Significance levels: * 10%, ** 5%, and *** 1%.

In the case of precipitation fluctuations, we observe that the beneficial impact of an expected precipitation rise on overall systemic risk—as observed in Column (2) of Table 2—is due to an increase in expected precipitation during Monsoon and post-monsoon seasons [Column (3) and (4) of Table 3]. On the other hand, the beneficial impact of an anomaly precipitation rise across all seasons with a marginal effect significantly higher for winter (-0.47 pp per 10 mm) and post-monsoon (-0.35 pp per 10 mm) seasons than pre-monsoon (-0.08 pp per 10 mm) and Monsoon (-0.11 pp per 10 mm) seasons.

4.3.2. Cluster-wise analysis

The group average marginal effect of 0.1°C temperature and 10 mm precipitation rise on systemic risk across broad industry clusters are presented in Table 4. We find that the asymmetric marginal effect of expected vis-á-vis anomaly temperature rise on systemic risk is consistently observed for all broad industry clusters [Columns (1) to (7)]. However, we observe an insignificant effect of an expected precipitation rise on systemic risk from the energy cluster [Column (4)]. Furthermore, we observe that an anomaly precipitation rise has an insignificant effect on systemic risk arising from broad clusters like technology [Column (3)], finance [Column (5)] and health care [Column (6)].

Thus, our findings for season-wise do confirm heterogeneous effects across different seasons but partially confirm heterogeneity in the case of cluster-wise analysis. Accordingly, we partially corroborate hypothesis 3 proposed.

4.4. Mechanism analysis

This section discusses the possible mechanisms that may explain our findings in the previous subsections relating to the decomposed class of GAMs. Investors expect certain payoffs and demand premiums for risks from firms vulnerable to weather variations (Venturini, 2022). Exposed firms suffer economic effects of weather variations due to the destruction of assets, adaptive investments, supply chain disruptions, and rise in input costs (Campiglio et al., 2023). These effects on exposed firms and subsequent impact on investor's decision-making are reflected in the systemic risk of the financial markets.

Table 4: **Cumulative marginal effect across different industry clusters**

	(1) **Cns**	**(2)** **Mfg**	**(3)** **Tech**	**(4)** **Engy**	**(5)** **Fin**	**(6)** **HC**	**(7)** **Others**
For 0.1°C temperature rise							
Expected ($T_{expected}$)	0.0093***	0.0125***	0.0103***	0.0274***	0.0125***	0.0034**	0.0144***
	(0.0011)	(0.0011)	(0.0017)	(0.0033)	(0.0016)	(0.0014)	(0.0011)
Anomaly ($\Delta T_{anomaly}$)	0.1395***	0.1417***	0.2250***	0.2533***	0.2012***	0.0676*	0.2077***
	(0.0281)	(0.0269)	(0.0473)	(0.0661)	(0.0476)	(0.0388)	(0.0300)
For 10 mm precipitation rise							
Expected ($\Delta P_{expected}$)	-0.0107***	-0.0118***	-0.0095**	-0.0054	-0.0142***	-0.0094***	-0.0128***
	(0.0023)	(0.0022)	(0.0040)	(0.0077)	(0.0040)	(0.0034)	(0.0024)
Anomaly ($P_{anomaly}$)	-0.0171***	-0.0321***	0.0039	-0.0365**	-0.0032	-0.0022	-0.0394***
	(0.0055)	(0.0057)	(0.0092)	(0.0183)	(0.0085)	(0.0069)	(0.0064)

This table includes the cumulative average slopes of decomposed weather variables on systemic risk obtained from a simple epsilon difference approach using cluster-wise varying coefficient GAM [Equation (8)]. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta\text{CoVaR}^{i}_{q,t}$ framework.

Column (1) represents the cumulative average marginal effect of decomposed weather variables for the consumer cluster. Column (2) presents results for the manufacturing cluster. Column (3) indicates the cumulative average marginal effect for the technology cluster. Column (4) is for the energy cluster. Column (5) presents results for the finance cluster. Column (6) is for the health care cluster, and Column (7) is for the other cluster.

Cluster-wise varying coefficient GAM has firm-fixed effects and year-fixed effects. The other control variables include quarterly disclosure dummies, three lags of dependent variables, and a log of firm size. Error term follows the Scaled-t distribution. Standard errors are in the parenthesis. Significance levels: * 10%, ** 5%, and *** 1%.

Weather variations may also influence energy costs for the firm. De Cian et al. (2007), for hot countries, demonstrate that the rise in summer temperature increases energy demand, whereas energy demand decreases for the rise in spring and fall temperature. Harish et al. (2020) find that temperature shocks increase the household energy requirements for India, especially in high-temperature regions. Baranitharan et al. (2021), using an artificial neural network, find that a model with weather variables accurately predicts the energy requirements for Indian states like Kerala and Tamil Nadu. This energy-weather relation indicates that weather variations may increase energy demand for the firms (increasing their input cost) but, at the same time, may also increase revenue for the energy firms.

Furthermore, Song and Fang (2023) and X. Wu et al. (2023) find that a positive temperature shock increases non-performing loans and asset price volatility in Chinese banks, resulting in higher bank systemic risk. These channels may impact a firm's operations due to financial constraints and increase the interest costs for the exposed firms.

Acemoglu et al. (2012) find that an economic shock to just one firm may significantly impact other sectors through inter-firm connectivity. Within India, weather fluctuations have a spillover effect through labour reallocation (Colmer, 2021) and changes in crop prices (Hossain and Ahsan, 2022). These spillover effects may result in supply chain disruptions for the firms, leading to inflationary conditions (Franzoni et al., 2023).

Apart from those mentioned above, there are multiple ways through which weather variations influence input costs for firms in India. These include the decline in labor supply (Somanathan et al., 2021), capital productivity (Kumar and Maiti, 2024a), agriculture production (Birthal et al., 2021), and overall economic growth (Jain et al., 2020; Kumar and Maiti, 2024a; Sandhani et al., 2023). Thus, numerous avenues exist that indicate the possible impact of weather fluctuations on firms' future cash flows, thereby influencing systemic risk in Indian financial markets.

Given the availability of monthly data at the India level, we focus on (1) Wholesale year-on-year inflation for food (WPIF), manufacturing (WPIM), and total (WPIT); (2) Overall inflation (CPI); (3) Bank credit supply growth to the food (FCgr) and non-food (NFCgr) sectors; and (4) Energy demand (PDgr). All data is acquired from the CEIC database from January 2005 to November 2022, except for FCgr and NFCgr, which are obtained from EPWRF for the period starting from April 2007 and February 2012, respectively.

The weather fluctuations may influence not only the mean economic variables mentioned above but also the volatility of these economic variables. If the uncertainty arises, it may further influence investors' choices. To capture the mean and volatility effect of weather variations, we use an Autoregressive model with Generalized Autoregressive Conditional Heteroskedasticity terms [AR(p)-GARCH(1,1)] to investigate the underlying mechanisms[8].

The lag order 'p' selection uses the Bayesian Information Criterion (BIC) to ensure model parsimony. To comprehend the impact of weather variations on mean and uncertainty of economic variables, we consider expected temperature (T_{expected}), temperature anomaly ($\Delta T_{\text{anomaly}}$), expected precipitation ($\Delta P_{\text{expected}}$), and precipitation anomaly (P_{anomaly}) as part of the mean and variance equation. We also use the dummy variable in the mean equation to control for January (the start of the calendar year), April (the start of the fiscal year), the global financial crisis (July 2008 to October 2010), and the period after the first lockdown (beginning March 2020).

Table 5 shows the results of weather impact in the mean and variance equations of economic variables. Variations in temperature and precipitation, as expected, have an impact on both mean and volatile economic outcomes. Column (1) shows that a temperature anomaly rise raises mean energy demand, while an expected precipitation rise lowers it. These temperature-related results align with short-run adaptation behaviours (intensive margin hypothesis) as demonstrated by Auffhammer and Mansur (2014). On the other hand, increased expected precipitation may minimize energy consumption by reducing irrigation needs (Knapp and Huang, 2017).

Columns (2) to (5) of Table 5 show the impact of weather fluctuations on inflation. In the case of wholesale inflation in manufacturing, Column (2) shows that a positive predicted temperature shock increases volatility, whereas a positive expected precipitation shock reduces it. However, Column (3) demonstrates that expected and anomaly temperature variations reduce price volatility for wholesale food inflation. We suggest that the decrease in volatility may be attributed to agricultural producers proactively responding to temperature variations or reacting to policies implemented to minimize the adverse effect of temperature rise. These differing effects across various inflation components have an overall insignificant impact on total wholesale inflation [Column (4)]. However, we find a significant positive marginal effect of a positive expected precipitation shock on overall inflation volatility [Column (5)] (Hristov & Roth, 2022).

Finally, we examine the impact of weather variations on credit supply. Columns (6) present the

[8]However, for the model with NFCgr as the dependent variable, convergence concerns need a different specification. To obtain reliable estimates, we use an AR(1)-ARCH(1) model, which incorporates conditional heteroskedasticity while maintaining model stability.

Table 5: **Mechanism analysis results**

	(1) **PDgr**	(2) **WPIM**	(3) **ΔWPIF**	(4) **ΔWPIT**	(5) **ΔCPI**	(6) **NFCgr**	(7) **FCgr**
Mean equation							
Marginal effect of temperature							
T_{expected}	0.246	-0.006	0.036	0.025	-0.018	-0.172***	0.856***
	(0.199)	(0.015)	(0.047)	(0.041)	(0.027)	(0.024)	(0.278)
$\Delta T_{\text{anomaly}}$	2.639**	0.976	-1.474	-0.589	0.781	2.852***	-5.794
	(1.344)	(0.903)	(1.754)	(1.343)	(0.781)	(0.663)	(5.825)
Marginal effect of precipitation							
$\Delta P_{\text{expected}}$	-0.067***	<-0.001	-0.001	<-0.001	-0.001	-0.004***	0.015
	(0.007)	(<-0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.024)
P_{anomaly}	0.0048	0.0023	-0.0022	-0.0060	0.0012	-0.0008	-0.0280
	(0.0041)	(0.0030)	(0.0056)	(0.0056)	(0.0030)	(0.0020)	(0.0260)
Variance equation							
Marginal effect of temperature							
T_{expected}	-0.756	0.745***	-0.260**	-0.039	-0.053	-0.117	0.407*
	(0.737)	(0.288)	(0.117)	(0.038)	(0.040)	(0.148)	(0.232)
$\Delta T_{\text{anomaly}}$	12.037	-5.525	-5.655**	1.136	0.164	2.998	-4.509
	(17.333)	(5.868)	(2.790)	(1.765)	(1.369)	(3.556)	(5.015)
Marginal effect of precipitation							
$\Delta P_{\text{expected}}$	-0.076	-0.045***	0.0115	0.0048	0.0042**	-0.007***	-0.017**
	(0.054)	(0.017)	(0.007)	(0.003)	(0.002)	(0.002)	(0.007)
P_{anomaly}	-0.004	-0.027	0.008	0.002	-0.002	-0.001	-0.007
	(0.058)	(0.021)	(0.010)	(0.006)	(0.005)	(0.014)	(0.042)
Observations	211	212	211	211	211	187	129
BIC	-689.67	402.76	1008.31	606.45	586.61	-973.79	-61.39
AR lags	12	14	12	1	0	1	4

This table presents the marginal effect of expected and anomaly temperature from mean and variance equations of the AR(p)-GARCH(1,1) model except in the case of non-food credit supply growth, which considers AR(1)-ARCH(1) for convergence. The dependent variables are monthly power demand growth [Column (1)], wholesale year-on-year inflation of manufacturing [Column (2)], first-difference of wholesale year-on-year inflation of food [Column (3)], first-difference of total wholesale year-on-year inflation [Column (4)], first-difference of consumer year-on-year inflation [Column (5)], credit supply growth to non-food sector [Column (6)], and food sector [Column (7)]. The stationarity is determined using the Augmented Dickey-Fuller test.

The lag term for AR is determined using BIC criteria. All models have dummy variables for January, April, the global financial crisis, and the lockdown period in the mean equation. Standard errors are in the parenthesis. Significance levels: * 10%, ** 5%, and *** 1%.

effects of temperature and precipitation variations on the growth of non-food credit supply. We suggest that banks likely reduce non-food loan supply in response to a rise in expected temperature due to concerns over higher default risks in sectors vulnerable to heat stress, such as manufacturing and construction. However, banks may increase loan supply during anomalous temperature variations, possibly capitalizing on short-term credit demand spikes from firms adapting to unexpected climate conditions.

In the case of food credit [Column (7) of Table 5], we observe an increase in loan supply in response to expected temperature variations, which likely reflects higher agricultural credit demand to finance adaptive measures such as irrigation or crop insurance. However, expected precipitation variations lead to a decline in both the mean and volatility of food and non-food credit growth, suggesting a combination of reduced borrowing needs (due to improved agricultural output) and potential declines in nominal interest rates as inflation expectations adjust.

Our findings reveal critical insights into how weather changes affect different economic indicators. These effects influence investor's risk perception through an effect on exposed firms and uncertainty in economic conditions. This chain of effects is likely to influence systemic risk in financial markets ultimately.

4.5. Robustness checks

We perform the robustness tests for the results of *the* optimal decomposed class of GAM tabulated in Column (2) of Table 2. Table 6 presents the cumulative average marginal estimates of decomposed weather variables for changes in specification, data alteration, and overfitting techniques. Our results demonstrate that our main results are robust and consistent in spite of these changes.

Column (1) of Table 6 reiterates the main results from Column (2) of Table 2. Columns (2) and (3) consider the economic activity of the year 2000 and year 2005, respectively, for computing weighted weather variables instead of the year 1995 as considered as per our main results. Column (4) includes the extended systemic risk data from February 1999 to July 2023. Columns (5) to (7) control for feedback effect by considering four-year, five-year, and six-year lags (instead of three) of the systemic firm-level risk in the optimal decomposed class of GAM.

In GAM, the knots determine the complexity of the basis function used to determine the smooth term. Notably, the higher the knots, the more flexibility is allowed, which can result in overfitting. Accordingly, we reduce the number of knots from ten to five as robustness in Column (8) of Table

6. Alternatively, we consider a thin plate regression spline technique with shrinkage (TPRSS) for basis function instead of double-penalty optimization [Column (9)].

5. Forecasting of future economic downturns

This section investigates how weather-induced systemic risk might be used to forecast future economic activity. We compute the predicted values for weather-related smooth terms for each observation using Equation (7)—the GAM's decomposed class. Therefore, we generate a monthly forecast time series of the weather-induced systemic risk ($\widehat{\text{WISR}}_{D,t}$), as follows:

$$\begin{aligned}\widehat{\text{WISR}}_{D,t} = \hat{w}_1(T_{\text{expected},t} \times P_{\text{anomaly},t-1}) + \hat{w}_2(\Delta T_{\text{anomaly},t-1} \times P_{\text{anomaly},t-1}) \\ + \hat{w}_3(\Delta P_{\text{expected},t-1} \times \Delta T_{\text{anomaly},t}) + \hat{w}_4(\Delta T_{\text{anomaly},t-1}) \\ + \hat{w}_5(T_{\text{expected},t})\end{aligned} \tag{9}$$

To anticipate future economic conditions, we compute the mean of the industrial production index ($\text{MIPI}_{t,n}$) for 'n' months ahead. The industrial production index is derived from the CEIC database. Finally, as employed by Allen et al. (2012), we propose the following predictive regression:

$$\text{MIPI}_{t,n} = \Gamma_0 + \Gamma_1 \widehat{\text{WISR}}_{D,t} + \Gamma_2' C_t + \sum_{i=1}^{12} \lambda_i \text{IPI}_{t+i-1} + \xi_{t,n} \tag{10}$$

C_t denotes a vector of control variables for the month 't', including the macroeconomic state variables. In addition to these control variables, we include contemporaneous and 11 lags of the industrial production index (IPI_t). $\xi_{t,n}$ represents the error term considered independently and identically distributed. Finally, the standard errors for slope coefficients are calculated using the Newey-West standard errors (Newey and West, 1987). The coefficient Γ_1 shows the impact of the rise in weather-induced systemic risk on the mean industrial production during the selected future 'n' period.

The findings, which are shown in Table 7, look at how well weather-induced systemic risk may predict the industrial production index over a range of forecasting periods, from one to twelve months. Panel (a) of the table depicts the overall impact of weather-induced systemic risk on the mean of the following 'n' months. We observe that for briefer monthly horizons (n = 1 to 6), the systemic risk coefficient remains insignificant at the 5% level, demonstrating weak short-term forecasting power. However, if the forecasting horizon grows longer than six months, the impact of systemic risk becomes statistically significant and negative, demonstrating that systemic risk has a tremendous potential to foresee economic downturns in the medium to long run.

Table 6: **Robustness checks: Cumulative marginal effect**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Main	**Economic activity wt.**		**Extended**	**Lags of dependent variable**			**Overfitting concerns**	
	Results	**Yr 2000**	**Yr 2005**	**Period**	**Lag 4**	**Lag 5**	**Lag 6**	**Reduced knots**	**TPRSS**
For 0.1°C temperature rise									
Expected	0.0125***	0.0124***	0.0156***	0.0042***	0.0150***	0.0119***	0.0132***	0.0080***	0.0147***
	(0.0009)	(0.0009)	(0.0010)	(0.0005)	(0.0010)	(0.0009)	(0.0009)	(0.0006)	(0.0009)
Anomaly	0.1951***	0.1886***	0.2443***	0.1177***	0.1881***	0.2338***	0.2418***	0.1123***	0.1612***
	(0.0147)	(0.0202)	(0.0225)	(0.0124)	(0.0203)	(0.0207)	(0.0202)	(0.0145)	(0.0227)
For 10 mm precipitation rise									
Expected	-0.0139***	-0.0152***	-0.0203***	-0.0158***	-0.0123***	-0.0111***	-0.0132***	-0.0076***	-0.0174***
	(0.0015)	(0.0016)	(0.0016)	(0.0013)	(0.0015)	(0.0016)	(0.0016)	(0.0013)	(0.0015)
Anomaly	-0.0268***	-0.0325***	-0.0346***	-0.0414***	-0.0442***	-0.0239***	-0.0310***	-0.0402***	-0.0387***
	(0.0040)	(0.0051)	(0.0044)	(0.0031)	(0.0050)	(0.0049)	(0.0049)	(0.0039)	(0.0052)
Obs.	190,376	190,376	190,376	259,927	189,478	188,580	187,682	190,376	190,376
Adj R^2	0.750	0.750	0.751	0.727	0.754	0.755	0.755	0.749	0.751

This table includes the cumulative average slopes of decomposed weather variables on systemic risk obtained from a simple epsilon difference approach. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta\text{CoVaR}^{i}_{q,t}$ framework.

Column (1) represents the main results from Column (2) of Table 2. Columns (2) and (3) consider a decomposed class of GAM for 2000-year and 2005-year economic activity-weighted weather, respectively. Column (4) considers systemic risk data from February 1999 to July 2023. Columns (5) to (7) extend the lags of dependent variables from three to four, five and six, respectively. To avoid overfitting concerns, we consider an alternative estimation strategy of reducing knots to 5 instead of 10 in Column (8) and using thin-plate regression spline with shrinkage instead of the double-penalty technique in Column (9).

All models have firm-fixed effects and year-fixed effects. The other control variables include quarterly disclosure dummies, three lags of dependent variables, and a log of firm size. Error term follows the Scaled-t distribution. Standard errors are in the parenthesis. Significance levels: * 10%, ** 5%, and *** 1%.

We explore the impact of rising weather-induced systemic risk in various seasons on future economic downturns. For this, we compute anticipated values of weather-induced smooth terms obtained from season-wise VC-GAM model [Equation (8)] for different seasons using Equation (9). We employ season-specific weather-induced systemic risk in Equation (10) instead of $\widehat{\text{WISR}}_{D,t}$. Panel (b) of Table 7 shows that systemic risk in pre-monsoon and winter seasons predicts short to medium-run future economic downturns. Specifically, the pre-monsoon systemic risk coefficient becomes significant as early as n = 3 months, implying that negative economic consequences from this season are forecast significantly earlier than other seasons. In contrast, the monsoon and post-monsoon seasons have generally weak to no predicting capacity, as indicated by the absence of significance over most forecasting horizons.

Finally, we investigate the ability to foresee weather-induced systemic risk across each broad cluster. Using a technique akin to season-wise analysis, we determine the cluster-wise systemic risk. We alternately use Equation (8) for every broad cluster. Panel (c) of Table 7 displays these findings. All clusters have consistently significant negative coefficients at medium to long horizons, similar to overall systemic risk results. However, broad clusters like healthcare and energy show predictive linkages with different degrees and timing of effects. In particular, weather-induced systemic risk from the healthcare cluster can be forecasted from shorter to longer horizons. In contrast, weather-induced systemic risk from the energy cluster can only be forecasted for longer periods. These findings reveal sectoral variability in systemic risk forecasting.

Overall, the findings highlight the importance of horizons for analyzing the forecasting ability of systemic risk on economic activity. While the short-term consequences appear limited, systemic risk has a rising potential to predict economic downturns over long periods.

6. Conclusion

This study offers insight into the impact of variations in the weather on systemic risk in Indian financial markets, highlighting the unique effects of temperature and precipitation on both systemic risk and economic forecasts. Overcoming the limits of aggregate data, we offer a more thorough understanding of how weather variations spread through Indian financial markets by utilizing a semi-parametric GAM model and decomposed weather variables.

Table 7: **Predictive ability of weather-induced systemic risk**

	Dependent variable: Mean industrial production index (MIPI$_{t,n}$) for future 'n' months											
Cluster	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$	$n=11$	$n=12$
(a) Weather-induced systemic risk as per decomposed class of GAM												
Marginal effect	0.41	-0.35	-1.32	-1.28	-1.60*	-1.56*	-1.95**	-2.18***	-2.17***	-1.92***	-1.79***	-1.88***
	(1.79)	(1.36)	(1.11)	(0.99)	(0.82)	(0.84)	(0.78)	(0.68)	(0.63)	(0.61)	(0.62)	(0.60)
(b) Weather-induced systemic risk across seasons												
Winter	0.00	-0.10	-0.64	-0.61	-0.60	-0.70*	-0.65**	-0.42	-0.23	-0.20	-0.21	-0.20
	(0.35)	(0.60)	(0.76)	(0.67)	(0.53)	(0.38)	(0.30)	(0.27)	(0.22)	(0.19)	(0.18)	(0.18)
Pre-monsoon	-0.30	-0.48	-0.95**	-0.99***	-0.83***	-0.58***	-0.50**	-0.47**	-0.39*	-0.32	-0.32	-0.39**
	(0.25)	(0.33)	(0.38)	(0.32)	(0.24)	(0.21)	(0.21)	(0.20)	(0.21)	(0.22)	(0.20)	(0.19)
Monsoon	-0.16	-0.07	-0.16	-0.07	-0.11	0.02	0.05	0.03	0.07	0.01	-0.09	-0.16
	(0.32)	(0.33)	(0.35)	(0.27)	(0.24)	(0.26)	(0.28)	(0.24)	(0.21)	(0.20)	(0.19)	(0.18)
Post-monsoon	0.05	0.07	-0.06	-0.05	-0.26	-0.11	-0.18	-0.35**	-0.30*	-0.16	-0.15	-0.21
	(0.45)	(0.40)	(0.29)	(0.24)	(0.23)	(0.20)	(0.20)	(0.17)	(0.16)	(0.17)	(0.16)	(0.14)
(c) Weather-induced systemic risk across broad clusters												
Consumer	0.83	-0.24	-1.59	-1.75	-2.05**	-2.00**	-2.40***	-2.69***	-2.56***	-2.25***	-2.01***	-2.16***
	(2.17)	(1.61)	(1.28)	(1.08)	(0.91)	(0.93)	(0.89)	(0.79)	(0.75)	(0.73)	(0.73)	(0.67)
Manufacturing	0.89	-0.22	-1.32	-1.34	-1.61*	-1.53*	-2.01**	-2.27***	-2.23***	-1.97***	-1.78***	-1.94***
	(2.05)	(1.52)	(1.27)	(1.12)	(0.90)	(0.91)	(0.84)	(0.73)	(0.68)	(0.65)	(0.64)	(0.59)
Technology	0.15	-0.34	-1.23	-1.37	-1.75**	-1.78**	-2.11***	-2.30***	-2.17***	-1.91***	-1.76***	-1.81***
	(1.61)	(1.25)	(1.05)	(0.89)	(0.70)	(0.69)	(0.65)	(0.60)	(0.58)	(0.57)	(0.58)	(0.56)
Energy	-0.11	-0.11	-0.30	-0.10	-0.42	-0.40	-0.77	-0.93*	-1.01**	-0.95**	-0.97**	-1.02**
	(1.05)	(0.88)	(0.92)	(0.91)	(0.71)	(0.72)	(0.62)	(0.54)	(0.48)	(0.42)	(0.42)	(0.42)
Finance	0.42	-0.11	-1.11	-1.24	-1.51*	-1.54*	-1.92**	-2.07***	-1.95***	-1.75***	-1.70***	-1.84***
	(1.84)	(1.39)	(1.15)	(1.00)	(0.88)	(0.86)	(0.79)	(0.71)	(0.67)	(0.62)	(0.61)	(0.59)
Health care	0.58	-0.55	-2.24**	-2.46**	-2.44***	-2.31**	-2.72***	-3.02***	-2.80***	-2.39***	-2.10***	-2.23***
	(2.06)	(1.49)	(1.08)	(0.95)	(0.89)	(0.95)	(0.87)	(0.74)	(0.73)	(0.72)	(0.70)	(0.63)
Others	0.14	-0.41	-1.13	-1.09	-1.42*	-1.39*	-1.79**	-1.95***	-1.94***	-1.71***	-1.56***	-1.64***
	(1.64)	(1.32)	(1.12)	(0.98)	(0.76)	(0.76)	(0.70)	(0.63)	(0.59)	(0.56)	(0.56)	(0.54)

The table reports the coefficient estimates of weather-induced systemic risk from the predictive regressions from Equation (10). The dependent variable is the mean of the industrial production index over the following 'n' months. Control variables include contemporaneous and 11-lags of industrial production index and macroeconomic state variables. Panel (a) considers overall weather-induced systemic risk obtained from Equation (7). Panel (b) has season-wise systemic risk from weather variations, whereas Panel (c) considers cluster-wise systemic risk from weather variations. Standard errors are Newey-west. Significance levels: * 10%, ** 5%, and *** 1%.

Several significant findings emerge from our analysis. First, aggregating weather variables leads to inaccurate estimates because it obscures the unique effects of expected and anomalous weather variations. The decomposed weather model demonstrates that, while temperature variations increase systemic risk, precipitation variations reduce it—a relation that the aggregate model does not capture. In addition, we identify asymmetric impacts, in which anomaly weather variations affect systemic risk more than expected changes. We ascribe these patterns to potential mechanisms, such as how the mean and volatility of economic outcomes of power consumption, supply chain disruptions, and loan supply are affected by expected and anomalous weather variations.

Additionally, our heterogeneity analysis highlights the complexity of weather-induced systemic risk by showing that the effects of weather variations differ depending on the season and industry cluster. Finally, we also show that, while weather-induced systemic risk has low short-term predictive capacity, it plays an important role in forecasting medium- and long-term economic activity.

These findings have significant consequences for policymakers and investors. Policymakers should integrate decomposed weather data into stress-testing frameworks to increase the precision of financial stability assessments and economic forecasts. This can improve stress-testing measures and establish a stronger platform for addressing climate-related financial risks. Investors, in turn, can benefit from the predictive power of weather-induced systemic risk by incorporating decomposed weather data into their portfolio management strategies. Strengthening portfolios can improve risk-adjusted returns and support market stability in general.

These results further emphasize the significance of a put-forward financial stability mechanism through which weather variations influence economic growth. Future studies should look into how different financial instruments react to weather variations to understand potential risk-hedging behaviour among investors better. Furthermore, while prior studies have looked at the importance of labour, capital, health, and trade as channels for the economic effects of weather variations, future studies should include financial stability as a vital channel for improving the reliability of damage function estimations. Finally, more research is needed to investigate the impact of weather variations on investor's psychological state while accounting for financial instability caused by bad economic situations due to weather variations.

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Appendix

A1. Summary statistics

Table A1 provides mean and standard deviation values of stock return, market capitalization, number of firms and observations in each industry. These industries are classified into seven broad clusters based on Industrial Benchmark Code. In total, we have 898 listed firms from period February 1999 to July 2023.

Table A1: **Sector-wise summary statistics**

Sector	**Broad Cluster**	**Returns Mean**	**Returns Std. Dev.**	**Obs.**	**No. of firms**	**Market capitalisation**
Aerospace and Defense	Manufacturing	1.11	15.52	430	2	0.36%
Chemicals	Manufacturing	1.28	17.58	15,480	72	2.03%
Construction and Materials	Manufacturing	0.67	18.35	6,020	28	0.40%
Electronic and Electrical Equipment	Manufacturing	1.22	17.80	430	2	0.01%
Forestry and Paper	Manufacturing	0.58	17.44	3,225	15	0.21%
General Industrials	Manufacturing	1.09	19.26	6,020	28	2.02%
Industrial Engineering	Manufacturing	1.01	16.68	11,180	52	0.70%
Industrial Metals and Mining	Manufacturing	0.97	17.36	7,740	36	4.78%
Industrial Transportation	Manufacturing	0.45	15.99	2,795	13	0.74%
Mining	Manufacturing	0.99	17.07	1,075	5	0.86%
Alternative Energy	Energy	2.16	23.33	430	2	0.02%
Electricity	Energy	0.46	13.65	860	4	0.77%
Oil and Gas Producers	Energy	0.39	17.88	1,290	6	3.67%
Oil Equipment and Services	Energy	1.37	17.21	645	3	0.07%
Banks	Finance	1.30	12.79	3,655	17	17.28%
Financial Services (Sector)	Finance	0.87	18.64	10,535	49	3.32%
Health Care Equipment and Services	Health care	0.94	15.47	1,290	6	0.30%
Pharmaceuticals and Biotechnology	Health care	0.96	16.22	12,900	60	6.30%
Software and Computer Services	Technology	1.02	20.02	8,600	40	8.41%
Support Services	Technology	1.06	15.47	1,505	7	0.39%
Technology Hardware and Equipment	Technology	0.54	19.40	3,225	15	0.21%
Automobiles and Parts	Consumer	0.92	14.75	9,890	46	4.12%
Beverages	Consumer	1.34	16.32	2,365	11	0.80%
Food Producers	Consumer	1.11	16.52	9,890	46	2.10%
Food and Drug Retailers	Consumer	1.85	14.97	215	1	0.01%
General Retailers	Consumer	-0.01	21.15	1,505	7	0.21%
Household Goods and Home Construction	Consumer	1.70	14.76	3,010	14	0.45%
Leisure Goods	Consumer	0.27	18.98	1,075	5	0.01%
Media	Consumer	0.33	16.95	1,505	7	0.05%
Personal Goods	Consumer	0.66	18.50	14,620	68	5.59%
Tobacco	Consumer	0.90	13.58	1,075	5	3.65%
Travel and Leisure	Consumer	0.95	15.15	3,870	18	0.49%
Gas, Water and Multiutilities	Others	1.81	12.02	430	2	0.18%
Fixed Line Telecommunications	Others	0.18	17.21	1,075	5	0.38%
Real Estate Investment and Services	Others	0.89	20.25	2,365	11	0.28%
Others	Others	1.08	16.41	40,850	190	28.87%

The clusters are defined based Industrial Benchmark Code.

A2. GAM estimation strategy

According to T. J. Hastie (2017), the Generalized Additive Model (GAM) is an extension of Generalized Linear Models that permits flexible, non-linear connections between predictors and the response variable. The model assumes the following structure.

$$g(E[Y]) = \alpha + \sum_{j=1}^{p} f_j(X_j) + \varepsilon, \tag{A1}$$

where α is the intercept, X_j represents the predictor variables, $f_j(.)$ is the smooth function of predictors, Y is the response variable, and g(.) is the link function (which in our instance is considered to be linear). This model allows for a non-normal error distribution for error term 'ε', which is the Scaled-t distribution in our case.

A2.1. Basis function

Basis functions are used to estimate the smooth functions $f_j(.)$. A basis function serves as a fundamental building component for the model, allowing it to approximate nonlinear interactions. $f_j(.)$ is expressed as a weighted sum of simpler functions rather than being estimated directly:

$$f_j(x) = \sum_{k=1}^{K} \beta_k \phi_k(x) \tag{A2}$$

where $\phi_k(x)$ represents the basis functions, β_k represents the associated coefficients, and K represents the number of basis functions employed.

A2.2. Preliminary analysis: Cyclical cubic splines

The preliminary analysis in Section 3 uses a cyclical cubic spline with 12 knots (K) to extract cyclical systemic risk throughout the year. Cyclical cubic splines are a type of cubic spline intended to provide smoothness and continuity at a periodic function's borders. As defined in Equation (A2), $K = 12$ knots in the basis functions indicate the number of months in a year, β_k are spline coefficient and $\phi_k(x)$ are cubic basis function. We also assume additional constraint of functional continuity $[f_j(x1) = f_j(x_K)]$, first derivative continuity $[f_j'(x1) = f_j'(x_K)]$, and second derivative continuity $[f_j''(x1) = f_j''(x_K)]$ to avoid artificial discontinuities in cyclical data.

A2.3. Hypothesis testing: Thin plate splines

In Sections 4.1 and 4.2, we use thin-plate splines (Duchon, 1977) to estimate $f_j(x)$s, enabling the inclusion of several variables in a smooth function. The selection of thin-plate splines over other splines is multivariate smooth function which is a limitation for other splines. As per Equation (A2), $\phi_k(x)$ are the thin plate spline basis functions evaluated at the covariates in x.

A2.4. Double-penalty technique

To estimate α and θ_k [Equation (A1) or (A2)], a double penalized regression technique is implied as follows:

$$\min\left\{\sum_{i=1}^{n}\left[Y_i-\alpha-\sum_{j=1}^{p}f_j(x_i)\right]^2+\lambda_1\sum_{k=1}^{K}\int\left(\frac{\partial^2 f_j(x)}{\partial x^2}\right)^2dx+\lambda_2\sum_{k=1}^{K}\int f^2(x)dx\right\}$$

where Y_i is the i-th response variable, and X_i is the i-th row of matrix X. The range space, which is the more complicated or "wiggly" portion of the smoother, is penalized by the parameter λ_1. λ_2 applies an extra penalty to the smoother's simpler half, or null space, in the double-penalty approach (see Marra and Wood, 2011). The smoothing parameters (λ_1 and λ_2) are obtained by minimizing the AIC[9] or fREML score. Using F-test statistics, we assess the significance of smooth terms with the null hypothesis that $f_j(x)=0$ for all values of x.

A2.5. Varying Coefficient GAM

For heterogeneity analysis (Section 4.3), we consider varying coefficient GAM structured as follows, a modification to Equation (A1):

$$g(E[Y])=\alpha+\sum_{j=1}^{p}f_j(X_j)D_l+\varepsilon, \tag{A3}$$

where $\beta^T(X)$ is a vector of unknown function coefficient of dummy variable D_l allowed to vary smoothly over the effect modifiers X. The double penalty technique is augmented to suit the varying coefficient GAM as follows:

$$\min\left\{\sum_{i=1}^{n}\left[Y_i-\alpha-\sum_{j=1}^{p}f_j(x_i)\right]^2+\lambda_1\sum_{k=1}^{K}\int\left(\frac{\partial^2\beta_k}{\partial x^2}\right)^2dx+\lambda_2\sum_{k=1}^{K}\int\beta_k^2dx\right\}$$

[9] AIC is preferred above BIC for model selection (Shao, 1997).

The rest of the estimation described in previous sections applies to varying coefficient GAM.

A3. Preliminary analysis

Table A2: **Results for preliminary analysis**

	(1)
Smooth term: Effective degree of freedom	
Months - Effective degrees of freedom	9.9440***
Parametric terms: Marginal effects	
$\Delta\text{CoVaR}^i_{q,t-1}$	0.4732***
	(0.0022)
$\Delta\text{CoVaR}^i_{q,t-2}$	0.1661***
	(0.0023)
$\Delta\text{CoVaR}^i_{q,t-3}$	0.1467***
	(0.0020)
$\log(\text{size})^i_t$	-0.0148***
	(0.0041)
Fixed effects	Firm, year
Adj R^2	0.738
AIC	771,494.50
fREML score	340,770.60

This table includes the Effective Degrees of Freedom for the cyclical smooth term and coefficient estimates for the parametric terms in Equation (5) in the main paper. The dependent variable is firm-level systemic risk in the Indian stock market computed using $\Delta\text{CoVaR}^i_{q,t}$ framework.
The F-test determines the significance of the EDF values for the smooth terms. The Akaike information criterion (AIC) and fast residual maximum likelihood (fREML) scores evaluate model fit using in-sample performance and complexity.
The model has firm-fixed effects and year-fixed effects. The other control variables include three lags of dependent variables, and a log of firm size. Standard errors are in the parenthesis. Error term follows the Scaled-t distribution. Significance levels: * 10%, ** 5%, and *** 1%.

A4. Hypothesis testing method

A4.1. Augmented Dickey-fuller unit-root test:

We present the unit root results of economic variables considered for GAM models in Table A3. The lags are considered based in BIC. In case of non-stationary series, we consider first difference to remove the unit-root.

Table A3: Augmented Dickey-fuller unit root results

Variables	**Lag Selection (BIC)**	**test-statistics**	Critical values (5%)
Aggregate temperature	11	-2.495	-3.43
Expected temperature	10	-6.168	-3.43
Anomaly temperature	12	-2.465	-3.43
Aggregate precipitation	11	-2.912	-3.43
Expected precipitation	11	-3.399	-3.43
Anomaly precipitation	9	-4.225	-3.43
Short-term liquidity	1	-5.278	-3.43
Change in 3-month treasury bill rate	1	-11.026	-3.43
Yield	1	-2.633	-3.43
Credit spread	1	-5.434	-3.43
Prime lending rate	1	-3.146	-3.43
Market returns	1	-10.312	-3.43
Market volatility	11	-6.789	-3.43

A4.2. Variables for mRMR algorithm

We consider 7 macroeconomic state variables for each class of GAM. This includes short-term liquidity (STLS_t), changes in the 3-month treasury bill rate ($\mathrm{CTB3}_t$), yield changes ($\Delta\mathrm{Yield}_t$), credit spread (Credit_t), prime lending rate changes ($\Delta\mathrm{PLR}_t$), monthly market returns (Mret_t), and volatility (Vol_t).

In case of aggregate class of GAM, we use first difference of aggregate temperature and precipitation variable (ΔT_t, ΔP_t, ΔT_{t-1}, and ΔP_{t-1}). Along with these aggregate variables, we also include interactions of these variables as follows: $\Delta T_t \times \Delta T_{t-1}$, $\Delta T_t \times \Delta P_t$, $\Delta T_t \times \Delta P_{t-1}$, $\Delta P_t \times \Delta T_{t-1}$, and $\Delta P_t \times \Delta P_{t-1}$. Together, we have 16 variables for the aggregate class of GAM.

In case of decomposed class of GAM, we use expected temperature, precipitation anomaly, and first difference of temperature anomaly and expected precipitation variable ($T_{\mathrm{expected},t}$, $T_{\mathrm{expected},t-1}$, $\Delta T_{\mathrm{anomaly},t}$, $\Delta T_{\mathrm{anomaly},t-1}$, $\Delta P_{\mathrm{expected},t}$, $\Delta P_{\mathrm{expected},t-1}$, $P_{\mathrm{anomaly},t}$, and $P_{\mathrm{anomaly},t-1}$). Along with these decomposed variables, we also include interactions of these variables resulting to 24 interaction variables. Together, we have 39 variables for the decomposed class of GAM.

A4.3. Selected GAM specification after mRMR algorithm

A4.3.1. Aggregate class:

1.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) + \zeta_t^i$$

2.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) +$$
$$+ \ s_2(\Delta\text{PLR}_t) \ + \ \zeta_t^i$$

3.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) +$$
$$+ \ s_2(\Delta\text{PLR}_t) \ + \ s_2(\Delta\text{Yield}_t) \ + \ \zeta_t^i$$

4.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) +$$
$$+ \ s_2(\Delta\text{PLR}_t) \ + \ s_2(\Delta\text{Yield}_t) \ + w_1(\Delta P_t) \ + \ \zeta_t^i$$

5.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) +$$
$$+ \ s_2(\Delta\text{PLR}_t) \ + \ s_2(\Delta\text{Yield}_t) \ + w_1(\Delta P_t) \ + w_2(\Delta T_t) \ + \ \zeta_t^i$$

6.
$$\Delta\text{CoVaR}_{q,t}^{i} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta\text{CoVaR}_{q,t-j}^{i} + \beta_4 \log(\text{size})_t^i + \gamma_i + \delta_y$$
$$+ \ D_{Jan} \ + \ D_{April} \ + \ D_{July} \ + \ D_{Oct} \ + \ + s_1(\text{Vol}_t) +$$
$$+ \ s_2(\Delta\text{PLR}_t) \ + \ s_2(\Delta\text{Yield}_t) \ + w_1(\Delta P_t) \ + w_2(\Delta T_t)$$
$$+ \ w_3(\Delta T_{t-1}) \ + \ \zeta_t^i$$

7.
$$\Delta \text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ + s_1(\text{Vol}_t) +$$
$$+\ s_2(\Delta \text{PLR}_t)\ +\ s_2(\Delta \text{Yield}_t)\ + w_1(\Delta P_t)\ + w_2(\Delta T_t)$$
$$+\ w_3(\Delta T_{t-1})\ +\ w_4(\Delta P_{t-1})\ +\ \zeta^i_t$$

A4.3.2. Decomposed class:

1.
$$\Delta \text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ + s_1(\text{Vol}_t) + \zeta^i_t$$

2.
$$\Delta \text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ + s_1(\text{Vol}_t) +$$
$$+\ s_2(\Delta \text{PLR}_t)\ +\ \zeta^i_t$$

3.
$$\Delta \text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ + s_1(\text{Vol}_t) +$$
$$+\ s_2(\Delta \text{PLR}_t)\ +\ w_1(T_{\text{expected,t} \times P_{\text{anomaly,t-1}}})\ +\ \zeta^i_t$$

4.
$$\Delta \text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \text{CoVaR}^i_{q,t-j} + \beta_4 \log(\text{size})^i_t + \gamma_i + \delta_y$$
$$+\ D_{Jan}\ +\ D_{April}\ +\ D_{July}\ +\ D_{Oct}\ +\ + s_1(\text{Vol}_t) +$$
$$+\ s_2(\Delta \text{PLR}_t)\ +\ w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}})$$
$$+\ w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}})\ +\ \zeta^i_t$$

5.

$$\begin{aligned}\Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3}\beta_j\Delta\text{CoVaR}^i_{q,t-j} + \beta_4\log(\text{size})^i_t + \gamma_i + \delta_y \\ + D_{Jan} + D_{April} + D_{July} + D_{Oct} + +s_1(\text{Vol}_t)+ \\ + s_2(\Delta\text{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\ + w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\text{CTB3}_t) + \zeta^i_t\end{aligned}$$

6.

$$\begin{aligned}\Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3}\beta_j\Delta\text{CoVaR}^i_{q,t-j} + \beta_4\log(\text{size})^i_t + \gamma_i + \delta_y \\ + D_{Jan} + D_{April} + D_{July} + D_{Oct} + +s_1(\text{Vol}_t)+ \\ + s_2(\Delta\text{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\ + w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\text{CTB3}_t) \\ + w_3(\Delta P_{\text{expected,t-1}} \times \Delta T_{\text{anomaly,t}}) + \zeta^i_t\end{aligned}$$

7.

$$\begin{aligned}\Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3}\beta_j\Delta\text{CoVaR}^i_{q,t-j} + \beta_4\log(\text{size})^i_t + \gamma_i + \delta_y \\ + D_{Jan} + D_{April} + D_{July} + D_{Oct} + +s_1(\text{Vol}_t)+ \\ + s_2(\Delta\text{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\ + w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\text{CTB3}_t) \\ + w_3(\Delta P_{\text{expected,t-1}} \times \Delta T_{\text{anomaly,t}}) + s_4(\text{Mret}_t) + \zeta^i_t\end{aligned}$$

8.

$$\begin{aligned}\Delta\text{CoVaR}^i_{q,t} = \beta_0 + \sum_{j=1}^{3}\beta_j\Delta\text{CoVaR}^i_{q,t-j} + \beta_4\log(\text{size})^i_t + \gamma_i + \delta_y \\ + D_{Jan} + D_{April} + D_{July} + D_{Oct} + +s_1(\text{Vol}_t)+ \\ + s_2(\Delta\text{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\ + w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\text{CTB3}_t) \\ + w_3(\Delta P_{\text{expected,t-1}} \times \Delta T_{\text{anomaly,t}}) + s_4(\text{Mret}_t) \\ + w_4(T_{\text{expected},t}) + \zeta^i_t\end{aligned}$$

9.

$$
\begin{aligned}
\Delta \mathrm{CoVaR}^{i}_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \mathrm{CoVaR}^{i}_{q,t-j} + \beta_4 \log(\mathrm{size})^{i}_{t} + \gamma_i + \delta_y \\
&+ D_{Jan} + D_{April} + D_{July} + D_{Oct} + + s_1(\mathrm{Vol}_t) + \\
&+ s_2(\Delta \mathrm{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\
&+ w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\mathrm{CTB3}_t) \\
&+ w_3(\Delta P_{\text{expected,t-1}} \times \Delta T_{\text{anomaly,t}}) + s_4(\mathrm{Mret}_t) \\
&+ w_4(T_{\text{expected},t}) + s_4(\mathrm{Credit}_t) + \zeta^{i}_{t}
\end{aligned}
$$

10.

$$
\begin{aligned}
\Delta \mathrm{CoVaR}^{i}_{q,t} = \beta_0 + \sum_{j=1}^{3} \beta_j \Delta \mathrm{CoVaR}^{i}_{q,t-j} + \beta_4 \log(\mathrm{size})^{i}_{t} + \gamma_i + \delta_y \\
&+ D_{Jan} + D_{April} + D_{July} + D_{Oct} + + s_1(\mathrm{Vol}_t) + \\
&+ s_2(\Delta \mathrm{PLR}_t) + w_1(T_{\text{expected,t}} \times P_{\text{anomaly,t-1}}) \\
&+ w_2(\Delta T_{\text{anomaly,t-1}} \times P_{\text{anomaly,t-1}}) + s_3(\mathrm{CTB3}_t) \\
&+ w_3(\Delta P_{\text{expected,t-1}} \times \Delta T_{\text{anomaly,t}}) + s_4(\mathrm{Mret}_t) \\
&+ w_4(T_{\text{expected},t}) + s_4(\mathrm{Credit}_t) + w_5(\Delta T_{\text{anomaly},t-1}) + \zeta^{i}_{t}
\end{aligned}
$$