Detecting Regime Change in Finance: A Framework with Hidden Markov Model

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by

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Certificate

This is to certify that this dissertation entitled Detecting Regime Change in Finance: A Framework with Hidden Markov Modeltowards the partial fulfilment of the BS-MS dual degree programme at the Indian Institute of Science Education and Research, Pune represents study/work carried out by Pathlavath Anitha at Indian Institute of Science Education and Research under the supervision of Prof. Arnab Kumar Laha, Associate Professor, Departnment of Operations and Decision Sciencess, Indian Institute of Management, Ahmedabad during the academic year 2023-2024.

Arnab Kumar Laha

Prof. Arnab Kumar Laha

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This thesis is dedicated to my supervisor, Prof. Arnab Kumar Laha

Declaration

I hereby declare that the matter embodied in the report entitled Detecting Regime Change in Finance: A Framework with Hidden Markov Model are the results of the work carried out by me at the Departnment of Operations and Decision Sciencess, Indian Institute of Management, Ahmedabad , under the supervision of Prof. Arnab Kumar Laha and the same has not been submitted elsewhere for any other degree.

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Abstract

Regime detection plays a vital role in understanding the dynamic nature of financial markets. This becomes especially crucial during times of political or economic turbulence, where shifts in market sentiment can occur rapidly. In financial markets, the conventional method of summarizing prices involves creating time series data, where transaction prices are sampled at fixed time intervals. This study proposes a novel approach called Directional Change, which sample market prices at peaks and troughs. Unlike conventional methods, DC allows data-driven sampling, capturing price changes as they occur. The study presents novel indicators for extracting valuable information from DC-recorded data, providing a new perspective on analyzing market dynamics and detecting regime changes with the help of Hidden Markov Model.

After identifying regimes,the study extends to other assets, where the regimes are positioned in a 2D indicator space to visualize their relative positions and assess whether regimes from different markets share similar statistical properties. This study presents a new methodology for detecting regime shifts in the markets, offering valuable insights for market analysis and tracking.

Contents

Chapter 1

Introduction

The financial markets are dynamic and complex systems, influenced by a multitude of factors ranging from economic policies and financial events to investor expectations. Regime changes, characterized by shifts in market behavior and structure, present significant challenges and opportunities for investors, regulators, and market participants alike. The implications of regime changes are far-reaching, impacting the performance of trading strategies and the stability of financial markets. Investors often depend on the belief that market patterns will persist, especially when employing trading algorithms that utilize machine learning methods. However, regime changes disrupt these assumptions, necessitating adaptive strategies to navigate shifting market dynamics. (17) demonstrated the effectiveness of regime-based asset allocation in mitigating losses and delivering significant benefits, highlighting the importance of recognizing and responding to regime changes for investors and regulators alike.

The process of gathering financial data presents a unique challenge due to the irregularity of transaction occurrences. Transactions can happen in rapid succession or have significant gaps between them, making it difficult to interpret the raw data. To address this challenge, researchers often turn to time series analysis as a means of summarizing the data. This involves recording key data points at fixed time intervals, such as daily closing prices(10), to create a structured representation of financial activity. However, while time series analysis is a popular method for studying market behavior, it has its limitations. One notable drawback is its reliance on predetermined time intervals, which may result in overlooking important market movements. This issue is particularly relevant in modern markets with high-frequency trading, where transactions occur continuously throughout the day. Traditional time series methods may struggle to capture the intricacies of these dynamic trading environments, potentially compromising the accuracy of market analysis and decision-making processes.

This paper moves beyond traditional time series analysis and adopts a data-driven approach called directional change (DC)(6). Unlike traditional methods, DC focuses on capturing statistical characteristics observed during different price events rather than relying solely on statistical properties found within time series data. In contrast to time series analysis, the DC identifies regime change movements by sampling market prices at extreme points (peaks and trough) as they occur. This approach offers a novel perspective on detecting regime changes in financial markets and provides valuable insights into market dynamics.

The subsequent chapters organised as Chapter 2 presents an overview of current research on regime change and Directional Change concepts. Chapter 3 delves into the detailed discussion of mathematical models. Following that, Chapter 4 focuses on detecting regimes using Indian stock indices. Finally, in Chapter 5, we take a step further by classifying these regimes into "normal" and "abnormal" categories.

Chapter 2

Regime Change Detection: Concepts and Techniques

2.1 Understanding Dynamics of Regime Change

Regime change in financial markets refers to shifts in the prevailing market conditions, dynamics, or governing factors that significantly alter the behavior of assets, trading patterns, and investment strategies. These changes can occur abruptly or gradually and are often characterized by transitions between different economic environments, such as periods of stability, volatility, expansion, or recession. Regime changes can be triggered by various factors, including shifts in monetary policy, economic indicators, geopolitical events, technological advancements, or market sentiment. For investors and traders, recognizing regime changes is crucial for adjusting portfolios, managing risks, and seizing opportunities in evolving market conditions. Strategies that perform well in one regime may underperform or become obsolete in another, emphasizing the importance of adaptability and flexibility in navigating the complexities of financial markets

2.1.1 Regime Change

The term "regime change" in this thesis refers to notable shifts in price behavior within financial markets. It signifies a significant transformation in the collective trading dynamics within a financial market. Upon analysis historical data from global financial markets, it becomes apparent that two main types of market regimes are discernible:A stable regime is recognized by its relatively low volatility and steady economic expansion, indicating a period of consistent growth and market stability. On the other hand, a volatile regime is characterized by economic contractions and heightened market turbulence, suggesting periods of uncertainty and fluctuating economic conditions. It raises the question of what distinguishes these changes from the regular fluctuations seen in such markets?

2.1.2 Factors Influencing Regime Change

Regime change is a complex phenomenon influenced by a multitude of interconnected factors spanning political, economic, social, and cultural domains. Understanding the underlying drivers of regime change is essential for predicting, analyzing, and responding to shifts in governance structures. Several key factors play significant roles in shaping the likelihood and trajectory of regime changeSudden market fluctuations can trigger economic instability, affecting employment rates, consumer confidence, and government policies. In extreme cases, market crashes can lead to widespread panic, exacerbating social inequality and political unrest.

Since the 2008 financial crisis(4), global markets have experienced extended periods where economic conditions and central bank policies strongly influence asset behavior. Shifts in these conditions cause significant changes in how equities, bonds, commodities, and currencies perform. These drastic price movements within asset classes can have far-reaching social and political consequences.(2)Shifts between economic regimes, often triggered by major external events such as the 1973 oil crisis(3) or the collapse of Lehman Brothers in 2008,(9) reflect fluctuations in the economy that accumulate gradually or are influenced by investor expectations. Abrupt changes are inherent to financial data, prompting extensive research into the reasons behind their manifestation in asset prices.

2.1.3 Methods for detecting regime changes

The Markov Switching Model, introduced by Hamilton in 1989, is widely recognized as a prominent nonlinear time series model. Also referred to as the Regime Switching Model, it offers a versatile framework for analyzing data exhibiting diverse behaviors across different regimes or states. Unlike traditional models, this approach acknowledges that the underlying dynamics of the data can vary over time. By accommodating transitions between different structures, the model effectively captures intricate and dynamic patterns inherent in the data. Its ability to switch between these structures enables it to portray the complexities of real-world phenomena more accurately. Through this flexibility, the Markov Switching Model proves invaluable in understanding and forecasting time series data in various fields, offering insights into regime-dependent behaviors and transitions that conventional models often overlook

Regime switching models find popularity in financial modeling due to several factors(2). Firstly, they align with the natural occurrence of regime changes in economies, which can be periodic or triggered by unpredictable events impacting various markets. Hamilton's work illustrated their effectiveness in describing economic cycles.Regime switching models stand out for their ability to capture common features present in financial data, including fat-tailed distributions, autoregressive conditional heteroskedasticity (ARCH) effects, and time-varying correlations..Despite not possessing complete understanding of the underlying model, they provide a valuable estimation for trend analysis. As a result, these models effectively reveal non-linear changes such as regime shifts, making it easier to identify price trends over different time periods. Essentially, regime switching models provide a suitable framework for explaining the distinct patterns seen in financial data.

Though regime-switching models have traditionally been utilized to identify economic regimes, their importance is widely acknowledged. However, these models primarily rely on time series analysis. In contrast, this text introduces an innovative approach called Directional Change(6), a alternative approach for sampling the data points of financial data.

2.2 Directional Change and Its Indicators

The tick data in a market encompasses every individual transaction, capturing a comprehensive record. However, these transactions occur at irregular intervals, which can pose challenges for analysis. To streamline the data and facilitate analysis, many opt to sample it at regular intervals, such as minute-by-minute, hourly, or daily. This structured sampling forms the basis of the time-series data commonly used in research and analysis(18).

In contrast, Directional Change (DC) offers a data-centric approach to exploring and uncovering patterns in financial data. Unlike traditional methods, DC allows for the analysis of financial time series using data-driven techniques, even when dealing with irregular time intervals. This approach empowers us to let the data itself dictate when to sample data points, providing a more flexible and dynamic way to study market behavior

One of the main advantages of the Directional Change (DC) method is its ability to pinpoint the most important movements in the market, while ignoring less significant changes. By setting a precise threshold, DC effectively filters out unnecessary details in price fluctuations. This allows analysts to focus solely on the essential aspects of market behavior, without being distracted by irrelevant information (1).

2.2.1 Why Directional change

1. DC offers a suitable approach for analyzing financial data due to several reasons. Firstly, it effectively handles sampling data at irregular time intervals.

   (6)In the Foreign Exchange (FX) market, transactions occur continuously throughout the day, creating what is known as High-Frequency Data (HFD). Traditional methods of summarizing HFD, such as selecting fixed time intervals like hourly or daily, often overlook significant fluctuations within these intervals, leading to a loss of critical information.

   However, employing an event-driven methodology like DC offers a solution to this challenge. Instead of relying on fixed time intervals, DC samples data points at specific market peaks and troughs based on predefined thresholds . This approach enables researchers to capture important market events and fluctuations effectively, ensuring that no crucial information is lost in the analysis of HFD.

2. DC directly records transactions without requiring any adjustments, in contrast to TS. Each extreme point and DC confirmation point noted in a DC summary represents a transaction within the trading day.

3. In time series analysis, data points usually denote recorded values of a variable at various time intervals. Nevertheless, there are instances when no transactions or observations take place during certain periods. In such scenarios, it becomes imperative to generate data points to ensure the uninterrupted flow of the time series.

4. In time series analysis, each data point serves as an approximation of the nearest transaction times.

5. DC, which captures all the extreme points that might be overlooked by traditional time series (TS) sampling methods. This methodological shift provides researchers with a powerful tool to unearth unique patterns within financial market data, patterns that could otherwise remain hidden when employing traditional time series analysis techniques (14).

2.2.2 Framework of DC

The concept of DC was initially introduced by Guillaume et al(8) as an alternative method for sampling data points, primarily employed to examine stylized facts within FX markets. This approach has also gained traction among traders, known as the Zig Zag indicator (13), who utilize it to eliminate extraneous noise from price fluctuations in financial markets. Both analysts and traders have found utility in applying this method to refine their understanding of market dynamics.

Within the DC framework, price movements are categorized into two events: directional-change (DC) events and overshoot (OS) events. A DC event is triggered by a specific percentage change in price, denoted by the observer-defined threshold value . An upturn is confirmed when the price rises by the threshold from the last low point, while a downturn is confirmed when the price falls by the threshold from the last high point. The price movement from the preceding low or high point to the confirmation point constitutes the DC event. Since different observers may interpret significance differently, they may identify distinct DCs and OSs depending on the observed data, thereby allowing for flexibility in defining

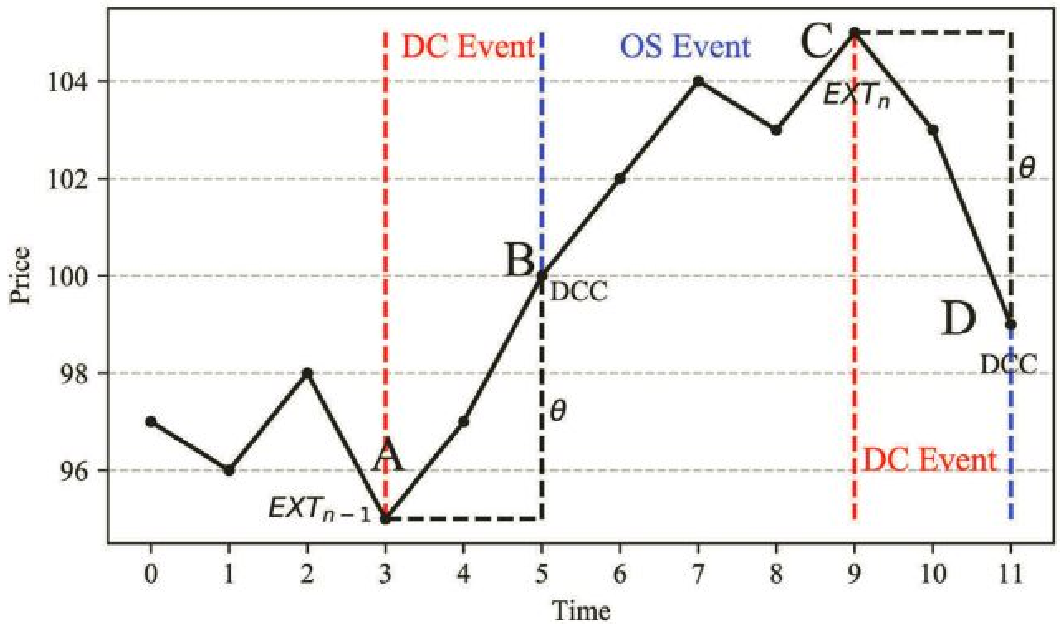

Figure 2.1: Directional change trends

DC events. Typically, a DC event isn't directly succeeded by an opposing DC event, but instead by an overshoot (OS) event. An OS event tracks the price movement between two consecutive DC events. It concludes once the subsequent DC event occur

When there's a price movement from point A to point B that exceeds a specified threshold , it confirms a DC Event. Point A is then identified as an Extreme point (EXT), and Point B becomes the Directional Change Confirmation (DCC) point. Similarly, the subsequent DC Event is acknowledged at point D. The price transition between two DC Events constitutes an OS Event, spanning from point B to C.

figure 4.2 DC Event is determined as:

$$\left| \frac{P_t - P_{EXT}}{P_{EXT}} \right| \geq \theta$$

P_t - Current price.

P_{EXT} - Price at the extreme point.

θ - Threshold.

2.2.3 Indicators

Various approaches exist to assess asset volatility, yet directly observing volatility in a price series remains elusive. Hence, statistical methods are necessary to gauge market dynamics. Tsang et al.(17) introduced a collection of indicators within the DC framework. Unlike the volatility ratio in traditional time series analysis, DC indicators serve as an additional means to glean insights from data. In this section, we outline three DC indicators: TMV, T, and R, which are subsequently utilized to identify regime changes in our study.

Total Price Movements Value (TMV):

This indicator quantifies the absolute percentage of price change within a trend. It assesses the absolute value of price fluctuations in a trend. Typically, it quantifies the overall price movement encompassing both a DC event and an OS event. It's defined as

$$TMV_{\mathrm{EXT}}(n) = \left| \frac{P_{\mathrm{EXT}}(n) - P_{\mathrm{EXT}}(n-1)}{P_{\mathrm{EXT}}(n-1) \times \theta} \right|$$

Here, $P_{\mathrm{EXT}}(n)$ = price at the n^{th} extreme point and

θ = threshold value.

Time:

This indicator measures the amount of the physical time (T) that it takes to complete a TMV trend.

$$T(n) = t_{EXT}(n) - t_{EXT}(n-1)$$

$t_{EXT}(n)$ = time at the n^{th} extreme point.

Return for Directional change:

The Time-Adjusted Return of DC is an indicator that quantifies the absolute return (R) within a latest trend. It is being determined by dividing the absolute TMV by the time interval T. This metric assesses the percentage of price change per unit of time; also, it helps in understanding the volatility over a wider scale. Moreover, it also serves as a mean to analyze how different factors influence the shifts in the market.

$$R(n) = \frac{TMV_{\mathrm{EXT}}(n)}{T(n)} \times \theta$$

Here, $R(n)$ = value of the time-adjusted return of Direcional change at the n^{th} extreme points.

Chapter 3

Mathematical Frameworks: Understanding the model

Within this section, we will introduce two distinct mathematical models: the Hidden Markov Model and the Naive Bayes classifier. These models will be integrated and utilized alongside the DC approach to examine regime changes in this book. Our selection of these models stems from their established maturity and reliability within mathematical modeling. Each model operates on its own set of assumptions. Through our analysis, we have demonstrated that the underlying assumptions of the Hidden Markov Model are substantiated by the data we have tested. While more contemporary mathematical models may offer improved outcomes, we opt for these established models for their proven efficacy.

3.1 Insights into Hidden Markov Models

The theory of Hidden Markov Models (HMM) originated in the 1960s and 1970s and gained widespread application across various domains including engineering, speech recognition, computational biology, and the physical sciences. In economic contexts, HMMs are utilized to analyze two sequences: the hidden market regime sequence and the observable price sequence, which is available to all participants. The goal of employing HMMs in this context is to infer the concealed market regime sequence based on the analysis of the observable price sequence.

Ghysels (12) employed Hidden Markov Models (HMMs) to evaluate the probability of economic recovery across different months. By examining business cycle data, Ghysels identified fluctuating transition probabilities from recession to expansion, notably higher during spring and December. This discovery diverges from conventional linear models, shedding light on previously overlooked seasonal trends within business cycles Kritzman et al (11)utilized the Hidden Markov Model (HMM) for asset allocation by focusing on economic regime variables like market turbulence, inflation, and economic growth instead of directly modeling asset return regimes. They developed regime-dependent investment strategies and tested their performance out-of-sample, demonstrating significant improvement in investment performance through the use of different strategies tailored to disparate economic regimes.

3.1.1 Definition

This model comprises two main components: the hidden states and the observable states.

Hidden States (H): These are the unobservable states hypothesized to exist within the system. Each hidden state is associated with probabilities of emitting observable symbols.

Observable States (O): These are the states or symbols that are directly observed. They are dependent on the hidden states.

State Space

- $S = \{s_1, s_2, \ldots, s_N\}$ denotes the set of hidden states.
- $V = \{v_1, v_2, \ldots, v_M\}$ denotes the set of observable symbols.

Transition Probabilities

Transition probabilities in a Hidden Markov Model (HMM) are denoted as
$a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$.
These represent the probability of transitioning from state s_i to state s_j at time t. The probabilities are encapsulated in the transition matrix $A = [a_{ij}]_{N \times N}$.

Emission Probabilities

Emission probabilities in an HMM are represented as $b_j(k) = P(o_t = v_k | q_t = s_j)$.
They signify the probability of observing symbol v_k given state s_j at time t. These probabilities are captured in the emission matrix $B = [b_j(k)]_{N\times M}$.

Initial State Distribution

The initial state distribution in an HMM is denoted as $\pi_i = P(q_1 = s_i)$,
representing the probability of initiating the system in state s_i. Here, distribution of initial state represented by $\pi = [\pi_1, \pi_2, \ldots, \pi_N]$.

The Markov chain is a stochastic model that depicts a series of events where the probability of each occurrence relies only on the event before it. This model serves as the foundation for the Hidden Markov Model (HMM).

This Markov assumption can be expressed as:

$$P(q_i = a | q_1, \ldots, q_{i-1}) = P(q_i = a | q_{i-1}) \tag{3.1}$$

where q_i represents the state at time i and a denotes a particular state.

3.1.2 Basic form of the Markov chain model

Let us consider a finite Markov Chain with n states, where n is a non negative integer, $\mathrm{n} \geq 2$. Denote by $\mathrm{p_{ij}}$ the transition probability from state $\mathrm{s_i}$ to state $\mathrm{s_j}, \mathrm{i}, \mathrm{j} = 1, 2, \ldots, \mathrm{n}$; then the matrix $\mathbf{A} = [\mathbf{p_{ij}}]$ is called the transition matrix of the Chain. Since the transition from a state to some other state (including itself) is a certain event, we have that $\mathbf{p_{i1}}+\mathbf{p_{i2}}+\ldots\ldots+\mathbf{p_{in}} = \mathbf{1}$, for $\mathrm{i} = 1, 2, \ldots, \mathrm{n}$. The row-matrix $\mathbf{P_k} = \left[\mathbf{p_1}^{(\mathbf{k})}\mathbf{p_2}^{(\mathbf{k})}\ldots\mathbf{p_n}^{(\mathbf{k})}\right]$, known as the probability vector of the Chain, gives the probabilities $p_i{}^{(k)}$ for the chain to be in state i at step k, for $i = 1, 2, \ldots, n$ and $\mathrm{k} = 0, 1, 2, \ldots$. We obviously have again that $\mathbf{p_1}^{(\mathbf{k})}+\mathbf{p_2}^{(\mathbf{k})}+\ldots+\mathbf{p_n}^{(\mathbf{k})} = \mathbf{1}$.

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,j} & \cdots \\ p_{2,1} & p_{2,2} & \cdots & p_{2,j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \ddots \\ p_{i,1} & p_{i,2} & \cdots & p_{i,j} & \cdots \\ \vdots & \vdots & \ddots & \vdots & \ddots \end{pmatrix}$$

Transition matrix

The transition matrix is a matrix that describes the transition probabilities Markov chain to move from one state to another

The probability for going from state i to j is calculated as:

$$\Pr(j \mid i) = P_{i,j}.$$

Definition 1. *A stochastic process $X = \{X_n : n \geq 0\}$ on a countable set S is a Markov Chain if, for any $i, j \in S$ and $n \geq 0$,*

$$\begin{aligned} P\{X_{n+1} = j \mid X_0, \ldots, X_n\} &= P\{X_{n+1} = j \mid X_n\}, \\ P\{X_{n+1} = j \mid X_n = i\} &= p_{ij}. \end{aligned}$$

The p_{ij} is the probability that the Markov chain jumps from state i to state j. These transition probabilities satisfy $\sum_{j \in S} p_{ij} = 1, i \in S$, and the matrix $\mathbf{P} = (p_{ij})$ is the transition matrix of the chain.

16.5 * Two-step and n-step transition probabilities The transition matrix tells everything about the evolution of the Markow chain from its initial state X_0 - If p_{ij} is the probability of transitioaing from state i to state j in abe step, what is the probability of transitioning from i to j in exactly two steps? That is, what is

$$p_{ij}^{(2)} = \mathbb{P}\left(x_{t+2} - j \mid X_t - i\right)?$$

By definitioe this is just

$$\mathbb{P}\left(X_{t+2}=j \mid X_t=i\right)=\frac{\mathbb{P}\left(X_{t+2}-j \& X_{\mathrm{t}}-i\right)}{\mathbb{P}\left(X_t-i\right)}.$$

The intermediate state X_{t+1} must taloe on one of the valoes $k \in S$. So the event

$$\left(X_{t+2}=j \& X_t=i\right)$$

is the disjoint naion

$$\bigcup_{k \in S}\left(X_t=i \& X_{t+1}=k \& X_{t+2}=j\right)$$

Thus we may write

$$\mathbb{P}\left(X_{t+2}=j \mid X_t=i\right)=\frac{\sum_{k \in S} \mathbb{P}\left(X_t-i \& X_{t+1}-k k X_{t+2}-j\right)}{\mathbb{P}\left(X_t=i\right)}.$$

By the multiplication rule (Section 4.8), for sach k,

$$\begin{aligned}\mathbb{P}\left(X_t=i \& X_{t+1}\right. & \left.=k \& X_{t+2}=j\right) \\ & =\mathbb{P}\left(X_t=i\right) \mathbb{P}\left(x_{t+1}=k \mid X_t=i\right) \mathbb{P}\left(x_{t+2}=j \mid x_{t+1}=k \& X_t=i\right).\end{aligned}$$

By the Marloov property

$$\mathbb{P}\left(X_{t+2}=j \mid X_{t+1}=k \& X_t=i\right)=\mathbb{P}\left(X_{t+2}=j \mid X_{t+1}=k\right).$$

Combining $\left(2^2\right)$, (3), and (4) gives

$$p_{ij}^{(2)}=\sum_{k \in S} p_{kx} p_{kj}$$

bat this just the i, j entry of the matrix $\boldsymbol{\varphi}^2$. Similarly, the probability $p_{ij}^{(\mathrm{s})}$ of transitioning from i to j in n steps is the i, j eatry of the matrix $\boldsymbol{P}^n$. That is, calculating the distribution of future states is just an exercise in matrix maltiplication. $\mathbb{P}\left(X_{t+n}=j \mid X_t=i\right)$ is the (i, j) entry of the matrix P^n. This provides a powerful tool for studving the behavioe of a Markwe chain.

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Chapter 4

Detecting Regimes

4.1 Introduction

Financial markets serve as the backbone of the global economy, facilitating the allocation of capital and enabling economic growth.However, these markets are not immune to fluctuations and uncertainties, with volatility being a persistent feature.This volatility is a normal part of market behavior, but it can intensify dramatically during periods of economic or geopolitical stress. In a crisis, investors may see sharp declines in the value of their holdings, and the urgency to sell can outpace the availability of buyers. . Understanding the nature of volatility and its implications is crucial for traders and investors seeking to navigate turbulent market conditions effectively.

Volatility refers to the degree of variation in the price of a financial instrument over time. It is a reflection of market uncertainty and risk, with higher volatility indicating greater price fluctuations. Various factors contribute to volatility in financial markets, including changes in economic indicators, geopolitical tensions, shifts in investor sentiment, and unexpected events such as natural disasters or pandemics.

During crises like the COVID-19 pandemic and the 2008-2009 financial crisis, market behavior undergoes significant shifts, reflecting the uncertainties faced by investors. (19)he COVID-19 pandemic triggered widespread panic and disruption, leading to increased volatility and asset price declines. Similarly, the 2008 financial crisis (7) stemmed from the collapse of the subprime mortgage market, causing a loss of confidence in financial institutions and a credit crunch. Both crises resulted in heightened uncertainty and risk aversion among investors, leading to sharp fluctuations in market sentiment. These crises highlight the importance of effective risk management and crisis preparedness for investors and underscore the significant impact that crises can have on market behavior and global economies.

Studying historical data is crucial for understanding market behavior and mitigating losses during crises. Historical analysis provides valuable insights into past market dynamics, including the patterns of volatility and the response of asset prices to various events. By examining previous crises such as the COVID-19 pandemic, researchers can identify common risk factors and vulnerabilities that contribute to market disruptions. This knowledge allows investors to develop robust risk management strategies and anticipate potential challenges during future crises.

Studies on detecting market regimes predominantly build on the framework of time series analysis which involves sampling data points at fixed intervals.This method allows researchers to examine how market dynamics evolve over time and identify distinct regimes characterized by different patterns of behavior.By observing price movements, trading volumes, and other relevant metrics at regular intervals, analysts can identify distinct market regimes characterized by different patterns of behavior. For example, regimes may differ in terms of volatility levels, trend direction, or trading activity. Time series analysis provides a systematic way to examine historical market data, enabling researchers to uncover underlying patterns and transitions between different market states. Techniques such as regime-switching models or Markov-switching models are commonly used to identify and characterize these regimes based on observed data patterns.

Here, in this chapter , we will be using a new approach called Directional change which is an alternative way of sampling data.In contrast to time series analysis, the DC identifies regime change movements by sampling market prices at extreme points (peaks and trough) as they occur. This approach offers a novel perspective on detecting regime changes in financial markets and provides valuable insights into market dynamics.

4.2 Overview of Methodology

This study focuses on analyzing the financial data to identify and detect market regimes We begin by obtaining historical price data for relevant indexes Instead of traditional fixed-interval sampling, we use the Directional Change (DC) approach to specifically capture data points at significant market peaks and troughs. This method allows for the segmentation of the data into upward and downward trends, providing a structured overview of market movements. For each trend, we calculate the absolute return (R), quantifying the magnitude of the price change and providing a measure of trend strength

Following the quantification of trend strength, the study employs a Hidden Markov Model (HMM) to predict market regimes based on the calculated R values. The HMM is a statistical model that infers underlying states from observed data, in this case, the R values representing trend strengths. By training the HMM on historical data, it can identify and classify different market regimes based on the patterns observed in the R values. These regimes represent distinct states of the market, such as periods of high volatility or stability , we name them here as regime 1(low volatile) and regime2 (high volatile).

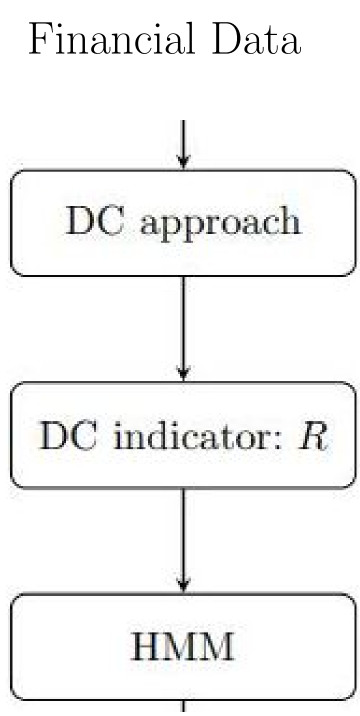


Figure 4.1: methodology

4.3 Data collection

In the data collection phase, historical data from key Indian indices including Nifty 50, Sensex, and Nifty Bank has been gathered. The data spans from January 2018 to December 2023, encompassing a substantial time frame to capture various market conditions, including the impact of the COVID-19 pandemic. Daily closing prices have been specifically collected for analysis, as they provide crucial insights into market performance and trends over time. The selection of this time range is significant as it covers the period before, during, and after the COVID-19 outbreak, allowing for a comprehensive examination of its impact on the financial markets. This data forms the foundation for the study's objective of identifying market regimes with the approach of direction change , facilitating a deeper understanding of market dynamics and behavior amidst significant events such as the COVID-19 pandemic.

4.4 Directional change Trends

In the analysis of uptrends and downtrends, the historical data of daily closing prices from Indian indices, namely Nifty 50, Sensex, and Nifty Bank, serves as the foundational dataset. Unlike traditional time series analysis, which adheres to fixed-interval sampling, the Directional Change (DC) method employed here operates differently. It allows for data sampling at significant market peaks and troughs, facilitating a more dynamic approach to trend identification. This method, devoid of fixed intervals, enables the recording of extreme price points retrospectively whenever a significant price change occurs in the opposite direction of the prevailing trend and reaches a predetermined threshold(6).

This threshold, set at 0.4 percent in this study, serves as a parameter for defining the significance of price changes. Traders have the flexibility to adjust this threshold based on their risk tolerance and trading strategies. The DC method records these extreme price points in a continuous series of uptrends and downtrends, delineated by the identified extreme points.

Figure 4.2 depicts the process of summarizing data into distinct up and down trends. The red line from point A to B indicates a significant price shift surpassing a predefined threshold, marking point A as an extreme point and the start of an uptrend. Similarly, at point C, another notable price drop beyond the threshold identifies it as the next extreme point, marking the end of the uptrend and the start of a downtrend. The interval between points B and C represents an overshoot event. This approach records prices as trends, with each trend marked by extreme points. By capturing both DC and overshoot events, this method provides a clear picture of market dynamics and price shifts.

4.5 Absolute Return

To compute returns for each trend, we rely on two main metrics: TMV (Total Price Movement) and T (Time Taken)(15). Let's illustrate this process using Figure 4.2 as an example.

Imagine the movement from point A to C in the figure, representing an uptrend. TMV calculates the percentage change in price between these extreme points, considering the predefined threshold. This calculation helps us gauge the extent of price change within the trend.

$$TMV_{\text{EXT}}(n) = \left| \frac{P_{\text{EXT}}(n) - P_{\text{EXT}}(n-1)}{P_{\text{EXT}}(n-1) \times \theta} \right|$$

Now, consider the time duration from point A to C in the figure. This duration, represented by T, indicates the total time taken to complete the uptrend.

$$T(n) = t_{EXT}(n) - t_{EXT}(n-1)$$

To derive returns (R(n)), we combine TMV and T. By dividing TMV by T multiplied by the threshold, we arrive at a normalized return measure. This computation factors in both the magnitude of price change and the duration of the trend.

$$R(n) = \frac{TMV_{\text{EXT}}(n)}{T(n)} \times \theta$$

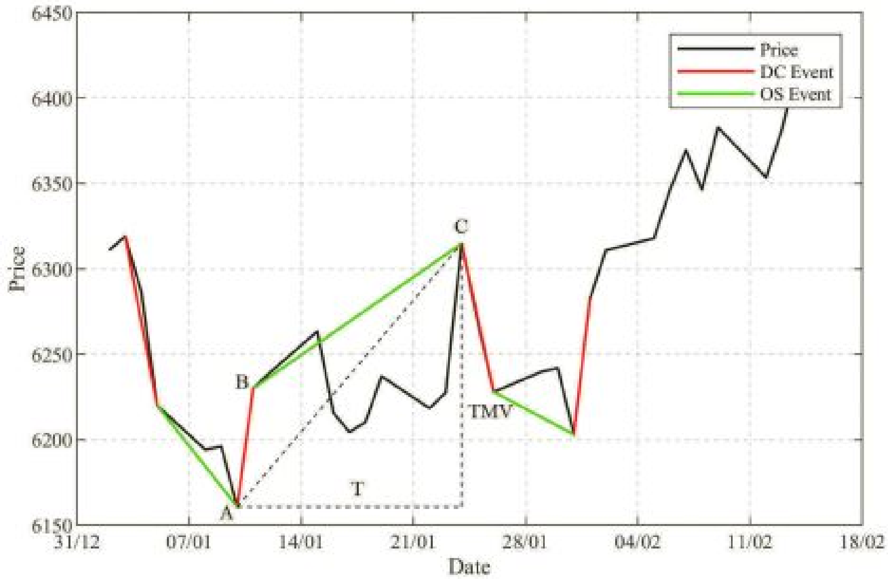


Figure 4.2: DC indicators

4.6 Regimes

Following the computation of R (Return) for each trend, the next step involves taking the absolute value of R. This absolute R value is then utilized to predict regimes with the assistance of a Hidden Markov Model (HMM).

The HMM model employed here is configured with two hidden states: state 0 and state 1, representing regime 1 and regime 2 respectively. These regimes signify low and high volatility environments. By utilizing a two-state HMM, the model aims to capture the transitions between these distinct volatility regimes based on the absolute R values calculated from the DC analysis.

This approach enables the identification and classification of market regimes characterized by varying levels of volatility.

4.7 Results and Discussion

In this sectin, we outline the detected regimes across the Nifty50, Nifty Bank, and Sensex indexes. This analysis provides stakeholders with a thorough understanding of market dynamics over the specified period. Regime 1, associated with low R values and consequent low volatility, signifies periods of stability in the market. Conversely, regime 2, characterized by high R values and increased volatility, indicates turbulent market conditions.

4.7.1 NIFTY 50

In the fig 4.3, initially, the graph exhibits a relatively stable trend, characterized by gradual but consistent growth, reflective of favorable market conditions and investor confidence. However, this stability is disrupted sharply with the onset of the COVID-19 pandemic in 2020, as depicted by a pronounced decline in the index. The graph showcases a steep downward slope during this period, indicative of the abrupt shock to the market caused by pandemic-induced disruptions. Then again it recovers in a few moths back to it stable condition.

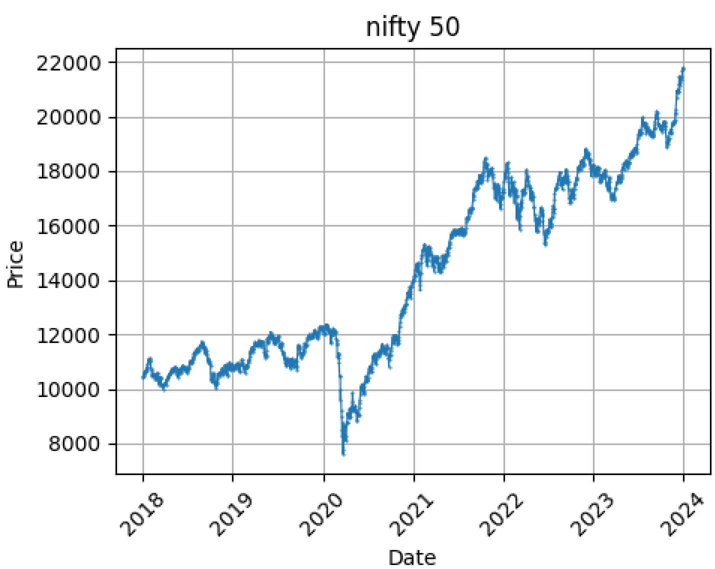


Figure 4.3

Figure 4.4 illustrates the time-adjusted return of R plot, generated based on the DC approach outlined in preceding sections. This plot provides a visual representation of market volatility, where higher returns correspond to increased volatility. Subsequently, these returns are input into the Hidden Markov Model (HMM), resulting in the detection of regime 1 and regime 2, as depicted in Figure 4.5. Our DC approach effectively categorizes price movements into regime 1 and regime 2, representing periods of low and high volatility, respectively.

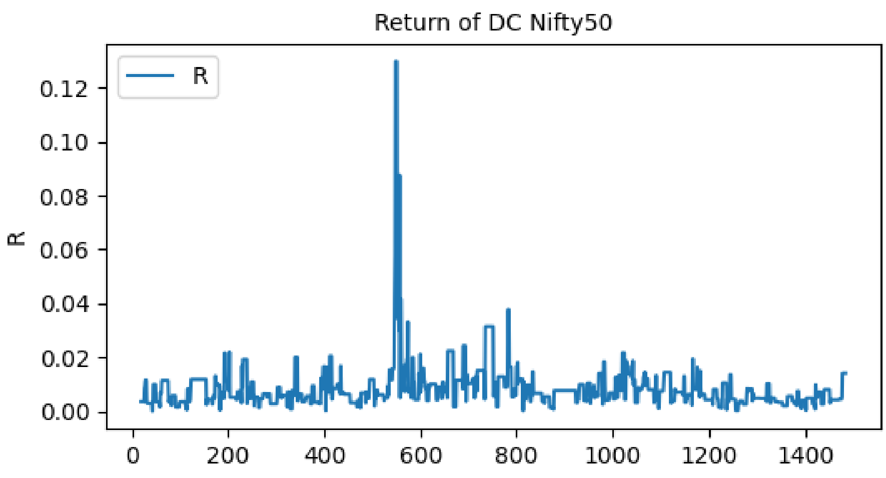


Figure 4.4

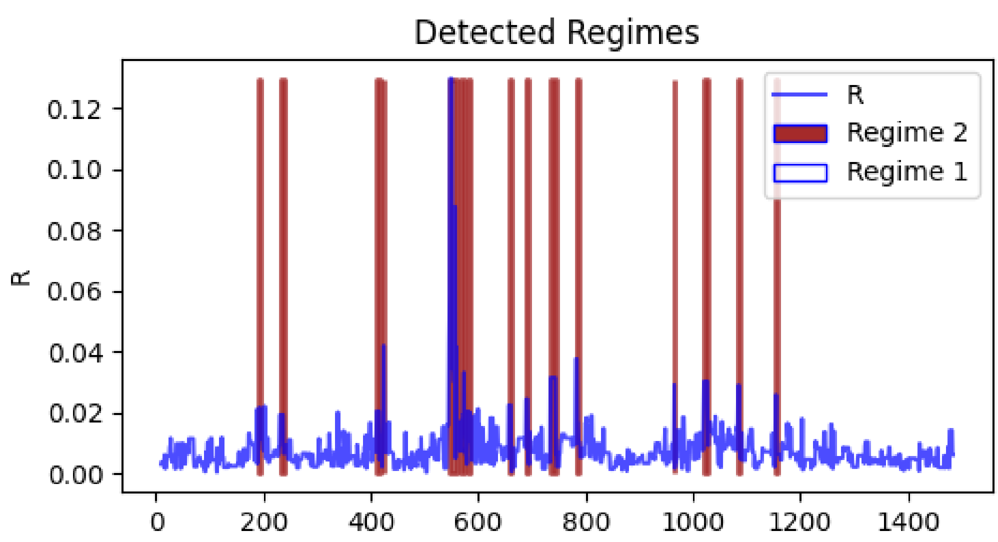


Figure 4.5

4.7.2 NIFTY BANK

In Figure 4.6, we examine the price movements of Nifty Bank over our selected timeframe. Notably, during the COVID-19 pandemic, Nifty Bank experienced significant volatility, characterized by sharp price fluctuations. However, before and after this period, the trends were relatively stable. This underscores the influence of major events, such as the pandemic, on market behavior, with heightened uncertainty leading to increased volatility.

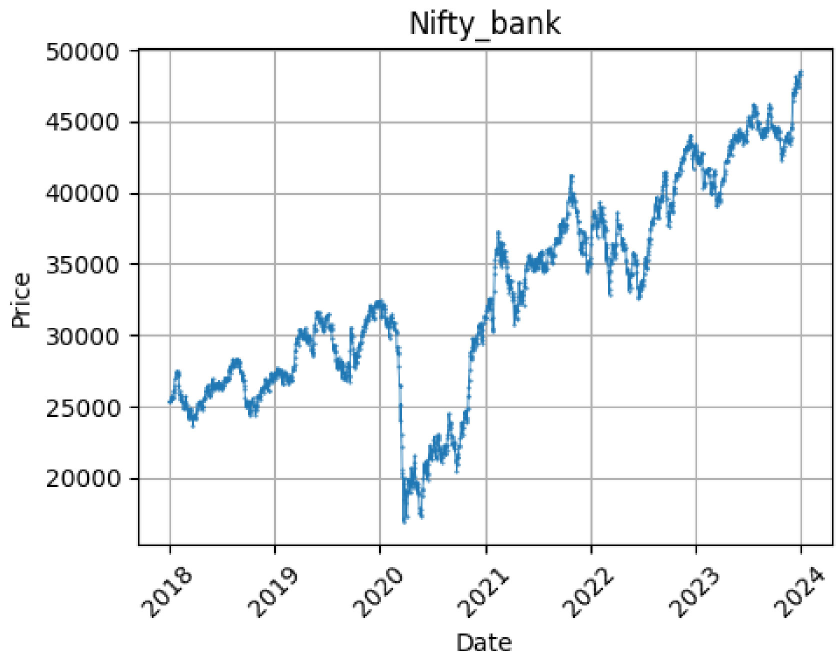


Figure 4.6

Figure 4.7 illustrates the time-adjusted return of R plot, generated based on the DC approach outlined in preceding sections. Subsequently, these returns are input into the Hidden Markov Model (HMM), resulting in the detection of regime 1 and regime 2, as depicted in Figure 4.8. Our DC approach effectively categorizes price movements into regime 1 and regime 2, representing periods of low and high volatility, respectively.

Here, we observe a key characteristic of the detected regimes: within each regime, volatility levels tend to be relatively consistent. Regime 1 periods exhibit lower volatility, while Regime 2 periods are marked by higher volatility. These regime changes often coincide with significant external events. Major disruptions like the COVID-19 pandemic or the Russia-

Ukraine war have the potential to destabilize markets, leading to shifts in investor sentiment and heightened volatility.

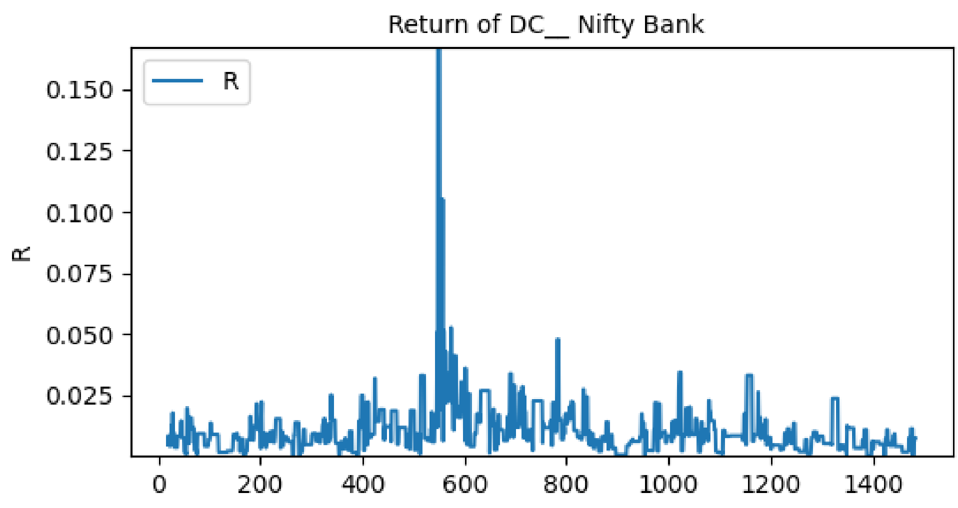


Figure 4.7

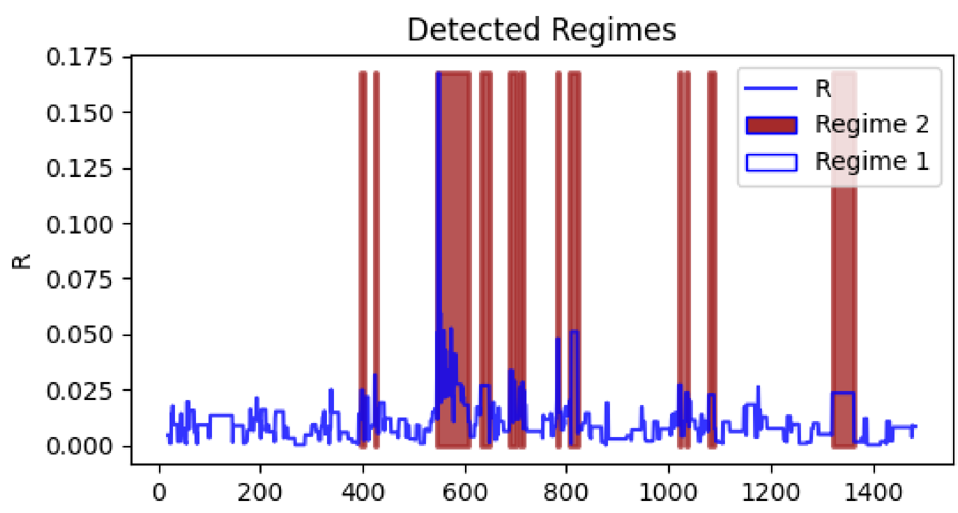


Figure 4.8

4.7.3 SENSEX

Fig 4.9 highlights the impact of the 2020 COVID-19 pandemic on the Sensex index. Just like the Nifty 50 and Bank Nifty, the Sensex experienced a sharp decline during this period of global economic uncertainty. This demonstrates the broad, interconnected nature of market responses to major events.

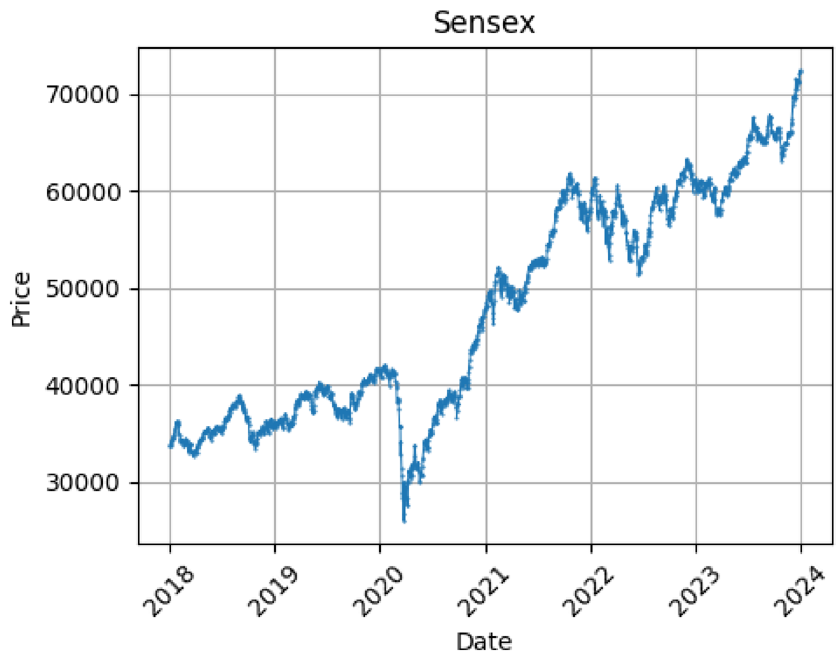


Figure 4.9

The Hidden Markov Model (HMM) analysis depicted in Figure 4.11 unveils a noteworthy similarity across different indices, including the Sensex. The detection of Regime 1, characterized by low volatility, and Regime 2, marked by high volatility, in the Sensex index aligns closely with the regimes observed in other major indices such as Nifty 50 and Bank Nifty. This consistency suggests that similar underlying market dynamics influence these diverse indices.

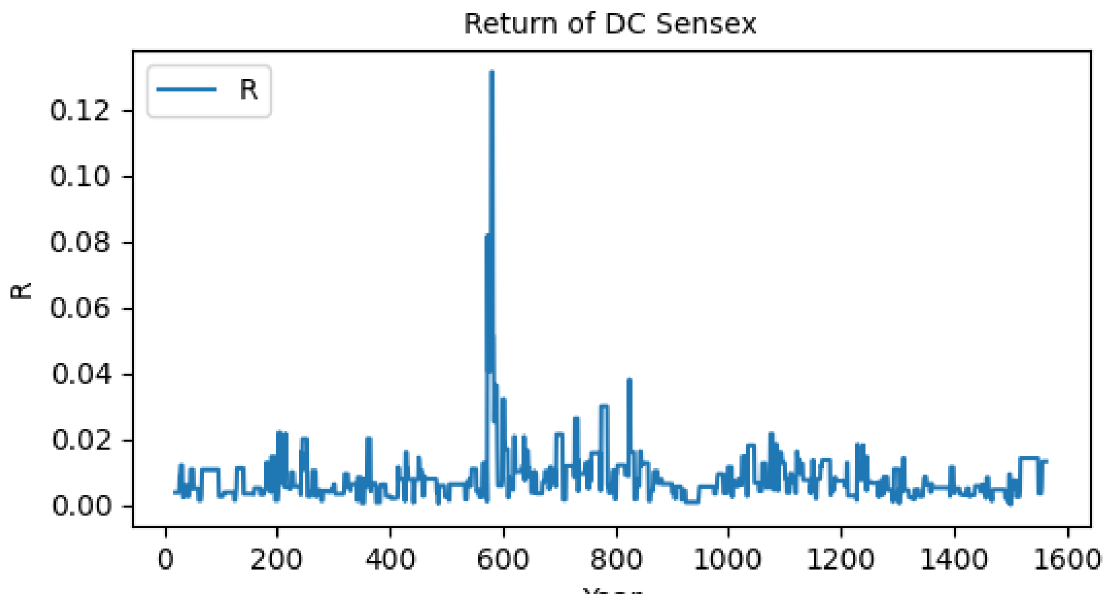


Figure 4.10

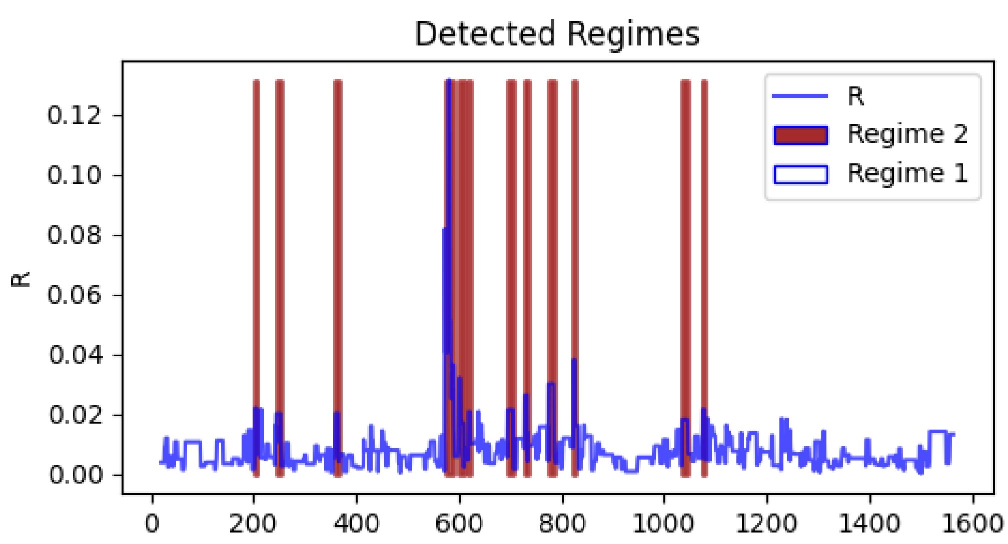


Figure 4.11

4.8 Conclusion

In this chapter, we embarked on a thorough exploration of the methodology behind identifying market regimes using the directional change approach. Our analysis provided a comprehensive examination of market behavior, highlighting the unique characteristics of this method in contrast to traditional approaches. By systematically detecting and recording significant market movements, the directional change approach offers practitioners a robust framework to gain insights into market dynamics accurately.

Setting it apart from conventional methods, the directional change approach ensures a meticulous representation of market fluctuations, enabling practitioners to develop a holistic understanding of market behavior. Throughout our discussion, we underscored the practical implications of employing this method in market analysis, emphasizing its ability to uncover underlying drivers of market regimes and inform investment strategies effectively.

Our study focused on three prominent Indian stock indices—Nifty 50, Bank Nifty, and Sensex—spanning a period from 2018 to 2023. Employing a threshold of 0.4 percentage we meticulously sampled the price data, segregating it into distinct upward and downward trends. This meticulous segmentation facilitated a granular analysis of market dynamics, capturing both minor fluctuations and major shifts in trends effectively.

Subsequently, leveraging the directional change indicator, we quantified the returns for each trend, providing valuable insights into market volatility and trend strength. The calculated returns served as essential inputs for the Hidden Markov Model (HMM), a powerful mathematical tool used for regime classification. By employing a two-state model, we successfully classified the data into two regimes: Regime 1 and Regime 2.

Regime 1, characterized by low returns, indicates periods of relative stability and low volatility in the market. During these phases, market movements tend to be moderate and predictable, with little fluctuation in asset prices. Investors may perceive Regime 1 as a period of calm, where risk levels are lower, and market sentiment is generally positive. This stability provides a favorable environment for strategic investment decisions, as the risk of significant losses is minimized.

On the other hand, Regime 2, characterized by high returns, signifies periods of heightened volatility and uncertainty in the market. During these phases, market movements become more erratic and unpredictable, with sharp fluctuations in asset prices. Investors may perceive Regime 2 as a period of increased risk, where market conditions are more challenging to navigate. Volatility may be driven by various factors, such as economic news, geopolitical events, or changes in investor sentiment. As a result, investors may adopt more cautious investment strategies or seek opportunities to capitalize on market fluctuations.

The classification of market regimes into Regime 1 and Regime 2 offers valuable insights into market behavior and dynamics. By distinguishing between stable and volatile periods, investors can better understand the underlying drivers of market movements and adjust their investment strategies accordingly. For instance, during periods of Regime 1, investors may opt for long-term investment strategies focused on asset preservation and steady growth. In contrast, during periods of Regime 2, investors may adopt more dynamic strategies, such as active trading or hedging, to manage risks and capitalize on market opportunities.

Our application of the directional change method effectively revealed significant changes in market behavior across the Nifty 50, Bank Nifty, and Sensex indices during the COVID-19 pandemic. This finding underscores the susceptibility of stock markets to external shocks, particularly unprecedented events like the pandemic. The observed regime shifts during this period indicated abrupt alterations in market sentiment, marked by heightened volatility and uncertainty among investors.

Chapter 5

Classifications of Regimes

5.1 Intoduction

In the preceding chapter, we explored the process of detecting market regimes through the directional change approach. Building upon this foundation, the focus of this chapter shifts towards the classification of identified regimes. Our primary objective is to classify these regimes into two distinct categories: normal and abnormal regimes (5). This classification will be achieved by mapping them onto a 2D indicator space and evaluating their separability.

Additionally, we will investigate whether normal regimes from different indices or markets exhibit similar properties. This investigation is aimed at gaining deeper insights into market dynamics and identifying any consistent patterns across various market segments.

Expanding on this, our aim is to discern whether normal and abnormal regimes exhibit distinguishable characteristics within the indicator space. Through this analysis, we seek to determine if these regimes display fundamentally different statistical behaviors. Furthermore, we will explore whether normal regimes from diverse markets share common statistical properties. If normal regimes cluster together regardless of their market origin, it could indicate the presence of universal underlying characteristics defining periods of stability. Similarly, our examination will extend to abnormal regimes to uncover any common indicators of market turbulence. Ultimately, our goal is to provide valuable insights into market behavior and enhance decision-making processes for investors.

5.2 Overview of Methodology

First , we use the Directional Change (DC) approach to specifically capture data points at significant market peaks and troughs. This method allows for the segmentation of the data into upward and downward trends, providing a structured overview of market movements. For each trend, we calculate the absolute return (R), quantifying the magnitude of the price change and providing a measure of trend strength Following the quantification of trend strength, the study employs a Hidden Markov Model (HMM) to predict market regimes based on the calculated R values. The HMM is a statistical model that infers underlying states from observed data, in this case, the R values representing trend strengths. By training the HMM on historical data, it can identify and classify different market regimes based on the patterns observed in the R values. These regimes represent distinct states of the market, such as periods of high volatility or stability , we name them here as regime 1(low volatile) and regime2 (high volatile).

Furthermore, the detected regimes are positioned within a 2D indicator space. This visualization allows us to examine the positioning of Regime 1 and Regime 2, potentially revealing clear separation between periods of differing volatility.

5.2.1 2D indicator space

In the Fig 5.1, one can see how 2D indicator space has been plotted. (5)Following the classification of trends into either regime 1 or regime 2, we proceeded to compute the average values of T (time taken) and TMV (total price movement) within each regime. Given the potential variations in T and TMV values across different markets and timeframes, we took steps to normalize these values. This normalization process involved scaling the values relative to the observed data set for each specific market, ensuring fair and accurate comparisons could be made across different contexts. The normalization formula scales data within a range of 0 to 1.

The normalization formula is expressed as:

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5.1}$$

Here, x_{norm} denotes the normalized value of x within the dataset observed for a specific market. The terms $\max(x)$ and $\min(x)$ refer to the maximum and minimum values present in the dataset, respectively.

Subsequently, the normalized average T and TMV values for each regime were plotted onto a two-dimensional indicator space. This graphical representation offers a visual insight into the positions of various market regimes, allowing for a clear understanding of their relative distributions and relationships. For instance, if the positions of regime 1 for the Nifty 50 and Bank Nifty indices closely converge in the indicator space, it indicates shared underlying properties between these regimes. Such insights are invaluable for traders seeking to navigate a diverse range of market conditions effectively.

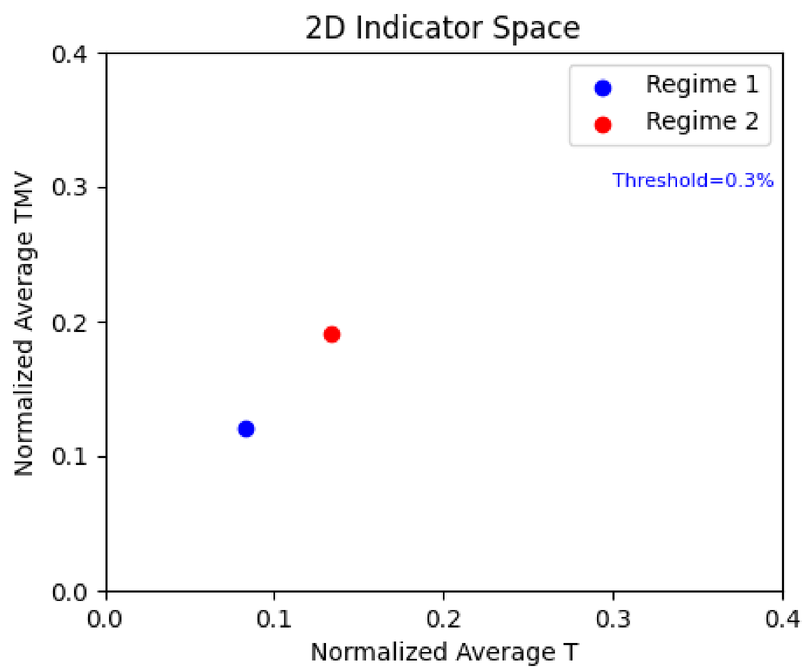


Figure 5.1

5.3 Emperical Study$_1$

In this section, we extend our analysis by visualizing the detected regimes from the previous chapter in a two-dimensional indicator space.

In this stage, we're looking to understand how normal and abnormal regimes are positioned within the two-dimensional indicator space. Also, we're interested in studying where normal regimes from various indices lie in comparison to each other. This will help us identify any commonalities or differences in their behavior. Through this examination, we hope to uncover insights into how markets behave and whether there are any consistent patterns across different market segments.

5.3.1 Detecting Regimes

Recall that in the previous chapter, we examined the market behavior of three major Indian market indices spanning the period from 2018 to 2023, which includes the volatile COVID-19 period. Using the Directional Change method, we effectively segmented the price movement datasets into regime 1 and regime 2. Here we briefly explain the procedure of detecting regimes:

Data sets:

1. Nifty 50
2. Bank Nifty
3. Sensex

Time period 01/01/2018 to 31/12/2023

In our regime detection process, we employ a threshold of $=0.4$ percentage to distinguish between upward and downward trends. For example, during an uptrend, we identify the start of a downtrend when the current price falls below the previous high by the specified threshold(16). Similarly, an uptrend commences when the price rises above the previous low by the same threshold. This method allows us to effectively summarize price movements into distinct upward and downward trends.

Following this, using a directional change indicator, we compute the Return for each trend. These returns serve as essential measures for assessing the strength and direction of market movements.

Subsequently, we input this trend data into a Hidden Markov Model (HMM). The HMM categorizes the price movements into two regimes: regime 1 and regime 2. Regime 1 typically represents normal market conditions characterized by low return values, while regime 2 indicates abnormal conditions with higher return values. This classification provides valuable insights into the underlying dynamics of market behavior, enabling traders to adjust their strategies accordingly.

5.3.2 classifying regimes

In the classification of regimes section, we plotted the detected regimes from three datasets onto a two-dimensional indicator space. This visualization provides a clear illustration of the classification of Regime 1 and Regime 2.The blue dots represent the normal regimes (Regime 1) of the three datasets, while the red points represent Regime 2.

It's essential to note that the x-axis represents the normalized average T (time duration), while the y-axis represents the normalized average TMV (total market value). Essentially, this means that the plot allows us to observe the total price change over different time durations for all the detected regimes. By examining this plot, one can easily discern between normal and abnormal regimes.

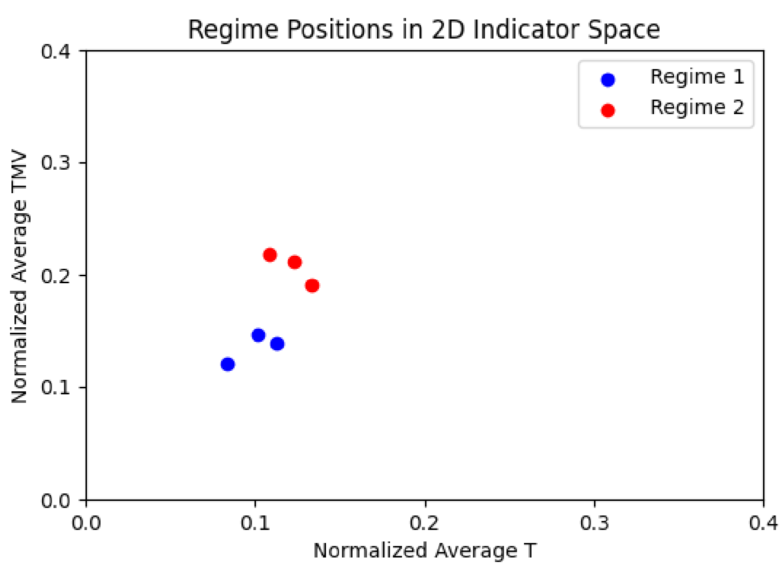


Figure 5.2

From Fig 5.2, it's apparent that normal regimes exhibit distinguishable characteristics from abnormal regimes. Notably, all three indices' Regime 1 positions cluster together, indicating similar behavior across different datasets. Similarly, Regime 2 points also exhibit clustering, suggesting consistent abnormal market behavior across the datasets.

5.3.3 Discussion

1. We have chosen 3 data sets Nifty 50, Nifty Bank, and Sensex, detected regimes for this.

2. Detected regimes were positioned into the 2D indicator space.

3. Here, we can see that ,all the Regime 1 of 3 data sets are separable from Regime 2.

4. And the positions of regimes from different datasets are closer to each other within the indicator space, it indicates that their statistical properties are similar.

This implies that traders can benefit from this information by understanding the transition from normal to abnormal regimes. By recognizing the commonalities in market behavior across various indices, traders can adjust their strategies accordingly to anticipate shifts in market dynamics. This insight enables traders to make informed decisions and adapt their approach based on the observed patterns in regime classification

5.4 Emperical Study$_2$

In this study, we've analyzed four stock indices from two distinct time periods to investigate regime changes using the Hidden Markov Model (HMM). For each index, we've employed 10 different thresholds to detect regime changes, resulting in a total of 10 regimes for each dataset.

These detected regimes, spanning various thresholds, provide insights into how different levels of significant price changes influence market behavior. By plotting all detected regimes onto a 2D indicator space, we aim to visualize their distribution and explore any discernible patterns or correlations.

This approach allows us to examine how regime positioning varies across different thresholds and datasets, providing valuable insights into market dynamics during the specified time periods. Additionally, analyzing regime changes across multiple indices offers a comprehensive understanding of market behavior and its response to significant events.

5.4.1 Data sets

Thresholds: 0.1%, 0.2%, 0.3%, 0.4%, 0.5%, 0.6%, 0.7%, 0.8%, 0.9%, 1.0%

Data set 1:

1. Nifty 50

2. Nifty Bank

Time period : 01/01/2018 to 31/12/2023 , covers covid period

Data set 2:

1.Nifty 50

2.SP500

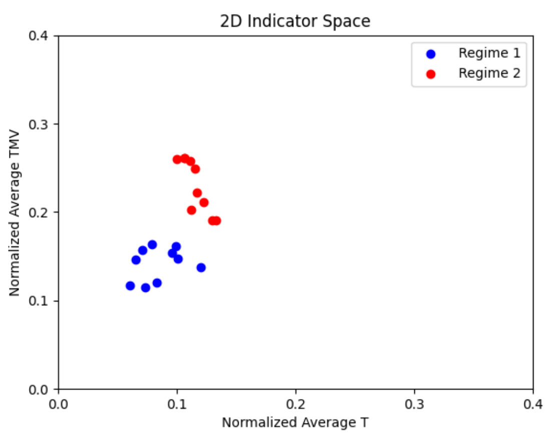
Time period : 01/01/2007 to 31/12/2023 , covers global financial period

5.4.2 Results

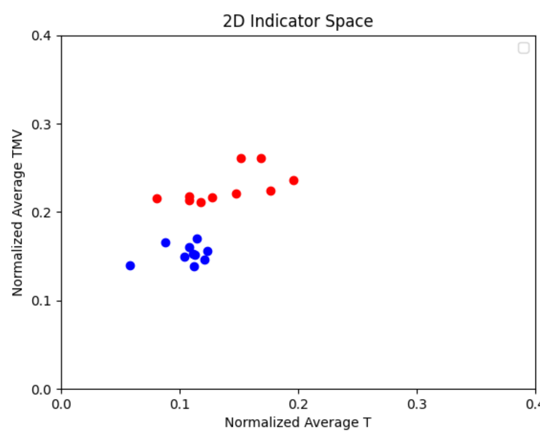
In the Results section, we present the visualization of detected regimes for the Bank Nifty and Nifty50 indices across different thresholds during the period covid. Figure (a) displays the positions of the 10 detected regimes of Bank Nifty, while Figure (b) illustrates the regimes detected with 10 different thresholds for Nifty50.

Subsequently, in Figure (c), we combine the regimes of both indices in one indicator space, showcasing all 20 regimes collectively. A notable observation from these plots is the distinct separation between regime 1 and regime 2. The same has done for Data set results can be seen fig (1,2,3)

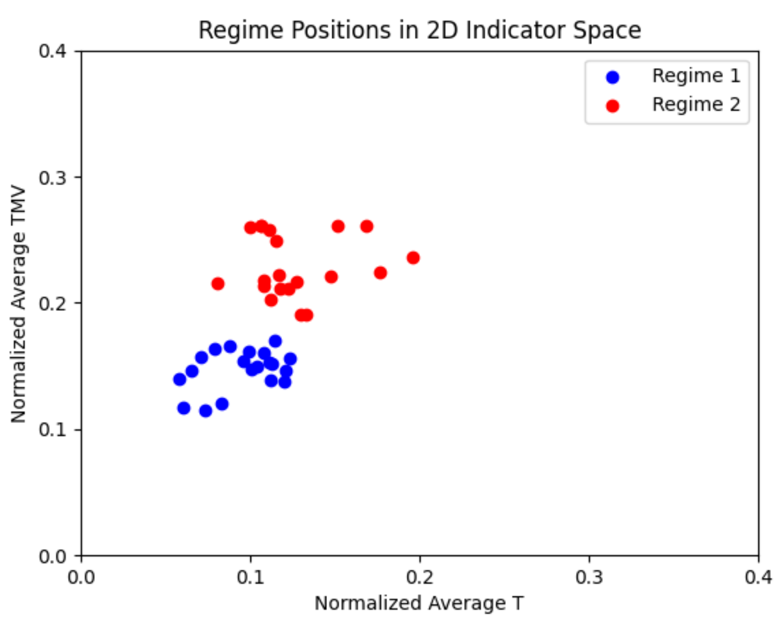
Data set 1 Results:



(a) Bank nifty



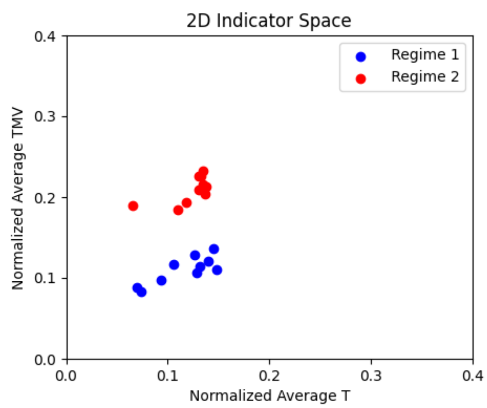
(b) Nifty 50



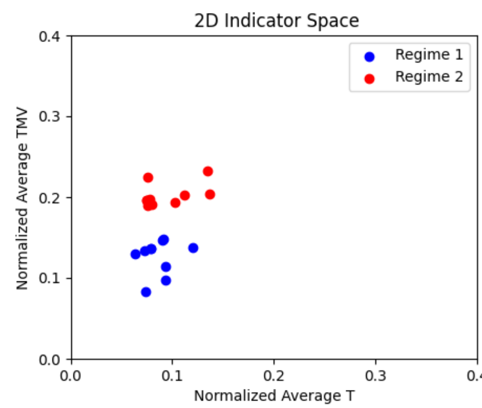
(c) Together

Specifically, in each plot, regime 1 and regime 2 occupy distinct positions within the indicator space, indicating significant differences in their behavior. Furthermore, the proximity of regime 1 positions from both datasets suggests a similarity in their normalized T and TMV values. The same trend is observed for regime 2, highlighting consistent properties across different thresholds and datasets.

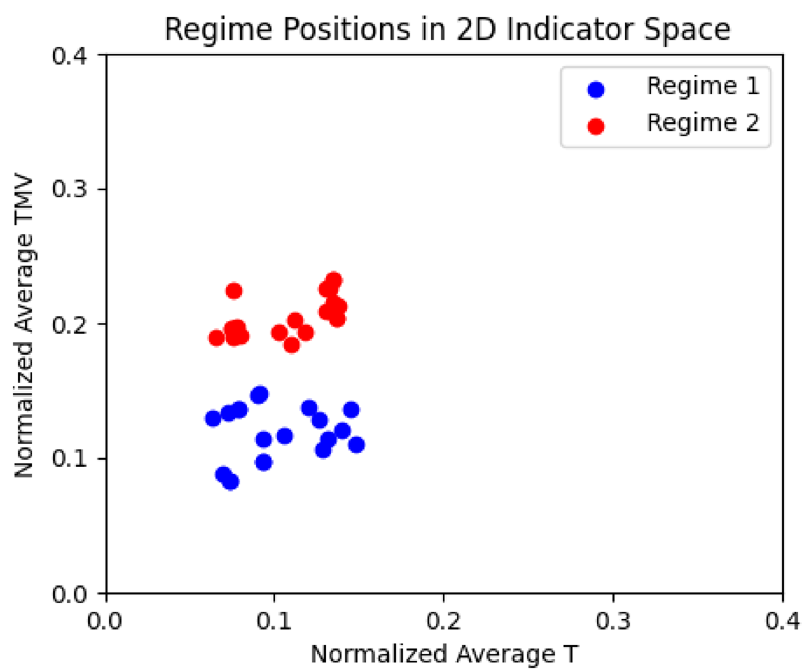
Data set 2 Results:



(a) Nifty 50



(b) SP500



(c) Together

5.4.3 Effect of threshold

our aim is to investigate the impact of varying thresholds on the positions of regimes. We seek to understand whether the positions of regimes are sensitive to the threshold values used in the analysis(6).

Figure 5.5 provides insight into the relationship between threshold values and regime positions. Notably, when employing smaller thresholds like 0.001 and 0.002, we observe a tendency for smaller total price movements (TMV) and shorter time intervals (T). Conversely, as the threshold increases, there is a corresponding rise in the TMV to T ratio, indicating larger price movements captured within the same timeframe.

An important observation emerges when comparing the behavior of regime 1 and regime 2. It becomes evident that regime 2 experiences more significant price changes within the same timeframe compared to regime 1. This indicates that regime 2 exhibits greater volatility, reflecting pronounced market fluctuations.

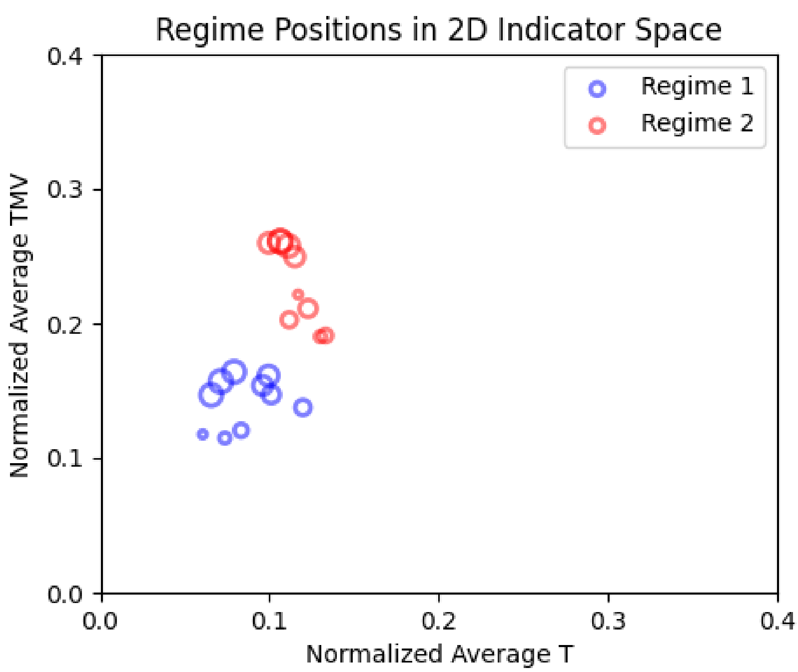


Figure 5.5

Thresholds: 0.1%, 0.2%, 0.3%, 0.4%, 0.5%, 0.6%, 0.7%, 0.8%, 0.9%, 1.0%

It's noteworthy to mention that while the choice of threshold does influence the positions of regimes to some extent, the relative positions of regime 1 and regime 2 remain consistent across different thresholds. Regardless of the threshold used, regime 1 and regime 2 are clearly distinguishable from each other. This implies that the distinctions between the two regimes are robust and independent of the threshold selection process.

5.4.4 Discussion

In this study, we conducted an analysis using two distinct datasets from contrasting time periods: Data 1 covering the COVID-19 period and Data 2 spanning the financial crisis of 2007-2008. Across both datasets, we detected regimes for four major stock indexes using ten different thresholds. Subsequently, we plotted all the detected regimes within a 2-dimensional indicator space to visualize their positions and observe any variations with respect to threshold levels.

Importantly, while the choice of threshold did influence the positions of regimes to some extent, particularly in terms of the magnitude of price changes captured within each regime, the relative positions of Regime 1 and Regime 2 remained consistent across different thresholds. This consistency suggests that the statistical properties of the regimes are robust and independent of the threshold used for detection.

While we noted some influence of threshold choice on regime positions, the relative positions of regime 1 and regime 2 remained consistent across different thresholds.This consistency suggests that the statistical properties of the regimes are robust and independent of the threshold used for detection.

Despite fluctuations in market conditions, we can still clearly distinguish between normal and abnormal market behavior. This emphasizes the robustness and reliability of our regime detection methodology. These insights are valuable for investors and analysts as they navigate through different market environments, offering a deeper understanding of market dynamics and aiding in decision-making processes.

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Chapter 6

Conclusion

The financial markets are dynamic and complex systems, influenced by a multitude of factors ranging from economic policies and financial events to investor expectations. Regime changes, characterized by shifts in market behavior and structure, present significant challenges and opportunities for investors, regulators, and market participants alike. Detecting regime change in financial markets is crucial for investors, regulators, and market stability. Regime shifts, driven by economic policies, major financial events, or shifting investor expectations, can disrupt market dynamics and trading strategies. Recognizing these changes allows investors to adapt strategies, reducing the risk of losses and seizing opportunities. For regulators, detecting regime change is vital for maintaining market stability and averting systemic risks. By identifying shifts in market regimes, regulators can intervene timely to mitigate potential crises

Throughout this thesis, we introduced a novel approach known as Directional Change for detecting these regime shifts within financial markets. Our definition of ”regime change” pertains to notable alterations in price behavior across different time periods and market conditions.

We delved into the traditional methods of regime change detection, particularly in time series analysis, highlighting the distinctions from the directional change approach. We elucidated the fundamental principles of directional change, its operational mechanics, and key indicators crucial for measuring trend returns.

Additionally, we explored two mathematical models, Hidden Markov Models (HMM) and Bayesian classifiers, which play a pivotal role in the detection of regime changes within financial markets. In the subsequent chapters, we applied the Directional Change framework to practically detect regimes in financial markets, focusing on prominent Indian stock indices such as Nifty 50, Bank Nifty, and Sensex during the COVID-19 period. Our analysis successfully identified regime changes, providing valuable insights into market behavior during this volatile period.

Furthermore, we advanced our analysis by classifying these detected regimes into normal and abnormal categories within an indicator space. We observed that regime 1 and regime 2 were clearly distinguishable across all datasets, regardless of the thresholds used. This robust separation underscores the consistent nature of regime classifications and their distinct characteristics.

In conclusion, our study highlights the importance of regime change detection in navigating financial markets effectively. By employing innovative methodologies like Directional Change and leveraging mathematical models, we can better understand market dynamics, adapt strategies, and mitigate risks, ultimately contributing to market stability and informed decision-making for investors and regulators alike.

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