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EVALUATING RAINFALL INDEX AS AN EFFECTIVE HEDGE FOR PEPPER PRICE RISK: A QUANTITATIVE ANALYSIS

Steevan Robert Tellis[1] and Dr. Ajoy S Joseph[2]

[1]Assistant Professor, Shri Madhwa Vadiraja Institute of Technology and Management, Bantakal, India.
[2]Professor and Head, Department of MBA, Srinivas Institute of Technology Valachil, Mangaluru, Karnataka, India

[1]steevan.mba@sode-edu.in
[2]ajoysj@gmail.com
[1]**ORCID ID:** 0009-0005-9886-9971

ABSTRACT
Pepper, one of the most traded spices globally, is highly vulnerable to price swings caused by weather disruptions, particularly erratic rainfall. Farmers and traders often struggle to manage this risk due to limited access to traditional hedging tools like futures contracts. In recent years, index-based weather derivatives have gained attention as potential alternatives. However, their effectiveness in stabilizing pepper prices remains underexplored.
This study examines whether rainfall index can serve as a reliable hedge against pepper price volatility. Using historical data of pepper prices from major pepper-producing regions in India, we analyze the correlation between rainfall deviations and price fluctuations. Regression-based hedging models are applied to determine optimal risk reduction strategies.
Our findings aim to assist farmers, agribusinesses, and policymakers in adopting low-cost, accessible risk management tools tailored to climate-sensitive crops like pepper. If successful, rainfall-indexed hedging could revolutionize financial resilience in spice-dependent economies, reducing reliance on volatile global markets.

Keywords: *Pepper price risk, Rainfall index, Price volatility, hedge, weather derivatives*

INTRODUCTION
Price volatility in agricultural commodities, such as pepper, poses significant financial risks for farmers, traders, and exporters. Since pepper cultivation is highly sensitive to climatic conditions, erratic rainfall patterns often lead to supply fluctuations, directly impacting market prices. While futures contracts are conventional hedging tools, their effectiveness is limited to liquidity constraints as the contracts are not available in commodities market in India. This study examines whether rainfall index data can effectively hedge pepper price risk in India, providing empirical evidence on its viability.

Data Sources and Methodology
The analysis relies on two key datasets:
1. Historical Rainfall Index Data from the National Commodity and Derivatives Exchange (**NCDEX**), which offers standardized precipitation metrics for major pepper-producing regions.
2. Pepper Price Data from the Central Arecanut and Cocoa Marketing and Processing Cooperative (**CAMPCO**), a leading authority on Indian spice market trends.

Using quantitative techniques—including time-series regression, correlation analysis, and hedging effectiveness ratios—this research assesses the predictive relationship between rainfall index and pepper price movements. The findings aim to guide stakeholders in adopting index-based insurance products for improved price risk mitigation.

REVIEW OF LITERATURE
The foundational work on agricultural risk management evolved significantly in the 21st century, moving from theoretical concepts to practical applications of index-based solutions. (Turvey, 2001) pioneered this shift by designing and pricing weather derivatives, demonstrating their potential as a direct hedge for specific agricultural event risks. This theoretical groundwork was soon followed by

rigorous empirical methodologies; (Vedenov, D. V., & Barnett, 2004) established key metrics for evaluating the efficiency of weather derivatives, providing a quantitative framework that remains central to analysis. Recognizing the developmental potential, (Skees, J. R., & Barnett, 2006) argued that these index-based products could be seamlessly integrated with microfinance to manage systemic risk for smallholder farmers, a demographic highly relevant to global pepper production. However, the core challenge of basis risk—the mismatch between the index payout and the actual loss—was rigorously addressed by (Woodard, J. D., & Garcia, 2008), who employed advanced quantile regression to better measure hedging effectiveness, particularly during the tail-end price spikes that characterize volatile markets.

As pilot programs proliferated globally, the literature expanded to include comprehensive reviews and critical assessments. (Miranda, M. J., & Farrin, 2012) synthesized the lessons learned, outlining the practical challenges and design principles crucial for the success of index insurance in developing countries. Concurrently, the limitations of traditional futures markets were highlighted by (Gilbert, 2010), who documented how financial speculation post-2008 exacerbated commodity price volatility, thereby strengthening the case for alternative risk transfer mechanisms like indices. The focus on empirical evidence continued with studies like (Jensen, N. D., Barrett, C. B., & Mude, 2016), which compared index insurance to other safety nets, and Collier, (Skees, J. R., & Barnett, 2006), which precisely quantified the welfare impacts of basis risk through field experiments. The technological frontier of index design has been advanced by (Bokusheva, 2017), who explored the use of satellite data for creating more precise indices, and (Huang, J., & Gao, 2021), who reviewed the application of machine learning for price prediction and risk modeling, offering sophisticated tools for future analysis.

Within the specific context of agricultural commodities, the detrimental effects of price volatility have been well-established. (Bellemare, M. F., Barrett, C. B. & Just, 2013) provided robust evidence of its negative welfare impacts on rural households, while (Geman, 2005) offered the essential quantitative models for understanding commodity price behavior. A critical conceptual study by (Leblois, A., Quirion, P., & Sultan, 2014) directly compared hedging price risk versus yield risk, a distinction central to using a weather index for price stabilization. Large-scale empirical evidence from programs in Mexico (Fuchs, A., & Wolff, 2011) and studies on adoption, such as (Hill, R. V., Hoddinott, J., & Kumar, 2013), shed light on the factors influencing the uptake of these products. Despite this extensive body of work, and even in the face of recent shocks that have heightened market volatility (The World Bank Group, 2021), commodity-specific analyses have been largely confined to staples. Notably, while the price volatility in spice markets has been documented, as in the case of Indian black pepper by (Kumar, R., & Chander, 2015), and industry reports like (International Society for Spices and Spices., 2019) have highlighted the need for risk management solutions, the literature has not translated these general calls into targeted, quantitative research for the pepper industry.

Research Gap

Despite a robust and evolving body of literature on index-based agricultural risk management, a critical gap exists in its specific application to high-value, perennial spices like pepper. While the principles of weather derivatives and the challenges of basis risk are well-understood for staple grains, no study has quantitatively designed and evaluated a Rainfall Index (RI) as a direct hedge for pepper price risk. The existing research has not established the empirical linkage between rainfall anomalies in key production basins (e.g., Vietnam, India, Brazil) and subsequent price movements in the global pepper market. Therefore, the core research gap is the absence of a targeted analysis that models this relationship, measures the hedging effectiveness of a spatially-specific RI, and evaluates the associated basis risk, thereby failing to provide a viable financial product blueprint for a commodity characterized by extreme price volatility.

OBJECTIVE:

Evaluating Rainfall Index as an Effective Hedge for Pepper Price Risk

DESCRIPTIVE STATISTICS:

The descriptive statistics of the Rain Index and Pepper Average Price reveal important insights into their behavior and potential hedging efficiency. The Rain Index has a mean of -1.1587 and a median of -1.42, indicating that on average, rainfall anomalies are slightly negative. However, the extreme range from -129.14 to 48.93, along with a high standard deviation of 19.5122, suggests significant variability in rainfall patterns. The negative skewness of -1.6359 shows that extreme low values are more frequent, and the high kurtosis of 12.1136 indicates the presence of extreme outliers. Furthermore, the Jarque-Bera test confirms that the Rain Index is not normally distributed, making it an unpredictable variable for hedging purposes.

On the other hand, the Pepper Average Price has a mean of 528.03 and a median of 537.5, showing a more stable distribution compared to the Rain Index. The price fluctuates between 322.5 and 607.5, with a standard deviation of 50.0921, indicating moderate volatility. The slight negative skewness (-0.2804) suggests that lower prices occur marginally more frequently than higher prices, and the kurtosis value of 2.3899 indicates a near-normal distribution with fewer extreme values. Although the Jarque-Bera test confirms that pepper prices are not perfectly normal, their distribution is significantly more stable than that of the Rain Index.

The contrast in volatility between these two variables suggests that while rainfall anomalies may influence pepper prices, the extent of their impact needs further investigation. The high unpredictability of rainfall makes it a challenging risk factor for price hedging. A simple regression-based hedge may not be sufficient, as the extreme values in rainfall data could cause sudden and severe price fluctuations. Given these characteristics, a more advanced risk management approach, such as GARCH modeling or non-linear hedging strategies, may be necessary to account for the dynamic relationship between rainfall and pepper prices.

Table 1: showing the descriptive statistics for rain index and pepper price

	RAIN_INDEX	PEPPER_AVG_PRICE
Mean	-1.158728	528.0339
Median	-1.42	537.5
Maximum	48.93	607.5
Minimum	-129.14	322.5
Std. Dev.	19.51215	50.09209
Skewness	-1.635962	-0.280433
Kurtosis	12.11363	2.389991
Jarque-Bera	4207.649	30.81484
Probability	0	0

Source: Author’s computation using EViews

Correlation Analysis:

The correlation matrix indicates the relationship between the Rain Index and Pepper Average Price. The correlation coefficient value of -0.1142 suggests a very weak negative correlation.

Table 2: showing the correlation Between Rain Index and Pepper Prices.

	RAIN_INDEX	PEPPER_AVG_PRICE
RAIN_INDEX	1	-0.114182722
PEPPER_AVG_PRICE	-0.114182722	1

Source: Author’s computation using EViews

This weak negative correlation implies that an increase in rainfall index (either excessive or deficient rainfall) is associated with a slight decline in pepper prices, but the effect is minimal. Since the correlation is close to zero, rainfall does not appear to be a strong determinant of pepper price fluctuations.

From a hedging efficiency perspective, this weak correlation suggests that using the Rain Index as a hedge against price volatility in pepper may not be very effective. A more effective hedge typically requires a strong negative correlation (closer to -1) to offset price fluctuations efficiently. The weak relationship here indicates that other factors, such as supply chain issues, market demand, and broader economic conditions, might have a stronger influence on pepper prices than rainfall alone.

REGRESSION ANALYSIS:

The regression analysis reveals that the Rain Index has a weak but statistically significant impact on pepper prices. The negative coefficient of -0.2931 suggests that as rainfall anomalies increase, pepper prices tend to decrease slightly. However, the effect is minimal, with each unit increase in the Rain Index reducing the pepper price by just 0.2931 units on average. While the p-value of 0.0002 confirms statistical significance, the R-squared value of just 1.3% indicates that rainfall explains only a tiny fraction of price variations.

Table 3: showing the Ordinary Least Squares (OLS) Regression Estimates.

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	527.6942	1.519773	347.2192	0
RAIN_INDEX	-0.293133	0.077788	-3.76838	0.0002
R-squared	0.013038	Mean dependent var		528.0339
Adjusted R-squared	0.01212	S.D. dependent var		50.09209
S.E. of regression	49.78762	Akaike info criterion		10.65526
Sum squared resid	2664717	Schwarz criterion		10.66452
Log likelihood	-5735.86	Hannan-Quinn criter.		10.65877
F-statistic	14.20066	Durbin-Watson stat		0.034616
Prob(F-statistic)	0.000173			

Source: Author's computation using EViews

Moreover, the **Durbin**-Watson statistic of 0.0346 suggests a strong presence of autocorrelation, meaning that past price movements influence current ones. This hints that a simple regression model may not be the best approach for capturing the dynamics of price fluctuations. Instead, more advanced models like ARIMA, GARCH, or VAR might be needed to properly account for time-dependent patterns.

From a hedging perspective, the weak correlation and low explanatory power of rainfall on pepper prices suggest that using the Rain Index alone as a hedging tool would be ineffective. While rainfall anomalies might contribute to price movements, they are not the primary driver. A more comprehensive approach that includes other economic, climatic, and market-related variables would be necessary to develop a meaningful hedging strategy.

Stationary Test:

Stationarity is a fundamental assumption in time series analysis, implying that a series' statistical properties (mean, variance, and autocorrelation) remain constant over time. The Augmented Dickey-

Fuller (ADF) test is a widely used unit root test that examines whether a time series is non-stationary due to the presence of a stochastic trend.

Table 4: showing the Augmented Dickey-Fuller test statistic for pepper.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.199134	0.6768
Test critical values:	1% level	-3.436267	
	5% level	-2.864041	
	10% level	-2.568153	

Source: Author's computation using EViews

The results of the Augmented Dickey-Fuller (ADF) test indicate that pepper prices are non-stationary, meaning they do not revert to a stable long-term mean and instead exhibit a trend over time. The test statistic of -1.1991 is higher than all critical values at the 1%, 5%, and 10% significance levels, meaning we fail to reject the null hypothesis that pepper prices have a unit root. Additionally, the high p-value of 0.6768 confirms that the series is likely to be influenced by long-term trends rather than short-term fluctuations.

From a hedging efficiency and modeling perspective, this non-stationarity suggests that a simple regression model may not be reliable, as it assumes a stable relationship over time. Instead, a more appropriate approach would be to transform the data, such as by taking the first difference of pepper prices to make the series stationary.

Table 5: showing the ADF test statistic for pepper at first difference

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.95787	0.0000
Test critical values:	1% level	-3.436267	
	5% level	-2.864041	
	10% level	-2.568153	

Source: Author's computation using EViews

The Augmented Dickey-Fuller (ADF) test on the first-differenced pepper price series shows that the series has become stationary after differencing. The test statistic of -15.9579 is much lower than all critical values at the 1%, 5%, and 10% significance levels, which means we reject the null hypothesis that the differenced series has a unit root. Additionally, the p-value of 0.0000 confirms strong statistical significance, indicating that the first-differenced series is now stationary.

This result is important because it means that while the original pepper price series was non-stationary, taking its first difference has successfully removed trends and made the data stable for further analysis. Since stationarity is a key requirement for many econometric models, we can now proceed with techniques such as time-series regression, ARIMA modeling, or cointegration tests to explore the relationship between rainfall index and pepper prices more accurately**.**

Stationary Test for Rain Index:

Now, the pepper prices are stationary at first difference, it is important to check the stationarity for rain index for cointegration test.

Table 6: showing the ADF test statistic for rain index

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.781607	0.0001
Test critical values:	1% level	-3.436216	
	5% level	-2.864018	
	10% level	-2.568141	
*MacKinnon (1996) one-sided p-values.			

Source: Author's computation using EViews

The Augmented Dickey-Fuller (ADF) test for the Rain Index indicates that the series is stationary in its original form. The test statistic of -4.7816 is lower than all critical values at the 1%, 5%, and 10% significance levels. This means we reject the null hypothesis that the Rain Index has a unit root. Additionally, the p-value of 0.0001 confirms strong statistical significance, reinforcing that the Rain Index does not exhibit a long-term trend and fluctuates around a stable mean.

This finding is crucial because it implies that the Rain Index and Pepper Prices have different statistical properties—the Rain Index is stationary, while pepper prices were non-stationary but became stationary after differencing. This mismatch suggests that a direct regression between the two variables might not be valid due to potential spurious results. Instead, a more appropriate approach would be to check for cointegration to see if there is a long-term equilibrium relationship between them.

Cointegration Test:

Cointegration test to check if rainfall index and pepper prices have a meaningful long-term relationship

The ARDL (Autoregressive Distributed Lag) model

Unlike traditional regression models, ARDL is flexible in handling mixed orders of integration.

From the Stationarity Tests:

- Pepper prices were non-stationary but became stationary after first-differencing (I(1)).
- The Rain Index was already stationary in levels (I(0)).

Since the two variables have different levels of integration, we used the ARDL model and Bounds Test to check for a long-run relationship. However, the Bounds Test showed no evidence of cointegration, meaning that rainfall anomalies do not have a stable long-term impact on pepper prices. This confirms that hedging pepper prices based on the Rain Index is ineffective, as their movements are not statistically connected in the long run.

Table 7: showing the ARDL test statistic (1,0)

Selected Model: ARDL(1, 0)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PEPPER_AVG_PRICE(-1)	0.984010	0.005588	176.0808	0.0000
RAIN_INDEX	-0.004342	0.014331	-0.302984	0.7620
C	8.541533	2.961666	2.884030	0.0040
R-squared	0.966985	Mean dependent var		528.0669
Adjusted R-squared	0.966924	S.D. dependent var		50.10365
S.E. of regression	9.112283	Akaike info criterion		7.259908
Sum squared resid	89095.16	Schwarz criterion		7.273795

Log likelihood	-3902.830	Hannan-Quinn criter.	7.265167
F-statistic	15713.85	Durbin-Watson stat	1.960661
Prob(F-statistic)	0.000000		
*Note: p-values and any subsequent tests do not account for model selection.			

Source: Author's computation using EViews

The ARDL model results suggest that past pepper prices strongly influence current prices**, as** indicated by the highly significant lagged price coefficient (0.9840, p = 0.0000**)**. This means that pepper prices exhibit strong persistence, where past price movements largely determine future prices. However, the Rain Index has an almost negligible impact on pepper prices**,** with a coefficient of -0.0043 and a high p-value (0.7620), indicating that rainfall anomalies do not significantly influence price fluctuations in the short term. The model explains 96.7% of the variation in pepper prices, but this is mainly due to the autoregressive nature of prices rather than the effect of rainfall.

The Durbin-Watson statistic (1.96) suggests no major autocorrelation issues, confirming that the model is statistically sound. These findings imply that hedging pepper prices based on rainfall anomalies would not be effective, as rainfall does not meaningfully drive price movements. To explore whether rainfall impacts pepper prices in the long run**,** conducting a Bounds Test for cointegration would be the next logical step.

Bounds Tests to Determine the Long Term Relationship:

The Bounds Test for Cointegration is used in ARDL models to check if a long-run relationship exists between variables. It compares the F-statistic from the regression to critical value bounds:

- If the F-statistic is above the upper bound (I(1)), there is evidence of a long-run relationship (cointegration).
- If the F-statistic is below the lower bound (I(0)), there is no cointegration, meaning the variables do not move together in the long run.
- If the F-statistic falls between the bounds, the result is inconclusive

Table 8: showing the ARDL Long Run Form and Bounds Test

Selected Model: ARDL(1, 0)				
Case 2: Restricted Constant and No Trend				
Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.541533	2.961666	2.884030	0.0040
PEPPER_AVG_PRICE(-1)*	-0.015990	0.005588	-2.861250	0.0043
RAIN_INDEX**	-0.004342	0.014331	-0.302984	0.7620
* p-value incompatible with t-Bounds distribution.				
** Variable interpreted as Z = Z(-1) + D(Z).				
Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RAIN_INDEX	-0.271553	0.890414	-0.304974	0.7604
C	534.1858	17.55440	30.43031	0.0000
EC = PEPPER_AVG_PRICE - (-0.2716*RAIN_INDEX + 534.1858)				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)

			Asymptotic: n=1000	
F-statistic	2.776335	10%	3.02	3.51
k	1	5%	3.62	4.16
		2.5%	4.18	4.79
		1%	4.94	5.58
		10%	3.113	3.61
		5%	3.74	4.303
		1%	5.157	5.917

Source: Author's computation using EViews

The results of the ARDL Long-Run Form and Bounds Test reveal that there is no long-run relationship between the Rain Index and pepper prices. In the levels equation, the coefficient of the Rain Index is -0.2716, but it is statistically insignificant with a p-value of 0.7604, indicating that rainfall anomalies do not have a meaningful long-term impact on pepper price levels. The constant term is significant, but this merely reflects the average level of pepper prices without explaining variations due to rainfall.

The Error Correction Term (ECT), represented by the lagged dependent variable coefficient (-0.01599, p = 0.0043), is statistically significant and negative, indicating that there is some adjustment towards equilibrium whenever there is a short-term disturbance. However, the speed of adjustment is very slow (1.59%), which suggests that any deviation from the long-run equilibrium is corrected very gradually over time.

Importantly, the F-Bounds test statistic (2.7763) is lower than the lower bound critical values at the 10%, 5%, and 1% significance levels, both for asymptotic and finite sample sizes. This leads to the conclusion that the null hypothesis of no levels relationship cannot be rejected. In simple terms, there is no evidence of cointegration between rainfall index and pepper prices, meaning rainfall does not influence pepper prices in the long run.

Overall, both the short-run ARDL model and the long-run bounds test results consistently indicate that rainfall variability has neither a significant short-term nor long-term impact on the average price of pepper. This implies that hedging strategies based on rainfall index would not be effective in mitigating price risks in the pepper market.

CONCLUSION

This study examined the hedging efficiency of the rain index on pepper prices, aiming to determine whether rainfall variations could serve as a reliable predictor for price movements. However, the findings indicate no significant relationship between the rain index and pepper price fluctuations. This suggests that factors other than rainfall—such as market demand, supply chain disruptions, policy changes, and global trade dynamics—play a more dominant role in influencing pepper prices.

The results highlight the limitations of using rainfall-based index as a hedging tool for pepper price volatility. While weather conditions may affect crop yields, their impact on market prices is not direct or consistent enough to serve as the basis for an effective hedging instrument. These findings call for further research into alternative risk management strategies that account for a broader range of economic and agronomic variables.

By ruling out the rain index as a viable hedge for pepper prices, this study contributes to a more nuanced understanding of agricultural risk management and emphasizes the need for diversified approaches to price risk mitigation in the pepper trade.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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