MEASURING EXCHANGE MARKET PRESSURE IN INDIA: A GENERAL APPROACH

Thesis Submitted
in Partial Fulfillment of the Requirements for the

DEGREE OF DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Sanjay Kumar

(Roll No.: 2K/17/Ph.D./HUM/02)

Under the Supervision of

Prof. Nand Kumar

To the Department of Humanities

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi – 110042, India

December, 2024

Acknowledgements

It is with immense pleasure that I express my profound gratitude to my thesis supervisor, Prof. Nand Kumar, from the Department of Humanities at Delhi Technological University, New Delhi. His invaluable guidance, unwavering support, and insightful suggestions have greatly enriched my research. Prof. Kumar's expertise and encouragement have been instrumental in the successful completion of this thesis. I am deeply thankful for his mentorship and the opportunities he provided me throughout this academic journey.

I am equally indebted to the expert panel comprising Prof. Sabri Boubaker, Professor of Finance at EM Normandie Business School, Paris, France, and Prof. Shakti Kumar, Professor of Economics at Jawaharlal Nehru University, New Delhi, for their invaluable feedback and constructive comments. Their critical insights and suggestions have significantly enhanced the quality and depth of this work.

I extend my sincere thanks to the members of the Departmental Research Committee (DRC), as well as all faculty members and research scholars of the Department of Humanities, for their valuable suggestions and encouragement. I am also grateful to my friends and peers for their constant support and motivation throughout this journey.

(Sanjay Kumar)

Dedication

This research is a tribute to my beloved wife, Madhumita, and my son, Ayon, whose unwavering support and boundless inspiration have been the guiding light through the challenges and solitude of this journey. Their love and encouragement have been my strength and solace.

I also dedicate this work to the cherished memory of my late parents, P. Prasad and Vijaya Prasad, whose values, sacrifices, and enduring influence continue to inspire and motivate me to strive for excellence.

This work stands as a testament to their profound impact on my life and my endeavors.

Candidate's Declaration

I, hereby, declare that the thesis work entitled "**Measuring Exchange Market Pressure in India: A General Approach**" is my original work carried out under the supervision of Prof. Nand Kumar . This Thesis has been prepared in conformity with the rules and regulations of Delhi Technological University, New Delhi. The research work presented and reported in the thesis has not been submitted, either in part or full, to any other University or Institute for the award of any other Degree or Diploma.

Sanjay Kumar

Roll No.: 2K/17/Ph.D./HUM/02

Department of Humanities

Delhi Technological University

New Delhi, India – 110042

Department of Humanities

Delhi Technological University

Bawana Road, Delhi – 110042, India

Certificate

This is to certify that the thesis titled "**Measuring Exchange Market Pressure in India: A General Approach**" submitted by Mr. Sanjay Kumar to Delhi Technological University for the award of the degree of Doctor of Philosophy in the Discipline of Economics, Department of Humanities is a record of Bona Fide work carried out by him. Sanjay Kumar has worked under my guidance and supervision, and has fulfilled the requirements for the submission of this thesis, which, to my knowledge, has reached requisite standards. The results contained in this thesis are original and have not been submitted to any other University or Institute for the award of any Degree or Diploma.

Prof. Nand Kumar

Department of Humanities

Delhi Technological University

New Delhi-110042

Department of Humanities

Delhi Technological University

Bawana Road, Delhi – 110042, India

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Title of the Thesis: Measuring Exchange Market Pressure in India: A General Approach

Total Pages: 267

Name of the Scholar: Sanjay Kumar

Supervisor(s):

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Department: Department of Humanities

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Measuring Exchange Market Pressure in India: A General Approach

Sanjay Kumar

ABSTRACT

This research proposes a general and empirical approach to measure Exchange Market Pressure (EMP) in India during 2001Q3 to 2022Q3. Existing models like the Girton-Roper Model impose structural restrictions and make assumptions about currency regimes. The proposed approach identifies components and weights of the EMP index through econometric estimation with minimal constraints. Three new EMP indices are constructed using this general method and compared with the Girton-Roper EMP index. The study estimates determinants affecting EMP through regression analysis and identifies periods of extreme currency stress in India based on the Eichengreen, Rose, and Wyplosz crisis threshold. The findings indicate that India experienced multiple currency crises during 2008-2022, with significant stress periods occurring in 2011Q4 and 2020Q1, aligning with global uncertainty periods. The research contributes a versatile EMP measurement approach applicable across currency regimes and provides insights for policymakers to monitor and manage exchange market pressures effectively.

Keywords: Exchange Market Pressure, Currency Crisis, Empirical Approach, Girton-Roper Model, India, Econometric Estimation, Global Uncertainty.

JEL Classification: C32; C51; C52; E42; E44; E52; E58; F31; F32; F33; F41; F47; G01; G15; G17

List of Publications

S. No.	Paper	Index	Status
1	Sanjay Kumar and Nand Kumar, "Testing Normality in EMP Indices: An Application and Power-Comparison of Tests," **Communications in Statistics - Theory and Methods**, Volume 52, Issue 2 (2023), Taylor and Francis.	SCIE	Published
2	Sanjay Kumar and Nand Kumar, "Long Memory and Forex Market Returns: An Empirical Analysis," **Business Analyst Journal**, Emerald.	Peer Rev.	Accepted
3	Sanjay Kumar and Nand Kumar, "EMP, Govt Debt, US Money Supply, GDP Growth," **International Journal of Maritime Engineering**, Special Issue, 2024.	SCI	Published
4	Sanjay Kumar and Nand Kumar, "Incorporating Asymmetric Volatility and Persistence: An EGARCH-based Extension of the Girton-Roper Model for Measuring Exchange Market Pressure in India," **Macroeconomics and Finance in Emerging Market Economies**, Taylor and Francis (Revise Decision Made).	Scopus	In Review (Second Stage)
5	Sanjay Kumar and Nand Kumar, "A Noble Robust Framework for Identification of Components Weights in the Girton-Roper Exchange Market Pressure Index," **Communications in Statistics - Theory and Methods**, Taylor and Francis.	SCI	Communicated

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List of Acronyms

AUD Australian Dollar

AIC Akaike Information Criteria

AR Autoregressive

ARCH Auto-Regressive Conditional Heteroscedasticity

ARDL Auto-regressive Distributed Lag Models

ARMA Autoregressive Moving Average

ADF Augmented Dicky-Fuller

BEA Bureau of Economic Analysis, USA

BIC Bayesian Information Criterion

BIS Bank of International Settlement

BKW Belsley-Kuh-Welsch

BOJ Bank of Japan

BOP Balance of Payment

BREAKS Least Squares with Breaks

BRL Brazilian Real

CEE Central and Eastern Europe

CAD Canadian Dollar

CHF Swiss Franc

CLT Central Limit Theorem

COINTREG Cointegration Regression

CNY Chinese Yuan

CSO Central Statistical Organisation

C-S Connolly and Michael and Da Silveira

CUSUM Cumulative Sum

CV Coefficient of Variation

DBIE Database on Indian Economy

DEM Deutschmark

DW Durbin- Watson

DWS Durbin-Watson Statistics

EIU Economist Intelligence Unit

EMP Exchange Market Pressure

EMPI Exchange Market Pressure Index

EMPIMER Exchange Market Pressure Index based on Market Exchange Rates

EMPINEER Exchange Market Pressure Index based on Nominal Effective Exchange Rates

EMPIREER Exchange Market Pressure Index based on Real Effective Exchange Rates

EGARCH Exponential General Autoregressive Conditional Heteroskedastic

ERM European Exchange Rate Mechanism

ERW Eichengreen, Rose and Wyplosz

ERWCT Eichengreen, Rose and Wyplosz Crisis Threshold

EVT Extreme Value Theory

FCD Foreign Currency Deposit

FRED Federal Reserve Economic Data

Forex Foreign Exchange

GARCH Generalised Auto-Regressive Conditional Heteroskedasticity

GBP Great Britain Pound

GDP Gross Domestic Product

GLM Generalized Linear Model

GMM Generalized Method of Moments

GREMPI Girton-Roper Exchange Market Pressure Index

HH Household

HT Hausman Test

HQC Hannan-Quinn Criterion

HECKIT Heckman Selection

IFS International Financial Statistics

IMF International Monetary Fund

INR Indian Rupees

ISLM Investment- Savings and Liquidity Preference Money Supply

ITL Italian Lira

IGARCH Integrated Generalised Autoregressive Conditional Heteroskedasticity

JPY Japanese Yen

KFG Krugman, Flood and Garber

IV Instrumental Variable

LERMS Liberalised Exchange Rate Management System

LML Limited Information Maximum Likelihood

LM Langrange Multiplier

LogLik Log-Likelihood

MA Moving Average

MOSPI Ministry of Statistics and Programme Implementation, India

MENA Middle East and North Africa

NBER National Bureau of Economic Research

NEER Nominal Effective Exchange Rate

NLS Non-Linear Least Squares

NPAs Non- Performing Assets

NPISH Non-profit Institutions Serving Households

OECD Organisation for Economic Cooperation and Development

OLS Ordinary Least Squares

PDL Polynomial Distributed Lag

PPP Purchasing Power Parity

QLR Quandt Likelihood Ratio

QREG Quantile Regression

RBI Reserve Bank of India

REER Real Effective Exchange Rate

LogLik Log-Likelihood

SC Schwarz Criterion

SIC Schwarz Information Criterion

SER Standard Error of Regression

SGL Subsidiary General Ledger

SIVT Sargan Instrument Validity Test

SRFs Standardised Report Forms

SRM2R84 Markov Switching Regression with Two Regimes

SRM3R84 Markov Switching Regression with Three Regimes

SRS2R84 Simple Switching Regression with Two Regimes

SRS3R84 Simple Switching Regression with Three Regimes

SSR Sum of Squared Residuals

Std. Dev. Standard Deviation

STEPLS Stepwise Least Squares

ROBUSTLS Robust Least Squares

TGARCH Threshold General Autoregressive Conditional Heteroskedastic

THRESHOLD Threshold Regression

TSLS Two Stage Least Squares

USD US Dollar

USA United States of America

VAR Vector Auto- Regression

VES Venezuelan Bolivar

VIF Variance Inflation Factor

VECM Vector Error Correction Model

WHO World Health Organisation

WON Korean Won

WUI World Uncertainty Index

ZAR South African Rand

Chapter 1

Introduction

In this introduction chapter, we will delve into several key aspects of Exchange Market Pressure (EMP) and its relevance to India's economic landscape. First, we will provide a historical background and simple mathematical foundation of the concept of EMPI, tracing its evolution in economic literature and its growing importance in international finance. We will then discuss the motivation behind this study, highlighting the need for a more flexible and empirically-driven approach to measuring EMP, particularly in the context of emerging economies like India. The chapter will outline the specific challenges in measuring EMP, including the limitations of existing models and the complexities of India's managed float regime. We will present the research questions that this thesis aims to address, focusing on the development of a general approach to EMP measurement and its application to India's foreign exchange market. Furthermore, we will elaborate on the significance of this study, emphasising its potential contributions to both academic literature and policy-making. The chapter will also provide an overview of the data sources and methodological approach employed in this research. Finally, we will outline the structure of the thesis, giving readers a clear road-map of the chapters to follow.

1.1 EMP Index: Historical Context and Mathematical Foundations

EMPI is a summary indicator of pressure on a currency. Poor macroeconomic fundamentals and policies, bank runs, moral hazards, weak corporate balance sheets, contagion, etc., may create financial stress in an economy. During periods

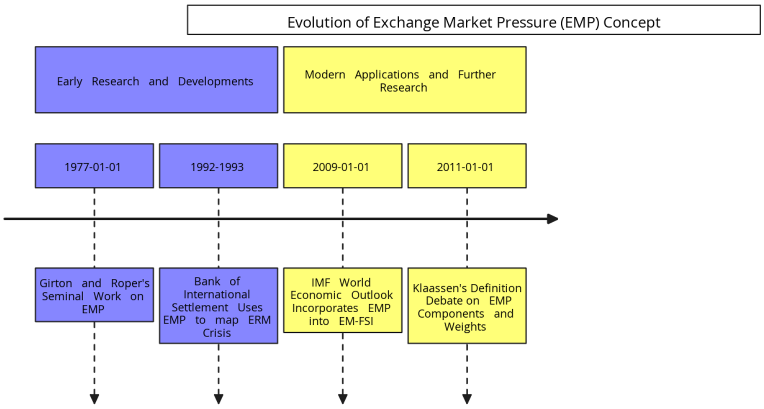

Figure 1.1: Evolution of the Concept of EMP
Source :Author's creation

of financial stress, the pressure on a currency may increase further, aggravated by speculators' strategic action. Extreme pressure on a currency is characterised as a currency crisis.

Documented evidence in financial crisis literature dates back to the early 21st century, while studies specifically on currency stress have a longer history, predating even the latter half of the 20th century. Currency stress has long captivated economists and financial analysts. Significant research on this topic can be traced back well before the latter half of the 20th century. Since 1977, following the seminal work of Girton and Roper (1977b), there have been efforts in the literature to comprehend currency shocks using the EMPI. International financial institutions began adopting the EMPI in the later part of the 20th century.

The Bank of International Settlement used the idea of EMP in the case of the European Exchange Rate Mechanism (ERM) crisis of 1992-1993. The IMF World Economic Outlook (2009) used the EMPI as a component of EM-FSI (Emerging Market Financial Stress Index). The literature on EMP has debated the choice of components and their weights in an EMPI (Klaassen and Jager, 2011). Figure 1.1 gives a synopsis of the evolution of the concept of EMP. Mathematically, EMP index can be shown with the help of the following formula:

$$EMP_t = \Delta s_t + \omega' \Delta a_t \tag{1.1}$$

$$\Delta s_t = EMP_t - \omega' \Delta a_t \tag{1.2}$$

For estimation purposes, we can write the above equation as below:

$$\Delta s_t = \alpha - \omega' \Delta a_t + \epsilon_t \tag{1.3}$$

Here, Δs_t represents the change in the exchange rate of a country (appreciation, rate of appreciation of domestic currency). Δa_t is the set of countermeasures started by a country at time t to control fluctuations in the exchange rate in the case of a managed float.These actions include interventions in the foreign exchange market, adjustments in interest rates, capital controls, or other measures aimed at influencing the exchange rate. In the case of a free float there is no intervention in the forex market, i.e. $EMP_t = \Delta s_t$. ω' is a row vector showing time-constant weights (effectiveness) of these countermeasures. Further details about the equation (1.3) are discussed in section 3.9.

In this thesis, we propose to develop a general method to create a time series of EMP indices for India for the 21st century.

Our method is characterised by its generality as it refrains from imposing any a priori structural model to derive an index of Exchange Market Pressure (EMP). This approach allows us to capture the complexities and nuances of currency market dynamics without predefined assumptions about how these dynamics should behave. By not being tied to specific structural models, our method remains flexible and adaptable to various economic contexts and conditions.

Moreover, the versatility of our method extends to its applicability across different currency regimes. Whether analysing managed float, fixed exchange rate, or free float regimes, our approach can effectively measure EMP by considering the interactions between exchange rate movements and policy interventions. This adaptability is crucial as it recognises the diverse policy frameworks that countries employ to manage their exchange rates.

In practical terms, our method enables a comprehensive assessment of currency market pressures by incorporating data on exchange rate changes and policy actions. This dynamic approach ensures that our EMPI reflects current market conditions accurately, providing valuable insights for policymakers, economists, and financial analysts alike.

By remaining general and versatile, our method not only enhances the understanding of currency stress dynamics but also supports informed decision-making in monetary policy and international finance. It empowers analysts to explore and interpret EMP trends across different economic environments without the constraints imposed by rigid structural assumptions.

1.2 Exchange Market Pressure: A Global Perspective

This section examines EMP patterns across eleven countries from 1993 to 2017, using market exchange rates in accordance with the Girton and Roper (1977b) framework. Figure 1.2 presents EMP indices for Australia, Brazil, Canada, China, India, Japan, South Africa, South Korea, Switzerland, United Kingdom, and Venezuela. This diverse set represents advanced economies, emerging markets, and developing nations, offering a comprehensive global perspective on EMP dynamics.

1.2.1 Key Observations

Analysis of Figure 1.2 reveals:

1. **Diverse EMP Patterns**: Advanced economies (Australia, Canada, Switzerland) exhibit more stable EMP, while emerging markets (Brazil, India, South Africa) show greater volatility. Venezuela displays extreme fluctuations, reflecting unique economic challenges.

2. **Crisis Identification**: Sharp EMP spikes often correspond to known currency stress periods. The 2008 global financial crisis is evident across mul-

tiple countries, particularly the UK, South Korea, and Brazil. Country-specific crises are also visible, such as the 1997 Asian financial crisis affecting South Korea and Brazil's early 2000s economic turmoil.

3. **India's EMP Profile**: India's EMP shows moderate volatility compared to other emerging markets, with notable spikes around 2008 and 2013. These spikes likely correspond to the global financial crisis and the "taper tantrum"[1]. This market exchange rate-based EMP measure provides insights into pressures faced by the Indian rupee during global economic turbulence.

4. **Emerging vs. Developed Economies**: Emerging markets generally exhibit higher EMP volatility and more pronounced spikes than developed economies, reflecting greater susceptibility to internal and external economic shocks.

5. **China's Unique Pattern**: China's EMP profile shows relative stability, punctuated by a significant spike around 2005, likely reflecting its managed exchange rate regime and increased currency flexibility around that time.

6. **Extreme Cases**: Venezuela's EMP pattern is notably extreme, reflecting severe economic challenges including hyperinflation and currency crises, contrasting sharply with more stable patterns in other countries.

These observations underscore EMP dynamics' complexity and the importance of methodological considerations in EMP studies. They also reinforce the relevance of focusing on India, a key emerging economy with distinct EMP characteristics warranting in-depth analysis.

Figure 1.2 illustrates EMP for selected countries based on market exchange rates, reflecting pressures faced by each currency in the open market. The variation in patterns is striking, with emerging markets showing more pronounced fluctuations compared to developed economies.

[1]The term "taper tantrum" refers to the surge in U.S. Treasury yields that occurred in 2013 when the Federal Reserve announced its plan to taper, or gradually reduce, the pace of its bond-buying program. See Krishnamurthy, A., Vissing-Jorgensen, A. (2013). The taper tantrum: Causes and consequences. Brookings Papers on Economic Activity, 2013(1), 45-126.

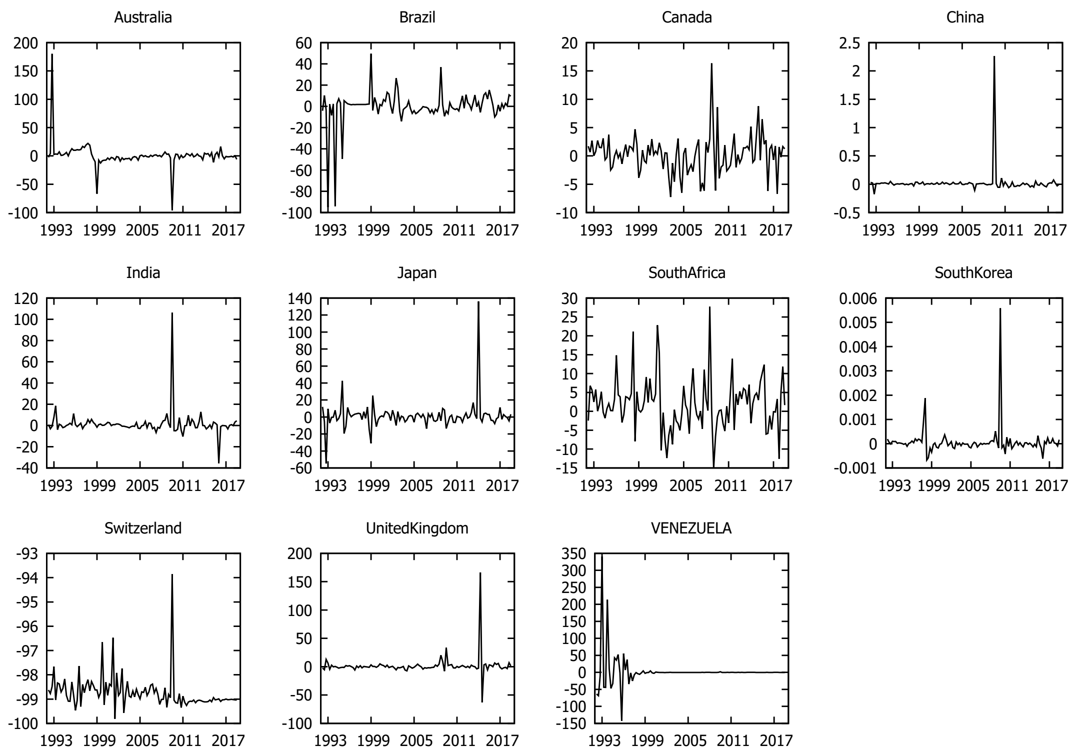

Figure 1.2: EMP Across Selected Countries
Source :Author's creation

This global perspective provides context for the subsequent focus on India. The following chapters will construct an EMPI for India, adhering to the Girton and Roper (1977b) framework. This approach allows for a nuanced understanding of India's EMP dynamics while maintaining theoretical consistency with established literature.

This analysis contributes to understanding currency pressures in emerging economies and informs policy decisions for exchange rate stability. By focusing on India and employing a rigorous methodological approach based on market exchange rates, this study aims to illuminate the complexities of EMP in a crucial emerging market context.

1.3 Importance of an Exchange Market Pressure Index (EMPI)

The EMPI is a crucial concept in international finance, as it captures the overall pressure on a country's currency in the foreign exchange market. Accurately measuring the EMPI is essential for policymakers, as it helps them assess the vulnerability of their currency to speculative attacks and devise appropriate policy responses.

EMPI plays a significant role in monetary policy formulation and economic management, particularly for emerging economies like India. It serves as a vital indicator for policymakers, acting as an early warning system for potential currency crises and allowing for pre-emptive measures. By providing insights into the effectiveness of foreign exchange interventions and monetary policy actions, the EMPI helps in managing exchange rate stability. Moreover, the EMPI sheds light on the economy's vulnerability to external shocks and speculative attacks.

The level of the EMPI can also indicate the degree of monetary policy independence within the context of the "impossible trinity", which posits that it is impossible to have all three of the following at the same time: a fixed exchange rate, free capital movement, and an independent monetary policy(Mundell, 1968) . Additionally, the EMPI assists in understanding pressures on the balance of payments, thereby guiding policy decisions related to trade and capital flows.

For countries adopting inflation targeting regimes, the EMPI is particularly useful in assessing exchange rate pass-through effects on domestic prices. By accurately measuring and analysing the EMPI, policymakers can make more informed decisions about intervention strategies, interest rate policies, and broader macroeconomic management. This underscores the importance of developing robust methods for measuring and analysing the EMPI, especially in the context of emerging markets with evolving exchange rate regimes.

1.4 Motivation and Background

The study of EMP has gained significant attention in international finance, particularly in the context of emerging economies like India. The motivation for this thesis arises from several critical aspects that highlight the need for a more comprehensive and robust approach to measuring and understanding EMP in the Indian context.

Firstly, existing models for calculating EMP, such as the widely used Girton-Roper Model, have certain limitations. These models often impose structural restrictions and make assumptions about currency regimes, which may not always hold in practice for India's managed float system. For instance, the Girton-Roper model assumes that monetary authorities use only foreign exchange reserves to defend their currency, ignoring other policy instruments like interest rates. These limitations underscore the need for a more general and empirical approach that can identify the components and weights of the EMPI with minimal constraints, making it specifically applicable to India's unique economic conditions.

Secondly, there is a notable gap in the literature regarding the availability of a continuous time series of EMP indices for India. Different researchers have focused on various time periods, with the latest available series ending in 2008 (Guru and Sarma, 2013). Given the significant changes in India's economic landscape and its increasing integration with global financial markets, extending the EMPI beyond 2008 is crucial for understanding the recent dynamics of India's foreign exchange market. This extension would provide valuable insights into how India's EMP has evolved in response to various global and domestic shocks, such as the global financial crisis, the taper tantrum, and the recent COVID-19 pandemic.

Thirdly, identifying periods of extreme currency stress or crisis in the Indian economy is of utmost importance for policymakers, investors, and market participants. A robust and reliable EMPI can serve as an early warning indicator, helping stakeholders to assess the vulnerability of the Indian rupee to speculative attacks and take appropriate measures to mitigate risks. By developing a general approach to EMP measurement and comparing it with the widely used Girton-Roper model, this thesis aims to evaluate the effectiveness of alternative methods in capturing exchange market pressure in the Indian context.

Furthermore, the findings of this research can have significant policy implications. By providing a comprehensive analysis of EMP in India using a general approach, this thesis can help policymakers design more effective interventions and strategies for maintaining stability in the foreign exchange market. The insights gained from this study can also contribute to the development of better risk management practices for businesses and investors exposed to currency fluctuations in India.

Moreover, this research can contribute to the broader literature on EMP and its measurement in emerging economies. The proposed general approach, if successful in capturing the nuances of India's EMP dynamics, can potentially serve as a foundation for future research on EMP in other emerging markets with similar economic characteristics.

Thus, the motivation for this thesis stems from the need to address the limitations of existing EMP models, bridge the gap in the literature by extending the EMP index for India, and provide a more comprehensive understanding of currency stress episodes in the Indian context. By developing a general and empirical approach to measuring EMP, specifically tailored to India's economic characteristics, this research aims to contribute to the development of more effective policies and strategies for managing exchange rate risks, ultimately promoting financial stability and economic growth in India.

1.5 Challenges

Conducting a comprehensive study on EMP in India presents several significant challenges that need to be addressed. These challenges arise from the complexities of India's foreign exchange market, the limitations of existing methodologies, and the need for robust and reliable empirical analysis.

One of the primary challenges is the selection of appropriate components and weights for constructing the EMPI. The existing literature offers a wide range of models and approaches, each with its own set of assumptions and limitations (Klaassen, 2011; Patnaik et al., 2017b). Determining the most suitable methodology for India's managed float exchange rate system requires a thorough evaluation and comparison of these models, taking into account their theoretical foundations, empirical performance, and applicability to India's unique economic and institutional setting.

Another critical challenge is the availability and quality of data. Constructing accurate and reliable EMP indices necessitates access to comprehensive and consistent time series data on key variables such as exchange rates, foreign exchange reserves, and interest rates (Guru and Sarma, 2013). The study relies on data from various sources, including the Reserve Bank of India, the International Monetary Fund, and the Federal Reserve Economic Data. Ensuring data integrity, harmonising data from different sources, and accounting for potential structural breaks and regime shifts in the time series are essential for robust empirical analysis. Additionally, determining an appropriate sample size that captures the relevant period of India's exchange rate history while maintaining statistical power is crucial.

Moreover, the dynamic nature of India's exchange rate policy and the ever-changing global economic landscape pose significant challenges for capturing the true extent of exchange market pressure. India has undergone significant changes in its exchange rate management over the years, transitioning from a fixed exchange rate system to a managed float (Kohli, 2003; Patnaik, 2007). Incorporating these policy changes and structural shifts into the EMPI requires the application of advanced econometric techniques, such as regime-switching models and structural break tests, to accurately capture the time-varying nature of EMP.

The development of a general and versatile method for measuring EMP, while advantageous, also presents challenges in terms of its applicability across different currency regimes. The proposed methodology must be robust enough to handle regime shifts and accommodate the unique characteristics of India's managed float system without compromising accuracy or relevance.

Identifying episodes of extreme currency stress or crisis in India is a complex task that requires careful consideration of various factors, such as the magnitude of exchange rate depreciation, the level of foreign exchange reserves, and interest rate differentials (Patnaik et al., 2013). Striking a balance between capturing genuine crisis episodes and avoiding false positives is a crucial challenge in this research. The choice of an appropriate crisis definition and threshold, such as the one proposed by Eichengreen et al. (1996), is essential for accurately identifying periods of heightened EMP in India.

The potential endogeneity between EMP and its components poses econometric challenges in estimating the weights of the EMPI. The bidirectional relationship between exchange rate changes, foreign exchange interventions, and interest rate adjustments can lead to biased and inconsistent estimates if not addressed properly (Tanner, 2001; Bielecki, 2005). Identifying suitable instrumental variables that are correlated with the endogenous regressors but uncorrelated with the error term is crucial for obtaining consistent estimates.

Furthermore, the presence of non-stationarity, volatility clustering, and asymmetric volatility in the time series data can affect the reliability of the empirical analysis. Conducting appropriate unit root tests, such as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, is necessary to ensure the stationarity of the variables (Dickey and Fuller, 1979; Phillips and Perron, 1988). Addressing volatility clustering and asymmetric volatility may require the use of advanced econometric models, such as GARCH and EGARCH, to capture the time-varying nature of volatility and its asymmetric response to positive and negative shocks (Bollerslev, 1986; Nelson, 1991).

Lastly, ensuring the robustness of the empirical findings is crucial for drawing reliable conclusions and policy implications. Conducting sensitivity analyses, such as alternative model specifications, different sample periods, and varying crisis thresholds, can help assess the stability and reliability of the results.

Addressing these challenges demands a multifaceted approach that combines theoretical insights, empirical analysis, and methodological innovation. By carefully navigating these challenges, this study aims to develop a comprehensive and reliable framework for measuring EMP in India, contributing to a deeper understanding of the country's foreign exchange market dynamics and informing policymakers in their efforts to maintain macroeconomic stability.

1.6 Problem Statement

In light of these challenges, this study aims to address the following research questions:

Is it possible to develop a general and purely econometric approach to measuring EMP that is based on minimal structural restrictions and can be applied to all currency regimes?

Can the components and weights of such a universally applicable EMP index be identified specifically for the Indian context?

Is it feasible to construct a comprehensive time series of the EMPI for India based on this general model?

How does the performance of this EMPI compare with that of the widely used Girton-Roper (G-R) model?

Can periods of extreme pressure or currency crisis be accurately identified using this index, and can it be asserted with a high degree of confidence that India experienced currency crises during specific periods, if any?

The primary objective of this research is to propose a novel and general approach to EMPI estimation that effectively identifies the key components of EMP and their respective weights while imposing minimal structural constraints and avoiding any arbitrary assumptions. By generating a comprehensive time series of EMP indices for India from 2001 onwards using the proposed methodology and conducting a rigorous comparison with the Girton-Roper EMP index, this study aims to provide a robust evaluation of the effectiveness of alternative methods in capturing exchange market pressure in the Indian context.

Moreover, by employing advanced econometric techniques and carefully analysing the EMP dynamics, this research seeks to identify instances of extreme currency stress in the Indian economy with a high level of precision. Through a meticulous assessment of the statistical significance of various determinants affecting EMP, this study endeavors to offer valuable insights and actionable recommendations for policymakers and researchers in effectively managing exchange rate risks and maintaining financial stability in India.

1.7 Significance and Contribution of the Study

Measuring EMP and identifying currency crisis episodes in India is of utmost importance for policymakers, investors, and researchers. This study contributes significantly to the existing literature on EMP and has far-reaching implications for managing exchange rate risks and maintaining financial stability in India. The significance of this study can be understood through the following points:

Enhancing the understanding of India's EMP dynamics: This study provides a comprehensive and up-to-date analysis of India's EMP dynamics, covering the period from the early 2000s to the present. By extending the EMP index beyond the existing literature, this research offers valuable insights into how India's foreign exchange market has responded to various global and domestic shocks, such as the global financial crisis, the taper tantrum, and the COVID-19 pandemic. A deeper understanding of India's EMP dynamics is crucial for policymakers to formulate effective strategies for managing exchange rate fluctuations and maintaining macroeconomic stability.

Developing a general and flexible approach to measuring EMP: The proposed general approach to measuring EMP in this study addresses the limitations of existing models, such as the Girton-Roper model, which impose strict assumptions about currency regimes and the behaviour of monetary authorities. By allowing for the data-driven determination of EMP weights and accounting for potential endogeneity issues, the general approach provides a more accurate and reliable measure of EMP. This flexible approach can be easily adapted to other emerging economies, contributing to the broader literature on EMP measurement and currency crisis detection.

Improving the identification of currency crisis episodes: Accurate identification of currency crisis episodes is crucial for understanding the dynamics of foreign exchange markets and economic vulnerabilities. This study employs a range of advanced econometric techniques to detect and date currency crises in India, with a particular focus on improving upon the Girton-Roper (GR) model. By applying and comparing various methodologies, this research aims to develop a more precise and robust framework for identifying currency crisis periods in the Indian context. The study systematically evaluates different approaches to enhance the GR model's performance in detecting currency crisis episodes. These methodologies are applied to historical Indian economic and financial data to identify periods of extreme currency pressure. By comparing the crisis episodes detected through these refined methods with those reported in existing literature, this research contributes to a more accurate chronology of currency crises in India. The findings of this study have significant implications for researchers and policymakers in the fields of international finance and monetary economics, providing a more reliable basis for analysing the causes and consequences of currency crises in emerging markets like India.

Informing policy decisions and risk management strategies: The findings of this study have significant policy implications for India's exchange rate management and financial stability. By providing insights into the effectiveness of various policy interventions, such as foreign exchange interventions and interest rate adjustments, this research can help policymakers to design more targeted and efficient measures to manage exchange rate risks. Moreover, the EMPI derived from the general approach can serve as a valuable tool for early warning systems and risk management strategies, enabling policymakers and investors to take proactive measures to mitigate currency risks.

Contributing to the academic literature on EMP and currency crises: This study makes significant contributions to the academic literature on EMP and currency crises, particularly in the context of emerging economies. By addressing the research gaps in the existing literature and proposing a novel approach to measuring EMP, this thesis opens up new avenues for future research in this area. The findings of this study can serve as a foundation for further investigations into the determinants of EMP, the transmission channels of currency crises, and the effectiveness of policy responses in mitigating the impact of such events.

Hence, this study on measuring EMP and identifying currency crisis episodes in India has significant implications for policymakers, investors, and researchers. By providing a comprehensive and reliable measure of EMP, improving the identification of currency crises, and informing policy decisions, this research contributes to the effective management of exchange rate risks and the promotion of financial stability in India. Moreover, the general approach proposed in this study has the potential to be applied to other emerging economies, contributing to the broader literature on EMP and currency crises.

1.8 Organisation of the Thesis

This thesis is organised into eight chapters, each covering various aspects of EMP and its implications. Below is a brief description of each chapter:

Chapter 1: Introduction

This chapter introduces the concept of the EMPI, highlighting its significance in understanding currency stress. It discusses the origins of the EMP index and its application by international financial agencies. The chapter also outlines the objectives and scope of the thesis, providing an overview of the research methodology and structure of the study. It sets the stage for the detailed analysis presented in the subsequent chapters.

Chapter 2: Literature Review and Research Objectives

This chapter provides a comprehensive review of EMP literature and outlines the study's objectives. It examines key theories and models, including the Girton-Roper Model and theEichengreen, Rose and Wyplosz Crisis Threshold (ERWCT), along with relevant empirical studies. The review identifies gaps in existing research, particularly in the context of emerging economies like India. Based on these gaps, the chapter presents the study's objectives: to develop a general, empirical approach to measure EMP in India, construct and compare various EMP indices, evaluate the Girton-Roper Model's applicability to India, and identify periods of currency crisis. The chapter concludes by highlighting the study's potential contributions to EMP literature and its implications for policy-making.

Chapter 3: Research Methodology and Model Specification

This chapter presents the research methodology and model specifications employed in this study. It begins by providing context through a brief overview of India's historical and current currency regimes. The research design is then outlined, including the approach, sample size determination, and data collection methods. The chapter elaborates on the Girton-Roper Model, detailing its theoretical foundation and econometric form. It then discusses the construction of four different EMP indices, explaining the weight equations used and the components of each index. The strengths and limitations of these indices are critically examined. The methodology for determining currency crisis thresholds based on these indices is also presented. The chapter further describes the econometric techniques employed, including regression analysis, diagnostic tests, and robustness checks used to estimate and validate the EMP indices. Finally, the chapter addresses the challenges encountered during the research process and the strategies used to mitigate these issues. This comprehensive methodology provides the foundation for the empirical analysis and findings presented in subsequent chapters.

Chapter 4: Result and Findings

This chapter presents the results of the ordinary least squares and instrumental variable estimations of the weight equations. It compares the EMP indices derived from the general approach with those based on the G.R. model. The chapter analyses whether India faced any currency crises from 2001 onwards, identifying specific periods of extreme currency stress. The findings are discussed in the context of global economic events and domestic policy changes. The chapter also includes graphical representations and tables to illustrate the results.

Chapter 5: Regression Diagnostics of Weights Equations

This chapter covers the diagnostic tests conducted on the regression models to ensure their validity. It includes tests for normality, stationarity, multicollinearity, autocorrelation, and heteroscedasticity. The chapter discusses the results of these tests and their implications for the reliability of the regression models. It also explains the corrective measures taken to address any issues identified during the diagnostics. The robustness of the EMP indices is evaluated through various sensitivity analyses.

Chapter 6: Robustness Check of Results

This chapter conducts comprehensive robustness tests to validate the empirical findings. It re-evaluates the key results from the Girton-Roper model regression, EMP indices construction, and currency crisis dating using alternative methodologies and specifications. The analysis aims to ensure the reliability and consistency of the findings across different approaches and strengthen their policy implications.

Chapter 7: Conclusion, Limitations, Policy Prescriptions and Future Research

This chapter synthesises the key findings on EMP in India, drawing conclusions about the effectiveness of different EMP indices and the Girton-Roper Model's applicability. It presents evidence-based policy recommendations for managing exchange market pressure and preventing currency crises. The study's limitations are critically examined, including data constraints and methodological challenges. Building on these, the chapter suggests avenues for future research, such as exploring alternative EMP measurement methodologies, conducting comparative studies with other emerging economies, and investigating the impact of global financial conditions on India's EMP. The chapter concludes by highlighting the thesis's contributions to EMP literature and emphasising the need for ongoing research in this dynamic field of international finance

These chapters collectively provide a comprehensive analysis of Exchange Market Pressure, its determinants, and its implications for currency stability in India.

Chapter 2

Literature Review

The foundation of any rigorous research study lies in the comprehensive review of existing literature. This chapter explores the extensive body of work on EMP, focusing on its application in the Indian context. We provide a detailed understanding of the theoretical underpinnings, empirical studies, and methodological approaches that have shaped EMP research. We begin with a historical overview of the EMP index's development, followed by a review of empirical studies applying these models across different countries and time periods. Special attention is given to studies on emerging markets, particularly India. The review identifies significant research gaps and unresolved questions that our study aims to address. Finally, we articulate the specific research questions and objectives guiding our study. This chapter sets the stage for subsequent chapters by laying a solid theoretical and empirical foundation, ensuring our research is grounded in a thorough understanding of the current state of knowledge in EMP.

2.1 Exchange Market Pressure Index

Girton and Roper (1977b) (henceforth G-R) developed a model of EMP based on monetary framework. Using money demand and supply equations and purchasing power parity, the model tries to explain the Canadian managed float during the period 1952-62. This is the first model to give a formula for creating an EMP. index.The model also,inter-alia, gives the determinants of EMP. The key message of this model is that an excess supply of domestic credit puts negative pressure on exchange market forcing currency depreciation or reserve loss or both. EMP index in this model is an equally weighted sum of change in exchange rate (expressed as appreciation) and change in **forex!** (**forex!**) reserve. Following are the sets of equations capturing the essence of the G-R model-

$$M_t = P_t Y_t^{\beta}{}_i e^{-\alpha i_t} \tag{2.1.1}$$

$$M_t^* = P_t^* Y_t^{*\beta *} e^{-\alpha * i_t *} \tag{2.1.2}$$

$$M_t = F_t + D_t = H_t \tag{2.1.3}$$

$$M_t^* = F_t^* + D_t^* = H_t^* \tag{2.1.4}$$

Here 't' denotes that we are dealing with time series data. $H_t =$ Supply of base money issued by central bank of the domestic economy at time t.
$P_t =$ General price level in the economy at time t.
$Y_t =$ Real national income at time t.
$i_t =$ Index rate of interest at time t.
α and β are the parameters of the model.
α =Discount factor/interest rate coefficient >0.
β =Elasticity of base money with respect to real national income >0.
$D_t =$ Base money created by domestic credit expansion at time t.
$F_t = =$ Base money created by purchase of foreign assets at time t = Local currency value of foreign exchange reserve (primary foreign assets) .
$F_t = \int_{-\infty}^{t} E(\tau) R'(\tau) d\tau$
$E_t =$ Value of primary assets of a country i in the currency of that country at time t
$R_t =$ Stock of international reserve at time t in a country.
$R_t' =$ Time derivative of $R(t)$.
$*$ = Indicates foreign country.

Money market equilibrium in the internal as well as external markets implies that changes in money demand and supply are equal. Therefore we take the Ln (denoted by small letters) and the first difference Δ (or equivalently time derivative, as we are dealing with data sequence with equal interval of time) of both sides of the equation 2.1.1 and 2.1.2.

$$\Delta m_t = \Delta d_t + \Delta f_t = \Delta p_t + \beta \Delta y_t - \alpha \Delta i_t = \Delta h \tag{2.1.5}$$

$$\Delta m_t^* = \Delta d_t^* + \Delta f_t^* = \Delta p_t^* + \beta \Delta y_t^* - \alpha \Delta i_t^* = \Delta h^* \tag{2.1.6}$$

In the above equation ($\Delta d_t = \frac{D(t)'}{H_{t-1}}$) (is rate of) change in domestic credit and ($\Delta f_t = \frac{F(t)'}{H_{t-1}} = \frac{E_t R_t'}{H_{t-1}}$) (is the rate of) change in locally held primary foreign assets. $\Delta i_t = \frac{di_t}{dt}$. $\Delta p_t = \frac{dP_t}{dt}$. $\Delta y_t = \frac{dy_t}{dt}$. The two together show rate of change in monetary base ($\Delta h_t = \frac{H_t'}{H_{t-1}}$). Subtracting equation (2.1.5) and (2.1.6) ,we have-

$$\Delta f_t - \Delta f_t^* = -\Delta d_t + \Delta d_t^* + \Delta p_t - \Delta p_t^* + \beta \Delta y_t - \beta^* \Delta y_t^* - \alpha \Delta i_t + \alpha^* \Delta i_t^* \tag{2.1.7}$$

Here, $\alpha = \alpha^*$
$\theta = \Delta p_t - \Delta p_t^* + \Delta s_t$
$\alpha\delta = \alpha \Delta i_t - \alpha^* \Delta i_t^* =$ change in uncovered interest rate differentials
Equation (2.1.7) can be re-written as

$$\Delta f_t - \Delta f_t^* + \Delta s_t = -\Delta d_t + \Delta d_t^* + \beta \Delta y_t - \beta^* \Delta y_t^* + \theta - \alpha\delta \tag{2.1.8}$$

If two countries have a fixed exchange rate regime and there is no intervention, the left side of the equation will be the bilateral real balance of payment and $\Delta s_t = 0$. If there is no intervention at all, the left side will be the rate of change in bilateral exchange rate and $\Delta f_t = -\Delta f_t^* = 0$. If the monetary authorities of the two countries intervene without committing to a fixed exchange rate, we have the composite variable $\Delta f_t + \Delta s_t =$ Exchange Market Pressure. And

$$\Delta f_t + \Delta s_t = -\Delta d_t + \Delta h_t^* + \beta \Delta y_t - \beta^* \Delta y_t^* + \theta - \alpha\delta \tag{2.1.9}$$

For empirical estimation this equation is to be expressed in stochastic form. We have,

$$\delta = \delta(\Delta d_t, \Delta h_t^*, X), \theta = \theta(\Delta d_t, \Delta h_t^*, X)$$
$$\delta_1 = \partial\delta/\partial\Delta d_t, \leq 0$$
$$\delta_2 = \partial\delta/\partial\Delta h_t^*, \geq 0 \tag{2.1.10}$$
$$\theta_1 = \partial\theta/\partial\Delta d_t, \geq 0$$
$$\theta_2 = \partial\theta/\partial\Delta h_t^*, \leq 0$$

Assuming that expression in equation 2.1.1.10 are linear , they can be substituted in the equation 2.1.1.9 -

$$\Delta f_t + \Delta s_t = -(1 + \alpha\delta_1 - \theta_1)\Delta d_t + (1 - \alpha\delta_2 - \theta_2)\Delta h_t^* + \beta\Delta y_t - \beta^*\Delta y_t^* + (\theta_x - \alpha\delta_x)x$$
$$\Delta s_t + \Delta f_t = -\phi\Delta d_t + \phi^*\Delta h_t^* + \beta\Delta y_t - \beta^*\Delta y_t^* + (\theta_X - \alpha\delta_X)X \tag{2.1.11}$$

Where, $\phi_i = (1 + \alpha\delta_1 - \theta_1)$
$\phi_j = (1 - \alpha\delta_2 - \theta_2)$
The form of the equation to be estimated is -

$$\Delta s_t + \Delta f_t = -\phi\Delta d_t + \phi^*\Delta h_t^* + \beta\Delta y_t - \beta^*\Delta y_t^* + \nu \tag{2.1.12}$$

Where, $(\theta_X - \alpha\delta_X)X = \nu$

X is the set of other variables which influence δ and θ. The set of X variables includes variables other than Δd_t and Δh_t^* that might affect δ and θ. We have the GR equation for exchange market pressure as below-

$$\Delta s_t + \Delta f_t = -\phi\Delta d_t + \phi^*\Delta h_t + \beta\Delta y_t - \beta^*\Delta y_t^* + \nu \tag{2.1.13}$$

Roper and Turnovsky (1980b) improved on the G-R model and presented a model of exchange market pressure in the Investment- Savings and Liquidity Preference Money Supply (ISLM) framework. Their model also assigns different weights to the two components of the exchange market pressure. Following are the basic equations of the model

$$Y_t = b_1Y_t - b_2i_t - b_3s_t + \mu_{1t} \tag{2.1.14}$$

$$M_t = a_1 Y_t - a_2 i_t + \mu_{2t} \tag{2.1.15}$$

$$i_t = i_t^* - E\Delta s_t \tag{2.1.16}$$

$$E\Delta s_t = \Theta(\bar{S} - S_t), 0 \leq \Theta \leq 1 \tag{2.1.17}$$

Here, Y_t= Current domestic real Gross Domestic Product (GDP).

$\bar{S}$ = Long run equilibrium exchange rate.

s_t= current nominal exchange rate (indirect quote). Measured in logarithmic

Δs_t= Rate of appreciation of domestic currency

i_t = Domestic interest rate.

i_t^* = Foreign interest rate

$i_t^* = \bar{i} + \nu_t$ M_t= Log of base money in domestic country.

$E\Delta s_t$ = Expected rate of appreciation of domestic currency over period (t+1,t) perceived at time t. $\mu_{1t}, \mu_{2t}, \nu_t$= Stochastic error terms.

Using above equations Roper and Turnovsky (1980b) give an equation for trade-off between change in **forex!** reserve (a component of m_t) and change in exchange rate.This equation, the authors name as the EMP. schedule. A positive intercept depicts positive EMP and a negative intercept depicts negative EMP. Zero intercept means zero EMP. The coefficient of Δs_t is negative which means that the monetary authority will have to sell **forex!** to maintain equilibrium if Δs_t falls that is the currency depreciates that will lead to decrease in its monetary base m_t

$$\Delta m_t = -[\frac{a_1(b_3 + b_2\theta)}{1 - b_1} + a_2\theta]\Delta s_t + \frac{a_1(u_{1t} - b_2\nu_t)}{1 - b_1} + u_{2t} - a_2\nu_t \tag{2.1.18}$$

We have-

$\Delta m_t = M_t - \bar{M}$, $\Delta s_t = s_t - \bar{S}$, $\Delta y_t = Y_t - \bar{Y}$

Weymark (1995b) gives the following model of Exchange Market Pressure-

$$EMP_t = \Delta s_t + \eta \Delta f_t \tag{2.1.19}$$

This formula for EMP. has been derived under the assumption that the central bank does not use domestic credit changes to influence EMP. Here,

$$\eta = \frac{-1}{a_2 + b_2} < 0$$

Here, a_2 = Elasticity of domestic price to nominal exchange rate.
b_2 = Elasticity of real money demand to rate of interest.
By using this model Weymark (1995b) has created central bank intervention index. Under managed float the central bank tries to control exchange rate fluctuations by buying or selling foreign exchange. Thus entire EMP. does not manifest as depreciation as a part is reflected in the changes in the level of foreign exchange reserve. Dividing both the sides of the equation (2.1.19) by EMP we have

$$1 = \frac{\Delta s_t}{EMP} + \frac{\eta \Delta f_t}{EMP}$$

Weymark defines her intervention index (ω) as below-

$$\omega = \frac{\eta \Delta f_t}{EMP} = \frac{\Delta f_t}{\frac{1}{\eta}[\Delta s_t + \Delta f_t]} \tag{2.1.20}$$

The intervention index takes the value between $-\infty < \omega < \infty$
The above three models ignore another component of the Exchange Market Pressure that is rate of interest. The Central Bank tries to release exchange rate pressure not only by selling foreign exchange but also by tampering with policy rate of interest. Pentecost et al. (2001b) try to capture this aspect of Exchange Market Pressure by their short term wealth augmented monetary model of foreign exchange market. Following is the final equation of this model -

$$EMP_t = \hat{e} + \beta(\Delta i_{mt} - \Delta i^*_{mt}) - \hat{r} = (\hat{d} - \hat{m}^*) + (1 - \alpha\phi)\hat{q} + (\alpha\lambda + \gamma - \delta)(\Delta i - \Delta i^*_t) - \varphi(\hat{\omega} - \hat{\omega}^*)$$

$$- \varphi(\Delta w_t - \Delta w^*_t) \tag{2.1.21}$$

Here,

$\hat{e}$ = Change in nominal exchange rate.

β = Rate of change of real money demand with respect to nominal short term interest rate.

i_{mt} = Nominal short term domestic interest rate on money balances.

i^*_{mt} = Nominal short term international interest rate on money balances.

$\hat{r}$ = Change in domestic **forex!** reserve as fraction of base money.

$\hat{d}$ = Change in domestic credit (D) as fraction of base money

$\hat{m}^*$ = Change in international money supply

α = Income elasticity of real money demand.

ϕ = Denotes the impact effect of a depreciation of the real exchange rate on the level of output.

q_t = Change in real exchange rate at time t .

λ = Rate of change in output with respect to relative interest rate differentials between domestic and foreign country.

γ = Rate of change in real money demand with respect to yield of domestic currency bonds.

δ = Rate of change in real money demand with respect to yield of foreign currency bonds.

i_t = Nominal yield on domestic currency bond.

i^*_t = Nominal yield on foreign currency bond.

φ = The wealth elasticity of money balances.

ω_t = Log of domestic non- bank private sector wealth.

ω^*_t = Log of foreign non- bank private sector wealth.

(all small letters except "i" show log of that variable and show first difference (change). Sine time frame is the same for all the variables hence Δ followed by a small letter shows the rate of change of that variable)

2.1.1 Recent Theoretical Extensions of EMP Models

Building on the foundational work of Girton and Roper (1977a), Roper and Turnovsky (1980a), Weymark (1995a), and Pentecost et al. (2001a), several theoretical advances have emerged that extend and refine EMP measurement frameworks.

A significant methodological advancement comes from Klaassen and Jager (2016), who propose a model-free measurement framework for EMP. Their approach minimizes structural assumptions while maintaining theoretical consistency, bridging the gap between strictly structural models and purely statistical approaches.

Patnaik et al. (2017a) develop a theoretical framework specifically designed for cross-country analysis. Their model addresses the challenges of comparing EMP across different exchange rate regimes and institutional settings, particularly valuable for studying emerging markets. Li and Heinz (2018) contribute by integrating capital flows into EMP measurement theory. Their framework expands our understanding of exchange market dynamics by explicitly modeling how international capital movements influence exchange market pressure. Goldberg and Krogstrup (2019) develop a comprehensive framework that combines capital flows with traditional EMP measures. Their approach introduces a new "capital flow pressures" metric that accounts for varying degrees of financial openness across countries, providing a more nuanced understanding of exchange market pressure in contemporary financial markets.

Du et al. (2020) establish a theoretical link between monetary policy credibility and exchange market pressure. By incorporating sovereign debt dynamics into their framework, they show how the credibility of monetary policy affects a country's vulnerability to exchange market pressure. Their model demonstrates that countries with lower monetary policy credibility face higher exchange market pressure during periods of global financial stress.

Chen and Rebucci (2021), propose a high-frequency EMP measurement framework capturing intraday market pressures.

A recent study by Suh (2023) introduced a novel Exchange Market Pressure (EMP) index that incorporates capital-flow management (CFM) measures, providing a more comprehensive approach to capturing hidden pressures in foreign exchange markets. This enhanced index demonstrated stronger predictive signals during currency crises, particularly in emerging markets such as South Korea and Malaysia. The findings emphasize the critical role of CFMs in managing exchange rate pressures and improving the robustness of EMP metrics.

2.1.2 Model Independent Approach of Eichengreen,Rose, and Wyplosz: Currency Crisis

Eichengreen et al. (1996), (henceforth ERW) take a statistical approach to EMP. They do not use any mathematical model rather their EMP. is a simple weighted average of the change in three components of EMP. of the country 'i' with respect to the reference country which is Germany.

$$EMP_{it} \equiv [(\alpha\%\Delta e_{it}) + (\beta\Delta(i_{it} - i_{G,t})) - \gamma(\%\Delta r_{it} - \%\Delta r_{G,t})) \tag{2.1.22}$$

Here
e_{it} = Price of a DM in 'i's country currency at time t.
i_{it} = Interest rate of country i at time t.
$i_{G,t}$ = Interest rate in Germany at time t.
r_{it} = Forex reserves (expressed as ratio of base money) of country i at time t .
$r_{G,t}$ = **forex!** reserves (expressed as ratio of base money) of Germany at time t.
Δ denotes first difference.
α, γ, β = Weights. Component of the EMP. index are weighted, by inverse of respective variances, to equalise their volatalities so that no one component dominates the index. [1] The extreme value of this index is defined as currency crisis as below -

$$\begin{aligned} Crisis_{it} &= 1, if EMP_{it} > 1.5\sigma_{EMP} + \mu_{EMP} \\ &= 0, Otherwise. \end{aligned} \tag{2.1.23}$$

ERW use their measure to study currency crisis and contagion. They use the

[1]For a discussion on choice of weights see Klaassen (2011)

quarterly panel data of 20 Organisation for Economic Cooperation and Development (OECD) countries for the period 1959-93.Their central finding is that a speculative attack elsewhere in the world increases the odds of attack on a domestic currency by eight percent (ibid p. 482).

According to Kaminsky et al. (1998b) currency crisis occurs when EMP. index moves three standard deviations (3σ) higher than its mean value. Using certain multiples of standard deviations to define a currency crisis will work only when the EMP. indices are normally distributed.

In practice,however, in the case of speculative attacks EMP does not tend to follow a normal distribution[2]. Empirical studies on the statistical distribution of EMP indices and their components have consistently shown that EMP indices generally do not follow a normal distribution (Pozo and Amuedo-Dorantes, 2003);(Pontines and Siregar, 2008). Kumar and Kumar (2023) have put the EMP. indices of eleven countries to normality check and have found that they are not normally distributed. Thus, use of standard deviation based thresholds would be inappropriate to identify currency crisis events. Extreme Value Theory (EVT) is used to identify crisis events in such cases[3]. There is another practical problem attached with the use of the ERW approach. For a country with fixed exchange rate the value of the denominator(which is variance) will be zero hence the ERW measure will show infinite EMP for countries which follow a currency peg. For example in a country like China where exchange rate has been historically inflexible this problem may arise (Patnaik et al., 2017b). This approach, however, is simple to apply, and the World Economic Outlook authored by Balakrishnan et al. (2009) uses the crisis threshold proposed by ERW to define currency crises.

[2]For a discussion of normality in case of speculative financial series see Fama (1965)

[3]For a discussion of EVT see, Pozo and Amuedo-Dorantes (2003); Siregar et al. (2004); Pontines and Siregar (2008); Jacobs (2007);Cumperayot and Kouwenberg (2013)

2.2 Exchange Market Pressure:Empirical Studies

G-R empirically estimated the following model:

$$EMP_c = -\beta_1 d_c + \beta_2 h_u + \beta_3 y_c - \beta_4 y_u \tag{2.2.1}$$

Here suffixes c and u refer to Canada and USA respectively. G-R estimated this model for the Canadian economy for the period 1952-74. All coefficients of the model were found to be significant. The estimated coefficients also had appropriate signs, validating the G-R model of EMP. A simplified version of the model was devised for Brazil by Connolly and Da Silveira (1979). The Connolly and Michael and Da Silveira (C-S) model retained the partial equilibrium approach of the G-R model but disregarded foreign variables (except foreign inflation rate) by making a small country assumption Mathur (1999). The mathematical form of the C-S model is as follows:

$$EMP = -\beta_1 d_b + \beta_2 \pi_u + \beta_3 y_b \tag{2.2.2}$$

Here suffixes b and u stand for Brazil and USA respectively. C-S estimated this model for Brazil for the period 1955-75 and for a sub-period of 1962-1975. On empirical estimation, it was found that, for both periods, all the coefficients had signs as per the G-R hypothesis; however, all three coefficients were significant only for the sub-period 1962-75. For the entire period, the coefficients of price and income were not significant. On the basis of the F test, for both periods, the monetary model was not rejected at the 1 percent level of significance. Following Sargen et al. (1975), they ran another regression using only the rate of change in nominal exchange rate as a component of EMP. They found that in this case, the results were poorer for the entire period and dramatically worse for the period 1962-75 when there were fewer exchange restrictions. On the basis of these results, C-S concluded that the monetary model of exchange market pressure performs fairly well for the 1955-75 period and very well for the 1962-

75 period in explaining movements of reserves and exchange rates. The subpar performance prior to 1961 was attributed to stricter exchange rate restrictions in Brazil, and the fact that purchasing power parity did not hold up well in the period before 1962. The monetary model, which is based on several assumptions including purchasing power parity, was tested by the authors. They concluded that it holds up particularly well after 1961.

Modeste et al. (1981) estimated the C-S model for the economy of Argentina over the period 1972-78. His findings were similar to those of G-R for Canada and C-S for Brazil. Estimated coefficients had correct signs and were close to their hypothesised values of minus one for d and plus one for p and y[4]. The estimated coefficients of d and y were significant at the 5 percent level of significance. However, the estimated coefficient of p was not significant. Based on the F test, the author found that not all the coefficients are simultaneously equal to zero, i.e., all the independent variables together had a significant effect on the dependent variable.

In the case of time series data, the relationship between variables may undergo a structural change. That is, the values of the estimated parameters may not remain constant for the entire period of analysis. This structural change may occur due to factors which are exogenous to the model. In the face of structural change, a model may become unfit for analysis and prediction purposes. On the basis of quarterly data, Hodgson and Schneck (1981) tested the stability of the EMP model for seven advanced countries. The sample period is from 1959-II to 1976-I for six of the countries, namely Canada, France, West Germany, Belgium, Netherlands and Switzerland. For the United Kingdom, the sample period is 1964-II to 1976-I, due to data availability issues. The authors found that during disruptions and rearrangements of world money markets, the stability of EMP models may suffer. For example, during the period from the mid-1960s through the early 1970s, there were important events like the oil crisis and the collapse of Bretton Woods[5]. During these periods, the empirical models showed

[4]There are strong and weak versions of the G-R model in the literature. In the strong version, the coefficients of the independent variables are hypothesised as one; in the weak version, there is no specific value for the coefficients. See Hodgson and Schneck (1981) for discussion

[5]For evolution of the global financial system, see Allen (2004)

instability. The equations for France, Germany, and Belgium began to show instability around 1965 or 1966. The disruption appeared to have continued into 1974 for Belgium and France, and into 1971 for Germany. The equations for the United Kingdom began to show instability around 1969. This continued for only one quarter for the Netherlands (1969-III) and until 1975 for the U.K. Switzerland's equation was unstable only during the period from 1962-II to 1962-III. Canada's equation was stable for the whole sample period.

Hodgson and Schneck (1981) used the following model for their stability analysis:

$$\begin{aligned} EMP_t = \alpha + \beta_1 \Delta s_{t+1} + \beta_2 \Delta y_t + \beta_3 \Delta p_t + \beta_4 \Delta a_t + \beta_5 \Delta d_t \\ + \beta_6 \Delta y_t^* + \beta_7 \Delta p_t^* + \beta_8 \Delta a_t^* + \beta_9 \Delta d_t^* + \beta_{10} \Delta f_t^* + \nu_t \end{aligned} \tag{2.2.3}$$

All the variables in this model have the same meaning as in all the previous equations. A new variable, denoted as a, is introduced in this model, which represents the deposit expansion multiplier. The world variables are weighted averages of the corresponding variables for individual countries. Kim (1985) used a modified form of the C-S approach to the G-R model to study the Korean economy for the period 1980-83. The following is Kim's model:

$$EMP_t = -\beta_1 \Delta d_t + \beta_2 \Delta p_t^* + \beta_3 \Delta y_t - \beta_4 \Delta mm_t \tag{2.2.4}$$

In this context, the new variable mm represents the money multiplier. The regression results strongly support the monetary model of EMP. All estimated coefficients have the correct sign and significantly differ from zero, as indicated by high t-values. The only exception is the foreign price variable, which has a low t-value. There is a strong relationship between EMP and domestic credit.

Ghartey (2002) empirically tested the G-R model for the Jamaican economy using quarterly data from the period 1962-II to 1997-IV. The model was estimated using Ordinary Least Squares (OLS). All reported results are consistent with the theory and other empirical studies. However, results are poor if only the percentage change in forex reserves (Δf_t) is used as a component of EMP. In this case, the coefficient of y is positive but insignificant.

In addition to the aforementioned studies, there are studies by Wohar and Burkett (1989) for Costa Rica, Thornton (1995) for Costa Rica, Mah (1991) for Korea, Bahmani-Oskooee and Bernstein (1999) for Canada, France, Germany, Italy, UK, US and Japan. Burdekin (1989) conducted studies for Canada and USA, Wohar and Lee (1992) for Japan, and Taslim (2003) for Australia. The G-R model was first adapted to Indian conditions by H.K.Pradhan and Kulkarni. They used quarterly data from 1976-85 to validate the G-R Model for India. They concluded that an increase in money supply puts pressure on the exchange market.

Although the G-R model, its C-S version, and some other versions of the monetary approach to EMP have performed well in empirical tests, they have some limitations. These models are partial equilibrium models and do not incorporate the role of expectations. Furthermore, all their empirical studies are based either on annual or quarterly data. Using monthly data might have been more appropriate for capturing the EMP and its determinants Mathur (1999).

Hallwood and Marsh (2004) incorporated expectation as an independent variable in the G-R equation and estimated the model for the economy of the United Kingdom during the interwar period from 1925-31. The following is the empirical model used by the authors for estimation:

$$\mathrm{EMP}t = \alpha - \beta_1 d_t + \beta_2 d_t^* - \beta_3(\Delta y_t - \Delta y_t^*) - \beta_4 \Delta q_t - \beta_5 E\Delta Ext + 1 - \beta_6 E\Delta(c_t) + \nu_t \tag{2.2.5}$$

In this equation, $E\Delta Ex_t$ is the expected movement of nominal exchange rate within the band and $E\Delta(c_t)$ is the expected movement of the central parity. Following is the relationship between exchange rate and central parity and the band around it as specified in Svensson (1993):

$$s_t = x_t + c_t$$

$$i_t = i_t^* + \delta_t$$

Based on the above two equations:

$$(i_t - i_t^*) - (x_t' - x_t)/d_t \leq E_t[dc_t]/dt \leq (i_t - i_t^*) - (x_t' - x_t)$$

The term $(i_t - i_t^*)$ (uncovered interest rate parity) has been substituted for $E_t[ds_t]/dt$. This model establishes that expectations also play an important role in exchange market pressure.

Mathur (1999) presented a modified version of the G-R model to incorporate expectation as an independent variable. Following is the modified model:

$$\text{EMP} = \beta_1 \Delta d_t + \beta_2 \Delta m_t^* + \beta_3 \Delta y_t + \beta_4 \Delta y_t^* + \alpha e_{it}^e + \nu_t \tag{2.2.6}$$

Here e_{it}^e = Change in expected rate of appreciation of currency. For expectation formation, the author uses the following equation:

$$ex_t = ex_{t-1} + \xi_t$$

Here, ex = Exchange rate. e = Percentage change in exchange rate. e^e = Expected percentage change in exchange rate. She conducted an empirical estimation of both the original G-R model and the modified G-R model (M-G-R) for India, using monthly data from December 1986 to July 1998. She found that the performance of the G-R model was not satisfactory. To account for potential structural changes that may have occurred in July 1991 due to the balance of payment crisis, when the Indian Rupees (INR) was substantially devalued, and the introduction of Liberalised Exchange Rate Management System (LERMS) in March 1992, she retested the G-R model. She divided the entire period into two sub-periods: December 1986 to June 1991 and March 1992 to July 1998. However, even in this case, the performance of the G-R model did not improve. The estimation results of the M-G-R model were a significant improvement over those of the G-R model. All coefficients in the M-G-R model were found to be significant, and the adjusted R^2 indicated a good fit. The coefficient of αe_{it}^e was found to be negative, which was contrary to the model's prediction. The author suggested that the poor performance of the model on empirical tests might be due to its partial equilibrium approach to EMP, which relates αe_{it}^{e} only to the money market and not to other sectors like balance of payments. The IMF (World Economic Outlook 2009) used the G-R index to gauge currency crises. The study created EMP indices for 26 emerging economies using data from 1997-2008. It concluded that the EMP index, as per the G-R model, effectively captures episodes of currency crises.

In all the theoretical models discussed above, we have a set of simultaneous equations. These equations are reduced to a single final equation of EMP through mathematical manipulation. This final equation demonstrates instantaneous and one-way causality between the dependent and independent variables. Granger (1969) suggests that data-wise causality may be bilateral and may come with lags. This is especially true when using longer time-frame data, such as quarterly data, instead of monthly data. He discusses various types of causality, including feedback causality (bilateral causality), instantaneous causality, and causality with lag. He suggests a test to empirically examine the question of causality, which is well-known in literature as the Granger causality test.[6]

In a more general approach to causality, Sims (1980) questions the genesis of the "a priori" restrictions on which various macroeconomic models are based. He suggests that it is feasible to estimate multivariate dynamic macro models in an autoregressive format without any restriction other than that on lag length. His approach to macroeconomic modelling, known as the Vector Auto- Regression (VAR) approach, is widely recognised.

Khawaja and Din (2007) used the Granger causality test for Pakistan. The data span of this study is from April 1991 to December 2005. They aimed to determine whether the authorities in Pakistan use the interest rate or domestic credit to manage the level of exchange market pressure. The Granger causality test suggests that during the period of liberalised capital account (with the introduction of the Foreign Currency Deposit (FCD) scheme from April 1991 to May 1998), the interest rate was used to manage exchange market pressure. However, during the period of capital control (post FCD freeze from June 1998 onwards),

[6]See Econometrica, July 1969, pp. 428-429.

the government used domestic credit as an instrument to manage EMP. The use of domestic credit to manage exchange market pressure continued in the post 9/11 period. By and large, evidence shows that money supply is mainly used to manage exchange market pressure.

Tanner (2000) conducted VAR studies of EMP for Brazil, Chile, Mexico, Indonesia, Korea, and Thailand for the period from 1990 to 1998. He concluded that shocks to domestic credit growth play a significant role in explaining EMP. Shocks to EMP differentials also affect EMP, but the evidence is weak. Below is the VAR model that Tanner estimated:

$$X_t = a_0 + a_1 X_{t-1} + a_2 X_{t-2} + \cdots + \nu_t \tag{2.2.7}$$

Here, X=$(\delta, \mathrm{EMP}, \Phi)$ is a matrix of domestic credit, EMP and interest rate differentials. a_i is a vector of coefficients. $\nu_t = (\nu_\delta, \nu_E, \nu_\Phi)$ is a vector of error terms. We have,

$$\nu_{\mathbf{t}} = \mathbf{B}\omega_t$$

B is a 3×3 correlation matrix among own error terms. High values for domestic credit and interest rate differentials result in a low value for EMP, a finding consistent with the G-R model. Using variance decomposition, the author found a significant two-way causality between domestic credit and EMP.

Kamaly (2003) studied EMP for Egypt, Israel, and Turkey for the period from 1990 to 2000 using VAR and OLS. The VAR results indicate that domestic credit plays a significant role in explaining EMP, a finding consistent with the evidence from other economies. The OLS results show that domestic credit has a negative relationship with EMP. These results support the predictions of the G-R model. The relevant equations for estimation in this study are the same as equations (2.2.6) and (2.2.7).

Khan (2010) studied the factors influencing EMP in Pakistan using a Vector Error Correction Model (VECM) for the period from 1982 to 2008. They found that domestic monetary conditions are the primary drivers of EMP fluctuations in Pakistan, a finding consistent with the predictions of the G-R model. While international monetary conditions also play a role, their impact on EMP is less significant.

Hegerty (2010) used the VAR framework for monthly data from 1996 to 2009 to study EMP for fifteen Central and Eastern Europe (CEE) countries. He found that the most important determinant of EMP is real effective exchange rate volatility. Sudden increases in EMP correspond to higher real exchange rate volatility. The author also found a lagged effect of this volatility on EMP. The main drivers of EMP, such as GDP, were found to be different for different groups of countries within the fifteen countries studied.

Dua and Sen (2014) created an EMP index using the model-independent approach following Eichengreen et al. (1996) for India for the period from January 1990 to April 2013. To check causality between EMP and its possible determinants, they conducted the Granger causality test by estimating the following two-variable VAR model for each set of variables, with 12 lags, for example:

$$\mathrm{EMP}t = \sum s = 1^{12} A_s \mathrm{EMP}t - s + \sum s = 1^{12} B_s fr_{t-s} + \varepsilon_t \tag{2.2.8}$$

$$fr_t = \sum_{s=1}^{12} C_s \mathrm{EMP}t - s + \sum s = 1^{12} D_s fr_{t-s} + \eta_t \tag{2.2.9}$$

Here, fr_t is the possible determinant of EMP, for example, fiscal deficit of the government, foreign exchange reserve, capital account balance, current account balance, GDP growth rate, output gap, price differential between India and the USA, interest rate differential between India and the USA, money supply growth, and net foreign institutional investment. ε_t and η_t are error terms. The Granger causality test shows bidirectional causality between foreign exchange reserves and EMP, foreign institutional investment and EMP; unidirectional causality from current account balance to EMP, capital account balance to EMP, GDP growth to EMP, money supply growth to EMP, and interest rate differential to EMP. Causality does not run in any direction between fiscal deficit and EMP.

Recent empirical studies have provided new insights into exchange market pressure dynamics in emerging economies. Li et al. (2020) analyzed exchange market pressure and monetary policy in Pakistan, demonstrating that both interest rates and foreign exchange reserves serve as effective policy instruments in managing EMP.

Ahmed et al. (2021) employed an autoregressive distributed lag approach to examine EMP determinants in Pakistan, finding significant relationships between trade openness, foreign exchange reserves, and exchange market pressure. Their research emphasizes how external sector vulnerability increases pressure on domestic currency.

Building on earlier work in the Indian context, Khan et al. (2021) investigated the relationships between economic uncertainty, stock market uncertainty, and monetary policy effectiveness, providing new insights into the transmission channels of exchange market pressure.

Recent empirical studies have explored various facets of Exchange Market Pressure (EMP), providing insights into its dynamics and determinants. For instance, Shaikh and Huynh (2021) examined the impact of the COVID-19 pandemic on global financial markets, including equity, commodity, and foreign exchange (FX) markets. Their findings revealed that pandemic-induced fears significantly influenced market volatility, highlighting the role of options as effective hedging instruments.

Further, Liu (2022) investigated the time-varying effects of economic uncertainty on China's EMP using a TVP-VAR model. The study identified that U.S. policy uncertainty leads to RMB appreciation pressure, while domestic Chinese uncertainty contributes to devaluation pressure, underscoring the critical interplay between domestic and external factors.

Similarly, Teker et al. (2022) applied ARIMA forecasting to estimate sectoral market risk premiums in Turkey and assess EMP volatility during the COVID-19 pandemic. Their analysis identified structural shifts in market risk premiums and highlighted increased volatility during this period.

These studies underscore the multifaceted nature of EMP, reflecting the influence of economic uncertainties, structural changes, and external shocks on market dynamics.

The empirical studies on EMP models have evolved significantly since the original Girton-Roper (G-R) model. These studies have tested the validity of the G-R model and its variants across various economies using different econometric techniques, including OLS, VAR, VECM, and Granger causality tests. The findings largely support the predictions of the G-R model, with domestic credit and monetary conditions being the key determinants of EMP in most cases. However, some studies have also highlighted the role of expectations, external factors, and structural changes in influencing EMP. The introduction of more sophisticated econometric techniques, such as VAR and VECM, has allowed for a more nuanced understanding of the bidirectional relationships between EMP and its determinants. Overall, the empirical evidence suggests that the G-R model and its extensions provide a useful framework for understanding and analysing exchange market pressure in different economic contexts, while also revealing the complexity and variability of EMP across different countries and time periods.

2.3 Currency Crisis

All the approaches of EMP discussed above give indicators of EMP and try to relate EMP to internal and external monetary conditions. These theories do not capture the reasons which result in sudden deterioration of the components of EMP. During the 1990s, currency crises have become a common occurrence around the world. Speculative attacks on currency wrecked havoc in the European Monetary System in 1992-93, in Mexico and Latin America in 1994-95, in East Asia in 1997-98, in Russia in 1998, in Brazil in 1999, and in Argentina and Turkey in 2000-2001 (Erturk, 2004). All these crises were sudden in nature, which resulted in a fall in forex reserves, huge depreciation of a currency, huge jumps in interest rates, or all in a very short period of time. Theories of speculative attack, given by Krugman (1979) and Flood and Garber (1984) (henceforth Krugman, Flood and Garber (KFG)), try to explain the sharp rise in EMP with the help of their model of speculative attack. According to the KFG model, speculators will force a currency peg to collapse if the “shadow exchange rate” —the exchange rate that would have been if the rate was floating—is sufficiently different from the peg. Following is the model:

$$m - p = y - \lambda i \tag{2.3.1}$$

$$i = i^* + \Delta s^e \tag{2.3.2}$$

From 2.3.1 and 2.3.2, we have:

$$m–p = y - \lambda(i^* + s^e) \tag{2.3.3}$$

Using purchasing power parity:

$$s = p - p^* \tag{2.3.4}$$

From 2.3.1 and 2.3.5, we have:

$$m - s = \bar{y} - \lambda\Delta s^e \tag{2.3.5}$$

Money Supply:

$$m = NDA + R$$

For external economy, $p^* - \lambda i^* = 0$ Fixed exchange rate conditions are $s = \bar{s}$ Thus,

$$m = \bar{s} + \bar{y} - \lambda\Delta s^e \tag{2.3.6}$$

Under floating exchange rate, $s = \tilde{s}$ Thus,

$$\tilde{s} = m - \bar{y} + \lambda\Delta s^e. \tag{2.3.7}$$

If the central bank maintains a fixed rate of growth of domestic credit:

$$\frac{\partial NDA}{\partial t}/NDA = \frac{\partial nda}{\partial t} \equiv \mu \Rightarrow nda_t = nda_0 + \mu t$$

As long as s is fixed at $\bar{s}$, we have:

$$\frac{\partial(R)}{\partial t} = -\frac{\partial(NDA)}{\partial t}$$

Flood and Garber shadow floating exchange rate

The shadow price equation is as follows:

$$\tilde{s}_t = nda_t - \bar{y} + \lambda\mu = nda_0 + \mu t - \bar{y} + \lambda\mu$$

After all reserves are lost, m will consist only of nda.

The time when the speculative attack happens is T; thus, the speculative attack will happen at $t = T$. The attack will happen when:

$$\tilde{s}_t = \bar{s} = nda_0 + \mu T - \bar{y} + \lambda\mu$$

$$\Rightarrow T = \frac{\bar{S} - nda_0 + \bar{y} - \lambda\mu}{\mu} \tag{2.3.8}$$

Following is a description of the symbols:

m = Log of money.

P = Log of domestic price.

y = Log of national income.

$\bar{y}$ = Log of long-term national income.

i = Domestic interest rate.

i^* = Foreign interest rate.

s = Nominal exchange rate.

$\bar{s}$ = Long-term nominal exchange rate.

$\tilde{s}$ = Shadow exchange rate.

s^e = Expected nominal exchange rate.

NDA = Net domestic credit = Monetary base.

nda = Net domestic credit when forex reserves are zero.

R = Forex reserves.

μ = Growth rate of domestic credit.

T = Time of speculative attack.

λ = Interest rate elasticity of real money demand.

The message of the KFG model is that expansion of domestic credit will lead to a currency crisis if a country does not have enough forex reserves. Speculators will hasten the exhaustion of reserves by attacking the currency, thereby resulting in a currency crisis.

The KFG model was given to explain the currency crises in Latin America during the 1960s and 1970s (Kaminsky Graciela, 2003). These countries had rapid domestic credit growth and low forex reserves, i.e., the countries had balance of payment problems.

The European countries whose currencies were attacked by speculators during 1992 and 1993 did not fit the explanation given by the KFG model. These countries did not have Balance of Payment (BOP) problems. There was no exceptionally rapid growth of domestic credit (Eichengreen et al., 1995). They were not having any forex limitation and were in a position to sustain the currency peg indefinitely, yet these countries faced speculative attacks and currency crises. Obstfeld (1996) puts forward a "Second Generation" view, in which central banks may decide to abandon the defence of an exchange rate peg when the social costs of doing so, in terms of unemployment and domestic recession, become too large. This change of perspective implied, in particular, that crises may be driven by self-fulfilling expectations, since the costs of defending an exchange peg may themselves depend on anticipations that the peg will be maintained (Velasco, 2001). Obstfeld (1996) gave his model in a game-theoretic framework. The model suggests that speculators may decide to attack a currency even if there is no BOP problem. It is a case of multiple equilibria; whether an attack will happen or not will depend on the relative payoffs of the 2×2 game with high forex reserves, low forex reserves, and intermediate forex reserves. "Second Generation" Models are also called "Escape Clause" Models because these models were given to explain the currency crisis in the ERM countries of 1992-93. Under the ERM arrangement, the member countries had an option to back out from defending their currency pegs if the real cost of the peg was high.

The above two approaches emphasise the role of government finances. The East Asian currency crisis of 1997 was, however, rooted more in private sector finances, which the First and Second Generation models do not consider. The East Asian crisis also underlined the role of global finances and contagion as it spread to emerging markets as well. The crisis also brought into focus the problems of bank runs, moral hazards, corporate balance sheets, contagion, etc. The "Third Generation" Model consists of a set of papers that focus on the multiplicity of problems related to private finances in explaining currency crises. Diamond and Dybvig propose the theory of bank runs. Corsetti and Roubini (1998) proposed moral hazard as a possible explanation for the Asian crisis. Eichengreen et al. (1996) propose the corporate balance sheet effect as a reason for currency crises. Gerlach and Smets (1995) emphasise the role of contagion in currency crises.

Recent theoretical developments have expanded and refined our understanding of currency crises. Krugman (2014) revisits the first-generation framework, incorporating global financial cycles and capital flows to explain modern crisis dynamics. His updated model demonstrates how traditional balance-of-payments considerations interact with contemporary financial market structures.

Flood and Marion (2017) enhance the analytics of currency crises by incorporating market microstructure and institutional features into the original framework. Their work bridges first-generation models with modern market dynamics.

Building on second-generation frameworks, Jeanne and Wyplosz (2019) develop a model of international lender of last resort, showing how institutional interventions can prevent self-fulfilling crises. Burnside et al. (2016) extend this line of research by analyzing how government guarantees interact with speculative attacks.

The third-generation perspective has evolved with Eichengreen and Hausmann (2019)'s analysis of "original sin redux", [7] examining how currency mismatches continue to generate financial vulnerabilities in emerging markets. Caballero and

[7] "original sin redux" revisits Eichengreen and Hausmann's concept of emerging markets' inability to borrow in their own currencies internationally, highlighting persistent currency mismatches that expose these economies to financial risks, particularly through balance sheet effects during depreciations (Eichengreen & Hausmann, 2019).

Simsek (2020) contribute by modeling asset price spirals and their amplification through aggregate demand channels.

Rey (2022) synthesizes these developments by analyzing how global financial cycles affect domestic monetary policy autonomy and crisis vulnerability, integrating insights from all three generations of crisis models.

2.4 Research Gap

Researchers in the field of EMP have explored various aspects of this phenomenon. Some studies, e.g., Eichengreen et al. (1996) and Kaminsky et al. (1998b), have focused on constructing EMP indices, while others, such as Tanner (2000) and Pentecost et al. (2001b), have examined the relationship between EMP indices and fundamental economic variables that explain fluctuations in these indices. Additionally, some others, for instance, IMF, have incorporated EMP indices as components of broader financial stress indices and utilised them as indicators of currency crises. Furthermore, certain studies, e.g., Krugman (1979) and Obstfeld (1996), have emphasised the role of speculative attacks on currencies without explicitly referring to EMP indices.

Studies aimed at creating an EMP index add exchange rate changes to a weighted combination of other components. Different studies choose different weights and components, leading to a wide difference in the numerical value of the EMP index for the same country during the same period. For example, Stavárek (2010) found that in the case of the Czech Republic, Hungary, Poland, and Slovakia, the correlation coefficient of the weights derived from the model-dependent and model-independent approach is 0.3080, 0.0005, 0.0189, and 0.1605 respectively, which is very poor.

Klaassen (2011) have demonstrated that the effectiveness of the components of the EMP index is crucial. Therefore, the selection of these weights should not be based on any pre-determined structural model or common sense, but should be derived from a purely empirical study with as few restrictive assumptions as possible. For instance, in the G-R model, a weight of one is assigned to the change in reserve, implying that a one percent change in reserve will alter the EMP index by one point, assuming all other factors remain constant. However, this may not always hold true, as the interconnectedness of the components and their relative importance in determining exchange market pressure may vary across countries and time periods.

The interpretation and normalisation of weights in the EMP index is a critical area that requires further research. Weymark (1995b) argues that these weights should be interpreted as "the elasticity of the exchange rate with respect to changes in foreign exchange reserves". These weights convert observed reserve changes into equivalent units of exchange rate changes, maintaining the underlying size of excess demand associated with the model components and the actual exchange rate policy implemented. Without proper normalisation, models like the Girton-Roper (G-R) model assume a simplistic one-to-one relationship between changes in forex reserves and corresponding adjustments in exchange rates, which may not reflect reality. Weymark (1995b) emphasises that empirical estimation of these weights, rather than reliance on theoretical values, ensures that they reflect actual economic conditions and the complex interactions influencing exchange rates.

There is a significant gap in the literature regarding the choice of weights in empirical estimates based on these models, leading to a set of common problems. Another issue with these models is their choice of instruments for defending the currency. For instance, the popular G-R model assumes that agencies use only forex reserves and not other instruments to defend a currency. This assumption may not hold true for countries with low forex reserves that use capital controls and tightening of domestic credit to adjust the pressure.

In scenarios where maintaining employment is prioritised, as highlighted by "Escape Clause " models[8] policymakers might choose not to defend the currency.

[8]The "Escape Clause" model, introduced by (Obstfeld, 1996), describes situations where policymakers might abandon a fixed exchange rate regime due to domestic economic concerns, even in the absence of a speculative attack. This model emphasizes the trade-off between maintaining a fixed exchange rate and addressing domestic economic issues, such as unemployment.

This decision can lead to currency crises or instability, shifting the pressure onto the real economy. During such periods of extreme pressure, the traditional models used to measure currency pressure, like the Girton-Roper Model, may become less reliable. This is because their underlying assumptions, such as purchasing power parity in the Girton-Roper Model, might no longer hold true.

Nicholas and Sophia (2002) have found that the G-R model fails for the period before 1961 when there were greater exchange rate restrictions because in such periods purchasing power parity may not hold. Thus, there is a serious gap in these models. Furthermore, in the case of India, we do not have a continuous time series of EMP indices as different researchers have focused on different time periods. The latest available series ends in 2008 (Guru and Sarma, 2013). There is a need to extend the series beyond this period.

2.5 Research Question

Is it possible to have a general and purely econometric approach to the measurement of EMP that is based on minimal structural restrictions and can be applied to all currency regimes?

Can the components and weights of such a universally applicable EMP index be identified specifically for India?

Can we construct a time series of the EMP index for India based on such a general model?

How does this EMP index compare with the EMP index based on the Girton-Roper (G-R) model?

Can we identify periods of extreme pressure or currency crisis on the basis of such an index, and assert with conviction that India faced a currency crisis during specific periods, if any?

2.6 Objectives of the Study

RO 1

The study aims to augment the baseline Girton-Roper (G-R) Model to capture the complexities of modern financial markets, including volatility clustering, long memory processes, persistence in exchange rate dynamics, regime changes, and structural breaks, while retaining its fundamental theoretical insights.

RO 2

In this study, our goal is to propose a general approach to Exchange Market Pressure (EMP) estimation. This approach aims to identify the components of EMP and their respective weights with minimal structural constraints, while simultaneously avoiding any arbitrariness.

RO 3

The study aims to generate a time series of EMP indices for India from 2001 onwards using the proposed method. Additionally, we create an EMP index for the same period using the G-R model to compare the two indices.

RO 4

Furthermore, we seek to identify instances of extreme currency stress in the Indian economy during this period, using the currency stress threshold proposed by Eichengreen et al. (1995).

Appendix

Table 2.1: Summary of Theoretical Literature Surveyed

Author	Year	EMP components	Weights	Conclusion
Girton-Roper	1977	Reserve changes, depreciation	1, 1	Pressure on exchange rate is managed by adjusting forex reserve, sale of one percent of the existing reserve reduces depreciation by one point
Roper-Turnovsky	1980	Exchange rate changes, change in monetary base	1, η (responsiveness of exchange rate changes to changes in monetary base)	Pressure on exchange rate is managed by adjusting monetary base, sale of one percent of the existing reserve reduces depreciation by η points
Weymark	1995	Exchange rate changes and reserve changes	1, η (elasticity of exchange rate to reserve management or reserve changes)	—
ERW	1996	Exchange rate change, interest rate change, reserve change	Inverse of respective variances	—

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Table 2.1 – *Continued from previous page*

Author	Year	EMP components	Weights	Conclusion
Pentecost	2001	Nominal exchange rate changes, domestic and foreign interest rate changes differentials, changes in reserves	1, elasticity of money demand to interest rate differentials, 1	—
Klaassen and Jager (2016)	Exchange rate changes, foreign reserves, interest rates	Data-driven weights based on relative price elasticities		EMP components' weights should be derived from actual market data rather than theoretical assumptions
Patnaik et al. (2017)	Exchange rate changes, foreign reserves	Ratio of exchange rate volatility to reserve volatility		Provides consistent measure for comparing EMP across countries with different exchange rate regimes
Li and Heinz (2018)	Exchange rate changes, reserves, interest rates	Precision-based weights derived from intervention data		Demonstrates how policy interventions affect EMP measurement
Goldberg & Krogstrup (2019)	Exchange rates, reserves, capital flows	Weights based on relative financial openness		Introduces integrated capital flow pressure measure
Du et al. (2020)	Exchange rates, sovereign yields, reserves	Policy credibility-based weights		Links monetary policy credibility to exchange market pressure
Chen and Rebucci (2021)	Exchange rates, reserves at intraday frequency	High-frequency weights based on market microstructure		Shows importance of intraday dynamics in EMP measurement

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Table 2.1 – *Continued from previous page*

Author	Year	EMP components	Weights	Conclusion
Jae-Hyun Suh	2023	Exchange-rate fluctuations, capital-flow management (CFM) measures	Dynamic adjustment based on market pressures	Enhanced EMP index detects hidden exchange pressures and provides stronger predictive signals, particularly in emerging markets like South Korea and Malaysia.

Source: Author's compilation

Table 2.2: Summary of Empirical Literature Surveyed

Model	Author	Sample period	Sample country	Finding
G-R Model	Girton Roper, 1977	1952-74	Canada	Excess supply of domestic currency causes exchange market pressure which is reflected in depreciation and forex loss
G-R Model	Connolly Silveira, 1977	1955-75, 1962-75	Brazil	Increase in domestic credit exerts significant negative pressure on exchange market for the entire period international price and domestic income put significant positive pressure on exchange market only for the sub-period 1962-75

Continued on next page

Table 2.2 – continued from previous page

Model	Author	Sample country	Sample period	Finding
G-R Model	Modeste, 1981	1972-78	Argentina	EMP is independent of the relative role of exchange rate change or forex reserve change in absorbing the pressure
G-R Model	Hodsgson, Schneck, 1981	Canada, France, West Germany, Belgium, Netherlands, Switzerland	1959II-1976I, 1964II-1976I for U.K.	During the periods of disruption EMP model becomes unstable
G-R Model	Kim, 1985	South Korea	1980-83	Conclusions of the G-R Model validated for South Korea
G-R Model	Ghartery, 2002	Jamaica	1962II-1997IV	Results consistent with the G-R Model
G-R Model	Hallwood-Marsh	United Kingdom	1925-31	Expectation of a positive adjustment in central parity puts negative pressure on exchange market
G-R Model	Pradhan-Kulkarni, 1989	India	1976-85	Increase in money supply leads to reserve losses and depreciation
Weymark Model	Weymark, 1995	Canada	1975-91	EMP increased during 1975II-1982IV,post 1984 EMP decreased Central Bank of Canada removed 96 percent of pressure by forex intervention

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Table 2.2 – continued from previous page

Model	Author	Sample country	Sample period	Finding
G-R Model	Mathur,1999	India	Dec 1986-July1998	Expectation of a depreciation of currency increase exchange market pressure
Weymark Model	Splonder,1999	Finland	1992-96	During 1993 EMP increased but post markka's float it decreased at the Bank of Finland reduced forex intervention
Weymark Model	Apergis,2002	Greece	1975-98	In the post 1992 Bank of Greece frequently intervened in the exchange market to stabilise currency
VAR Model	Tanner,2002	Brazil, Chile, Mexico, Indonesia, Korea, Thailand	1990-98	Shocks to domestic credit growth are important in Explaining EMP
VAR Model	Bautista and Bautista,2005	Phillipines	1900I-2004I	Contracting domestic credit growth and raising interest rate both reduce EMP
VAR Model	Garcia and Malket,2005	Argentina	1993-2004	Rise in domestic credit increased exchange market pressure
Weymark Model	Jeisman,2005	Australia	1971-2001	Intervention by the Reserve Bank of Australia magnified pressure on AUD

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Table 2.2 – continued from previous page

Model	Author	Sample country	Sample period	Finding
VAR Model	Khwaza and Din,2007	Pakistan	1991-2005	In the period of liberalised capital account interest rate was used to manage EMP in the period of capital control domestic credit was used to manage EMP
ERW Model	Mandilras and Bird,2008	Latin America	1970-2000	Increase in foreign debt increases pressure on currency to depreciate
G-R Model	IMF 2009	26 emerging economies	1997-2008	EMP index captures more 80 percent of currency crisis noted in literature
VAR Model	Li et al. (2020)	1987-2013	Pakistan	Interest rates and forex reserves effective in managing EMP. Monetary policy autonomy varies with exchange rate regime.
ARDL Model	Ahmed et al. (2021)	1976-2018	Pakistan	Trade openness and forex reserves significantly influence EMP. External sector vulnerability increases currency pressure.

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Table 2.2 – continued from previous page

Model	Author	Sample country	Sample period	Finding
Monetary Model	Khan et al. (2021)	2003-2019	India	Economic uncertainty and stock market volatility affect money demand, impacting monetary policy effectiveness.
Regression Model	Shaikh and Huynh, 2021	2020–2021	Global	Pandemic-induced fears significantly influenced volatility; options were effective as hedging instruments
TVP-VAR Model	Liu, 2022	2001–2020	China	U.S. uncertainty led to RMB appreciation; Chinese uncertainty triggered devaluation pressure
ARIMA Forecasting	Teker et al., 2022	2016–2021	Turkey	Structural shifts identified in market risk premiums and EMP volatility during the COVID-19 pandemic

Source: Author's compilation

Table 2.3: Summary of Currency Crisis Literature Surveyed

Model	Author	Year	Findings
KFG	Krugman, Flood, Garber	1979	Speculators attack a currency if the shadow exchange rate is sufficiently different from the pegged rate, i.e., when a country has a BOP problem.

Continued on next page

Table 2.3 – continued from previous page

Model	Author	Year	Findings
Obstfeld Game Theoretic Model	Obstfeld	1996	Speculators may attack a currency even without a BOP problem. Attacks depend on relative payoffs in a game-theoretic framework.
Updated First-Generation Model	Krugman	2014	Incorporates global financial cycles and capital flows into the original framework.
Self-Fulfilling Attacks Model	Burnside et al.	2016	Shows how government guarantees interact with speculative attacks.
Enhanced First-Generation Model	Flood and Marion	2017	Integrates market microstructure and institutional features.
Original Sin Redux Model	Eichengreen and Hausmann	2019	Examines currency mismatches and financial vulnerabilities in emerging markets.
International Lender Model	Jeanne and Wyplosz	2019	Shows how institutional interventions can prevent self-fulfilling crises.
Asset Price Spirals Model	Caballero and Simsek	2020	Models crisis transmission through asset prices and aggregate demand.
Global Financial Cycles Model	Rey	2022	Integrates insights across generations of crisis models, focusing on international spillovers.

Source: Author's compilation

Chapter 3

Research Methodology and Model Specification

A robust research methodology is crucial for any empirical study. This chapter outlines the methodological framework for analysing EMP in the Indian context, serving as a roadmap for the study's execution. We begin by describing India's currency regimes, providing historical context for the empirical analysis. The research design is then elaborated, covering the approach, sample size determination, and data collection methods. We discuss the rationale behind choosing specific time periods, variables, and data sources, including an overview of the statistical and econometric tools used. The chapter details the models used to construct EMP indices, presenting their theoretical foundations and econometric forms. We explain the construction of various EMP indices and the methodology for determining crisis thresholds. Diagnostic tests for the regression models are described, addressing issues of normality, stationarity, multi-collinearity, autocorrelation, and heteroscedasticity. We also discuss potential endogeneity issues and the use of instrumental variable techniques. Finally, we outline challenges encountered during the research process and strategies to overcome them. This comprehensive methodology provides the foundation for the empirical analysis and findings presented in subsequent chapters.

3.1 Description of the Study Area: Currency Regimes in India

India abandoned the fixed parity of INR with Pound Sterling in September 1975 and linked it to a weighted basket of currencies of its main trading partners (Mathur, 1999). This regime was replaced in March 1992 by partial convertibility which was called LERMS. In this system, the Reserve Bank of India (RBI) allowed 40 percent of current account transactions to be exchanged at RBI rates and the rest at the existing market rates. INR was formally put on full current account convertibility during 1994.

While the de-jure currency regime in the country, post 1993, has been a managed float, the de-facto currency regime has been different during different periods (Guru and Sarma, 2013).[1] The gradual liberalisation of the capital account, which began in the early 1980s, has played a significant role in shaping India's exchange rate regime. The increased integration with the global financial markets has made the exchange rate more responsive to capital flows and external shocks. However, despite the progressive liberalisation, India still maintains various types of capital controls (Tarapore Committee, 2006).

Global economic events have also had a significant impact on India's exchange rate policy. The Asian financial crisis of 1997-98 and the global financial crisis of 2008-09 led to increased volatility in the foreign exchange market and put pressure on the INR. During these periods, the RBI had to intervene more actively to manage the exchange rate and maintain financial stability. The move towards an inflation-targeting framework in 2016 has also influenced the exchange rate policy, as the RBI now focuses on maintaining price stability while also considering the impact of exchange rate fluctuations on the broader economy. A glance at the table 3.1 gives an idea of the chronological evolution of currency regime in India and the triggers for switch.

INR comes under pressure in the domestic market due to its excess supply.

[1]For a classification of de-facto exchange rate regimes, see Reinhart and Rogoff (2004).

Table 3.1: Evolution of Currency Regimes in India, 1947-2023

Period	Exchange Rate Regime	Source	Triggers for Change
1947-1966	Fixed exchange rate	Joshi and Little (1998)	Independence, Bretton Woods system
1966-1975	Fixed exchange rate with devaluations	Joshi and Little (1998)	Balance of payments crisis, wars with Pakistan and China
1975-1979	Managed float	Joshi and Little (1998)	Partial liberalisation, oil price shocks
1979-1993	Crawling peg	Patnaik et al. (2015)	Managed depreciation, balance of payments crisis
1993-2008	Managed float	Patnaik et al. (2015)	Economic liberalisation, capital account convertibility
2008-2023	Floating exchange rate	Ilzetzki et al. (2019); IMF (2023)	Global financial crisis, inflation targeting framework

Source: Author's compilation based on the listed references.

The Reserve Bank of India, sometimes, allows the market forces to work freely and lets the INR find its own level. At times, it also intervenes by buying INR, thereby depleting India's foreign exchange reserves. The RBI also has the option of increasing its policy rate of interest to check the selling pressure on the local currency. As a result of these steps, the currency may not depreciate, but the pressure may shift to foreign exchange reserves or domestic interest rates.

3.2 Research Design

Research design pertains to the comprehensive structure of a research project. It should be crafted in such a way that allows the researcher to thoroughly answer the questions posed at the outset of their research. In this study, we begin by pinpointing the research gaps in the baseline models of EMP. We then formulate pertinent research questions and establish an experimental research design to address these questions. Experimental research design is highly effective in investigating causal relationships. In this design, a researcher identifies some controlled/exogenous variables and associates them with uncontrolled/endogenous variables to ensure the research questions are comprehensively answered. In this study, we employ an econometric model-based approach to accomplish our objective.

3.3 Sample Size Determination

Choice of the size of sample will depend on precision required in research. If the size of the population is infinite, the following formula will give the size of the sample to be taken:

$$n = \frac{z^2 \cdot N \cdot \sigma_\rho^2}{(N-1)e^2 + z^2\sigma_\rho^2} \tag{3.3.1}$$

Here,
N = size of population.
n = size of sample.
e = acceptable error (precision).
σ_ρ = standard deviation of population.
z = z-table value at a pre-chosen level of confidence.

The formula for estimating the required sample size when the population size is infinite is:

$$n = \frac{z^2 \cdot \sigma^2}{e^2} \tag{3.3.2}$$

Here,
n = size of sample.
e = acceptable error (precision).
σ^2 = variance of population.
z = z-table value at a pre-chosen level of confidence.

3.4 Sample Size Time Series

In time series analysis, determining an appropriate sample size is crucial for ensuring the reliability and validity of research findings. While traditional sample size formulas are well-established for cross-sectional studies, considerations for time series data in economics often differ (Brooks, 2008).

Sample Size and Period

This study on EMP utilises a sample period spanning from 2001:Q3 to 2022:Q3, encompassing 21 years and yielding 84 quarterly observations. Table 3.2 presents a summary of the sample characteristics and justifications for the chosen sample size.

Table 3.2: Sample Size Justification for Time Series Data

Consideration	**Justification**
Econometric Techniques	Adequate for ARIMA, VAR, GARCH models, and other time series analysis techniques.
Degrees of Freedom	Provides enough degrees of freedom for model estimation and hypothesis testing.
Economic Events Coverage	Captures significant economic events, policy changes, and external shocks from 2001:Q3 to 2022:Q3.
Comparison to Similar Studies	Consistent with sample sizes used in similar EMP studies.
Practical Considerations	Time period selection is based on data availability and relevance.
Structural Breaks and Cycles	Allows for the analysis of structural breaks and economic cycles over a substantial period.
Model Complexity	Ensures the models can handle complex relationships and interactions within the data.

Source: Author's compilation

Factors Influencing Sample Size Choice

The sample size of 84 quarterly observations was determined based on several factors:

Econometric Techniques

The sample size exceeds the minimum threshold of 50 observations suggested by Wooldridge (2016) for robust time series analysis. This ensures the data is adequate for ARIMA, VAR, GARCH models, and other time series analysis techniques.

Degrees of Freedom

The sample size provides enough degrees of freedom for model estimation and hypothesis testing, allowing for robust estimation and inference (Greene, 2018).

Economic Events Coverage

The 21-year period captures multiple economic cycles, including significant events such as the 2008 global financial crisis and the COVID-19 pandemic, enhancing the analysis of EMP dynamics under various economic conditions (Hamilton, 2020). This coverage allows the analysis of structural breaks and economic cycles over a substantial period.

Comparison to Similar Studies

The sample size aligns with those used in comparable EMP studies, such as Li et al. (2020) with 60 quarterly observations and Ahmed et al. (2021) with 72 observations. This consistency ensures the sample is adequate for comparison and analysis within the context of existing research.

Practical Considerations

The time period selection is based on data availability and relevance, ensuring consistent data availability and quality across all variables included in the models (International Monetary Fund, 2023).

Structural Breaks and Cycles

The chosen period allows for the examination of potential structural breaks in the relationship between EMP and its determinants (Bai and Perron, 2003).

Model Complexity

The sample size of 84 observations ensures the models can handle complex relationships and interactions within the data, which is essential for accurate and reliable analysis of EMP (Greene, 2018).

Power Analysis

A power analysis was conducted for the main statistical tests using the approach outlined by Cohen (1988). G*Power software (Faul et al., 2007) was employed to calculate the required sample size for detecting medium effect sizes (f = 0.15) in multiple regression analyses with up to 5 predictor variables, at a significance level of = 0.05 and a desired power of 0.80. Table 3.3 presents the results of this power analysis.

Table 3.3: Power Analysis Parameters and Results

Parameter	**Value**
Effect Size (f^2)	0.15 (medium)
Significance Level (α)	0.05
Power (1-β)	0.80
Number of Predictors	5
Required Sample Size	92
Actual Sample Size	84

Source: Author's calculation

Figure 3.1 illustrates the power curve for the sample size determination, demonstrating the relationship between sample size and statistical power.

Figure 3.2 displays the distribution of sample size and effect size, providing additional context for the power analysis.

Distribution of Sample Size and Effect Size As shown in Table 3.2 and Figures 3.1 and 3.2, while the actual sample size of 84 is slightly below the ideal of 92, it is considered adequate given the time series nature of the data and the coverage of multiple economic cycles.

Choice of Start Date

The start date of 2001:Q3 was selected to align with the period shortly after the euro's introduction as an accounting currency on January 1, 1999, and just

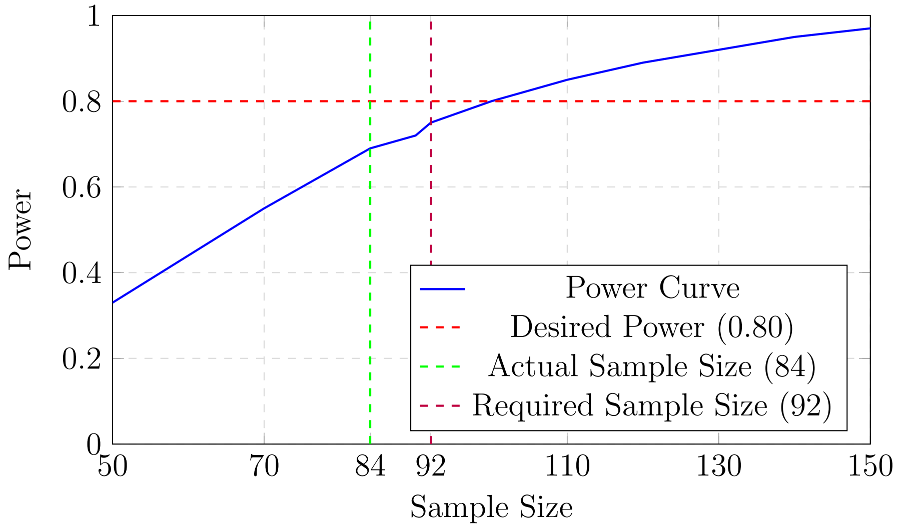


Figure 3.1: Power Curve for Sample Size Determination

Source: Author's creation

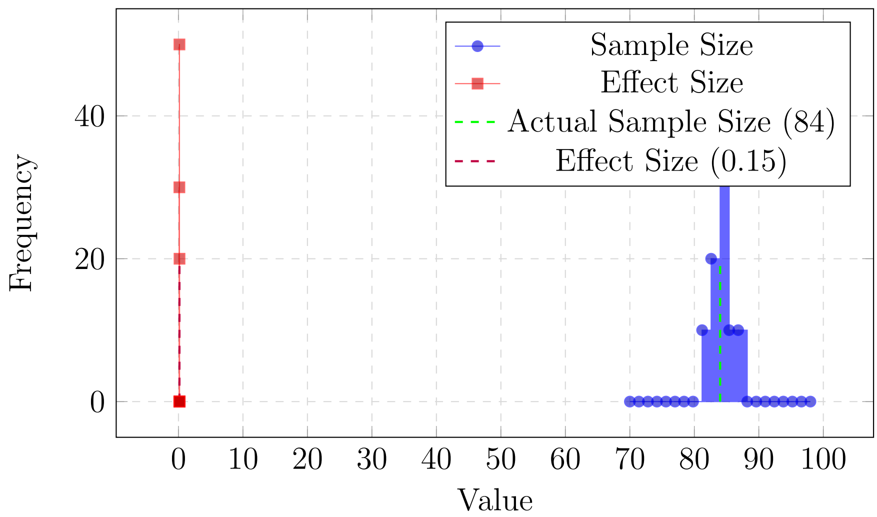


Figure 3.2: Distribution of Sample Size and Effect Size

Source: Author's creation

before the circulation of physical euro banknotes and coins on January 1, 2002. This timeframe captures the crucial transition period in the European monetary system, which had significant implications for global currency markets (Verbeek, 2017).

Limitations and Mitigation Strategies

A larger sample size could potentially improve the precision of estimates. However, extending the sample further into the past could introduce issues related to structural changes in the global economy and financial markets (Stock and Watson, 2015). To mitigate potential limitations of the sample size, robust econometric techniques, including bootstrapping (Efron and Tibshirani, 1994) and rolling window analysis (Zivot and Andrews, 2002), are employed to ensure the stability and reliability of results.

The sample size of 84 quarterly observations is deemed sufficient for the econometric analysis employed in this study on EMP. As demonstrated in Tables 3.3 and 3.2 and Figures 3.1 and 3.2, the sample provides an adequate balance between statistical power, coverage of economic cycles, and relevance to contemporary market conditions (Gujarati and Porter).

3.5 Data

To run the regression in (2.1.13) as per the G-R Model, we require data on the following variables:

1. Forex reserve of India in INR terms.
2. INR-US Dollar (USD) exchange rate (indirect quote).
3. Domestic assets held by the RBI.
4. Real GDP of India.
5. Monetary base of USA.
6. Real GDP of USA.

Besides, to estimate the weight of EMP using equations (3.11.1), (3.11.2), and (3.11.3), we require the data on quarterly nominal interest rate among others. Following is a discussion on the sources of data:

Forex Reserve Data (India)

Foreign Exchange Reserve Data (India)

India's foreign exchange reserve data were obtained from the International Financial Statistics (International Financial Statistics (IFS)) database of the International Monetary Fund (International Monetary Fund (IMF)), accessible at IMF (2019). The specific series used is 'International Reserves, Official Reserve Assets, IMF Reserve Position' under the 'International Liquidity Selected Indicators' category. Originally reported in millions of USD, these figures were converted to INR for consistency with other variables in this study. The IFS database provides this data based on the Standardised Report Forms (SRFs), ensuring comparability across countries.

Market Exchange Rate (INR/USD)

The exchange rate of Indian National Currency to US Dollar is taken from FRED (2021) and is based on the average of daily rates. We have matched the exchange rate data to the corresponding quarters since we require quarterly data. RBI is the original source of this data though we have used Federal Reserve Economic Data (FRED) (Federal Reserve Economic Data) for format-related reasons.

Domestic Assets held by Indian Monetary Authority

Data on the domestic assets held by the RBI is obtained by subtracting foreign exchange reserve from monetary base. All values are in INR.

Monetary Base Data

India:

Data about monetary base of India is taken from DBIE (2021). This is a time series publication of the Reserve Bank of India. Monetary base data is available in the head 'Reserve Money Components and Sources'. We have used the fourth column (label- Reserve Money) of the table. The data is in INR Crores. The monetary base of India is defined as Reserve Money, which is the sum of Currency in circulation, Bank's deposits with RBI, and Other deposits with RBI.

USA:

Girton and Roper (1977b) have estimated their model by using three alternative indicators of monetary base of USA: M_1, M_2, and H. The coefficients of the estimated regressions are the same in all three cases. We have estimated our regression using H. The source of data is FRED (2023b).

Real GDP

India:

India'sGDP series is originally available at CSO (2019). However, we used the series available at fre (2023) for data formatting reasons.

USA:

The data about the real GDP of USA is taken from FRED (2023c).

Nominal Interest Rate

We have taken the weekly average of call money rates reported by Database on Indian Economy (DBIE). The data is available online on DBIE,RBI (2023). This data is reported on a weekly basis. The call money rate is an overnight interest rate that is used by banks to lend and borrow money from each other. This rate is a suitable index for estimating short-term interest rate dynamics, as it captures short-term changes in interest rates that are relevant to many financial transactions.

The time series of call money rates is easily available. Additionally, since the call money rate is based on transactions between banks, it is a reliable indicator of market liquidity conditions, which is an important factor affecting the interest rate dynamics.

Furthermore, the call money rate is often used as a benchmark rate for other short-term rates, such as the repo rate and the inter-bank lending rate. This makes it a suitable index for estimating short-term interest rate dynamics in many financial models and applications.

Overall, the call money rate is a suitable index of interest rates for estimating short-term interest rate dynamics due to its availability, reliability, and use as a benchmark rate. Call money rates data is also available at FRED (2023a). We have used this data source as it gives rates starting from 1968 whereas DBIE,RBI (2023) starts from 2011. This data is also available in various time frames like monthly, quarterly, etc.

3.6 Reliability Tests

We will test the models being used in this research for their data admissibility, theoretical consistency, regressor's exogeneity (though in weak form), parameter constancy, data coherence (i.e., randomness of errors), and inclusiveness (whether the model encompasses all the rival models, especially model 10.3).

Time series data will be data admissible only if the condition of stationarity is satisfied. Stationarity test is required to ensure that the regression results are not spurious (Granger et al., 1974). Stationarity will be tested by plotting the graph of the variable as well as by applying the Augmented Dickey-Fuller(Dickey and Fuller, 1979) test for unit root . Additionally, we will employ the Phillips-Perron test (Phillips and Perron, 1988), which is a more robust test for unit root in the presence of serial correlation and heteroscedasticity . We will also use the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) to complement the ADF and PP tests, as it tests the null hypothesis of stationarity against the alternative of a unit root .

Absence of serial correlation and heteroscedasticity among the residuals of the model is very important for the errors to be truly white noise and for reliable results in hypothesis testing. Durbin-Watson test Durbin and Watson (1950) and White's test White (1980) will be applied to check for these. We also conduct the Breusch-Godfrey test (Breusch, 1978) with four lags to check the presence of autocorrelation in the data . To get rid of autocorrelation or heteroscedasticity, if any, we will use HAC (Heteroscedasticity and Autocorrelation Consistent) estimates (Newey and West, 1987). Additionally, we will employ the Ljung-Box test (Ljung and Box, 1978) to check for higher-order serial correlation in the residuals .

Classical Linear Regression Model is based on the assumption of no multicollinearity among the independent variables. In the presence of linear relationship among regression coefficients, they may become indeterminate or their variances may get inflated, thereby widening confidence intervals and leading to errors in hypothesis testing. The variance inflation factor (VIF) (Marquardt, 1970) and pairwise correlation coefficients will be used to check for the presence of multicollinearity among independent variables.

Hausman test (Hausman, 1978) of exogeneity will be done to check for the exogeneity of the independent variables . Additionally, we will conduct the Ramsey RESET test (Ramsey, 1969) to check for model mis-specification and omitted variable bias . This test helps to determine whether the functional form of the model is appropriate and whether there are any significant variables missing from the model. We will also employ the Engle-Granger cointegration test (Engle and Granger, 1987) to check for the presence of a long-run equilibrium relationship between the variables .

To ensure the stability of the model parameters over time, we will perform the Chow breakpoint test (Chow, 1960). This test helps to identify any structural breaks in the data that could lead to parameter instability. If structural breaks are detected, we will consider using dummy variables or splitting the sample into sub-periods to account for the breaks. We will also use the Cumulative Sum (CUSUM) and CUSUM of squares tests (Brown et al., 1975) to check for parameter stability .

We will assess the normality of the residuals using the Jarque-Bera test (Jarque and Bera, 1987) and the Shapiro-Wilk test (Shapiro and Wilk, 1965). If non-normality is detected, we will consider using robust standard errors or transforming the variables to achieve normality.

To identify influential observations and outliers, we will calculate the Mahalanobis distances (Mahalanobis, 1936) . Observations with high Mahalanobis distances will be carefully examined and, if necessary, removed from the analysis to ensure the robustness of the results.

Finally, we will assess the inclusiveness of the models by comparing their performance using various model selection criteria, such as the Akaike Information Criteria (AIC) (Akaike, 1974) and the Schwarz Information Criterion (SIC) (Schwarz, 1978). These criteria help to determine which model best fits the data while penalising for model complexity. The model with the lowest AIC and SIC values will be considered the most inclusive and parsimonious.

By conducting these additional tests and model comparisons, we aim to ensure the robustness and reliability of our research findings.

Absence of serial correlation and heteroscedasticity among the residuals of the model is very important for the errors to be truly white noise and for reliable results in hypothesis testing. Durbin-Watson test Durbin and Watson (1950) and White's test White (1980) will be applied to check for these. We also conduct the Breusch-Godfrey test with four lags to check the presence of autocorrelation in the data Breusch (1978). To get rid of autocorrelation or heteroscedasticity, if any, we will use HAC (Heteroscedasticity and Autocorrelation Consistent) estimates Newey and West (1987). Classical Linear Regression Model is based on the assumption of no multicollinearity among the independent variables. In the presence of linear relationship among regression coefficients, they may become indeterminate or their variances may get inflated, thereby widening confidence intervals and leading to errors in hypothesis testing. The variance inflation factor (VIF) Marquardt (1970) and pairwise correlation coefficients will be used to check for the presence of multicollinearity among independent variables.

Hausman test of exogeneity will be done to check for the exogeneity of the independent variables Hausman (1978).

3.7 Data Cleaning, Seasonality and Endonegneity

After collecting the data in Excel sheets, the variables will be labeled and an analysis will be done in terms of some standard descriptive statistics. To account for potential seasonal effects in the Indian data and ensure parity with foreign data released by international agencies, which is typically deseasonalized, we will include seasonal dummy variables in our regression model if required. This approach allows us to control for seasonality without the need for explicit deseasonalization of the data, and is commonly used in econometric analysis. There will be a very limited number of missing data, which can at best be called the 'ignorable' cases under the 'missing completely at random' (MCAR) assumption (Cameron and Trivedi, 2005). We will search for natural instrumental variables with the right properties to solve the endogeneity problem in our analysis.

3.8 Software Tools

This study employed a diverse array of statistical, econometric, and data processing tools to ensure a comprehensive and robust analysis of Exchange Market Pressure (EMP) in India. The selection of these tools was based on their analytical capabilities, reliability, and suitability for the specific requirements of this research.

3.8.1 Statistical and Econometric Software

R: An open-source statistical programming language, R was used for its flexibility in data manipulation, statistical modeling, and graphical output. Specific packages such as tidyverse' for data cleaning and visualisation, lmtest' for diagnostic testing of linear regression models, and 'urca' for unit root testing and cointegration analysis were utilised.

Stata: This powerful statistical software package was employed for its user-friendly interface and comprehensive econometric capabilities. Stata's time series and panel data analysis features were particularly useful for examining the temporal aspects of EMP.

EViews: Specialised econometric software that excels in time series analysis. EViews was used for its advanced forecasting tools and ability to handle complex econometric models, including ARIMA and GARCH specifications.

GRETL (GNU Regression, Econometrics and Time-series Library): An open-source alternative that offers a wide range of econometric tools. GRETL was used for cross-validation of results obtained from other software and for its specialised features in handling economic time series data.

Microsoft Excel: While primarily used for initial data organisation and basic calculations, Excel's data analysis toolpak was also employed for preliminary statistical tests and data visualisation.

G*Power: Was used for conducting a priori power analysis to determine the appropriate sample size and for post hoc power analysis to assess the statistical power of our tests.

These tools were instrumental in assessing the impact of key determinants on EMP, including:

Changes in credit creation by the Indian monetary authority

Fluctuations in the monetary base of the USA

Variations in the real GDP of India

Changes in the real GDP of the USA

Each software package offered unique strengths, and their combined use ensured the robustness of the analysis and provided opportunities for result validation across platforms.

3.8.2 Data Visualisation Tools

In addition to the statistical software, specialised data visualisation tools were employed:

Python Was used for creating interactive and dynamic visualisations of EMP trends and relationships between variables.

ggplot2 (R package): Was used for producing publication-quality graphs and charts to illustrate key findings.

3.8.3 Document Preparation and Presentation

LaTeX: This document preparation system was the primary tool for writing the thesis. LaTeXwas chosen for its superior handling of mathematical equations, consistent formatting, and professional typesetting, which were crucial for presenting complex economic models and statistical results.

Microsoft Word: Was used as a supplementary tool for collaborative editing and for preparing documents that required compatibility with non-LaTeXusers.

Microsoft PowerPoint: Was used for creating presentations of research findings for seminars, conferences, and the final thesis defence.

3.8.4 Reference Management

Mendeley: Was used for managing bibliographic references and citations. This Elsevier software integrated seamlessly with MS Word, ensuring consistent and accurate citation formatting throughout the thesis.

BibTeX: Was also employed for managing and formatting references throughout this thesis. BibTeX, a reference management tool integrated well within the LaTeX environment, facilitating the creation of a structured and well-organized bibliography.

3.8.5 Data Acquisition

FRED® (Federal Reserve Economic Data): Was used for accessing and downloading economic time series data. The 'fredr' package in R was employed to directly import FRED data into our analysis environment.

By integrating these diverse tools and methodologies, the study ensured a robust and comprehensive analysis of EMP. The combination of empirical data handling, advanced econometric modelling, and rigorous statistical testing provided a thorough evaluation of various EMP indices and their effectiveness in capturing economic stress in the Indian context.

The use of multiple software packages not only enhanced the accuracy and reliability of the findings but also allowed for cross-validation of results. This multi-tool approach offered valuable insights into the nuances of EMP measurement and its determinants, contributing to both the methodological rigour of the study and the depth of its economic analysis.

Furthermore, the careful selection and application of these tools supported the reproducibility of the research, a key consideration in modern economic studies.

3.9 A General Method for Estimating Time Series of EMP Indices

As per the objectives set in section 2.6, we can give a general expression for EMP as below:

$$EMP_i(t) = \Delta s_t + \omega_1 a_1(t) + \omega_2 a_2(t) + \cdots + \omega_n a_n(t) \tag{3.9.1}$$

This equation shows that the exchange market pressure at time t is a combination of (rate of) appreciation of currency of a country (Δs_t) at time t and all the n number of ω-weighted actions ($a_n(t)$) (expressed in the form of rate of change) taken by a country, in time t, to maintain EMP_t at the same level.

Each weight in this equation represents the effectiveness of the component $a_n(t)$ in controlling EMP_t. $a_i(t)$ could be in the form of any intervention in the forex or money markets like sale of USD from reserves, modulation of interest rates, etc.

In the G-R Model, there is only one action variable to control the EMP of country i at time t. That action variable is $\Delta f_i(t)$. In this case, the weight of $\Delta f_i(t)$ is one, which is derived on the basis of the model. This means that the effectiveness of $\Delta f_i(t)$ in controlling EMP is one, implying that the sale of USD reduces EMP by the same amount as the reduction in forex reserve. Since this result is derived on the basis of a monetary model, one cannot question its theoretical logic (Please vide section 2.4 for more discussion on it), but the effectiveness of the central bank intervention in the forex market to control EMP is an empirical issue. Hence, the weight of $\Delta f_i(t)$ should be empirically derived. Furthermore, during periods of structural instability, the model-dependent derivation of weight serves no purpose. For example, during the period of speculative attacks on currency, linear models of EMP, as given in equation (2.1.13), lose their relevance. Hence, it is important to derive the weights of the components of EMP empirically. In the case of Weymark's model (1997), as given in equation (2.1.19), the weight of $\Delta f_i(t)$ is η.

In practice, however, monetary authorities may take a number of policy actions simultaneously to keep a currency from depreciating.

For estimation purposes, we can write the above equation 3.9.1 as below:

$$\Delta s_t = \alpha - \omega_1 a_1(t) - \omega_2 a_2(t) - \cdots - \omega_n a_n(t) + \epsilon \tag{3.9.2}$$

Here, the fixed component of EMP is subsumed in α, and the variable part of EMP is subsumed in the random error term.

3.9.1 Identification

Estimation of equation (3.9.2) with the OLS method will have serious problems. This is because on the right side we have included $EMP_i(t)$ in the random error term. This may result in $E(\epsilon_t)$ not being equal to zero and one or more of the exogenous variables may start covarying with the error term. This is the problem of endogeneity or reverse causality. This will create a problem in the identification because identification requires that there are as many moments as the parameters. For example, in the following model we have:

$$Y = \beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \cdots + \beta_k X_k(t) + \epsilon_t.$$

We have $k+1$ parameters, hence we require $k+1$ moment conditions for their identification and estimation. These moment conditions are:

$$E(\epsilon_t) = 0$$

$$Cov(X_1(t), \epsilon_t) = 0$$

$$\vdots$$

$$Cov(X_k(t), \epsilon_t) = 0$$

But in the case of equation (3.9.2), this condition is not fulfilled. This endogeneity problem is also noted by Girton and Roper (1977b) when they say,"the monetary approach continues to regard the quantity of intervention necessary to achieve a fixed rate target as endogenous, but it shifts the focus for an explanation to monetary equilibrium conditions ". Thus, explaining the EMP rather than endogeneity of intervention was an issue for Girton and Roper. Here we are interested in finding the weight or effectiveness of endogenous intervention, hence we must address the endogeneity issue.

This problem can be solved if, instead of subsuming the outcome variable in the random error term of the regression model in (3.9.2), we replace the outcome variable by its lagged counterpart. This will ensure that the outcome variable on the right-hand side does not create an endogeneity problem.

To implement this dynamic transformation of our regression model in equation (3.9.2), we require a mathematical equation to express regime-dependent persistence in EMP. The following important propositions, based on a survey of the existing EMP literature, are important in this context:

EMP persists in the case of managed float.

In the case of free float, EMP does not persist.

In the case of an intermediate currency regime, persistence is reduced by a fraction (λ) of float.

The point of persistence of EMP is noted in the Annual Report of the Bank of International Settlement (BIS) (BIS, 1993) in the context of the ERM crisis of 1992-93. IMF also talks about the persistence of EMP. Klaassen (2011) has shown the regime-dependent persistence of EMP by using the model of Weymark (1995b). He has shown that EMP persists in the case of managed float while in the case of free float it does not persist.

We propose the following equation to model regime-dependent persistence of EMP:

$$\begin{aligned} EMP_{(t)} = \beta &+ \rho_1(EMP_{t-1} - \lambda_1 \Delta s_{t-1}) \\ &+ \rho_2(EMP_{t-2} - \lambda_2 \Delta s_{t-2}) \\ &+ \rho_3(EMP_{t-3} - \lambda_3 \Delta s_{t-3}) \\ &+ \cdots + u(t) \end{aligned} \tag{3.9.1.1}$$

In this equation, the intercept captures the fixed part of $EMP_i(t)$ and the rest capture the floating and the random part. The lagged variables capture the persistence in EMP_t. Adjustment of EMP_{t-k} by $\lambda \Delta s_{t-k}$ shows the reduction in persistence of EMP caused by float in currency. ρ is the persistence parameter with $0 \leq \rho \leq 1$. No persistence means $\rho = 0$. The amount of persistence is reduced by a fraction of float in the same period. Here λ is the outlet parameter which captures the fraction of persistence reduction due to float. In a country with less intervention in the currency market, float will be more, resulting in less persistence and EMP tending more towards its natural/fixed rate.

Using equation (3.9.2) and replacing its EMP component (which is subsumed in its random error term) by (3.9.1.1), we have:

$$\begin{aligned} \Delta s_t = \alpha &- \omega_1 \Delta a_1(t) - \omega_2 \Delta a_2(t) - \omega_3 \Delta a_3(t) - \omega_4 \Delta a_4(t) - \cdots \\ &+ \beta + \rho_1[EMP_{t-1} - \lambda_1 \Delta s_{t-1}] + \rho_2[EMP_{t-2} - \lambda_2 \Delta s_{t-2}] \\ &+ \rho_3[EMP_{(t-3)} - \lambda_3 \Delta s_{t-3}] + \cdots + u(t) \end{aligned} \tag{3.9.1.2}$$

$$\begin{aligned} \Delta s_t = \gamma &- \omega_1 a_1(t) - \omega_2 a_{2i}(t) - \omega_3 a_{3i}(t) - \omega_4 a_4(t) - \cdots \\ &+ \rho_1[\Delta s_{t-1} + \omega_1 a_1(t-1) + \omega_2 a_2(t-1) - \lambda_1 \Delta s_{t-1}] \\ &+ \rho_2[\Delta s_{t-2} + \omega_2 a_2(t-2) + \omega_3 a_3(t-2) - \lambda_2 \Delta s_{t-2}] \\ &+ \rho_3[\Delta s_{t-3} + \omega_2 a_2(t-3) + \omega_3 a_3(t-3) - \lambda_3 \Delta s_{t-3}] + \cdots + u(t) \end{aligned} \tag{3.9.1.3}$$

We will reduce Equation (3.9.1.3) to one period lag, and one action variable. This simplifies the equation by removing the need to consider multiple lags of the variables. The modified equation would be as follows:

$$\Delta s_t = \gamma - \omega_1 a_1(t) + \rho_1 \omega_1 a_1(t-1) + \rho_1(1 - \lambda_1)\Delta s_{t-1} + u(t) \tag{3.9.1.4}$$

Generally, policymakers intervene in the market directly as well as indirectly to check pressure on currency. Assuming that there are two action variables and one period lag, (3.9.1.3) can be written as:

$$\Delta s_t = \gamma - \omega_1 a_1(t) - \omega_2 a_2(t) + \rho_1 \omega_1 a_1(t-1) + \rho_2 \omega_2 a_2(t-1) + \rho_1(1-\lambda_1)\Delta s_{t-1} + u(t) \tag{3.9.1.5}$$

In this simplified equation, we consider only the current period values and the values from the previous period. This assumption reduces the complexity of the equation and simplifies the estimation process.

In equation (3.9.1.5), the dependent variable Δs_t is a function of the exogenous variables a_1 and a_2, the lagged dependent variable Δs_{t-1}, and the error term u_t. Therefore, the endogeneity problem is eliminated as the error term u_t is uncorrelated with the exogenous variables and any other omitted variables. For the estimation of this model, along with other conditions, the condition of absence of serial correlation must be fulfilled, i.e., $E(u(t-1)u(t)) = 0$.

The inclusion of lagged variables in equation (3.9.1.5) also helps in removing serial correlation in the error term and helps in storing stationarity. In general, including lagged variables in a model can help address serial correlation in the error term and improve stationarity, depending on the specific context and model specification. By including lagged variables, we are accounting for the dependence between current and past observations, which can help capture any temporal patterns or autocorrelation in the data.

Serial correlation in the error term refers to the situation where the error terms in a model are correlated with each other over time. This violates the assumption of independence between error terms and can lead to biased and inefficient parameter estimates. By including lagged variables, we introduce additional explanatory variables that can help capture the correlation structure and reduce the serial correlation in the error term.

Incorporating lagged variables can be useful for ensuring stationarity in certain time series models. Stationarity implies that the statistical properties of a time series, such as its mean and variance, remain constant over time. In some cases, including lagged variables can help stabilise the mean or remove trends, leading to a stationary series.

However, the specific impact of lagged variables on addressing serial correlation and stationarity depends on the model, data characteristics, and the underlying process being modelled. This emphasises the importance of conducting post-regression statistical diagnostics to validate.

These discussions apply to equation (3.9.1.4) as well.

3.10 Econometric form of the G. R. Model

In this research we intend to empirically estimate the G-R Model equation given in (2.1.13) in the following form

$$EMP_t = \beta_1 \Delta d_{it} + \beta_2 h_{ut} + \beta_3 \Delta y_{it} + \beta_4 \Delta y_{ut} + \nu \tag{3.10.1}$$

Suffix 'i' and 'u' in the above equation show that the variables are related to India and USA respectively.

This is the original model given by Girton and Roper (1977b). This model requires the creation of a time series of EMP indices as per the formula of Girton and Roper , running this regression will give us determinants of average changes in EMP indices. Our objective in this research is also to create EMP indices based on proper empirical weights for its components, as the second component in the Girton and Roper (1977b) EMP index is added to the first component without multiplying it with proper weights.

3.11 Weight Equations

For estimating weights of the components of EMP indices we run the following regressions as per the discussions in the section 3.9:

$$\Delta s_t = \gamma - \omega \Delta f_t + \rho_1 \omega \Delta f_{t-1} + \rho_1 (1 - \lambda_1) \Delta f_{t-1} + u(t) \tag{3.11.1}$$

$$\Delta s_t = \gamma - \omega_1 \Delta f_t - \omega_2 \Delta i_t + \rho_1 \omega_1 \Delta f_{t-1} + \rho_2 \omega_2 \Delta i_{t-1} + \rho_1 (1 - \lambda_1) \Delta s_{t-1} + u_t \tag{3.11.2}$$

The above equations are based on equations (3.9.1.4) and (3.9.1.5). In these two equations we have replaced a_{1i} by rate of change in forex reserve Δf_t and $a_2 i$ by Δi_t. Forex reserve adjustments and interest rates adjustments in this case are two action variables taken to modulate the EMP. At times only interest rates adjustment may be used hence we will estimate the following equation for this purpose:

$$\Delta s_t = \gamma - \omega \Delta i_t + \rho_1 \omega \Delta i_{t-1} + \rho_1 (1 - \lambda_1) \Delta s_{t-1} + e_t \tag{3.11.3}$$

3.12 Four EMP Indices

Based on these two action variables we can create a time series of EMP indices as per the following equations and estimate the same.

$$EMP_t = \Delta s_t + \omega \Delta f_t \tag{3.12.1}$$

$$EMP_t = \Delta s_t + \omega_1 \Delta f_t + \omega_2 \Delta i_t \tag{3.12.2}$$

$$EMP_t = \Delta s_t + \omega \Delta i_t \tag{3.12.3}$$

In equation (3.12.1), the weight is estimated using equation (3.11.1). Similarly, in equation (3.12.2), the weight is estimated using equation (3.11.2). Lastly, in equation (3.12.3), the weight is estimated using equation (3.11.3).

Besides the above three equations we have the EMP index as derived from the Girton and Roper Model which. The equation is

$$EMP_t = \Delta s_t + \Delta f_t \tag{3.12.4}$$

All the variables and parameters in the above equations are already explained while deriving these equations.

3.13 Crisis Threshold

Following Eichengreen et al. (1996), we define a currency crisis as an extreme value of the EMP index. However, in our context, depreciation and loss of forex reserves are represented by negative values in the EMP calculation. Therefore, we modify the crisis identification formula as follows:

$$\text{Crisis if } EMP_t < \mu_{EMP} - 1.5 \times \sigma_{EMP} \tag{3.13.1}$$

Here, σ_{EMP} = sample standard error of EMP, μ_{EMP} = sample mean of EMP.

Thus, the crisis threshold is at $1.5 \times \sigma$ below the mean EMP. If the EMP index at a point falls 1.5× standard deviations lower than the mean EMP of the entire sample period, we classify it as a currency crisis. This approach aligns with the IMF's methodology, adapted to our negative-value convention for depreciation and reserve loss.

To visualise the distribution of EMP values and the crisis threshold:

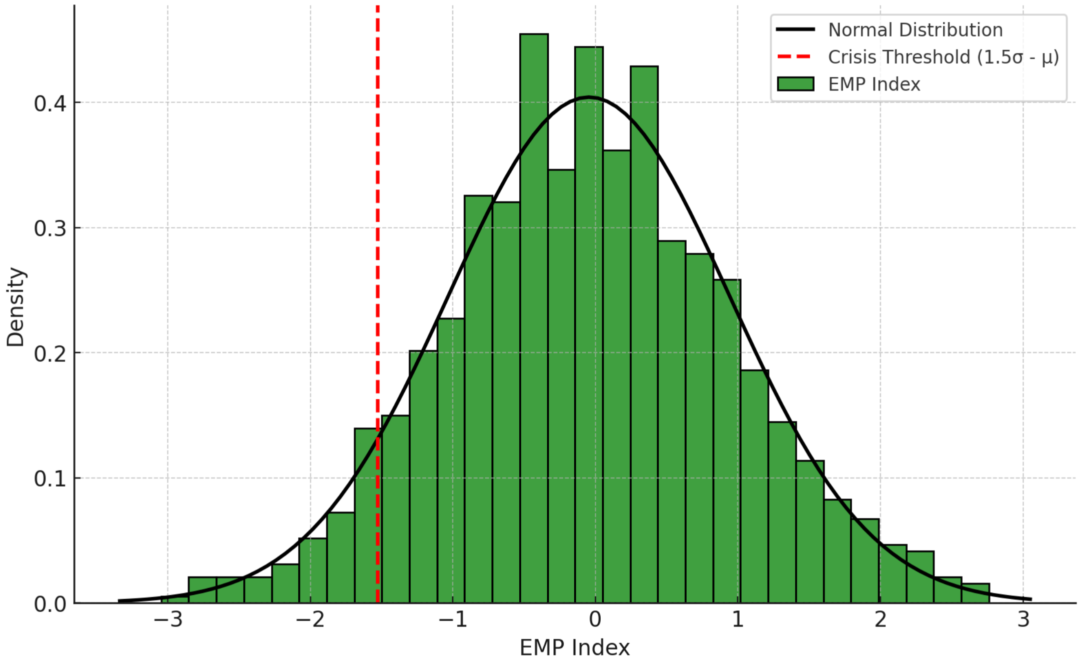


Figure 3.3: Distribution of EMP Index with Crisis Threshold

Source: Author's calculations

Figure 3.3 illustrates the distribution of EMP index values based on simulated data. The green histogram represents the frequency distribution of the EMP index, while the black curve shows the fitted normal distribution. The red dashed line indicates the crisis threshold at 1.5σ below the mean. Any EMP value falling to the left of this threshold line would be classified as a currency crisis.

This approach, while widely used due to its simplicity and reproducibility, has limitations. It doesn't capture market pressure duration and assumes a roughly normal distribution of EMP values. Nevertheless, it remains valuable for empirical research in international finance and macroeconomics, providing a clear and consistent method for identifying currency crises across different economies and time periods.

The visualisation helps in understanding the relative frequency of crisis events and how they relate to the overall distribution of EMP values in the sample. It's important to note that in our context, more negative values of EMP indicate higher pressure on the currency, reflecting either depreciation, loss of forex reserves, or both.

3.13.1 Decision Tree for Currency Crisis Identification

The decision tree illustrated in Figure 3.4 provides a structured approach to identify currency crises based on the Exchange Market Pressure (EMP) index. The steps in the decision tree are as follows:

Start: Collect EMP Data: The process begins with the collection of data required to compute the EMP index.

Step 1: Calculate EMP Index: The four EMP indices are calculated using the equations (4.4.1), (4.4.2), (4.4.3), and (4.4.4).

Step 2: Compute Mean ($\mu_{\mathbf{EMP}}$): The mean of the EMP index values is computed.

Step 3: Compute Standard Deviation ($\sigma_{\mathbf{EMP}}$): The standard deviation of the EMP index values is computed.

Step 4: Set Threshold $= \mu_{\mathbf{EMP}} - 1.5 \times \sigma_{\mathbf{EMP}}$: A threshold for identifying crises is set based on the computed mean and standard deviation.

Step 5: Classify EMP Values: The EMP values are classified based on the threshold. If an EMP value is below the threshold, it is classified as a 'Crisis'. Otherwise, it is classified as 'No Crisis'.

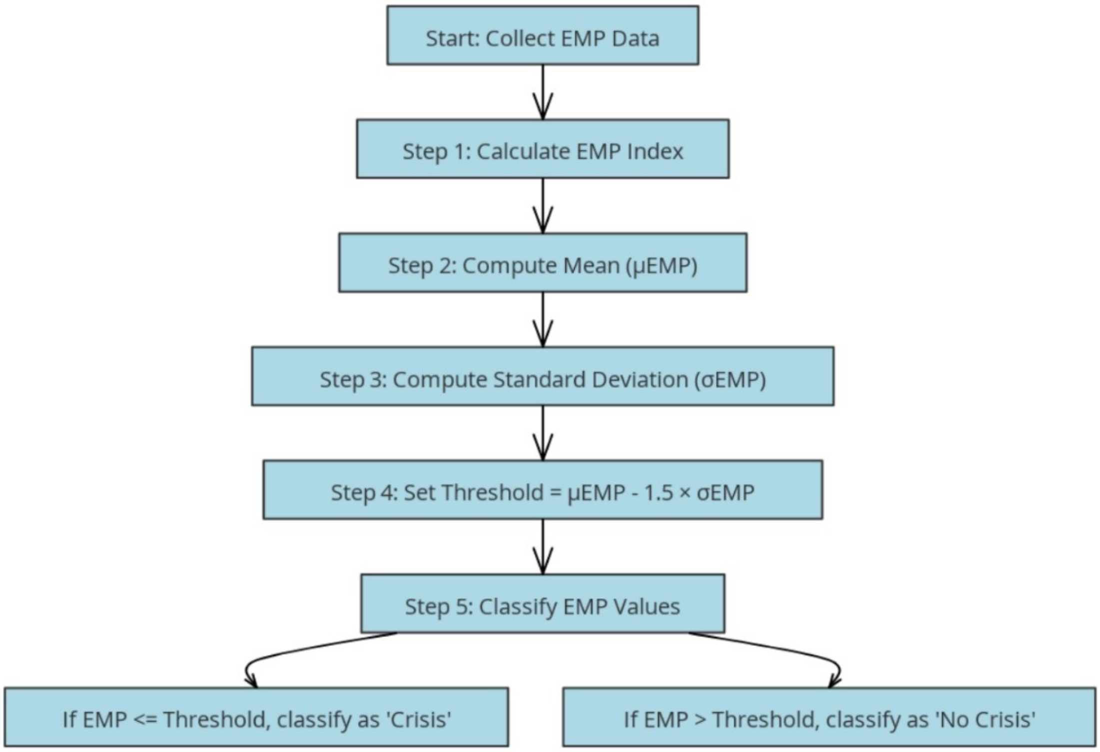


Figure 3.4: Decision Tree for Currency Crisis Identification

Source: Author's creation

Chapter 4

Result and Findings: Exchange Market Pressure Dynamics and Crisis Episodes in India

This chapter presents key findings from our EMP analysis in India, derived from various econometric models and indices. We begin with OLS and instrumental variable estimations of weight equations for EMP indices, highlighting significant relationships between crucial variables. The chapter identifies currency crises in India from 2001 onwards, discussing these episodes in the context of global economic events and domestic policies. We explore relationships between EMP and macroeconomic variables, considering global events' impact on India's foreign exchange market. Findings are contextualised within existing literature, offering novel insights into EMP in emerging markets. This analysis contributes to understanding currency pressures in developing economies, providing valuable insights for policymakers and researchers in international finance.

4.1 Ordinary Least Squares, Estimation of G-R Model

Initially we run a simple Ordinary Least Squares (OLS) to the data as per G-R Model equation (3.10.1) and the results are produced in Table 4.10

The regression results show the model explaining exchange market pressure Exchange Market Pressure (EMP) as a function of change in credit creation by Indian monetary authority (Δd_{it}), change in monetary base in the USA (Δh_{ut}), change in real Gross Domestic Product (GDP) of India (Δy_{it}), and change in real GDP of the USA (Δy_{ut}). The coefficients of (Δh_{ut}) is significant , and all others are insignificant at 5% significance level. The signs of the coefficients are also not as per the G-R Model except for (Δd_{it}).

The overall fit of the model is also poor, as evidenced by the low R-squared of 0.105712, which suggests that only about 10.57% of the Variation in EMP is explained by the independent Variables. The adjusted R-squared, which adjusts for the number of parameters in the model, is at 0.072590, indicating that the model is not a good fit for the data.

Additionally, the F-statistic of 7.044613 and its corresponding p-value of 0.000064 suggest that the model as a whole is statistically significant. The Durbin-Watson statistic of 1.77385 (with p vale of 0.174 and 0.8258 for positive and negative correlation respectively)indicates that there is no evidence of autocorrelation in the residuals. Breusch-Godfrey Langrange Multiplier (LM) test of autocorrelation also shows that there is no autocorrelation in the residuals. White's test of heteroscedasticity also indicates no heteroscedasticity in the residuals.

Having a significant F-statistic while observing low values for both R-squared and adjusted R-squared can initially seem counter-intuitive. However, this phenomenon is not uncommon and can arise due to specific characteristics inherent in both the data and the model being utilised.

The F-statistic serves as a tool to gauge the overall significance of a regression model. By comparing the Variance accounted for by the model against the unexplained Variance, the F-statistic determines whether the model, taken as a whole, provides a superior fit to the data than a model devoid of any predictors. This implies that, within the current model, at least one of the predictors is contributing to elucidating the Variability in the response Variable.

On a different note, R-squared and adjusted R-squared are measures designed to assess how effectively the model's predictors clarify the Variation observed in the response Variable. R-squared quantifies the proportion of total Variability in the response Variable that can be attributed to the predictors in the model. Conversely, adjusted R-squared considers the number of predictors present in the model and penalises the inclusion of irrelevant predictors that may not significantly contribute to explaining Variation.

When encountering a situation where a significant F-statistic coincides with low R-squared and adjusted R-squared values, it suggests that while the overall model holds statistical significance, the predictors themselves fall short in accounting for a substantial portion of the total Variation in the response Variable. In simpler terms, while the model does have some capability to explain Variation, there remains a notable amount of unexplained Variation that the predictors are failing to capture. It's crucial to note that statistical significance and practical significance are not always aligned. A significant F-statistic indicates that the model is more favourable than no model, but it does not necessarily indicate strong practical utility or robust predictive capabilities. The poor fit of the Girton-Roper Model to Indian data during the chosen sample period could be attributed to various factors. These factors may stem from model specification related issues, data-related issues or violations of the model's underlying assumptions specific to the G-R Model's framework. To thoroughly examine these potential causes of poor fit, we will address each issue individually.

1. Weak Predictors: The predictors in use may not wield significant influence in explaining the variation. Weak relationships with the response variable can undermine their explanatory power.

2. Missing Variables: The absence of key predictors in the model can lead to unresolved variation. This could be due to omitted variables specific to the Indian economic context or limitations in data availability.

3. Model Misspecification: The G-R Model's formulation may not fully capture the unique characteristics of India's economy, leading to misspecification issues.

4. Nonlinear Relationships: Linear regression models might not be adept at capturing the nuances of nonlinear relationships between predictors and the

response. The G-R Model's linear formulation may oversimplify complex economic interactions in the Indian market.

5. Volatility Clustering: Financial time series often exhibit periods of high volatility followed by periods of low volatility. The G-R Model may not adequately capture this phenomenon, leading to poor fit during volatile periods.

6. Persistence and Long Memory: Many economic and financial time series display persistence, where shocks have long-lasting effects. Long memory processes, where past events continue to influence future outcomes over extended periods, may not be well-captured by the G-R Model's assumptions.

7. Outliers, Influential Points, and Structural Breaks: These interrelated factors can disproportionately impact R-squared values and model fit. Temporal instability refers to changing relationships between variables over time, which can manifest as outliers, influential points, or structural breaks. Structural breaks represent sudden changes in the underlying data-generating process—such as policy changes, economic crises, or shifts in market conditions. These elements can lead to misleading conclusions about the model's explanatory power and the overall stability of the estimated relationships.

8. Small Sample Size: Achieving high R-squared values becomes more challenging in smaller sample sizes.

9. External Shocks: The model may not adequately account for external economic shocks or global economic conditions that significantly impact India's economy.

10. Multicollinearity: High multicollinearity among predictors can confound attempts to isolate the individual effects of each predictor, potentially resulting in lower R-squared values.

11. Heteroskedasticity: The assumption of constant variance may be violated, especially given the dynamic nature of financial markets in emerging economies.

12. Autocorrelation: Temporal dependencies might exist that the G-R Model doesn't account for, potentially leading to inefficient estimates and unreliable inference.

13. Non-normality of Residuals: The presence of non-normal errors violates a key assumption of many statistical tests and may indicate underlying complexities in the data not captured by the model.

14. ARCH Effects: The presence of time-varying volatility cannot be entirely ruled out, especially in financial time series from emerging markets.

15. Regime Changes: Shifts in monetary or fiscal policy regimes during the sample period may not be adequately captured by the static nature of the G-R Model.

Points 1, 2, and 3 and 4 are model related issues and do not apply to our study because the framework of our research being firmly rooted in the theoretical model provided by G-R Model. This theoretical framework guides our choice of predictors and assumptions about relationships, thereby mitigating concerns about weak predictors, missing Variables, and nonlinear relationships. In the realm of economic modelling, non-linearity often plays a crucial role in capturing the intricate dynamics of Various financial phenomena, The question of non-linearity, currency crisis etc. is addressed by Krugman (1979) Flood and Garber (1984). In this research we are not looking into any theoretical model explaining non-linearity though we are definitely concerned with periods of extreme volatility or currency crisis as defined by Eichengreen et al. (1996).We will identify these periods, mark them as outliers and will try to address related issues. Point number 8 is addressed while discussing the sample size in Section 3.4 Other points will be taken up and addressed one by one as we move ahead. The issue of volatility clustering, persistence and long memory is a characteristic feature of the time series data and it is not out of place here to examine our data for the same.

Refer to the Figure 4.1. Analysis of INR/USD exchange rates (2001-2022) re-

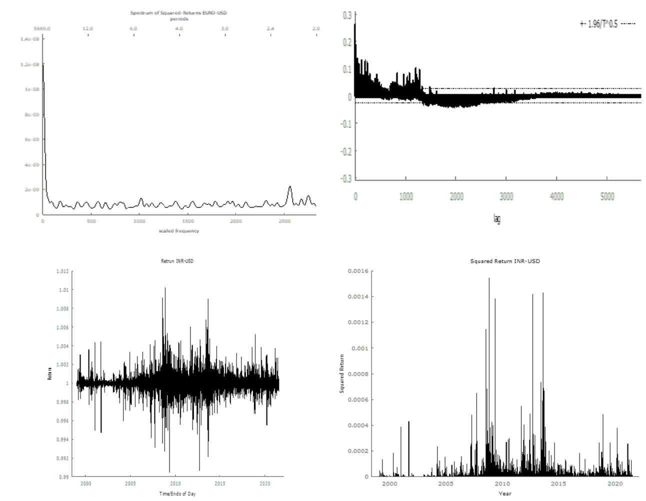


Figure 4.1: Statistical Properties of INR/USD Exchange Rate (2001-2022). Note:Market exchange rate data were obtained from historical exchange rate databases of Federal Reserve Economic Data (FRED).

Source: Author's creation

veals long memory persistence and volatility clustering, which the linear Girton-Roper model fails to capture. Evidence includes power concentration at lower frequencies in the periodogram and slow decay in autocorrelations of squared log returns. Log returns of INR/USD exhibit periods of high volatility interspersed with relative calm, indicating volatility clustering. Notably, extreme fluctuations are evident during major economic events, particularly the 2008 global financial crisis and the 2020 COVID-19 pandemic. These periods show large spikes in squared log returns, signifying intense market turbulence. Given these observations, we can conclude that the Girton-Roper model, being a linear model developed in the 1970s, fails to adequately capture these complex dynamics in the INR/USD exchange rate data. The model's limitations stem from its age and linear nature:

The Girton-Roper model was developed in 1977, predating many of the advances in financial econometrics that address non-linear dynamics and long memory processes. As a linear model, it assumes a constant relationship between variables, which doesn't account for the observed volatility clustering and extreme events. The model doesn't incorporate mechanisms to capture long memory persistence, which is evident in the INR/USD data. It lacks the flexibility to adapt to structural changes in the economy and financial markets that have occurred since its development.

Consequently, applying the Girton-Roper model to the Indian rupee-US dollar exchange rate data from 2001 to 2022 is likely to result in a poor fit. The model's inability to account for long memory, volatility clustering, and extreme events means it will struggle to accurately represent the complex dynamics observed in the modern foreign exchange market. To improve the modelling of INR/USD exchange rates, more sophisticated approaches that can handle these non-linear dynamics, such as GARCH-type models, or regime-switching models, would be more appropriate. These modern techniques can better capture the observed characteristics of the exchange rate series and provide more accurate insights into its behaviour. **Looking for Outliers, Leverage Points and Structural Breaks**

While both outliers and structural breaks can compromise the model's performance, it's important to recognise that they do so in distinct ways, affecting the underlying relationships differently.

When outliers are not adequately addressed, they tend to pull the regression line towards them, causing a poor fit because they represent exceptions to the general trends within the dataset. structural breaks introduce abrupt changes in the data-generating process. These shifts can manifest as change in relationship among Variables. Ignoring structural breaks can result in a model that assumes a consistent relationship throughout the entire dataset, even when such a uniform relationship does not exist.

Mahalanobis Distances

Mahalanobis distance is a statistical measure used to assess the similarity between an observation and a group's centroid in multiVariate analysis. In this case, the distances likely to indicate how different each year's data point is from the centroid in the multiVariate space defined by the Variables $EMPI_t$, Δd_{it}, Δh_{ut}, Δy_{it}, and Δy_{ut}.Years with exceptionally high Mahalanobis distances, can be found by looking at the Figure 4.3 and the Table 4.15. The outlier periods are 2007:4

2008:4, 2009:2, 2009:4,2014:1,2020:2,2020:3,2021:2,2021:3,2021:4.

Leverage Points

Leverage points are important because they can strongly influence the estimated coefficients, model fit, and predictions. If a leverage point has a significant impact on the model, its presence or absence can lead to substantial changes in the results. Therefore, it's crucial to examine and understand the reasons behind the influence of these points. The leverage of a data point measures how far the predictor Variables (independent Variables) of that data point are from the mean of the predictor Variables. Leverage values are between 0 and 1, with higher values indicating greater influence. There is no universally agreed-upon threshold for what constitutes a high leverage point. However, in practice, data points with leverage values significantly greater than the average leverage (p/n, where p is the number of predictor Variables, and n is the number of data points) are often considered leverage points In the regression result given in the Table 4.10 the leverage points are 2008:4, 2009:4, 2020:2, 2020:3, 2021:2,2021:3,2021:4.

Looking for Structural Break

Wald Test for Structural Break

Result of the Wald Test of structural break are reported in the Figure 4.4. The graph suggests that there may be structural changes in the period from 2010-2013 and 2017 onwards. The line representing the test statistic intersects the black dashed line (5% critical value) in these periods, which implies a significant alteration or "rupture" in the fundamental structure of the time series.

Table 4.10 reports the results of Various diagnostic tests, including the Quandt Likelihood Ratio (QLR) test for structural break, the Ramsey RESET test for specification, the LM test for autocorrelation, White's test for heteroskedasticity, the normality test for residuals, and the ARCH test.

QLR Test for Structural Break

The Quandt Likelihood Ratio (QLR) test yielded a chi-square test statistic of 31.8421 with 5 degrees of freedom at the observation point 2019:2. The associated p-value is 0.000207883, which is significantly less than 0.05. This leads to the rejection of the null hypothesis of no structural break, suggesting a structural break in the time series data around the second period of 2019.

Reset Test for Specification

The test was conducted with the null hypothesis of an adequate model specification. The F-statistic was 1.60772 with 2 and 79 degrees of freedom. The p-value was 0.206829, which is greater than the commonly used significance level of 0.05. Therefore, there is not enough evidence to reject the null hypothesis, suggesting the model's specification is adequate.

LM Test for Autocorrelation

The Langrange Multiplier (LM) test was conducted to check for autocorrelation in the error up to the 4th order. The test statistic (LMF) is 0.70266 and the associated p-value is 0.592479.

A p-value greater than 0.05 means, there's not enough evidence to reject the null hypothesis, which in this case is that there's no autocorrelation. So, the error terms in the regression reported in the table do not show significant autocorrelation up to the 4th order.

White's Test for Heteroskedasticity

In our study, we used White's test for heteroskedasticity. The LM statistic was 11.964 with a p-value of 0.609191, indicating no evidence of heteroskedasticity in our regression model's errors.

Test for Normality of Residuals

We conducted a normality test on our model's residuals. The Chi-square statistic was 19.5253, and the p-value was 5.75632e-05. This low p-value led us to reject the null hypothesis of normal distribution, indicating non-normality in our model's errors.

ARCH Test

We conducted an Auto-Regressive Conditional Heteroscedasticity (ARCH) test of order 4. The LM statistic was 1.15446 with a p-value of 0.885539, indicating no evidence of ARCH effects in our data.

Switch Regression Analysis: Accounting for Outliers and Structural Breaks

The regression results indicate that there is no evidence of heteroskedasticity or ARCH effects in the model's errors, as suggested by the White's Test and ARCH Test respectively. However, the Test for Normality of Residuals indicates non-normality in the model's errors

This could be due to outliers or structural breaks in the data. Outliers could be extreme values that deviate significantly from other observations. These could be due to specific events or shocks in the Indian or world economy during the period of study.

Structural breaks refer to a shift in the underlying relationships between Variables over time. This could be due to significant economic events or policy changes. For instance, in 2001, 2007-2009, and 2019-2020, there were significant events both in India and globally that could have caused structural breaks.

In 2001, a peak in business activity occurred in the US economy in March marking the end of an expansion and the beginning of a recession (National Bureau of Economic Research of Economic Research (2001) . This recession had a global impact with many countries experiencing economic downturns Kose et al. (2010). In India, this period was marked by a slowdown in the IT sector and other export-oriented firms due to the global recession Dixit (2016).

The period from 2007 to 2009 was marked by the global financial crisis, which was by far the deepest and most synchronised of the four recessions since 1975 Kose et al. (2010) . The crisis threatened the global financial system with total collapse, led to sharp declines in stock prices, and caused a decline in consumer lending and lower investments in the real sector Verick and Islam (2010) . In India, this period saw a multi-crore loss in business and export orders, tens of thousands of job losses, especially in key sectors like IT, automobiles, industry and export-oriented firms Kamble (2013) .

The most recent recession occurred from 2019 to 2020. According to the

National Bureau of Economic Research (NBER) chronology, a peak occurred in February 2020 and a trough occurred in April 2020 of Economic Research (2020) . This period was marked by the COVID-19 pandemic which had far-reaching economic consequences including decreased business in the services sector during lock-downs, a stock market crash, and an impact on financial markets Fernandes (2020). In India, this period saw a significant contraction in GDP growth due to factors such as increasing Non- Performing Assets (NPAs) in the banking sector and the effects of lockdown measures on Various sectors of the economy Sanh et al. (2021) The regression exhibits multiple structural breaks and numerous outliers. We will remove outliers and run the regression. To address the problem of multiple structural breaks we will run switch regression. A switching regression model is used to either classify un-observable states or to estimate the transition probabilities for these un-observable states in a time series.

Result of Switch Regression and Interpretation Across Distinct Regimes

The results of the switching regression models are presented in Tables 4.11,4.12,4.13,4.14 We present below the summary of statistical metrics to chose the best of the four model which we have run-

Table 4.1: Summary of Statistical Metrics for Different Models

Model	SSR	Log-Lik	AIC	SC	HQC	SE of Reg	DW Stat
Model 1 (SRS2R84)	0.072486	192.0869	-4.311593	-3.993272	-4.186310	0.031298	1.804004
Model 2 (SRS3R84)	0.072486	202.7893	-4.423555	-3.931604	-4.225795	0.032307	1.734811
Model 3 (SRM2R84)	0.0742566	202.7893	-4.198848	-3.851588	-4.225795	0.031298	1.879896
Model 4 (SRM3R84)	0.072019	208.4219	-4.462427	-3.854722	-4.218135	0.032307	1.794322

Source: Author's calculations

Note: Model names are defined as follows:

Model 1: Simple Switching Regression with Two Regimes (SRS2R84)

Model 2: Simple Switching Regression with Three Regimes (SRS3R84)

Model 3: Markov Switching Regression with Two Regimes (SRM2R84)

Model 4: Markov Switching Regression with Three Regimes (SRM3R84)

Abbreviations: Sum of Squared Residuals (SSR), Log-Likelihood (LogLik), AIC, Schwarz Criterion (SC), Hannan-Quinn Criterion (HQC), SE! (SE!), Durbin-Watson Statistics (DWS).

Based on the parameter given in 4.1 Model 4, Markov Switching Regression with Three Regimes (SRM3R84), appears the best but its useless because the p value of the coefficients are not available same logic applies to Model 2, Simple Switching Regression with Three Regimes (SRS3R84). Thus we have to chose between Model 1, Simple Switching Regression with Two Regimes (SRS2R84), and Model 3 Markov Switching Regression with Two Regimes (SRM2R84). Model 1 exhibits a slightly lower Sum of Squared Residuals (SSR) and an adequate Log-Likelihood (LogLik). However, Model 3 demonstrates favourable results in terms of Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQC), and Durbin-Watson Statistics (DWS), implying a more balanced trade-off between fit and model complexity. Additionally, Model 3 shows no signs of autocorrelation, as indicated by a higher Durbin-Watson Statistic.

Considering these factors, Model 3 Markov Switching Regression with Two Regimes (SRM2R84), emerges as the most suitable choice, as it offers a better overall balance between model fit and complexity, making it the preferred model for this analysis.

Interpretation of the Results of the Model 3

Result of Model 3, Markov Switching Regression with Two Regimes (SRM2R84), are reported in 4.13

To differentiate the regimes in terms of volatility and stability, we can look at the LOG(SIGMA) values and the transition probabilities.

LOG(SIGMA) values:

Regime 1: -4.240176 (p-value = 0.0000)

Regime 2: -3.287281 (p-value = 0.0000)

The LOG(SIGMA) values represent the log of the standard deviation of the error term in each regime. A lower LOG(SIGMA) value indicates lower volatility. In this case, Regime 1 has a lower LOG(SIGMA) value (-4.240176) compared to Regime 2 (-3.287281), suggesting that Regime 1 is associated with lower volatility and is thus more stable.

Transition Probabilities:

The transition probability matrix is given as:

	*Regime*1	*Regime*2
*Regime*1	0.887865	0.063106
*Regime*2	0.887865	0.063106

The transition probabilities indicate the likelihood of moving from one regime to another. In this case, the probability of staying in Regime 1 (0.887865) is higher than the probability of moving from Regime 1 to Regime 2 (0.063106). Similarly, the probability of moving from Regime 2 to Regime 1 (0.887865) is higher than staying in Regime 2 (0.063106).

The high probability of staying in Regime 1 and the high probability of transitioning from Regime 2 to Regime 1 suggest that Regime 1 is more stable and persistent compared to Regime 2.

Expected Duration: Furthermore, the expected durations of each regime are: Regime 1: 8.917834
Regime 2: 1.067357

The expected duration of Regime 1 is much longer than that of Regime 2, indicating that the system tends to spend more time in Regime 1, further supporting its stability.

In conclusion, based on the lower volatility (indicated by the lower LOG(SIGMA) value), the high probability of staying in Regime 1, and the longer expected duration of Regime 1, we can infer that Regime 1 is more stable compared to Regime 2 in the Markov Switching Regression with Two Regimes.

Regime 1

1.Δd_{it}: The coefficient for Δd_{it} is -0.00685, and the p-value is 0.4277. This indicates that a one-unit change in domestic credit (Δd_{it}) does not have a statistically significant impact on Exchange Market Pressure (EMP) during this regime. In practical terms, changes in domestic credit creation do not significantly affect EMP in Regime 1.

2.Δh_{ut}: The coefficient for Δh_{ut} is -0.032610, and the p-value is 0.1937. Similarly, a one-unit change in high powered money supply in the USA (Δh_{ut}) does not have a statistically significant impact on EMPI in Regime 1. This Variable also lacks significance as a determinant of EMP during this regime.

3.Δy_{it}: The coefficient for Δy_{it} is -0.064445, and the p-value is 0.6347. In Regime 1, a one-unit change in India's real GDP (Δy_{it}) does not significantly influence EMP. The high p-value suggests that changes in India's GDP do not have a substantial impact on EMP during this regime.

4.Δy_{ut}: The coefficient for Δy_{ut} is 0.396299, and the p-value is 0.3049. In Regime 1, a one-unit change in the USA's real GDP (Δy_{ut}) does not have a statistically significant effect on EMP. Despite the positive coefficient, the p-value indicates that this influence is not significant during this regime.

Regime 2

1. Δd_{it}: The coefficient for Δd_{it} remains the same at -0.00685, and the p-value is 0.4277. Once again, this Variable does not have a statistically significant impact on EMP during Regime 2. Therefore, in both regimes, changes in domestic credit creation does not significantly affect EMP.

2.Δh_{ut}: The coefficient for Δh_{ut} also remains consistent at -0.032610, and the p-value is 0.1937. Just like in Regime 1, high powered money supply in the USA (Δh_{ut}) does not significantly influence EMP in Regime 2. This Variable lacks statistical significance in both regimes.

3.Δy_{it}: The coefficient for y_{it} changes to -1.200290, and the p-value is 0.0105. In Regime 2, a one-unit change in India's GDP (Δy_{it}) has a statistically significant negative impact on EMPI. The negative coefficient suggests that an increase in India's GDP results in a negative pressure on exchange market of India during this regime. This finding is not consistent with the G-R Model as the model predicts a positive sign for this coefficient. This suggests that a 10 percent in rise in India's GDP in Regime 2 will lead to $(-1.20090 \times 0.10 = 0.12009)$ 0.12009 points or $(-1.20090 \times 0.10 = 0.12009 \times 100 = 12.009\%)$ 12.009% negative pressure on its exchange market i.e the Indian Rupees (INR) will depreciate by 12.009 percent to US Dollar (USD) or India will lose its reserves by 12.009 percent from the base of its previous quarter reserves or both. One possibility is that India's economic growth during Regime 2 is primarily driven by increased domestic demand for imported goods and services. In this scenario, a higher demand for foreign currency to facilitate these imports would put downward pressure on the INR.

4.Δy_{ut}: The coefficient for y_{ut} changes to 2.953739, and the p-value is 0.0294. In Regime 2, a one-unit change in the USA's GDP (Δy_{ut}) has a statistically significant positive impact on EMP. The positive coefficient implies that an increase in the USA's GDP leads to positive pressure on India's exchange market during this regime. This finding is not consistent with the Girton and Roper Model. This suggests that a 10 percent rise in the USA's GDP in Regime 2 will lead to $(2.953739 \times 0.10 = 0.2954) i.e. 0.2954$ points or $(2.953739 \times 0.10 = 0.2954 \times 100)$ $= 29.54$ % positive pressure on India's exchange market, i.e., the INR will appreciate by 29.54 percent relative to the USD, or India will gain reserves by 29.54 percent from the base of its previous quarter reserves or both. The rationale behind this finding could be that an increase in the USA's GDP may lead to increased demand for Indian exports, resulting in higher foreign currency inflows into India. Additionally, higher economic growth in the USA may attract more foreign investments into India, further contributing to the appreciation of the INR or the accumulation of foreign reserves. It is important to note that this finding is not only in-consistent with the Girton and Roper Model's prediction, the magnitude of the impact (29.54 % for a 10 % increase in the USA's GDP) seems relatively large as it relates to Regime 2 which is more volatile and less-durable in comparison to Regime 1.

In summary, the relationship between these Variables and Exchange Market Pressure (EMP) is not consistent across the two regimes. Changes in India's and the USA's real GDP become significant determinants of EMP in Regime 2 but not in Regime 1. One should, however note that the results still do not match the results as suggested by the theoretical model of .G-R Model In our ongoing analysis, we have diligently applied Various methodologies to address the challenges posed by outliers and multiple structural breaks in our dataset. Despite these efforts, the data continues to exhibit a poor fit with our current model.

The model in question, developed in the 1950s for the Canadian managed float, was designed in a different era. It was a time when the complexities of financial time series, such as non-linearity and persistence, were not fully understood or accounted for. The presence of threshold effects, where the relationship between Variables changes once certain economic indicators cross specific levels, was not considered. Additionally, the model did not incorporate asymmetric responses, where the exchange market reacts differently to positive and negative shocks in macroeconomic Variables.

Furthermore, the model may not be fully equipped to handle the intricacies of today's financial data, such as regime shifts, where the underlying economic relationships change due to structural transformations, policy changes, or external shocks. The existence of feedback loops and self-fulfilling expectations, which can amplify the impact of market sentiment on exchange rates, were not taken into account.

Moreover, the model did not consider the potential influence of contagion and spillover effects from other economies or financial markets, which can introduce nonlinearities and complexities that are difficult to incorporate into a linear framework. Lastly, the presence of speculative attacks and market inefficiencies, which can create abrupt changes or discontinuities in the relationship between economic Variables and exchange market pressure, were not fully understood or accounted for. The Girton-Roper Model relies on several key assumptions, each critical for its accurate application. These assumptions include a stable demand for money function with a constant money multiplier, adherence to purchasing power parity (PPP), equilibrium in the money market, and equal growth rates for domestic and foreign interest rates, with a constant interest rate differential.

Non-fulfillment of these conditions can lead to specific challenges in model fitting. If the demand for money is unstable or the money multiplier varies, the relationship between monetary variables and exchange market pressure (EMP) may become unpredictable, leading to poor model performance. Similarly, if PPP does not hold, the model's predictions about exchange rate movements may not align with the actual data, resulting in inaccuracies. Additionally, if there is disequilibrium in the money market, fluctuations in interest rates could occur, which the model may fail to capture effectively. Lastly, if domestic and foreign interest rates do not grow at the same rate or if the interest rate differential fluctuates, the model's ability to predict the impact on EMP may be compromised.

Our analysis indicates that these conditions may not hold true in our dataset, further complicating the model fitting process and potentially leading to unreliable results. In fact, several studies have highlighted these issues in the context of India's economy. For instance, Adil et al. (2020a) explored stability issues of money demand in India's open economy since the 1990s . They found that traditional money demand functions may have problems due to lack of factoring financial innovation into the money demand function (Adil et al., 2020b). Study by Khan et al. (2021) acknowledges money demand instability and investigated the impact of economic uncertainty, stock market uncertainty and monetary uncertainty on money demand in India over the period 2003Q1–2019Q4.

Purchasing Power Parity (PPP)) theory, which explains exchange rate movements between two countries' currencies based on changes in their respective price levels, has been found to have limited applicability in India in the short to medium term (Bahmani-Oskooee and Nasir, 2005). This divergence is clearly illustrated in Figure 4.1, which compares PPP and market exchange rates for INR/USD from 2001 to 2022. As evident from Figure 4.1, there is a persistent and significant gap between the PPP rate and the market exchange rate throughout the period. Analysis of PPP and market exchange rates for INR/USD from 2001 to 2022 reveals a persistent divergence. The market rate consistently exceeds the PPP rate, indicating an undervaluation of the Indian Rupee. For instance, in 2010,

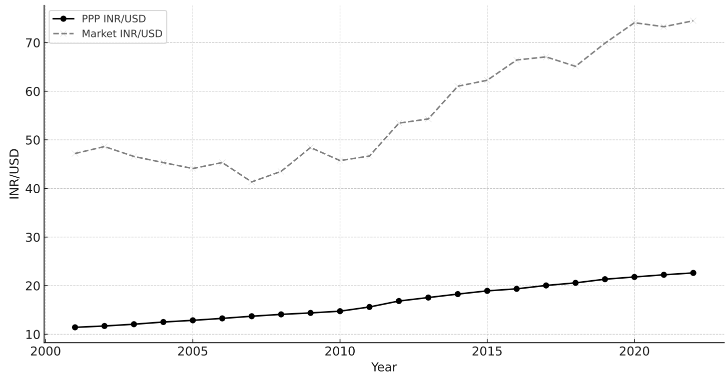


Figure 4.2: Purchasing Power Parity (PPP) and Market Exchange Rates for INR/USD (2001-2022).
Note: Data for PPP rates were retrieved from the Penn World Table 7.1 through the Federal Reserve Economic Data (FRED). Market exchange rate data were obtained from historical exchange rate databases.

Source: Author's creation

the PPP rate was 16.84 INR/USD, while the market rate was 45.73 INR/USD. Both rates show an upward trend, signifying the Rupee's depreciation, with the market rate increasing more steeply. The market rate exhibits higher volatility due to factors like interest rates and capital flows, while the PPP rate adjusts more gradually. These significant deviations suggest that PPP does not hold for INR/USD in the short to medium term. This persistent deviation from PPP underscores the limitations of models that rely on PPP assumptions, such as the Girton-Roper model, when applied to the Indian context.

Acknowledging the limitations of our current approach, we are pivoting our strategy. Our new plan involves the iterative integration of non-linear transformations and lagged versions of Variables into our model. We aim to explore Various time series models to identify the most suitable fit.

The objective is to more effectively capture the inherent non-linearity, persistence, and volatility clustering in financial time series. This includes addressing the issues of outliers and structural breaks present in our data. These characteristics of the data necessitate the inclusion of Autoregressive Moving Average (ARMA) and Polynomial Distributed Lag (PDL) terms in our regression.

Moreover, given the presence of volatility clustering, outliers, and multiple structural breaks in our dataset, we may need to consider regime-switching modelling approaches and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) methods.

Our previous attempts with models such as Switch Regression and OLS which were conducted without the inclusion of PDL and ARMA terms, did not yield satisfactory results. Therefore, we believe that this revised approach will provide a more robust and accurate model for our data.

This approach will involve rigorous testing and validation to ensure that each modification improves the model's fit with the data. We remain committed to this iterative process, confident that it will enhance our model's performance and make it more relevant to contemporary financial data.

Discovering the Optimal Fit: An Iterative Approach to Model Selection within the Girton Roper Framework

In addition to the models discussed above, we explored a wide range of regression models including - Non-Linear Least Squares (NLS), Autoregressive Moving Average (ARMA), Two Stage Least Squares (TSLS), Two Stage Non-Linear Least Squares, Generalized Method of Moments (GMM), Limited Information Maximum Likelihood (LML), k-Class, Cointegration Regression (COINTREG), Auto-Regressive Conditional Heteroscedasticity (ARCH), Binary Choice (Logit, Probit, Extreme Value), Ordered Choice, Censored or Truncated Data (including Tobit), Integer Count Data (Count), Quantile Regression (QREG) (including LAD), Generalized Linear Model (GLM), Stepwise Least Squares (STEPLS), Robust Least Squares (ROBUSTLS), Heckman Selection (HECKIT) (Generalized Tobit), Least Squares with Breaks (BREAKS), Threshold Regression (THRESHOLD), and Auto-regressive Distributed Lag Models (ARDL). Some of these models can not be applied to our data and some and most of the model are giving bad results.

In the context described, the Exponential General Autoregressive Conditional Heteroskedastic (EGARCH) model complemented by (Polynomial Distributed Lag (PDL)) and Autoregressive Moving Average (ARMA) terms emerges as a robust approach, aligning with the fundamental framework laid out by the G-R Model.

Conventional Generalised Auto-Regressive Conditional Heteroskedasticity (GARCH) models, foundational as they are, lack the adaptability to effectively encapsulate the nuanced volatility patterns observed in the dataset. The standard GARCH formulation, while insightful in specific contexts, falls short in encompassing the asymmetric volatility responses, intricate lag structures, and nonlinear effects inherent in the data.

Similarly, extensions such as Threshold General Autoregressive Conditional Heteroskedastic (TGARCH) or Integrated Generalised Autoregressive Conditional Heteroskedasticity (IGARCH) do not align seamlessly with the G-R Model's fundamental principles. TGARCH, relying on threshold effects, assumes a linear response to volatility shifts, disregarding the broader nonlinear dynamics, non-stationarity of volatility, and lagged effects evident in the dataset. Meanwhile, IGARCH, while incorporating long memory processes and persistence, overlooks the asymmetric volatility responses and non-linear effects characterizing the dataset.

Contrarily, the EGARCH model, when augmented by PDL and ARMA terms, remains aligned with the Girton and Roper Model's foundational framework while offering an adaptable and comprehensive approach. Its capacity to account for both asymmetric effects on volatility, volatility clustering, persistence, and intricate lag structures aligns with the principles of conditional heteroscedasticity, non-stationarity, and nonlinear dynamics, which are not explicitly addressed in the G-R Model. By embracing these additional complexities, the EGARCH model with PDL and ARMA terms provides a more precise representation of the dataset's intricate dynamics, while still adhering to the core principles of the G-R Model.

Therefore, while other GARCH models may provide foundational insights into volatility patterns, their limitations in aligning with the Girton and Roper framework underscore the superiority of the EGARCH model with PDL and ARMA terms for this particular analysis, as it remains more faithful to the guiding principles of the G-R Model.

This EGARCH specification allows us to capture asymmetric volatility and persistence in EMP, addressing the limitations of the base model and providing a more comprehensive framework for analysing EMP in the Indian context. The model accounts for the potential asymmetric effects of positive and negative shocks on EMP volatility, which is particularly relevant given India's managed float regime and the frequent interventions by the Reserve Bank of India. Additionally, the inclusion of ARMA and PDL terms helps to capture the complex dynamics and potential non-linearities in India's foreign exchange market. By incorporating these features, our model provides a more flexible and nuanced approach to measuring EMP in India, accounting for the unique characteristics of the country's foreign exchange market and the presence of asymmetric volatility and persistence in EMP dynamics. This approach allows for a more accurate assessment of exchange market conditions and the effectiveness of policy interventions in India's managed float regime.

Interpretation of the Results of EGARCH Model with ARCH- in- Mean and (PDL) **and (ARMA) Terms**

Based on our iterative process and the characteristics of the data, we arrive at an EGARCH-based extension of the Girton-Roper model. The final model specification is as follows: Mean Equation:

$$
\begin{aligned}
EMP_t = \alpha &+ \beta_1 \Delta d_{it} + \beta_2 \Delta h_{ut} + \beta_3 \Delta y_{it} + \beta_4 \Delta y_{ut} \\
&+ \delta \sqrt{h_t} + \sum_{i=1}^{p} \gamma_i PDL_{i,t} \\
&+ \sum_{j=1}^{q} \phi_j EMP_{t-j} + \sum_{k=1}^{r} \theta_k \varepsilon_{t-k} + \varepsilon_t
\end{aligned}
$$

Variance Equation:

$$\log(h_t) = \omega + \sum_{l=1}^{s} \alpha_l g(z_{t-l}) \qquad + \sum_{n=1}^{m} \beta_n \log(h_{t-n})$$

where:

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|], \quad z_t = \frac{\varepsilon_t}{\sqrt{h_t}} \tag{4.1.1}$$

Here, all the variables from the base Girton-Roper model remain as previously defined, and:

$PDL_{i,t}$ are the polynomial distributed lag terms of the dependent variable

EMP_{t-j} are the autoregressive terms of the dependent variable

ε_{t-k} are the moving average terms of the error

ε_t is the error term at time t, assumed to follow a generalized error distribution (GED)

$g(z_t)$ is the news impact curve, where θ and γ determine the sign and magnitude of the asymmetry

h_t is the conditional variance at time t

The result of the EGARCH Variant of G-R Model with ARCH- in- mean Polynomial Distributed Lag (PDL)) and Autoregressive Moving Average (ARMA) terms is presented in Table 4.16. Here is an interpretation of the key points of the table-

Coefficient Estimates (LOG(GARCH) Model)

C(19): This coefficient is associated with the LOG(GARCH) model. A value of -10.36742 with a negative z-statistic (-5.602381) and a very low p-value (0.0000) suggests a statistically significant impact. It signifies the contribution of the 19th lag in capturing the conditional volatility of the model.

C(20) and C(21): These coefficients represent additional terms in the LOG(GARCH) model. Both have significant impacts, as indicated by their low p-values (0.0040 and 0.1627, respectively).

C(22): The coefficient is 0.143071, indicating a less significant impact compared to the previous terms, as reflected in its higher p-value (0.5563).

Coefficients of the ARCH-in- Mean Model

@SQRT(GARCH): This coefficient is associated with the square root of the GARCH term. With a coefficient of -0.067787, a z-statistic close to zero (-0.456917), and a high p-value (0.6477), it seems less influential in this context.

Δd_{it}: The coefficient for Δd_{it} is -0.013102, and the p-value is 0.0001 it follows that a one-unit change in India's domestic credit growth rate (Δd_{it}) has a statistically significant negative impact on EMPI. The negative coefficient suggests that an increase in India's domestic credit growth rate results in a negative pressure on the exchange market of India during this regime. This finding is consistent with the Girton and Roper Model, which predicts a negative sign for this coefficient. This suggests that a 10 percent rise in India's domestic credit growth rate in will lead to ($-0.013102 \times 0.10 = -0.0013102$) -0.0013102 points or ($-0.013102 \times 0.10 = -0.0013102 \times 100 = -0.13102\%$) -0.13102% negative pressure on its exchange market, i.e., the INR will depreciate by 0.13102 percent against the USD, or India will lose 0.13102 percent of its reserves from the base of its previous quarter reserves, or a combination of both.

Δy_{it}: With a coefficient of -0.188401, a z-statistic of -2.927305, and a p-value of 0.0034, this indicates that when India's real GDP growth rate increases by one point, $EMPI_t$ decreases by 0.1884 units. This suggests that a 10 percent rise in India's real GDP growth rate will lead to ($-0.188401 \times 0.10 = -0.0188401$) -0.0188401 points or ($-0.188401 \times 0.10 = -0.0188401 \times 100 = -1.88401\%$) -1.88401% negative pressure on its exchange market, i.e., the INR will depreciate by 1.88401 percent against the USD, or India will lose 1.88401 percent of its reserves from the base of its previous quarter reserves, or a combination of both.

However, this finding is not in line with what the Girton and Roper Model predicts. The theoretical Girton and Roper Model predicts the sign of this coefficient to be positive, meaning that an increase in real GDP should either lead to an appreciation of the currency or an increase in forex reserves, or both. In the case of India, we observe the reverse happening. This may be due to import-led growth, where the increase in GDP is primarily driven by a surge in imports, leading to a higher demand for foreign currency and consequently putting pressure on the domestic currency to depreciate or causing a decline in forex reserves.

Δh_{ut}: The coefficient is -0.043720, The p-value is 0.0393, which is significant. Sign of this coefficient is not in line with the coefficient of the Girton and Roper Model. The coefficient for Δh_{ut} is reported as -0.043720, with a p-value of 0.0393, indicating statistical significance at the conventional 5%-level threshold. This outcome signifies a reliably inverse relationship between changes in the monetary base of the USA (Δh_{ut}) and the Exchange Market Pressure Index ($EMPI_t$) in India, based on the statistical analysis conducted.

In the context of a 10% increase in the USA's monetary base, this relationship can be quantified as follows:

$$\text{Impact} = -0.043720 \times 0.10 = -0.004372$$

This calculation translates into a 0.4372% negative impact on India's $EMPI_t$, suggesting that the Indian exchange market experiences a negative pressure as a result of an expanded monetary base in the USA. Consequently, this could imply a slight depreciation of the INR against the USD or a marginal decrease in India's foreign exchange reserves, contrary to the initial expectation that an increase in the USA's monetary base would exert positive pressure on India's exchange market.

Δy_{ut}: This coefficient is 0.575442, with a low p-value of 0.0003, indicating statistical significance. This suggests that a one-point increase in the real GDP of the USA is associated with an increase of approximately 0.5754 units in $EMPI_t$ of India. In other words, a 10 percent rise in the real GDP of the USA will lead to $(0.575442 \times 0.10 = 0.0575442)$ 0.0575442 points or $(0.575442 \times 0.10 =$

$0.0575442 \times 100 = 5.75442\%$) 5.75442% positive pressure on India's exchange market, i.e., the INR will appreciate by 5.75442 percent against the USD, or India's forex reserves will increase by 5.75442 percent from the base of its previous quarter reserves, or a combination of both.

However, the sign of this coefficient is not as per the prediction of the theoretical Girton and Roper Model. Empirically, this result seems justifiable, as an increase in the real GDP of the USA may increase the demand for Indian exports. A growing US economy may lead to higher consumption and investment, which could translate into increased demand for Indian goods and services. This, in turn, would lead to an inflow of foreign currency into India, causing the INR to appreciate or India's forex reserves to increase, or both.

PDL01 to PDL011: Each term captures the impact of past values on $EMPI_t$. For example coefficeints of PDL02, PDL03, PDL09, PDL010, PDL11 are significant and their values are -0.032357, 0.005617, -0.194860, 0.073994, 0.018608,in the same order. The PDL terms, or lagged values of the dependent Variable, play a crucial role in capturing the memory or persistence in the series. In this context, the coefficients of PDL02, PDL03, PDL09, PDL010, and PDL11 being significant suggests that the values of $EMPI_t$ are influenced by its own past values at these specific lags.

For instance, a significant coefficient of -0.032357 for PDL02 indicates that a one-unit increase in $EMPI_{t-2}$ leads to a decrease of approximately 0.032357 units in $EMPI_t$, all else being equal. This suggests a negative short-term memory effect, where recent changes in EMPI have a noticeable impact on its current value.

Similarly, the positive coefficient of 0.073994 for PDL010 implies that a one-unit increase in $EMPI_{t-10}$ leads to an increase of approximately 0.073994 units in EMPI_t, indicating a positive long-term memory effect. This means that changes in EMPI from ten periods ago continue to influence its current value, highlighting the importance of capturing long-term dependencies in the series.

Overall, significant coefficients of PDL terms indicate the presence of memory or persistence in the series,

Autoregressive (AR)(12) and Moving Average (MA)(12): These coefficients are associated with Autoregressive (AR) and Moving Average (MA) terms. AR(12) has a coefficient of 0.479215, suggesting a positive impact on EMP_t. MA(12) has a coefficient of -0.861600, indicating a negative impact on EMP_t. Both coefficients are highly significant (p-values close to zero). The AR(12) and MA(12) terms in the model represent the impact of past values and past errors, respectively, on the current value of EMP_t.

The positive coefficient of 0.479215 forAR(12) suggests that past values of EMP from twelve periods ago have a positive impact on the current value. This implies that if the EMP was high twelve periods ago, it is more likely to be high today, and vice versa. This can be interpreted as a form of momentum or persistence in the series, where past trends tend to continue into the present.

On the other hand, the negative coefficient of -0.861600 for MA(12) indicates that past errors in forecasting EMP_t from twelve periods ago have a negative impact on the current value. This means that if there was a large forecasting error twelve periods ago, it is likely to be corrected in the current period. This can be seen as a form of mean reversion, where large deviations from the mean are likely to be followed by corrections back towards the mean.

Overall, the significant coefficients of AR(12) and MA(12) suggest that both past values and past errors play important roles in explaining the current value of EMP_t, providing insights into the dynamics and predictability of the series.

Comparison of Models

Table 4.2 presents a comparison of the results from different regression models :

The Table 4.2 gives the performance of alternative models based on several metrics like SSR, Log-Likelihood (LogLik), AIC, Standard Error of Regression (SER), R^2 (Coefficient of Determination), and $\overline{R}^2$ (Adjusted Coefficient of Determination). Among these models, the Exponential General Autoregressive

Table 4.2: Comparison of Models

Model	**SSRed**	**Log-likelihood**	**AIC**	**SER**	R^2	$\overline{R}^2$
OLS	0.0715	180.2927	-352.5854	0.0297	0.1057	0.0726
MSR (Two Regimes)	0.0743	202.7893	-4.1988	0.0313	–	–
MSR (Three Regimes)	0.0720	208.4219	-4.4624	0.0323	–	–
SSR (Two Regimes)	0.0725	192.0869	-4.3116	0.0313	–	–
SSR (Three Regimes)	0.0725	202.7893	-4.4236	0.0313	–	–
EGARCH with PDL and ARMA	0.0217	182.8164	-5.2727	0.0225	0.6765	0.5485

Source: Author's calculation.

Note:
MSR – Markov Switch Regression. SSR – Simple Switch Regression SSRed – Sum of Squared Residual
AIC – Akaike Information Criterion SER – Standard Error of Regression

Conditional Heteroskedastic (EGARCH) with PDL and ARMA stands out as the most promising.

The EGARCH model with PDL and ARMA showcases notably lower SSR, indicating better overall fit compared to other models. Its LogLik and AIC scores are significantly superior, portraying higher goodness of fit and better information criteria. Additionally, it demonstrates a substantially lower SER, suggesting a more accurate representation of the data.

One of the most compelling aspects of the EGARCH model is its impressive R^2 and $\overline{R}^2$ values, standing at 0.676452 and 0.548538, respectively. These values signify a robust explanatory power of the model in explaining the variability of the dependent variable, outperforming other models in this aspect.

Furthermore, an intriguing finding is that the EGARCH model with PDL and ARMA yields the highest number of significant regression coefficients. This signifies its ability to capture essential relationships within the data, strengthening its credibility and reliability in making predictions or inferences.

In summary, the EGARCH model with PDL and ARMA emerges as the most favourable choice among the models assessed, showcasing superior performance across multiple criteria and exhibiting a strong explanatory capacity with a substantial number of significant coefficients in its regression analysis.

4.2 Least Square Estimates of Weight Equations

This section focuses on estimating the weight ω in three different equations: equation (3.11.1) equation (3.11.2) and equation (3.11.3). The results of the regression are reported in table 4.17,4.18 and 4.19. The result of the regression of equation (3.11.1) suggests that only 3.74 percent variations in the Δs_t are explained by the independent variables, their joint effect together on Δs_t is significant as indicated by very low p value of F statistics. Coefficient of Δf_t is significant whereas coefficient of Δf_{t-1} is insignificant. The sign of the coefficient of Δf_{t-1} is also not as per the model 4.17. Equation (3.12.1) is to be based on the weight derived from this equation, we can go with the equation (3.11.1), though the result is not that strong. This is because our interest here lies in the estimation of the weight of the action variable Δf_t, based on the theoretical model we derived in the equation (3.11.1). Further post-regression diagnostics of this result in presented in the chapter 5
The result of the regression equation (3.11.2) is giving us a weight of 11.2760 for Δf_t and 0.0168286 for Δi_t. We accept these values as they are significant and have the sign as per the theoretical model presented in equation (3.11.2). We will base the EMP index in equation (3.12.2) as per these weights. For post-regression diagnostics of these estimates please vide chapter 5. Similar discussions apply to the regression result of equation (3.11.3). Through this we estimate the weight of Δi_t to be used in the EMP index as per equation (3.12.3). The numerical value of the weight is 0.0165941, has appropriate sign and is statistically significant. Refer to chapter 5 for post-regression diagnostics.

To summarise, the empirical findings from these three equations suggest that the adjustment of forex reserve and interest rate individually as well as jointly served as significant action variables in controlling currency deprecation in India for the period of our analysis and hence the weights derived here must form an important component of the EMP indices for the country.

4.3 Instrumental Variable Estimation of Weight Equations

In our exploration of weight equations (3.11.1) , (3.11.2),(3.11.3) we encounter the intricate challenge of endogeneity, where the interplay between independent and dependent variables can introduce bias. While we have attempted to mitigate this issue by incorporating an equation for regime-dependent persistence, the empirical treatment of endogeneity requires a robust approach. In this context, instrumental variable regression emerges as a necessary tool.

In the realm of regression analysis, endogeneity can distort the true relationships between variables, leading to unreliable coefficient estimates. By relying solely on theoretical adjustments, we may not fully capture the nuanced dynamics of real-world data. This is where instrumental variable regression comes into play. It offers a practical method to address endogeneity by introducing external variables—instrumental variables—that are correlated with the endogenous variables of interest but unaffected by the error term.

Instrumental variable regression operates in two stages. First, we select instrumental variables that satisfy the conditions of relevance and exogeneity. These instruments should possess a meaningful association with the endogenous variables while avoiding any connection with the error term. Once these instruments are identified, we proceed to the second stage, where we employ two-stage least squares (2SLS) regression. This involves regressing the endogenous variables on the chosen instruments to generate predicted values. Subsequently, these predicted values are integrated into the original weight equations, enabling the estimation of coefficients that disentangle the endogeneity bias.

Our instrumental variable regression analysis yields revised coefficient estimates for weight equations (3.11.1) (3.11.2),(3.11.3). By accounting for endogeneity through this empirical approach, we attain a clearer understanding of the causal relationships between independent variables and weight. This analytical path underscores the significance of both theoretical and empirical remedies when grappling with endogeneity concerns.

4.3.1 Choice of Instrumental Variable

To address this concern in the context of our empirical investigation involving Equations (3.11.1), (3.11.2), and (3.11.3), the selection of appropriate instrumental variables is crucial. This subsection aims to provide a comprehensive rationale for our choice of instrumental variables, focusing on the utilisation of Δf_t^2 and Δi_t^2.

One of the fundamental challenges we encounter in our analysis pertains to the endogeneity of the independent variables Δf_t and Δi_t. During periods characterized by speculative attacks, as discussed by Krugman (1979) in his influential work on balance-of-payments crises, rapid and pronounced changes often manifest in the variables Δf_t and Δi_t. Despite these abrupt fluctuations, the underlying currency values frequently fail to stabilise, suggesting the presence of unobserved factors that significantly impact the equilibrium. This observation inherently implies that the errors inherent in the equations, represented by Equations (3.11.1), (3.11.2), and (3.11.3), do not possess a direct and substantial relationship with the squared terms Δf_t^2 and Δi_t^2. Instead, it is plausible to posit that these errors exhibit a stronger correlation with the actual levels of Δf_t and Δi_t.

To bolster our proposition for employing Δf_t^2 and Δi_t^2 as instrumental variables, we draw insights from the research conducted by Klaassen and Jager (2011). In their notable study, they emphasise the significance of incorporating Δf_t^2 and Δi_t^2 as instrumental variables for Δf_t and Δi_t for estimating the weight equations. The inclusion of squared changes is particularly pertinent when evaluating speculative pressures and comprehending the intricate dynamics of exchange markets. This empirical validation aligns seamlessly with our motivation for selecting Δf_t^2 and Δi_t^2 as suitable instrumental variables to address the endogeneity challenge.

By incorporating these instrumental variables, our endeavour is to enhance the robustness and reliability of parameter estimates and subsequent inferences in our regression analysis.

4.3.2 Result of Estimation of Weight Equations

Weight Equation (3.11.1)

The results of the instrumental variable regression for Weight Equation (3.11.1), is presented in the Table 4.20. The coefficient associated with Δf_t in Weight Equation (3.11.1) is -10.4735. This coefficient gives the weight of Δf_t in the EMP equation (3.12.1). The coefficient's significance is indicated by the extremely low p-value of 0.0000, suggesting that this relationship is highly likely to be statistically significant.

Several diagnostic tests are performed to validate the results of this instrumental variable regression: The Hausman Test (HT) assesses the consistency of Ordinary Least Squares (OLS) estimates. In this case, the null hypothesis is that OLS estimates are consistent. The test statistic $\chi^2(1)$ is 0.0276898 with a p-value of 0.86784. Since the p-value is high, we do not have sufficient evidence to reject the null hypothesis. This implies that the instrumental variable approach gives the same result as OLS approach as there may not be endogeneity problem in the original equation.

The weak instrument test examines the strength of the instruments used in the regression. The first-stage F-statistic is 97513.8, which is quite high. This indicates that the instruments, particularly Δf_t^2, are strong and provide adequate instrument strength for Δf_t. A high F-statistic implies that the instrument is sufficiently relevant for the endogenous variable.

Weight Equation (3.11.2)

The results of the instrumental variable regression for Weight Equation (3.11.2), can be found in the Table 4.21, the coefficients of both Δf_t and Δi_t are of particular interest. The coefficient of Δf_t is -10.1311.The coefficient of Δi_t is -0.0312216. Both these coefficients are significant The Hausman Test (HT), aimed at evaluating the consistency of Ordinary Least Squares (OLS) estimates, is conducted. The null hypothesis posits that OLS estimates are consistent. The test statistic, $\chi^2(2)$, has a value of 11.3228, with a corresponding p-value of 0.00347768. The low p-value provides evidence to reject the null hypothesis, suggesting that the instrumental variable approach is more appropriate than OLS.

Sargan Instrument Validity Test (SIVT) is not available in this case.

Weight Equation (3.11.3)

In the Table 4.22, the instrumental variable regression results for Weight Equation (3.11.3) is presented. The coefficient estimates provide insights into the relationships between the variables. Notably, the coefficient of Δi_t is of particular interest. The coefficient for Δi_t is estimated to be -0.0308063 with a very low p-value of 0.0000, showting that it is highly significant. The Hausman Test (HT) assesses whether the instrumental variable (IV) estimates are consistent compared to ordinary least squares (OLS) estimates. The null hypothesis is that OLS estimates are consistent. In this case, the test statistic is $\chi^2(1) = 10.1547$, with a p-value of 0.00143931. The low p- value implies that the null hypothesis that OLS estimates are consistent is not rejected. Hence in this case we will go by the weights given by the OLS estimates.

Weak Instrument Test:This test evaluates the strength of the instrumental variable. The first-stage F-statistic is 606.164, which helps assess the instrument's validity. A higher F-statistic indicates stronger instruments. A summary of estimated weights through instrumental variable regression and OLS regression is given in the table 4.3 below:

Table 4.3: Estimation of Weights using IV and OLS, Dependent variable Δs_t

Equation	IV		OLS		Instrument	Sargan IV Validity Test H_0: All instruments valid	IV Hausman Test H_0: OLS estimates consistent
	Coefficient/Weight	p-value	Coefficient/Weight	p-value			
Weight Eq. 5.1 (Δf_t)	-10.4735	0.0000	**-9.98602**	0.0000	Δf_t^2	$F(1, 81) = 97513.8$	Not Rejected ($\chi^2(1) = 0.0277$, p = 0.8678)
Weight Eq. 5.2 (Δf_t)	**-10.1311**	0.0001	-8.95831	0.0001	Δf_t^2	NA	Rejected ($\chi^2(2) = 11.3228$, p = 0.0035)
Weight Eq. 5.2 (Δi_t)	**-0.0312216**	0.0000	-0.0164523	0.0000	Δi_t^2	NA	Rejected ($\chi^2(2) = 11.3228$, p = 0.0035)
Weight Eq. 5.3 (Δi_t)	-0.0308063	0.0000	**-0.0165941**	0.0000	Δi_t^2	$F(1, 81) = 606.164$	Not Rejected ($\chi^2(1) = 10.1547$, p = 0.0014)

Source: Author's Calculation

4.4 Three EMP Indices Based on a General Approach

In this study, we aim to create three distinct Exchange Market Pressure (EMP) indices using different equations and weights obtained from Instrumental Variable (IV) and Ordinary Least Squares (OLS) methods. The weights are derived from the analysis presented in the Section 4.2.We use OLS-based weights when the null hypothesis in the Hausman Test (HT) is not rejected, and IV-based weights when the null hypothesis in the Hausman Test (HT) is rejected.

These indices are called EMP indices based on a general method because they are not derived from any a-priori theoretical model (as opposed to the EMP index based on Girton and Roper Model) nor are they constrained by any a-priori assumption about a particular currency regime.

The equations for constructing the EMP indices are as follows:

EMP Index Based on Equation (3.12.1)

$$EMP_t = \Delta s_t + \mathbf{9.98602}\Delta f_t \tag{4.4.1}$$

We utilise the weight obtained from Weight Equation (3.11.1) for (Δf_t) component of this EMP index.

EMP Index Based on Equation (3.12.2)

$$EMP_t = \Delta s_t + \mathbf{10.1311}\Delta f_t - \mathbf{0.0312216}\Delta i_t \tag{4.4.2}$$

For (Δf_t) and (Δi_t) components of this EMP index, we incorporate the weights from Weight Equation (3.11.2) .

EMP Index Based on Equation (3.12.3)

$$EMP_t = \Delta s_t - \mathbf{0.0165941}\Delta i_t \tag{4.4.3}$$

Here, we employ the weight derived from Weight Equation (3.11.3) for (Δi_t) component of this EMP index.

EMP Index Based on the Girton and Roper Model

As per equation (2.1.13)

$$EMP_t = \Delta s_t + \mathbf{1} \times \Delta f_t \tag{4.4.4}$$

In the case of the Girton and Roper Model the weight of the second component of the EMP index is 1.

4.5 Comparison of Results Based on Four EMP Indices

Based on the Table 4.23, this section provides a comprehensive comparative analysis of the summary statistics of four Exchange Market Pressure (EMP) indices: GREMPI/EMP (4.4.4), EMPI (4.4.1), EMPI (4.4.2), and EMPI (4.4.3). These indices are crucial indicators of the pressure experienced by a country's exchange rate due to various factors such as changes in the exchange rate, foreign exchange reserves, and interest rates.

Mean and Median Comparison

The mean and median values of the EMP indices offer valuable insights into the average and typical levels of exchange market pressure. The negative mean values, ranging from -0.0058322 to -0.0043338, indicate an overall tendency towards a depreciating domestic currency relative to USD over the observed period. Similarly, the median values, ranging from -0.0029395 to 0.00074259, suggest that a significant portion of observations experience negative pressure, potentially reflecting consistent downward pressure on the exchange rate.

Dispersion and Spread

The Standard Deviation (Std. Dev.) and Coefficient of Variation (CV) measure the variability and relative variability of the EMP indices. The moderate to slightly high values of the Std. Dev., ranging from 0.029837 to 0.036652, indicate notable fluctuations in the exchange market pressure over time. This variability is further highlighted by the CV values, ranging from 5.1532 to 8.4572, suggesting that the magnitude of fluctuations relative to the mean is relatively high, especially for EMPI (4.4.2). Such high variability may signify periods of increased uncertainty and volatility in the exchange market. EMPI (4.4.2) is more volatile, may be, because of the fact that it is more properly able to capture exchange market pressure as it is composed of three components i,e change in exchange rate, change in forex reserve and change in interest rate.

Skewness and Kurtosis

The skewness and excess kurtosis provide insights into the shape and tail behaviour of the distributions of the EMP indices. The negative skewness values, ranging from -2.6618 to -1.2088, suggest that the distributions are moderately to highly skewed to the left, indicating a heavier concentration of extreme negative values. This skewness indicates a tendency for the exchange market pressure to experience sharper negative movements than positive ones. The excess kurtosis values, ranging from 2.9213 to 12.140, indicate varying degrees of heavy-tailedness, implying a higher likelihood of extreme values in the tails of the distributions. Such heavy-tailedness may signal the presence of rare but significant events impacting the exchange market. Here are the skewness values for each of the EMP indices: GREMPI/EMP (4.4.4): Skewness = -1.2088 EMPI (4.4.1): Skewness = -1.2626 EMPI (4.4.2): Skewness = -2.6618 EMPI (4.4.3): Skewness = -1.7584 Therefore, EMPI (4.4.2) has the highest skewness among the listed EMP indices, indicating a more pronounced asymmetry in its distribution towards lower values, with a longer left tail. Please refer to the figure 4.5

Percentiles and Missing Observations

The 5th percentile (5% perc.), 95th percentile (95 % perc.), inter-quartile range (IQ Range), and missing observations provide additional insights into the distributional characteristics and data completeness of the EMP indices. The narrow range between the 5th and 95th percentiles and the small inter-quartile range suggest that the majority of observations fall within a relatively narrow range, indicating a degree of stability in the indices. The minimal missing observations indicate that the dataset is largely complete and reliable for analysis, enhancing the credibility of the statistical findings.

Practical Implications

The analysis of the EMP indices' summary statistics has several practical implications for policymakers, investors, and analysts. Firstly, the negative mean and median values suggest a consistent downward pressure on the domestic currency, which may raise concerns about currency depreciation and its potential impacts on trade and investment. Secondly, the high variability and skewness of the indices indicate that the exchange market has experienced periods of significant instability and asymmetric movements, requiring careful monitoring and risk management strategies. Thirdly, the heavy-tailedness of the distributions suggests the potential for extreme events that could disrupt the exchange market, emphasising the need for robust contingency plans and risk assessments.

4.6 Did India Face Any Currency Crisis 2001-onwards

This section examines whether India faced any currency crises during the sample period. As per the criterion given by Eichengreen et al. (1995) the crisis thresholds of the four EMP Indices for the entire sample period are reported in the Table 4.4.

Table 4.4: Eichengreen, Rose and Wyplosz Crisis Threshold (ERWCT)

Exchange Market Pressure Index (EMPI)	**ERWCT Value**
GREMI	-0.0509132
EMPI (4.4.1)	-0.0503347
EMPI (4.4.2)	-0.059316
EMPI (4.4.3)	-0.0555121

Source: Author's calculation.

Figure 4.6 and Table 4.9 provide a detailed view of the crisis periods in India based on Eichengreen, Rose and Wyplosz Crisis Threshold (ERWCT) for various Exchange Market Pressure Indices (EMPI). These periods are essential for understanding the dynamics of India's exchange market and its vulnerability to external economic shocks during different time frames. The first, second and the fourth vertical patches in the Figure 4.6 show the periods of US recession as identified by National Bureau of Economic Research (2024). The third vertical patch shows the period of "global uncertainty" starting from 2012 to 2019, Ahir et al. (2022), World Uncertainty Index (WUI), Economist Intelligence Unit (EIU), The Economist Group.

The main drivers of global uncertainty in 2012 were the euro area debt crisis, the US fiscal cliff, and the slowdown in China's growth. These events had spillover effects on other countries, especially those with strong trade and financial linkages. India was affected by the global uncertainty shocks. Another important event occurring in the sample period is that of COVID-19.

In March 2020, the World Health Organisation (WHO) declared COVID-19 a pandemic Organization (2020). This declaration prompted India to impose a nationwide lockdown on March 24, 2020, which resulted in a significant shrinkage of economic activity. The fourth vertical patch is showing this period as well as the period of US recession as discussed above.

Our study finds four crises periods on the basis of all of the four EMP indices. The first phase of crisis in the case all indices is around the period of the US recession of 2008 January to 2009 June. The second crisis in three cases is just before the start of global uncertainty. In the case of EMPI (4.4.2) the second crisis is during global uncertainty. The remaining two crises in the case of three EMP indices are during 2012 to 2019 which is the period of global uncertainty. In the case of EMPI (4.4.2) three crises are during global uncertainty. Following are the details

On the basis of GREMPI

2008:4 Crisis (Worst Crisis):

Peak/Best Quarter: 2007:4 Trough/Worst Quarter: **2008:4** Peak to Worst Duration: 5 quarters Start of Crisis: 2008:3 End of Crisis: 2009:1 Crisis Duration: 5 quarters.

2011:4 Crisis:

Peak/Best Quarter: 2011:2 Trough/Worst Quarter: 2011:4 Peak to Worst Duration: 3 quarters Start of Crisis: 2012:2 End of Crisis: 2012:4 Crisis Duration: 3 quarters.

2012:2 Crisis:

Peak/Best Quarter: 2012:1 Trough/Worst Quarter: 2012:2 Peak to Worst Duration: 2 quarters Start of Crisis: 2012:2 End of Crisis: 2012:3 Crisis Duration: 1 quarter.

2013:3 Crisis:

Peak/Best Quarter: 2012:4 Trough/Worst Quarter: 2013:3 Peak to Worst Duration: 3 quarters Start of Crisis: 2013:2 End of Crisis: 2014:4 Crisis Duration:

8 quarters

Table 4.5: Crisis Periods Based on ERW Crisis Threshold - GREMPI

		GREMPI			
Peak/Best Quarter	**Trough/Worst Quarter**	**Peak to Worst Duration**	**Start of Crisis**	**End of Crisis**	**Crisis Duration**
2007:4	**2008:4**	5Q	2008:3	2009:1	5Q
2011:2	2011:4	3Q	2011:3	2012:1	3Q
2012:1	2012:2	2Q	2012:2	2012:3	1Q
2012:4	2013:3	3Q	2013:2	2014:4	7Q

Source: Author's calculation.

During the COVID-19 pandemic the EMP index goes down i.e. there is depreciation as well loss of forex but there is no crisis. This index shows lowest volatility in comparison to all the other three indices with a value of coefficient of variation at 5.1532. In the entire sample period the index stays below the ERWCT 4.65 % of times. The lowest value the index achieves during the entire sample period is -0.10783 which is during 2008:4, thus this period is the worst crisis phase for Indian currency as per this indicator.

On the basis of The EMPI Equation (4.4.1)

2008:4 Crisis (Worst Crisis):

Peak/Best Quarter: 2007:4 Trough/Worst Quarter: **2008:4** Peak to Worst Duration: 5 quarters Start of Crisis: 2008:3 End of Crisis: 2008:4 Crisis Duration: 2 quarters Interpretation is the same as the first crisis phase based on the GREMPI.

The following three crises periods based on this indicator are during the period of "global uncertainty" 2012 to 2019 as described above so the interpretation is the same. 2011:4 Crisis:

Peak/Best Quarter: 2011:2 Trough/Worst Quarter: 2011:4 Peak to Worst Duration: 6 quarters Start of Crisis: 2011:3 End of Crisis: 2012:1 Crisis Duration: 3 quarters

2012:2 Crisis:

Peak/Best Quarter: 2012:1 Trough/Worst Quarter: 2012:2 Peak to Worst Duration: 2 quarters Start of Crisis: 2012:2 End of Crisis: 2012:3 Crisis Duration: 2 quarters

2013:3 Crisis:

Peak/Best Quarter: 2012:4 Trough/Worst Quarter: 2013:3 Peak to Worst Duration: 5 quarters Start of Crisis: 2013:2 End of Crisis: 2013:3 Crisis Duration: 1 quarters.

Table 4.6: Crisis Periods Based on ERW Crisis Threshold - EMPI Equation (4.4.1)

		EMPI (4.4.1)			
Peak/Best Quarter	**Trough/Worst Quarter**	**Peak to Worst Duration**	**Start of Crisis**	**End of Crisis**	**Crisis Duration**
2007:4	**2008:4**	5Q	2008:3	2008:4	2Q
2011:2	2011:4	6Q	2011:3	2012:1	3Q
2012:1	2012:2	6Q	2012:2	2012:3	7Q
2012:4	2013:3	5Q	2013:2	2013:3	1Q

Source: Author's calculation.

This index shows a volatility 5.3479 as measured by coefficient of variation . In the entire sample period the index stays below the ERWCT 4.65 % of times. The lowest value the index achieves during the entire sample period is -0.10784, this happens during 2008:4 , thus this period is the period of the worst currency crisis for India as per this indicator. These last two values of this index are the same as the values of the GREMPI.

On the basis of The EMPI Equation (4.4.2)

2009:1 Crisis:

Peak/Best Quarter: 2008:1 Trough/Worst Quarter: 2009:1 Peak to Worst Duration: 5 quarters Start of Crisis: 2008:4 End of Crisis: 2009:2 Crisis Duration: 3 quarters. The crisis period is roughly during the aftermath of the US financial crisis as identified by the National Bureau of Economic Research (NBER). The worst quarter

2012:1 Crisis (Worst Crisis):

Peak/Best Quarter: 2011:3 Trough/Worst Quarter: **2012:1** Peak to Worst Duration: 3 quarters Start of Crisis: 2011:4 End of Crisis: 2012:2 Crisis Duration: 3 quarters.

2012:3 Crisis:

Peak/Best Quarter: 2012:2 Trough/Worst Quarter: 2012:3 Peak to Worst Duration: 1 quarter Start of Crisis: 2012:3 End of Crisis: 2012:4 Crisis Duration: 3 quarters.

2013:3 Crisis:

Peak/Best Quarter: 2013:1 Trough/Worst Quarter: 2013:3 Peak to Worst Duration: 3 quarters Start of Crisis: 2013:3 End of Crisis: 2014:1 Crisis Duration: 3 quarters.

Table 4.7: Crisis Periods Based on ERW Crisis Threshold - EMPI Equation (4.4.2)

		EMPI (4.4.2)			
Peak/Best Quarter	**Trough/Worst Quarter**	**Peak to Worst Duration**	**Start of Crisis**	**End of Crisis**	**Crisis Duration**
2008:1	2009:1	5Q	2008:4	2009:2	3Q
2011:3	**2012:1**	3Q	2011:4	2012:2	3Q
2012:2	2012:3	1Q	2012:3	2012:4	3Q
2013:1	2013:3	3Q	2013:3	2014:1	3Q

Source: Author's calculation.

This index achieves its lowest value of -0.21583, indicating that the India faced the deepest currency crisis in terms of this index. Volatility value of this index is 5.4572 which is the second highest after the volatility value of EMPI (4.4.3). India remained in crisis phase 5.88 % times (highest number of times) in the entire sample period as per this index this value is the same as the one based on EMPI (4.4.3).

On the basis of The EMPI Equation (4.4.3)

2008:4 Crisis:

Peak/Best Quarter: 2007:4 Trough/Worst Quarter: 2008:4 Peak to Worst Duration: 5 quarters Start of Crisis: 2008:1 End of Crisis: 2009:1 Crisis Duration: 5 quarters.

2011:4 Crisis (Worst of the worst crisis):

Peak/Best Quarter: 2011:2 Trough/Worst Quarter: **2011:4** Peak to Worst Duration: 3 quarters Start of Crisis: 2011:3 End of Crisis: 2011:4 Crisis Duration: 2 quarters.

2012:2 Crisis:

Peak/Best Quarter: 2012:1 Trough/Worst Quarter: 2013:1 Peak to worst duration: 5 quarters. Start of crisi: 2012:1. End of crisis : 2012:2. Crisis Duration: 2 quarters. 2013:3 Crisis Peak/Best Quarter: 2012:4 Trough/Worst Quarter: 2013:3 Peak to worst duration: 4 quarters. Start of crisis: 2013:2. End of crisis : 2013:4. Crisis Duration: 3 quarters.

Table 4.8: Crisis Periods Based on ERW Crisis Threshold - EMPI Equation (4.4.3)

		EMPI (4.4.3)			
Peak/Best Quarter	**Trough/Worst Quarter**	**Peak to Worst Duration**	**Start of Crisis**	**End of Crisis**	**Crisis Duration**
2007:4	2008:4	5Q	2008:1	2009:1	5Q
2011:2	**2011:4**	8Q	2011:3	2011:4	1Q
2012:1	2012:2	2Q	2012:1	2012:2	2Q
2012:4	2013:3	7Q	2013:2	2013:4	3Q

Source: Author's calculation.

The index achieves a lowest value of -0.16459 which is the second lowest value after the one given by the EMPI (4.4.2). India's exchange market was most volatile as per this index with a coefficient of variation at 5.98. India remained in crisis phase during the entire sample period 5.88 % times as per this index. This value is the same as the value given by the index EMPI (4.4.2) . India faced the worst of the worst or the most severe currency crisis as per this indicator during the period of 2011:4. This is almost near the start of the period of global uncertainty of 2012-19.

Table 4.9: Crisis Periods Based on ERW Crisis Threshold - Summary

EMPI	Worst Crisis Quarter	Lowest EMPI Value	Coefficient of Variation	% of Time Below ERWCT
GREMPI	2008:4	-0.10783	5.1532	4.65%
EMPI (4.4.1)	2008:4	-0.10784	5.3479	4.65%
EMPI (4.4.2)	2012:1	-0.21583	5.4572	5.88%
EMPI(4.4.3)	2011:4	-0.16459	5.9800	5.88%

Source: Author's calculation.

In summary, our analysis of the four Exchange Market Pressure Index (EMPI) reveals that India faced currency crises during the periods of global economic turmoil, such as the US recession of 2008-2009 and the period of global uncertainty from 2012 to 2019. The worst crisis quarters and the lowest EMPI values vary slightly across the different indices, but they all point to significant pressure on the Indian currency during these challenging times.

The GREMPI and EMPI (4.4.1) identify the fourth quarter of 2008 as the worst crisis period, coinciding with the height of the US financial crisis. On the other hand, EMPI (4.4.2) and EMPI (4.4.3) indicate the first quarter of 2012 and the fourth quarter of 2011, respectively, as the most severe crisis periods, which are associated with the onset of the global uncertainty phase.

The coefficient of variation and the percentage of time the indices remain below the Eichengreen, Rose and Wyplosz Crisis Threshold (ERWCT) provide insights into the volatility and the duration of the crises. EMPI (4.4.3) exhibits the highest volatility, followed closely byEMPI (4.4.2). Both these indices suggest that India was in a crisis phase for 5.88% of the entire sample period, higher than the crisis durations indicated by the GREMPI and EMPI (4.4.1).

These findings highlight the vulnerability of the Indian currency to global economic shocks and the importance of monitoring Exchange Market Pressure Indices to assess the risk of currency crises. The results also underscore the need for policymakers to be vigilant and proactive in managing the country's exchange rate and implementing measures to mitigate the impact of external pressures on the domestic economy.

Appendix: Tables

Table 4.10: OLS Regression Results, Summary Statistics, and Tests, Dependent Variable EMP_t

Variable	Coefficient	Std. Error	z	p-value
Δd_{it}	-0.0012	0.0034	-0.3470	0.7286
Δh_{ut}	-0.0367	0.0182	-2.018	0.0436
Δy_{it}	-0.3678	0.2257	-1.630	0.1032
Δy_{ut}	0.8788	0.6267	1.402	0.1608
Mean dependent var	-0.0064	S.D. dependent var	0.0302	
Sum squared resid	0.0715	S.E. of regression	0.0297	
R^2	0.1057	Adjusted R^2	0.0726	
$F(4, 81)$	7.0446	P-value(F)	0.0001	
Log-likelihood	180.2927	Akaike criterion	-352.5854	
Schwarz criterion	-342.8148	Hannan–Quinn	-348.6554	
$\hat{\rho}$	0.1116	Durbin–Watson	1.7739	
Chow test (2008:1)	p-value = 0.0028	LM test (autocorrelation)	p-value = 0.5925	
QLR test	p-value = 0.0002	White's test (heteroskedasticity)	p-value = 0.6092	
CUSUM test	p-value = 0.0850	Test for normality of residuals	p-value = 0.0001	
RESET test	p-value = 0.2068	Test for ARCH of order 4	p-value = 0.8855	
Chow test (2012:1)	p-value = 0.0001			

Source: Author's calculation.

Table 4.11: Switch Regression with Two Regimes. Dependent variable: EMP_t Method: Simple Switching Regression (BFGS Marquardt steps), Sample: 2001Q3 - 2022Q2, Included observations: 84, Number of states: 2, Standard errors & covariance computed using observed Hessian, Random search: 25 starting values with 10 iterations using 1 standard deviation, Convergence achieved after 15 iterations.

	Regime 1		Regime 2	
Variable	Coefficient	P-value	Coefficient	P-value
Δd_{it}	0.002079	0.8185	-0.004422	0.189
Δh_{ut}	-0.074824	0.3131	-0.013679	0.000
Δy_{it}	-0.35687	0.0381	-0.297991	0.0381
Δy_{ut}	0.777869	0.1324	1.554236	0.000
LOG(SIGMA)	-3.476350	0.0000	-7.783759	0.000
P1C	1.918045	0.000		

Mean dependent var	-0.006456	S.D. dependent var	0.030359
Sum squared resid	0.072486	S.E. of regression	0.031298
Log-likelihood	192.0869	Akaike criterion	-4.311593
Schwarz criterion	-3.993272	Hannan–Quinn	-4.18631
Durbin Watson Stat	1.804004		

	1	2
1	0.871920	0.128080
2	0.871920	0.128080

1	2
7.807634	1.146894

Source: Author's calculation.

Table 4.12: Switch Regression with Three Regimes.Dependent variable:EMP_t, Method: Simple Switching Regression (BFGS Marquardt steps), Sample: 2001Q3 2022Q2, Included observations: 84, Number of states: 3, Standard errors covariance computed using observed Hessian, Random search: 25 Starting values with 10 iterations using 1 standard deviation, Failure to improve objectives after three iterations.

	Regime 1		Regime 2		Regime 3	
Variable	Coefficient	P-value	Coefficient	P-value	Variable	Coefficient
Δd_{it}	0.002847	NA	-0.000129	NA	-0.001532	NA
Δh_{ut}	-0.037646	NA	-0.146605	NA	-0.002553	NA
Δy_{it}	-0.186567	NA	-1.037133	NA	-0.027451	NA
Δy_{ut}	0.373087	NA	4.654536	NA	1.727696	NA
LOG(SIGMA)	-3.800388	NA	2.459970	NA	-14.46124	NA
P1C	2.896416	NA				
P2C	0.252415	NA				

Mean dependent var	-0.006456	S.D. dependent var	0.030359
Sum squared resid	0.072486	S.E. of regression	0.031298
Log-likelihood	202.7893	Akaike criterion	-4.423555
Schwarz criterion	-3.931604	Hannan–Quinn	-4.225795
Durbin Watson Stat	1.734811		

Constant Transition Probability

	1	2	3
1	0.887865	0.063106	0.049029
2	0.887865	0.063106	0.049029
3	0.887865	0.063106	0.049029

Constant Expected Duration

1	2	3
8.917834	1.067357	1.051556

Source: Author's calculation.

Table 4.13: Switch Regression with Two Regimes.Dependent variable: EMP_t, Method: Markov Switching Regression (BFGS Marquardt steps), Sample: 2001Q3 2022Q2, Included observations: 84, Number of states: 2, Standard errors covariance computed using observed Hessian, Random search: 25 Starting values with 10 iterations using 1 standard deviation, Convergence achieved after 14 iterations.

	Regime 1		Regime 2	
Variable	Coefficient	P-value	Coefficient	P-value
Δd_{it}	0.003682	0.6806	-0.003727	0.8549
Δh_{ut}	-0.036482	0.0685	-0.100354	0.5465
Δy_{it}	0.048658	0.6837	-1.200290	0.0105
Δy_{ut}	0.644889	0.1221	2.953739	0.0294
LOG(SIGMA)	-4.240176	0.0000	-3.287281	0.0000
P11C	0.782141	0.3294		
P21C	-0.143029	0.9026		

Mean dependent var	−0.006456	S.D. dependent var	0.030359
Sum squared resid	0.0742566	S.E. of regression	0.031298
Log-likelihood	202.7893	Akaike criterion	−4.198848
Schwarz criterion	−3.851588	Hannan–Quinn	−4.225795
Durbin Watson Stat	1.879896		

Constant Transition Probability

	1	2	3
1	0.887865	0.063106	0.049029
2	0.887865	0.063106	0.049029
3	0.887865	0.063106	0.049029

Constant Expected Duration

1	2	3
8.917834	1.067357	1.051556

Source: Author's calculation.

Table 4.14: Switch Regression with Three Regimes.Dependent variable: EMP_t Method: Markov Switching Regression (BFGS Marquardt steps) sample: 2001Q3 2022Q2 Included observations: 84 Number of states: 3 Initial probabilities obtained from ergodic solution Standard errors covariance computed using observed Hessian Random search: 25 Starting values with 10 iterations using 1 standard deviation Failure to improve objectives (non-zero gradients) after 14 iterations.

	Regime 1		Regime 2		Regime 3	
Variable	Coefficient	P-value	Coefficient	P-value	Variable	Coefficient
Δd_{it}	0.021695	NA	-0.007619	NA	-0.006334	NA
Δh_{ut}	-0.033686	NA	-0.044454	NA	-0.002553	NA
Δy_{it}	-0.097619	NA	-0.361551	NA	-0.311851	NA
Δy_{ut}	1.255712	NA	0.812728	NA	1.549723	NA
LOG(SIGMA)	-13.56041	NA	-3.460010	NA	-7.836896	NA
P1C	2.896416	NA				
P2C	0.252415	NA				

Mean dependent var	-0.006456	S.D. dependent var	0.030359
Sum squared resid	0.072019	S.E. of regression	0.032307
Log-likelihood	208.4219	Akaike criterion	-4.462427
Schwarz criterion	-3.854722	Hannan–Quinn	-4.218135
Durbin Watson Stat	1.794322		

Transition Matrix Parameter

P11-C	-3.651764	P12-C	7.6618998	P21-C	-0.927068
P22-C	2.112160	P31-C	-5.930369	P32-C	0.970878

Constant Transition Probabilities

	1	2	3
1	0.900071	2.08E-07	.099929
2	0.999995	2.77E-38	4.70E-06
3	1.60E-49	1.00000	0.000000

Constant Expected Duration

	1	2	3
1	10.00711	1.00000	1.00000

Source: Author's calculation.

Table 4.15: Mahalanobis distances from the centroid using the variables: $\mathrm{EMPI}_t \Delta d_{it}$, Δh_{ut}, Δy_{it} Δy_{ut}
Sample Period:2001:2 - 2022:3, 85 valid Observations

Outlier Periods	**NBER Recession Periods**
2007:4	2001:1-2001:4
2008:4	2007:4-2009:2
2009:2	
2009:4	
2014:1	
2020:2	2019:4-2020:2
2020:3	
2021:2	
2021:3	
2021:4	

Source: Author's calculation.

Table 4.16: ML EGARCH Model with PDL and ARMA Terms

Dependent Variable: EMPI_t

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Sample (adjusted): 2007Q2 - 2022Q2

Included observations: 61 after adjustments

Failure to improve likelihood (non-zero gradients) after 96 iterations

Coefficient covariance computed using the outer product of gradients

MA Backcast: 2004Q2 - 2007Q1

Presample variance: backcast (parameter = 0.7)

	Regime 1		Regime 2	
Variable	Coefficient	P-value	Coefficient	P-value
LOG(GARCH) Model				
C(19)	-10.36742	0.0000	3.136856	0.0040
C(20)	3.136856	0.0040	0.615514	0.1627
C(21)	0.615514	0.1627	0.143071	0.5563
C(22)	0.143071	0.5563	-0.067787	0.6477
Regression Model				
@SQRT(GARCH)	-0.067787	0.6477	-0.013102	0.0001
Δd_{it}	-0.013102	0.0001	-0.188401	0.0034
Δy_{it}	-0.188401	0.0034	-0.043720	0.0393
Δh_{ut}	-0.043720	0.0393	0.575442	0.0003
Δy_{ut}	0.575442	0.0003	-0.025264	0.4484
PDL01	-0.025264	0.4484	-0.032357	0.0000
PDL02	-0.032357	0.0000	0.005617	0.0000
PDL03	0.005617	0.0000	-0.021767	0.4813
PDL04	-0.021767	0.4813	0.001682	0.8500
PDL05	0.001682	0.8500	0.008479	0.2682
PDL06	0.008479	0.2682	0.002460	0.0770
PDL07	0.002460	0.0770	9.08E-05	0.7805
PDL08	9.08E-05	0.7805	-0.194860	0.0152
PDL09	-0.194860	0.0152	0.073994	0.0014
PDL010	0.073994	0.0014	0.018608	0.0000
PDL011	0.018608	0.0000	0.479215	0.0000
AR(12)	0.479215	0.0000	-0.861600	0.0000
MA(12)	-0.861600	0.0000		

Variance Equation

Table 4.17: Estimation of Weights as per equation (3.11.1) using OLS, with observations from 2001:2–2022:2 ($T = 85$), Dependent variable Δs_t

	Coefficient	**Std. Error**	**t-ratio**	**p-value**
const	-0.00457158	0.00333861	-1.369	0.1747
Δf_t	-9.98602	3.00969	-3.318	0.0014
Δf_{t-1}	-1.99006	3.62681	-0.5487	0.5847
Δs_{t-1}	0.226297	0.104228	2.171	0.0328
Mean dependent var	-0.006249		S.D. dependent var	0.030408
Sum squared resid	0.072090		S.E. of regression	0.029833
R^2	0.071825		Adjusted R^2	0.037448
$F(3, 81)$	15.55451		P-value(F)	4.45e-08
Log-likelihood	179.9710		Akaike criterion	-351.9420
Schwarz criterion	-342.1714		Hannan–Quinn	-348.0120
$\hat{\rho}$	-0.012851		Durbin's h	-0.428085

Source: Author's calculation.

Table 4.16 – continued from previous page

	Regime 1		Regime 2	
Variable	Coefficient	P-value	Coefficient	P-value
R-squared	0.676452	Adjusted R-squared		0.548538
S.E. of regression	0.022465	Akaike info criterion		-5.272670
Sum squared resid	0.021702	Schwarz criterion		-4.511371
Log likelihood	182.8164	Durbin-Watson stat		2.147762

Inverted AR Roots

0.94, 0.81 - 0.47i, 0.81 + 0.47i, 0.47 - 0.81i, 0.47 + 0.81i, 0.00 + 0.94i, 0.00 - 0.94i, -0.47 + 0.81i, -0.47 - 0.81i, -0.81 + 0.47i, -0.81 - 0.47i, -0.94

Inverted MA Roots

0.99, 0.86 + 0.49i, 0.86 - 0.49i, 0.49 + 0.86i, 0.49 - 0.86i, -0.00 - 0.99i, -0.00 + 0.99i, -0.49 - 0.86i, -0.49 + 0.86i, -0.86 + 0.49i, -0.86 - 0.49i, -0.99

Source: Author's calculation

Table 4.18: Estimation of Weights as per equation (3.11.2) using OLS, with observations from 2001:2–2022:2 ($T = 85$), Dependent variable Δs_t

	Coefficient	Std. Error	t-ratio	p-value
const	−0.00494856	0.00323715	−1.529	0.13037
Δf_t	−8.95831	9.35953	−0.9571	0.3414
Δf_{t-1}	−3.33631	9.36840	−0.3561	0.7227
Δi_t	−0.0164523	0.00639590	−2.572	0.0120
Δi_{t-1}	−0.00327193	0.00668698	−0.4893	0.6260
Δs_{t-1}	0.214743	0.110086	1.951	0.0546

Mean dependent var	−0.006249	S.D. dependent var	0.030408
Sum squared resid	0.066509	S.E. of regression	0.029015
R^2	0.143686	Adjusted R^2	0.089489
$F(5, 79)$	2.651183	P-value(F)	0.028744
Log-likelihood	183.3958	Akaike criterion	−354.7916
Schwarz criterion	−340.1357	Hannan–Quinn	−348.8966
$\hat{\rho}$	−0.028732	Durbin's h	NA

Constant Transition Probability

	1	2
1	0.927241	0.072759
2	0.927241	0.072759

Source: Author's calculation.

Table 4.19: Estimation of Weights as per equation (3.11.3) using OLS, with observations from 2001:2–2022:2 ($T = 85$), Dependent variable Δs_t

	Coefficient	Std. Error	t-ratio	p-value
const	−0.00519371	0.00320623	−1.620	0.1091
Δi_t	−0.0165941	0.00633966	−2.618	0.0106
Δi_{t-1}	−0.00357094	0.00663737	−0.5380	0.5920
Δs_{t-1}	0.232429	0.107465	2.163	0.0335

Mean dependent var	−0.006249	S.D. dependent var	0.030408
Sum squared resid	0.067348	S.E. of regression	0.028835
R^2	0.132882	Adjusted R^2	0.100766
$F(3, 81)$	4.137613	P-value(F)	0.008809
Log-likelihood	182.8629	Akaike criterion	−357.7258
Schwarz criterion	−347.9552	Hannan–Quinn	−353.7958
$\hat{\rho}$	−0.033492	Durbin's h	−2.278982

Source: Author's calculation.

Table 4.20: Instrumental Variable Regression using HAC Model, Weight Equation 5.1

	Coefficient	Std. Error	t-ratio	p-value
const	-0.00456179	0.00335864	-1.358	0.1782
ΔF_t	-10.4735	1.73565	-6.034	0.0000
ΔF_{t-1}	-2.02835	3.66611	-0.5533	0.5816
Δs_{t-1}	0.225500	0.103060	2.188	0.0315

Mean dependent var	$-0.006249.$	.	S.D. dependent var.	0.030408.
Sum squared resid	0.072092.	.	S.E. of regression.	0.029833.
R^2	0.071801.	.	Adjusted R^2.	0.037423.
$F(3, 81)$	60.50139.	.	P-value(F).	1.26e–20.
Log-likelihood	627.3504.	.	Akaike criterion.	$-1246.701.$
Schwarz criterion	$-1236.930.$	.	Hannan–Quinn.	$-1242.771.$
$\hat{\rho}$	$-0.012871.$	.	Durbin's h.	$-0.380664.$

Hausman test
Null hypothesis: OLS estimates are consistent
Asymptotic test statistic: $\chi^2(1) = 0.0276898$
with p-value = 0.86784
Weak instrument test –
First-stage $F(1, 81) = 97513.8$

Source: Author's calculation.

Note: TSLS - Two-Stage Least Squares, HAC - Heteroskedasticity and Autocorrelation Consistent. Observations are from 2001:2 to 2022:2 ($T = 85$). Dependent variable is Δs_t, Indpendent variables ΔF_t, ΔF_{t-1}, and $\Delta s_{t-1}.\Delta F_t$ is instrumented by ΔF_t^2. HAC standard errors are computed with a bandwidth of 3 using the Bartlett kernel.

Table 4.21: Instrumental Variable Regression using HAC, Weight Equation 5.2

	Coefficient	Std. Error	t-ratio	p-value
const	-0.00520973	0.00332324	-1.568	0.1210
ΔF_t	-10.1311	2.40232	-4.217	0.0001
ΔF_{t-1}	-4.71116	3.77444	-1.248	0.2157
Δi_t	-0.0312216	0.00396498	-7.874	0.0000
Δi_{t-1}	-0.00547353	0.0150691	-0.3632	0.7174
Δs_{t-1}	0.203974	0.111373	1.831	0.0708

Mean dependent var	$-0.006249.$	.	S.D. dependent var.	0.030408.
Sum squared resid	0.071039.	.	S.E. of regression.	0.029987.
R^2	0.132067.	.	Adjusted R^2.	0.077134.
$F(5, 79)$	48.75359.	.	P-value(F).	9.31e–23.
Log-likelihood	552.3814.	.	Akaike criterion.	$-1092.763.$
Schwarz criterion	$-1078.107.$	.	Hannan–Quinn.	$-1086.868.$
$\hat{\rho}$	$-0.036811.$	.	Durbin's h.	NA.

Hausman test –
Null hypothesis: OLS estimates are consistent
Asymptotic test statistic: $\chi^2(2) = 11.3228$
with p-value = 0.00347768

Source: Author's calculation.

Note: TSLS - Two-Stage Least Squares, HAC - Heteroskedasticity and Autocorrelation Consistent. Observations are from 2001:2 to 2022:2 ($T = 85$). Dependent variable is Δs_t, Independent variables ΔF_t, ΔF_{t-1}, Δi_t, Δi_{t-1} and Δs_{t-1}. ΔF_t and Δi_t are instrumented by ΔF_t^2, Δi_t^2. HAC standard errors are computed with a bandwidth of 3 using the Bartlett kernel.

Table 4.22: Instrumental Variable Regression using HAC, Weight Equation 5.3

	Coefficient	Std. Error	t-ratio	p-value
const	-0.00549236	0.00323939	-1.695	0.0938
Δi_t	-0.0308063	0.00383543	-8.032	0.0000
Δi_{t-1}	-0.00572554	0.0153256	-0.3736	0.7097
Δs_{t-1}	0.225750	0.109796	2.056	0.0430

Mean dependent var	-0.006249	S.D. dependent var	0.030408
Sum squared resid	0.071527	S.E. of regression	0.029716
R^2	0.122625	Adjusted R^2	0.090130
$F(3, 81)$	37.36239	P-value(F)	2.93e–15
Log-likelihood	-44.88138	Akaike criterion	97.76276
Schwarz criterion	107.5334	Hannan–Quinn	101.6928
$\hat{\rho}$	-0.042404	Durbin's h	NA

Hausman test –
Null hypothesis: OLS estimates are consistent
Asymptotic test statistic: $\chi^2(1) = 10.1547$
with p-value = 0.00143931

Weak instrument test –
First-stage $F(1, 81) = 606.164$

Source: Author's calculation.

Note: TSLS - Two-Stage Least Squares, HAC - Heteroskedasticity and Autocorrelation Consistent. Observations are from 2001:2 to 2022:2 ($T = 85$). Dependent variable is Δs_t, Independent variables Δi_t, Δi_{t-1} and Δs_{t-1}. Δi_t is instrumented by Δi_t^2. HAC standard errors are computed with a bandwidth of 3 using the Bartlett kernel.

Table 4.23: Summary Statistics of EMP Indices, using the observations 2002:1–2023:2

Variable	Mean	Median	Minimum	Maximum
GREMPI/EMP 6.4.4 $EMP_t = \Delta s_t + \mathbf{1} \times \Delta f_t$	−0 0058322	−0 0029395	−0 10783	0 068690
EMPI 6.4.1 $EMP_t = \Delta s_t + \mathbf{9.98602} \Delta f_t$	−0 0055792	−0 0025106	−0 10784	0 067481
EMPI 6.4.2 $EMP_t = \Delta s_t + \mathbf{10.1311} \Delta f_t - \mathbf{0.0312216} \Delta i_t$	−0 0043338	0 00074259	−0 21583	0 067462
EMPI 6.4.3 $EMP_t = \Delta s_t - \mathbf{0.0165941} \Delta i_t$	−0 0055621	−0 00075993	−0 16459	0 068824

Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
GREMPI/EMP 6.4.4 $EMP_t = \Delta s_t + \mathbf{1} \times \Delta f_t$	0 030054	5 1532	−1 2088	2 9213
EMPI 6.4.1 $EMP_t = \Delta s_t + \mathbf{9.98602} \Delta f_t$	0 029837	5 3479	−1 2626	3 0964
EMPI 6.4.2 $EMP_t = \Delta s_t + \mathbf{10.1311} \Delta f_t - \mathbf{0.0312216} \Delta i_t$	0 036652	8 4572	−2 6618	12 140
EMPI 6.4.3 $EMP_t = \Delta s_t - \mathbf{0.0165941} \Delta i_t$	0 033300	5 9869	−1 7584	5 8151

Variable	5% perc.	95% perc.	IQ Range	Missing obs.
GREMPI/EMP 6.4.4 $EMP_t = \Delta s_t + \mathbf{1} \times \Delta f_t$	−0 065056	0 034558	0 032444	0
EMPI 6.4.1 $EMP_t = \Delta s_t + \mathbf{9.98602} \Delta f_t$	−0 065020	0 034621	0 031544	0
EMPI 6.4.2 $EMP_t = \Delta s_t + \mathbf{10.1311} \Delta f_t - \mathbf{0.0312216} \Delta i_t$	−0 072853	0 036853	0 029950	1
EMPI 6.4.3 $EMP_t = \Delta s_t - \mathbf{0.0165941} \Delta i_t$	−0 069020	0 034698	0 031943	1

Source: Author's calculation.

Figure 4.3: Multivariate Outliers: Mahalanobis Distances

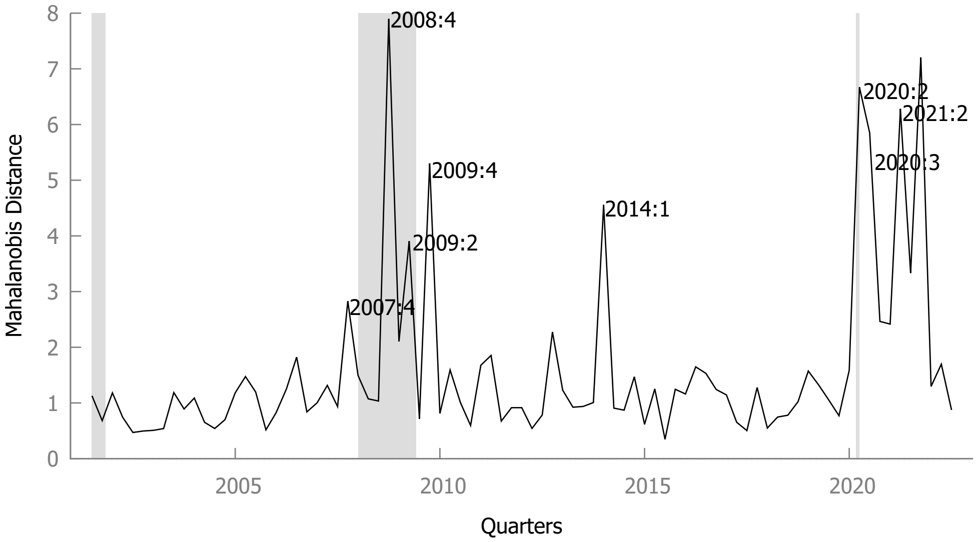


Figure 4.4: Visualising Structural Break: Wald Test for Regression in Table 6.2

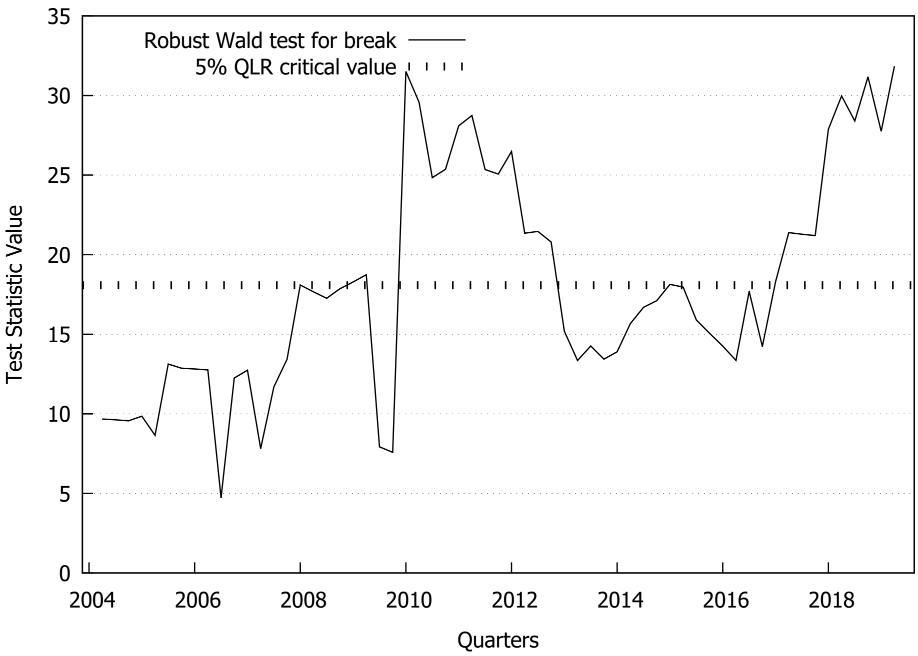


Figure 4.5: Histogram:Four EMPI

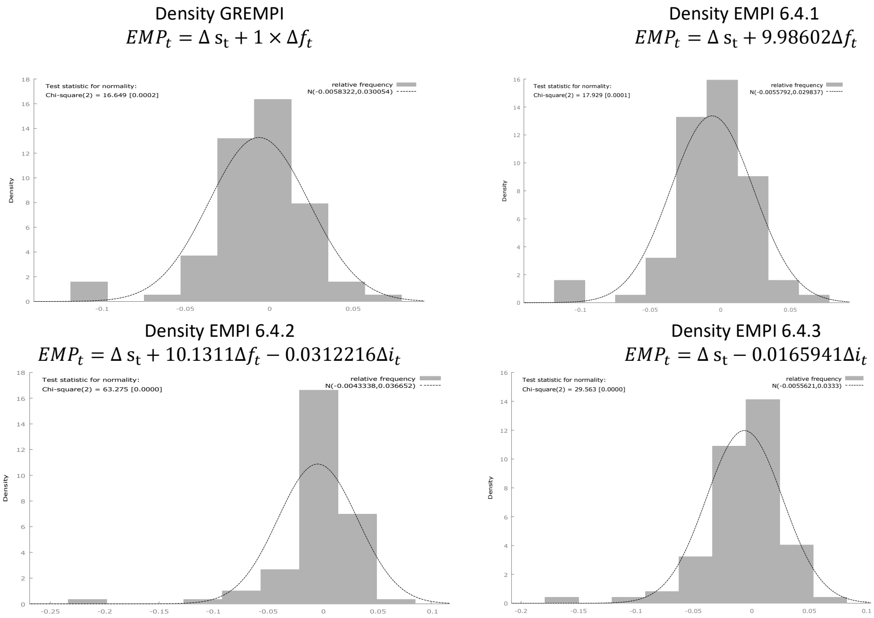
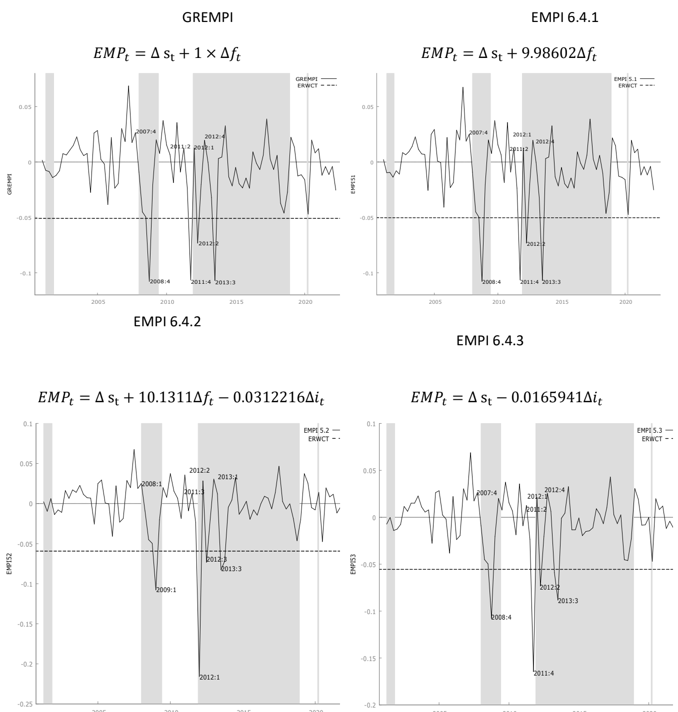


Figure 4.6: Currency Crisis: Four EMPIs and ERW Crisis Threshold



Vertical patches in the graphs are detailed as below-

2001:04 2001:11. US Recession, NBER.

2008:01 2009:06. US Recession, NBER.

2012:00 2019:00. Global Uncertainty, WUI.

2020:03 2020:04. US Recession as per NBER and start of COVID -19 related disruption as per WHO.

Chapter 5

Regression Diagnostics of Weights Equations

This chapter covers the diagnostic tests conducted on the regression models to ensure their validity. It includes tests for normality, stationarity, multi-collinearity, autocorrelation, and heteroscedasticity. The chapter discusses the results of these tests and their implications for the reliability of the regression models. It also explains the corrective measures taken to address any issues identified during the diagnostics. The robustness of the EMP indices is evaluated through various sensitivity analyses.

5.1 Test of Normality

Based on the tables 5.1,5.2 and 5.3 we can analyse the results of the normality tests for the residuals of three regression models. The tables show the frequency distribution of residuals in different intervals, along with cumulative percentages and normality test statistics (chi-square and p-values). Let's interpret the results for each case:

Table 5.1 for (3.11.1)

From the table, it can be observed that the residuals are distributed across different intervals. The "Test for normal distribution" section reports a chi-square value of 12.978 with a p-value of 0.00152. Since the p-value is less than the conventional significance level of 0.05, we reject the null hypothesis that the residuals follow a normal distribution. In other words, the residuals for Equation

(3.11.1) are not normally distributed.

Table 5.2 for Equation (3.11.2)

Similar to the first table, this table also presents the frequency distribution of residuals in different intervals. The "Test for normal distribution" section reports a chi-square value of 15.027 with a p-value of 0.00055. As the p-value is less than 0.05, we again reject the null hypothesis, indicating that the residuals for Equation (3.11.2) are not normally distributed.

Table 5.3 for Equation (3.11.3)

In this table, the frequency distribution of residuals is presented for various intervals. The "Test for normal distribution" section reports a chi-square value of 12.094 with a p-value of 0.00154. As the p-value is less than 0.05, we reject the null hypothesis, suggesting that the residuals for Equation (3.11.3) are not normally distributed.

Assuming the residuals are not normally distributed, we can invoke the Central Limit Theorem (CLT) to assume normality. The CLT states that the sum or average of a large number of independent and identically distributed random variables tends to follow a normal distribution. In regression, this applies to residuals, as they result from various influences leading to deviations from normality.

Therefore, even if normality tests show that residuals are not normally distributed, the CLT allows us to assume normality for parameter estimates and hypothesis tests, provided the sample size is sufficiently large.

In summary, despite non-normal residuals, the CLT justifies assuming normality for valid parameter estimates and hypothesis tests in large samples.

5.2 Test of Stationarity

Based on the three tables 5.4, 5.5 and 5.6 we can analyze the stationarity of the residuals for three regression models, which correspond to weight equations (3.11.1),(3.11.2), and (3.11.3). The Augmented Dicky-Fuller (ADF) test results in the tables are used to assess the stationarity of the residuals.

Weight Equation (3.11.1)**, Table 5.4**

The ADF test for the residuals of weight equation 5.1 reveals that both the "Test with Constant" and "Test with Constant and Trend" show statistically significant test statistics (-4.79358 and -5.03381, respectively) with very low asymptotic p-values (5.296×10^{-5} and 0.0001552, respectively). These results indicate that the residuals of the weight equation (3.11.1) are stationary, suggesting that the model captures the long-run equilibrium relationship between variables.

Weight Equation (3.11.2)**, Table 5.5**

For weight equation (3.11.2), the ADF test also indicates the presence of stationarity in the residuals. Both the "Test with Constant" and "Test with Constant and Trend" show highly significant test statistics (-5.08256 and -5.52245, respectively) with very low asymptotic p-values (1.379×10^{-5} and 1.49×10^{-5}, respectively). These results support the assumption of stationarity in the residuals for weight equation 5.2.

Weight Equation (3.11.3)**, Table 5.6**

The ADF test results for weight equation 5.3 also confirm the stationarity of the residuals. The "Test with Constant" and "Test with Constant and Trend" exhibit significant test statistics (-5.04818 and -5.60377, respectively) with low asymptotic p-values (1.625×10^{-5} and 9.825×10^{-6}, respectively). These findings suggest that the residuals of weight equation 5.3 are stationary.

In conclusion, all three weight equations (3.11.1),(3.11.2), and (3.11.3) display stationary residuals based on the ADF test results. This suggests that the regression models for all three weight equations have adequately captured the underlying relationships and trends in the data. The stationarity of residuals is crucial for making reliable statistical inferences and ensuring the model's validity in predicting future values.

5.3 Test of Multicollinearity

In the context of statistical modelling, multicollinearity refers to the presence of high correlations among independent variables in a regression model. It can lead to unstable parameter estimates and hinder the interpretability of the model. In this analysis, we examine the presence of multicollinearity in three weight equations: (3.11.1),(3.11.2), and (3.11.3), using two diagnostic tests: Variance Inflation Factor (VIF) and Belsley-Kuh-Welsch (BKW) Collinearity Diagnostics.

Table 5.7 displays the results for Equation (3.11.1), focusing on three variables: ΔF_t, ΔF_{t-1}, and Δs_{t-1}. The VIF values for all variables are close to 1, indicating a lack of multicollinearity. Typically, VIF values greater than 5 or 10 raise concerns about multicollinearity, but in this case, all VIF values are well below those thresholds.

The second part in Table 5.7 presents the BKW diagnostics. The condition index, cond, is used to assess multicollinearity. A cond value greater than 30 suggests "strong" near-linear dependence, and a value between 10 and 30 indicates "moderately strong" dependence. However, all cond values for Equation 5.1 are well below 10, suggesting no evidence of excessive collinearity.

Moving on to Table 5.8, which corresponds to Equation (3.11.2), the VIF values for the variables ΔF_t, ΔF_{t-1}, Δi_t, Δi_{t-1}, and Δs_{t-1} are all close to 1. Again, no signs of multicollinearity are evident in this equation.

The second part in Table 5.8 shows the BKW diagnostics for Equation 5.2. Similar to the previous table, all cond values are below 10, indicating no significant multicollinearity issues.

Lastly, we examine Equation (3.11.3) in Table 5.9. The VIF values for the variables Δi_t, Δi_{t-1}, and Δs_{t-1} are all close to 1, suggesting no multicollinearity concerns.

In the second part of Table 5.9, the BKW diagnostics also show no evidence of excessive collinearity, as all cond values are well below 10.

In conclusion, based on the diagnostic tests performed, there is no evidence of multicollinearity in any of the three weight equations ((3.11.1), Equation (3.11.2), and Equation (3.11.3)). The VIF values are all close to 1, and the cond values are comfortably below 10 in all cases. This lack of multicollinearity suggests that the independent variables in the weight equations can be reliably used to explain the dependent variable without significant interference from correlations between the predictors. We can confidently interpret the parameter estimates and draw valid inferences from the results of these regression models.

5.4 Test of Autocorrelation

The diagnostic regressions given in tables 5.10, 5.11 and 5.12 present the results of the Breusch-Godfrey test for autocorrelation up to order 4 in three different equations: Equation (3.11.1),(3.11.2) and (3.11.3). Autocorrelation, also known as serial correlation, occurs when the error terms of a regression model are correlated with each other over time. This violates one of the basic assumptions of ordinary least squares (OLS) regression, which assumes that the error terms are independent and identically distributed (i.i.d).

Equation (3.11.1)

This equation represents a model with a dependent variable, denoted as $\hat{e}$, and several independent variables, including ΔF_t, ΔF_{t-1}, Δs_{t-1}, $\hat{e}_1$, $\hat{e}_2$, $\hat{e}_3$, and $\hat{e}_4$. The results indicate that the coefficients of ΔF_t, ΔF_{t-1}, Δs_{t-1}, $\hat{e}_1$, $\hat{e}_2$, and $\hat{e}_3$ are not statistically significant, as their p-values are greater than the conventional significance level of 0.05. However, the coefficient of $\hat{e}_4$ is statistically significant at the 5% level, with a p-value of 0.0286.

The Breusch-Godfrey test statistic for this equation is denoted as LMF (Lagrange Multiplier F-statistic) with a value of 2.265770 and a corresponding p-value of 0.0697. The alternative statistic, TR^2 (the square of the t-ratio), has a value of 8.951130 and a p-value of 0.0623. The Ljung-Box Q' statistic, used to test the null hypothesis of no autocorrelation, has a value of 7.34149, with a p-value of 0.119. However, none of these p-values suggest strong evidence of autocorrelation in Equation (3.11.1).

Equation (3.11.2)

This equation involves a different set of independent variables, including ΔF_t, ΔF_{t-1}, Δi_t, Δi_{t-1}, Δs_{t-1}, $\hat{e}_1$, $\hat{e}_2$, $\hat{e}_3$, and $\hat{e}_4$. Similar to Equation (3.11.1), the coefficients of ΔF_t, ΔF_{t-1}, Δi_t, Δi_{t-1}, Δs_{t-1}, $\hat{e}_1$, $\hat{e}_2$, and $\hat{e}_3$ are not statistically significant, as their p-values are greater than 0.05. However, the coefficient of $\hat{e}_4$ is statistically significant at the 5 % level, with a p-value of 0.0324.

The Breusch-Godfrey test statistic (LMF) for Equation 5.2 has a value of 1.725398 and a corresponding p-value of 0.153. The alternative statistic, TR^2, has a value of 7.162686, with a p-value of 0.128. Additionally, the Ljung-Box Q' statistic has a value of 6.57574, with a p-value of 0.16. Again, the p-values for these test statistics do not provide strong evidence of autocorrelation in Equation 5.2.

Equation (3.11.3)

This equation includes a set of independent variables, namely Δi_t, Δi_{t-1}, Δs_{t-1}, $\hat{e}_1$, $\hat{e}_2$, $\hat{e}_3$, and $\hat{e}_4$. Among these variables, only the coefficient of $\hat{e}_4$ is statistically significant at the 5 % level, with a p-value of 0.0475.

The Breusch-Godfrey test statistic (LMF) for Equation 5.3 is 1.678962, with a p-value of 0.163. The alternative statistic, TR^2, has a value of 6.818866, with a p-value of 0.146. The Ljung-Box Q' statistic has a value of 5.63046, with a p-value of 0.228. Once again, the p-values for these test statistics do not indicate strong evidence of autocorrelation in Equation (3.11.3).

Overall, based on the diagnostic regressions and the Breusch-Godfrey test results, there is limited evidence of autocorrelation in the three equations. The statistically significant coefficient of $\hat{e}_4$ in all three equations suggests the presence of autocorrelation at lag 4, but the test statistics' p-values are generally not low enough to confidently assert the presence of autocorrelation. It is essential to interpret these results cautiously and consider additional diagnostics and potential remedies if autocorrelation is of concern in the regression analysis.

5.5 Test of Heteroscedasticity

Based on the results from the three regressions, which relate to Weight Equation (3.11.1), Weight Equation (3.11.2), and Weight Equation (3.11.3), we have conducted heteroskedasticity tests to assess the presence of non-constant variance in the residuals. The tests used are White's Test and Breusch-Pagan Test. The results of the tests are reported in the Tables 5.13, 5.14 and 5.15

Weight equation (3.11.1)**, Table 5.13**

In Equation (3.11.1), the p-value for the constant term "const" is 0.0157, which is statistically significant at the 5% level . The Test-R statistic (TR^2)for this equation is 2.45, and its associated p-value is 0.0973. Since the p-value of TR^2 is greater than the significance level of 5%, we fail to reject the null hypothesis of homoskedasticity. Therefore, there is no significant evidence of heteroskedasticity in this equation.

Weight equation (3.11.2)**, Table 5.14**

In Equation (3.11.2), the constant term continues to show strong statistical significance at the 5% level with a p-value of 0.0003 . The coefficient of Δi remains statistically significant at the 5% level with a p-value of 0.0341, while Δi_{t-1} and Δs_{t-1} are not statistically significant at the 5% level (p-values = 0.3697 and 0.0694, respectively). The Test-R statistic (TR^2) for this equation is 1.85, and its associated p-value is 0.1732. Since the p-value of TR^2 is greater than the significance level of 5%, we fail to reject the null hypothesis of homoskedasticity. Therefore, there is no significant evidence of heteroskedasticity in this equation.

Weight equation (3.11.3)**, Table 5.15**

In Equation (3.11.3), the constant term remains highly statistically significant at the 5% level with a p-value of 2.06e-05* . The coefficient of the product term $\Delta i \Delta i_{t-1}$ continues to show strong statistical significance at the 5% level with a p-value of 8.10e-05. The coefficient of Δs_{t-1} is not statistically significant at the 5% level (p-value = 0.1309). The Test-R statistic (TR^2) for this equation is 3.10, and its associated p-value is 0.0785. Since the p-value of TR^2 is greater than the significance level of 5%, we fail to reject the null hypothesis of homoskedasticity. Therefore, there is no significant evidence of heteroskedasticity in this equation.

With the level of significance set at 5%, and considering the Test-R statistic (TR^2) for each equation, the diagnostic regressions suggest that there is no evidence of heteroskedasticity in all three equations: Equation (3.11.1) (Weight of F), Equation (3.11.2) (Weight of F and I), and Equation (3.11.3) (Weight of I only). The constant terms in each equation are statistically significant at the 5% level, indicating the presence of constant variance in the error terms. Moreover, the Test-R statistic (TR^2) for all equations is not statistically significant at the 5% level, further confirming the absence of heteroskedasticity.

By establishing the absence of heteroskedasticity at the selected level of significance, we can bolster our confidence in the dependability and validity of the regression analysis outcomes. The inferences drawn from these models are built on resilient estimates, leading to a more precise comprehension of the interconnections between the variables. Addressing heteroskedasticity is crucial to attaining unbiased and efficient parameter estimates, ensuring the accuracy of our statistical conclusions. With the chosen level of significance level and Test-R statistics, we have validated the reliability of the regression results, enabling us to make well-founded decisions and interpretations based on these robust estimates.

Appendix

Table 5.1: Normality Test Regression Result of Equation 5.1

Interval	Midpoint	Frequency	Relative (%)	Cumulative (%)
< -0.086186	-0.096637	3	3.53	3.53 *
$-0.086186 - -0.065283$	-0.075734	1	1.18	4.71
$-0.065283 - -0.044379$	-0.054831	0	0.00	4.71
$-0.044379 - -0.023476$	-0.033928	8	9.41	14.12 ***
$-0.023476 - -0.0025732$	-0.013025	23	27.06	41.18 *********
$-0.0025732 - 0.018330$	0.0078784	31	36.47	77.65 *************
$0.018330 - 0.039233$	0.028781	13	15.29	92.94 *****
$0.039233 - 0.060136$	0.049685	5	5.88	98.82 **
≥ 0.060136	0.070588	1	1.18	100.00
Total		86	100.00	
Test for normal distribution		$\chi^2(2)$	p	
		12.978	0.00152	

Source: Author's calculation.

Table 5.2: Normality Test, Regression Result of Equation 5.2

Interval	Midpoint	Frequency	Relative (%)	Cumulative (%)
< -0.097747	-0.10932	2	2.35	2.35
$-0.097747 - -0.074597$	-0.086172	0	0.00	2.35
$-0.074597 - -0.051447$	-0.063022	1	1.18	3.53
$-0.051447 - -0.028296$	-0.039872	7	8.24	11.76 **
$-0.028296 - -0.0051461$	-0.016721	23	27.06	38.82 *********
$-0.0051461 - 0.018004$	0.0064290	32	37.65	76.47 *************
$0.018004 - 0.041154$	0.029579	17	20.00	96.47 *******
$0.041154 - 0.064305$	0.052730	2	2.35	98.82
≥ 0.064305	0.075880	1	1.18	100.00
Test for normal distribution		$\chi^2(2)$	p	
		15.027	0.00055	

Source: Author's calculation.

Table 5.3: Normality Test Regression Result Equation 5.3

Interval	Midpoint	Frequency	Relative (%)	Cumulative (%)
< -0.096185	-0.10725	1	1.18	1.18
$-0.096185 - -0.074055$	-0.085120	1	1.18	2.35
$-0.074055 - -0.051926$	-0.062991	1	1.18	3.53
$-0.051926 - -0.029797$	-0.040862	7	8.24	11.76 **
$-0.029797 - -0.0076684$	-0.018733	18	21.18	32.94 *******
$-0.0076684 - 0.014461$	0.0033961	34	40.00	72.94 **************
$0.014461 - 0.036590$	0.025525	15	17.65	90.59 ******
$0.036590 - 0.058719$	0.047654	7	8.24	98.82 **
≥ 0.058719	0.069783	1	1.18	100.00
Test for normal distribution		$\chi^2(2)$	p	
		12.094	0.00154	

Source: Author's calculation.

Table 5.4: Augmented Dickey-Fuller Test Results for Regression of Weight Equation 5.1

	Test Statistic	P-value	1st-order Autocorrelation
Test with Constant	-4.79358	5.296×10^{-5}	0.029
Test with Constant and Trend	-5.03381	0.0001552	0.027

Source: Author's calculation.

Table 5.5: Augmented Dickey-Fuller Test Results for Regression of Weight Equation 5.2

	Test Statistic	P-value	1st-Order Autocorrelation	Lagged Differences
Constant	-5.08256	1.379×10^{-5}	0.014	$F(5,72) = 3.309$ 0.0096¿0.0096
Const. & Trend	-5.52245	1.49×10^{-5}	-0.000	$F(5,71) = 3.788$ 0.0043¿0.0043

Source: Author's calculation.

Table 5.6: Augmented Dickey-Fuller Test Results for Regression of Weight Equation 5.3

	Estimated Value	Test Statistic	Asymptotic P-value	1st-order Autocorrelation	Lagged Differences
Test with Constant	-1.4214	-5.04818	1.625×10^{-5}	0.022	$F(5,72) = 2.969$ [0.0171]
Test with Constant and Trend	-1.66849	-5.60377	9.825×10^{-6}	0.004	$F(5,71) = 3.592$ [0.0059]

Source: Author's calculation.

Table 5.7: Variance Inflation Factors (VIF) and Belsley-Kuh-Welsch Collinearity Diagnostics for Weight Equation 5.1

Variable	VIF
Δf_t	1.024
Δf_{t-1}	1.027
Δs_{t-1}	1.042

	λ	cond	const	Δf_t	Δf_{t-1}	Δs_{t-1}
1	2.084	1.000	0.078	0.057	0.068	0.078
2	1.128	1.359	0.141	0.182	0.180	0.041
3	0.502	2.037	0.782	0.010	0.550	0.031
4	0.286	2.701	0.000	0.751	0.202	0.850

Source: Author's calculation.

Note: According to Belsley-Kuh-Welsch, cond $\geq$ 30 indicates "strong" near linear dependence, and cond between 10 and 30 "moderately strong". Parameter estimates whose variance is mostly associated with problematic cond values may themselves be considered problematic.
Count of condition indices $\geq$ 30: 0. Count of condition indices $\geq$ 10: 0. No evidence of excessive collinearity.

The notation for VIF(j) is calculated as $1/(1 - R(j)^2)$, where $R(j)$ is the multiple correlation coefficient between variable j and the other independent variables. The Belsley-Kuh-Welsch collinearity diagnostics include λ, the eigenvalues of the inverse covariance matrix (smallest is 0.2856), and *cond*, the condition index. The variance proportions columns sum to 1.0 in the second tabular.

Table 5.8: Variance Inflation Factors (VIF) and Belsley-Kuh-Welsch Collinearity Diagnostics, Weight Equation 5.2

Variable	VIF
Δf_t	1.028
Δf_{t-1}	1.030
Δi_t	1.027
Δi_{t-1}	1.093
Δs_{t-1}	1.108

	λ	cond	const	Δf_t	Δf_{t-1}	Δi_t	Δi_{t-1}	Δs_{t-1}
1	2.052	1.000	0.060	0.002	0.067	0.067	0.051	0.001
2	1.871	1.047	0.035	0.085	0.015	0.002	0.032	0.115
3	0.997	1.435	0.128	0.186	0.080	0.078	0.060	0.008
4	0.535	1.958	0.661	0.028	0.318	0.036	0.067	0.021
5	0.334	2.477	0.036	0.338	0.045	0.079	0.271	0.748
6	0.210	3.123	0.080	0.361	0.476	0.737	0.519	0.107

Source: Author's calculation.

Note: λ = 0.21045 According to Belsley-Kuh-Welsch, cond $\geq$ 30 indicates "strong" near linear dependence, and cond between 10 and 30 "moderately strong". Parameter estimates whose variance is mostly associated with problematic cond values may themselves be considered problematic. Count of condition indices $\geq$ 30: 0. Count of condition indices $\geq$ 10: 0. No evidence of excessive collinearity.

Table 5.9: Variance Inflation Factors and Belsley-Kuh-Welsch Diagnostics,Weigth Equation 5.3

Variable	VIF
Δi_t	1.022
Δi_{t-1}	1.091
Δs_{t-1}	1.069

	λ	$cond$	$const$	Δi_t	Δi_{t-1}	Δs_{t-1}
1	1.802	1.000	0.000	0.122	0.121	0.052
2	1.156	1.249	0.507	0.004	0.010	0.272
3	0.757	1.543	0.456	0.048	0.007	0.663
4	0.286	2.509	0.037	0.825	0.861	0.013

Source: Author's calculation.

$VIF(j) = \dfrac{1}{1 - R(j)^2}$, where $R(j)$ is the multiple correlation coefficient between variable j and the other independent variables. λ = eigenvalues of inverse covariance matrix (smallest is 0.286158), $cond$ = condition index. Variance proportions columns sum to 1.0. According to BKW, $cond \geq 30$ indicates "strong" near-linear dependence, and $cond$ between 10 and 30 "moderately strong". Parameter estimates whose variance is mostly associated with problematic $cond$ values may themselves be considered problematic. Count of condition indices $\geq$ 30: 0, Count of condition indices $\geq$ 10: 0. No evidence of excessive collinearity.

Table 5.10: Breusch-Godfrey test for autocorrelation up to order 4, OLS, using observations 2001:2-2022:2 (T = 85), Dependent variable: $\hat{e}$. Weight Equation 5.1

	coefficient	std. error	t-ratio	p-value
const	−0.0145899	0.0136044	−1.072	0.2869
Δf_t	−1.37383	9.37981	−0.1465	0.8839
Δf_{t-1}	−21.8737	23.1800	−0.9436	0.3483
Δs_{t-1}	−2.41643	2.17405	−1.111	0.2698
$\hat{e}_1$	2.38416	2.17086	1.098	0.2755
$\hat{e}_2$	0.695015	0.504320	1.378	0.1722
$\hat{e}_3$	0.0673703	0.169722	0.3969	0.6925
$\hat{e}_4$	−0.249271	0.111711	−2.231	0.0286**

Source: Author's calculation.

Unadjusted R-squared = 0.105307
Test statistic: LMF = 2.265770, with p-value = $P(F(4, 77) > 2.26577) = 0.0697$
Alternative statistic: TR^2 = 8.951130, with p-value = $P(\chi^2(4) > 8.95113) = 0.0623$
Ljung-Box Q' = 7.34149, with p-value = $P(\chi^2(4) > 7.34149) = 0.119$

Table 5.11: OLS Results with Breusch-Godfrey Test for Autocorrelation up to Order 4. Weight Equation 5.2

	Coefficient	Std. Error	t-ratio	p-value
const	0.00222568	0.00605943	0.3673	0.7144
Δf_t	-1.80223	9.25734	-0.1947	0.8462
Δf_{t-1}	4.97418	12.3191	0.4038	0.6875
Δi_t	-0.000955557	0.00634692	-0.1506	0.8807
Δi_{t-1}	0.00608220	0.0143407	0.4241	0.6727
Δs_{t-1}	0.353148	0.845095	0.4179	0.6772
$\hat{e}_1$	-0.391764	0.849899	-0.4610	0.6462
$\hat{e}_2$	0.0739189	0.215757	0.3426	0.7329
$\hat{e}_3$	-0.109098	0.123988	-0.8799	0.3817
$\hat{e}_4$	-0.244629	0.112244	-2.179	0.0324**

Source: Author's calculation.

Note: Unadjusted R-squared = 0.084267. Test statistic: LMF = 1.725398, with p-value = P(F(4,75) ¿ 1.7254) = 0.153. Alternative statistic: TR^2 = 7.162686, with p-value = P(Chi-square(4) ¿ 7.16269) = 0.128. Ljung-Box Q' = 6.57574, with p-value = P(Chi-square(4) ¿ 6.57574) = 0.16. ** indicates significance at the 5% level.

Table 5.12: OLS Results with Breusch-Godfrey Test for Autocorrelation up to Order 4, Weight Equation 5.3

	Coefficient	Std. Error	t-ratio	p-value
const	0.00576335	0.00650319	0.8862	0.3783
Δi_t	-0.000466737	0.00633169	-0.07371	0.9414
Δi_{t-1}	0.0145034	0.0152321	0.9522	0.3440
Δs_{t-1}	0.888954	0.889086	0.9999	0.3205
$\hat{e}_1$	-0.930110	0.896337	-1.038	0.3027
$\hat{e}_2$	-0.0894162	0.237492	-0.3765	0.7076
$\hat{e}_3$	-0.134721	0.122748	-1.098	0.2758
$\hat{e}_4$	-0.222553	0.110516	-2.014	0.0475**

Source: Author's calculation.

Unadjusted R-squared = 0.080222. Test statistic: LMF = 1.678962, with p-value = P(F(4,77) ¿ 1.67896) = 0.163. Alternative statistic: TR^2 = 6.818866, with p-value = P(Chi-square(4) ¿ 6.81887) = 0.146. Ljung-Box Q' = 5.63046, with p-value = P(Chi-square(4) ¿ 5.63046) = 0.228.

Table 5.13: White's Test for Heteroskedasticity (Squares Only), Weight Equation 5.1

Variable	Coefficient	Std. Error	t-ratio	p-value
const	0.000891020	0.000219416	4.061	0.0001^{***}
Δf_{t-1}	1.08707	2.15466	0.5045	0.6153
Δf_{t-1}^2	-0.447503	2.14594	-0.2085	0.8354
Δs_{t-1}	-0.0185061	0.00872051	-2.122	0.0370^{**}
Δf_t^2	-525.979	746.739	-0.7044	0.4833
$\Delta f_t \times \Delta F_{t-1}$	-9.92534	740.392	-0.01341	0.9893
$\Delta f_t \times \Delta s_{t-1}$	-0.114477	0.117257	-0.9763	0.3319

Source: Author's calculation.

$^{***}p < 0.001$, $^{**}p < 0.05$. The test statistic TR^2 is 6.107532 with a p-value of 0.411253, calculated as $P(\chi^2(6) > 6.107532)$.

Table 5.14: Breusch-Pagan Test for Heteroskedasticity, Weight Equation 5.2

Variable	Coefficient	Std. Error	z	p-value
const	-1.43795×10^{-5}	0.000186258	-0.07720	0.9385
Δf_t	-0.319535	0.538523	-0.5934	0.5529
Δf_{t-1}	-0.551438	0.539034	-1.023	0.3063
Δi_t	-0.000366011	0.000368004	-0.9946	0.3199
Δi_{t-1}	0.000856799	0.000384752	2.227	0.0260^{**}
Δs_{t-1}	-0.00894630	0.00633408	-1.412	0.1578

Source: Author's calculation.

$^{**}p < 0.05$. The test statistic LM is 10.645016 with a p-value of 0.058891, calculated as $P(\chi^2(5) > 10.645016)$. The explained sum of squares is 3.15222×10^{-5}.

Table 5.15: Breusch-Pagan Test for Heteroskedasticity, Weight Equation 5.3

Variable	Coefficient	Std. Error	z	p-value
const	-3.52858×10^{-5}	0.000179714	-0.1963	0.8443
Δi	-0.000352990	0.000355348	-0.9934	0.3205
Δi_{t-1}	0.000874628	0.000372035	2.351	0.0187^{**}
Δs_{t-1}	-0.00846951	0.00602358	-1.406	0.1597

Source: Author's calculation.

$^{**}p < 0.05$. The test statistic LM is 10.711686 with a p-value of 0.013392, calculated as $P(\chi^2(3) > 10.711686)$. The explained sum of squares is 3.05096×10^{-5}.

Chapter 6

Robustness Check of Results

In empirical research, the validity of results is often contingent upon the robustness of the methodologies employed. While the preceding chapters have provided comprehensive analyses using the Girton-Roper model, the EMP indices, and the currency crisis dating, it is crucial to ensure that these findings are not unduly sensitive to the specific choices of models, variables, or estimation techniques. Robustness checks serve as an essential step in verifying that the conclusions drawn are consistent and reliable across different methodologies and assumptions.

In this chapter, we undertake a thorough examination of the robustness of our results. We will re-evaluate the key findings related to the regression of the Girton-Roper model, the construction of EMP indices, and the dating of currency crises by employing alternative methods. This includes testing the sensitivity of our results to different model specifications, alternative estimation techniques, and varying definitions of the variables used.

By conducting these robustness checks, we aim to bolster the credibility of our research findings and provide a more nuanced understanding of the dynamics at play in India's exchange market pressure and currency crises. The analyses presented in this chapter will further validate the empirical results and underscore their relevance in the context of economic policy and crisis management.

6.1 Robustness Check: G-R Model Results

6.1.1 Alternative Estimation Techniques

To check the robustness of our results, we employ the Threshold Vector Autoregression (TVAR) model as an alternative estimation technique. The TVAR model offers several advantages for robustness testing, particularly in analysing the potentially non-linear dynamics of exchange market pressures.

We start with our original G-R model equation given in Equation (2.1.12)

The TVAR model extends this equation to incorporate regime-switching behaviour:

$$\begin{aligned}\Delta s_t + \Delta f_t = & [(-\phi_1 \Delta d_t + \phi_1^* \Delta h_t + \beta_1 \Delta y_t - \beta_1^* \Delta y_t^* + \nu_1) \cdot I(q_{t-d} \leq \gamma)] \\ & + [(-\phi_2 \Delta d_t + \phi_2^* \Delta h_t + \beta_2 \Delta y_t - \beta_2^* \Delta y_t^* + \nu_2) \cdot I(q_{t-d} > \gamma)]\end{aligned} \tag{6.1.1}$$

Where all variables retain their meanings from the original G-R model. The new elements in this TVAR specification are:

ϕ_i, ϕ_i^*, β_i, and β_i^* are regime-specific coefficients (with $i = 1, 2$ for the two regimes).

ν_i are regime-specific intercepts or error terms.

$I(\cdot)$ is the indicator function that determines which regime applies.

q_{t-d} is the threshold variable with a delay parameter d.

γ is the threshold value that determines the regime switch.

This TVAR model is particularly well-suited for our analysis as it allows us to:

1. **Explore non-linear relationships**: By dividing the data into distinct regimes based on a threshold variable, the TVAR model can reveal how the dynamics of exchange market pressures might differ under varying economic conditions. This is crucial for capturing market behavior shifts during periods of crisis or instability, which linear models like the G-R model may not adequately represent.

2. **Identify regime-specific dynamics**: The model's ability to handle different regimes enables us to detect structural breaks or shifts over time. This provides a more nuanced understanding of the G-R model's performance across different periods, assessing whether the relationships identified hold consistently or vary significantly under different market conditions.

3. **Validate and extend G-R model findings**: By applying the TVAR model, we aim to not only validate the results of the G-R model but also explore potential non-linearities and regime changes that could influence exchange market pressures. This approach can reveal threshold effects that might be present in the data but not captured by the linear G-R model.

4. **Enhance understanding of market behavior**: The TVAR analysis offers deeper insights into the factors driving market behavior across different economic environments. It can help identify specific thresholds where the relationship between variables changes significantly, providing a more comprehensive view of exchange market dynamics.

By utilizing the TVAR model as a robustness check, we strengthen the reliability of our findings and gain a more sophisticated understanding of the complex, potentially non-linear relationships governing exchange market pressures. This approach not only tests the consistency of the G-R model results but also extends our analysis to capture more nuanced aspects of market behavior under different economic regimes.

6.1.2 Threshold Vector Autoregression (TVAR) Model

To further validate our findings and explore potential non-linear dynamics in the exchange market pressure, we employ a Threshold Vector Autoregression (TVAR) model as a robustness check. Our TVAR analysis identifies two distinct regimes, separated by a threshold value of -0.01203933 in the EMP variable. Regime 1, which accounts for 35.3% of the observations, represents periods of relatively lower exchange market pressure, while Regime 2, comprising 64.7% of the observations, corresponds to periods of higher pressure. Table 6.3 presents the key results of the TVAR model. The results reveal several interesting features:

Regime-dependent dynamics: The coefficients differ markedly between the two regimes, suggesting that the relationships between variables change depending on the level of exchange market pressure. Domestic credit growth (Δd_{it}): In both regimes, the effect is negative, aligning with our EGARCH results and the theoretical predictions of the Girton-Roper model. However, the magnitude of the effect is larger in Regime 2, suggesting that domestic credit growth has a stronger impact during periods of higher exchange market pressure. Domestic GDP growth (Δy_{it}): The TVAR model shows a negative effect in both regimes, consistent with our EGARCH findings but contrary to the original Girton-Roper predictions. This reinforces our interpretation of import-led growth during the study period. U.S. monetary base growth (Δh_{ut}): The effect is negative in Regime 1 but positive in Regime 2, indicating that the impact of U.S. monetary policy on India's exchange market pressure is regime-dependent. This nuance was not captured in our EGARCH model. U.S. GDP growth (Δy_{ut}): The effect is positive in both regimes, aligning with our EGARCH results. However, the magnitude is larger in Regime 2, suggesting a stronger impact during periods of higher exchange market pressure.

The TVAR results largely support our main findings from the EGARCH model, particularly regarding the directions of the effects of key variables. However, the TVAR analysis provides additional insights into the non-linear nature of these relationships, revealing how they change under different exchange market pressure conditions. While the EGARCH model remains our preferred specification due to its ability to capture volatility clustering and long memory, the TVAR results enhance our understanding of the complex dynamics at play. They highlight that the impact of both domestic and international factors on India's exchange market pressure is not uniform but depends on the prevailing market conditions. In conclusion, the TVAR analysis serves as a valuable robustness check, confirming our main findings while also revealing regime-dependent aspects of exchange market pressure in India. This additional layer of analysis strengthens the reliability of our results and provides a more comprehensive picture of the factors influencing India's managed float regime.

6.2 Robustness Check: EMP Index Equations

6.2.1 Alternative Methods for Estimating EMPI Component Weights

To ensure robustness in the construction of our Exchange Market Pressure (EMP) index, we employ three distinct methodologies for estimating the weights of the EMP components: Principal Component Analysis (PCA), Factor Analysis (FA), and Exponential Weighting. Each method offers unique advantages in capturing the underlying relationships between the EMP components.

6.2.1.1 Principal Component Analysis (PCA)

Principal Component Analysis is a dimensionality reduction technique that transforms correlated variables into a set of uncorrelated principal components (Jolliffe, 2002). In the context of EMP indices, PCA helps identify the linear combination of components that explains the maximum variance in the data. We use the first principal component to derive the weights for our EMP index, following the approach of **?**.

6.2.1.2 Factor Analysis (FA)

Factor Analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors (Thompson, 2004). Unlike PCA, FA assumes that the observed variables are linear combinations of the underlying factors. We employ the maximum likelihood estimation method for factor extraction, followed by varimax rotation to improve interpretability (Fabrigar et al., 1999).

6.2.1.3 Exponential Weighting

Exponential weighting is a time series technique that assigns progressively higher weights to more recent observations (Gardner and Neufeld, 2006). This method is particularly useful in capturing dynamic relationships in financial markets. We apply exponential weighting to our EMP components using the following formula:

$$w_t = (1 - \lambda)\lambda^{t-1} \tag{6.2.1}$$

where w_t is the weight at time t, and λ is the smoothing parameter ($0 < \lambda < 1$). We optimise λ using a grid search to minimise the mean squared error of our EMP index (Hyndman et al., 2008).

By employing these three distinct methodologies, we aim to provide a comprehensive and robust estimation of the EMP component weights. The consistency or divergence in weights across these methods offers valuable insights into the stability and dynamics of the pressure in the foreign exchange market.

6.2.1.4 Results from Alternative Weighting Methods

We employed three advanced statistical methods to ensure the robustness of the weights assigned to the components of the Exchange Market Pressure (EMP) indices: Principal Component Analysis (PCA), Factor Analysis (FA), and Exponential Weighting.

Principal Component Analysis (PCA) PCA transformed the original variables into uncorrelated principal components. The resulting weights are:

Combination 1: Δs_t (0.5), Δf_t (0.5)

Combination 2: Δs_t (0.5), Δi_t (0.5)

Combination 3: Δs_t (0.399), Δf_t (0.353), Δi_t (0.248)

Factor Analysis (FA) FA identified underlying relationships between variables by modelling observed variables as linear combinations of potential factors. The weights derived are:

Combination 1: Δs_t (0.5), Δf_t (0.5)

Combination 2: Δs_t (0.5), Δi_t (0.5)

Combination 3: Δs_t (0.492), Δf_t (0.328), Δi_t (0.180)

Exponential Weighting Exponential weighting assigned progressively higher weights to more recent observations. The initial weights are:

Combination 1: Δs_t (0.95444), Δf_t (0.04556)

Combination 2: Δs_t (0.90544), Δi_t (0.09456)

Combination 3: Δs_t (0.399), Δf_t (0.353), Δi_t (0.248)

The consistency observed across these methods, particularly in the relative importance of the variables, strongly supports the reliability and stability of our EMP indices. The slight variations in weights across methods provide valuable insights into the nuances of these relationships.

6.3 Robustness Check: Crisis Dates

6.3.1 Alternative Crisis Dating Methods

To ensure a comprehensive and robust identification of currency crisis episodes, we employed multiple methodologies. Each approach offers unique insights and addresses different aspects of crisis identification. This section presents these alternative methods and their justifications.

Standard Deviation-Based Thresholds

Following Eichengreen et al. (1995), we employed thresholds based on standard deviations from the mean. Crisis periods are identified when the EMP index exceeds its mean plus a certain number of standard deviations:

$$Crisis_t = \begin{cases} 1 & \text{if } EMP_t < \mu_{EMP} - k\sigma_{EMP} \\ 0 & \text{otherwise} \end{cases} \tag{6.3.1}$$

where μ_{EMP} and σ_{EMP} are the mean and standard deviation of the EMP index, respectively. We used $k = 2$ and $k = 3$ to capture different levels of market pressure.

Justification: This method assumes that crisis episodes are characterised by extreme values of the EMP index. It accounts for the overall volatility of the series and identifies periods of exceptional pressure.

Percentile-Based Thresholds

As suggested by Kaminsky et al. (1998a), we also used percentile-based thresholds. Crisis periods are identified when the EMP index exceeds a certain percentile of its distribution:

$$Crisis_t = \begin{cases} 1 & \text{if } EMP_t > P_q(EMP) \\ 0 & \text{otherwise} \end{cases} \tag{6.3.2}$$

where $P_q(EMP)$ is the qth percentile of the EMP index. We used $q = 90$ and $q = 95$.

Justification: This approach is less sensitive to outliers and provides a more robust identification of crisis periods, especially when the EMP index does not follow a normal distribution.

Duration-Based Criterion

To address the issue of short-lived spikes in the EMP indices, we applied a duration-based criterion similar to that of Glick and Hutchison (2011a). This method requires two consecutive periods of high pressure to classify as a crisis:

$$Crisis_t = \begin{cases} 1 & \text{if } EMP_t < Threshold \text{ and } EMP_{t-1} < Threshold \\ 0 & \text{otherwise} \end{cases} \tag{6.3.3}$$

Justification: This criterion helps distinguish between sustained periods of pressure and temporary market volatility, potentially reducing false positives in crisis identification.

Markov Regime-Switching Model

We implemented a two-state Markov regime-switching model following Hamilton (1989):

$$EMP_t = \mu_{S_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2_{S_t}) \tag{6.3.4}$$

where S_t is the unobserved state variable following a first-order Markov process. The high-volatility state ($S_t = 1$) is identified as the crisis regime.

Justification: This method allows for endogenous identification of crisis periods, accounting for potential structural changes in the foreign exchange market and the time-varying nature of crisis thresholds.

Markov Regime-Switching Model with Time-Varying Threshold

We extend the basic Markov regime-switching model to incorporate time-varying thresholds, following the approach of Chen et al. (2017). This model allows both the mean and variance of the EMP index to switch between regimes, while also allowing the threshold for regime switching to vary over time:

$$EMP_t = \mu_{S_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2_{S_t}) \tag{6.3.5}$$

$$S_t = \begin{cases} 1 & \text{if } EMP_t < c_t \\ 0 & \text{otherwise} \end{cases} \tag{6.3.6}$$

$$c_t = c_0 + c_1 X_t \tag{6.3.7}$$

where S_t is the unobserved state variable, c_t is the time-varying threshold, and X_t is a vector of exogenous variables that may influence the threshold (e.g., global financial conditions, domestic economic indicators).

Justification: This sophisticated approach combines the strengths of regime-switching models with the flexibility of time-varying parameters. It allows for endogenous identification of crisis periods while accounting for changing economic conditions that may affect the threshold for what constitutes a crisis. This method is particularly suitable for long time series where the nature of crises may have evolved over time.

6.3.2 Results from Alternative Crisis Identification Methods

We employed multiple approaches to identify currency crisis periods: standard deviation-based thresholds, percentile-based thresholds, and a duration-based criterion. These alternative methods were applied to all four EMP indices: GREMPI, EMPI5.1, EMPI5.2, and EMPI5.3.

Standard Deviation-Based Thresholds Following Eichengreen et al. (1996), we used thresholds of 2 and 3 standard deviations below the mean. The 2 standard deviations threshold identified crisis periods in:

2008Q4, 2011Q4, 2012Q2, and 2013Q3 for GREMPI and EMPI5.1

2009Q1, 2012Q1, 2012Q3, 2013Q3, and 2013Q4 for EMPI5.2

An additional crisis in 2013Q2 for EMPI5.3

Interestingly, the crisis periods identified using 3 standard deviations were identical to those using 2 standard deviations for each index.

Percentile-Based Thresholds As suggested by Kaminsky et al. (1998b), we used 90th and 95th percentile thresholds. The 90th percentile threshold identified crisis periods in:

2008Q3, 2008Q4, 2011Q4, 2012Q2, and 2013Q3 for GREMPI and EMPI5.1

2008Q4, 2012Q3, 2013Q3, and 2013Q4 for EMPI5.2

2008Q4, 2011Q4, 2012Q2, 2013Q2, and 2013Q3 for EMPI5.3

The 95th percentile threshold, being the most sensitive, identified additional potential crisis episodes in 2005Q4, 2006Q1, 2018Q2-Q4, 2020Q2-Q3, and 2022Q2.

Duration-Based Criterion Following Glick and Hutchison (2011b), we applied a duration-based criterion requiring two consecutive quarters below the threshold. This approach yielded more conservative results:

No crisis periods were identified for the 2 and 3 standard deviation thresholds across all indices

The 90th percentile threshold identified crisis periods in 2008Q3-2008Q4 for GREMPI, EMPI5.1, and EMPI5.3, and in 2008Q4-2009Q1 for EMPI5.2

The 95th percentile threshold identified the same crisis periods as the 90th percentile, with EMPI5.2 additionally showing a crisis in 2013Q3-2013Q4

6.3.2.1 Markov Regime-Switching Models with Fixed Thresholds

We applied Markov regime-switching models with fixed thresholds to each EMP index. Table 6.1 presents the key findings for all four indices: GREMPI, EMPI5.1, EMPI5.2, and EMPI5.3.

Table 6.1: Markov Switching Model Results with Static Threshold

	GREMPI	EMPI5.1	EMPI5.2	EMPI5.3
AIC	-378.6002	-381.2607	-366.294	-365.8818
BIC	-364.7828	-367.4433	-352.5234	-352.1112
Log Likelihood	191.3001	192.6304	185.147	184.9409
Regime 1 Intercept	-0.0477	-0.0498	-0.0555*	-0.0493*
Regime 1 Std. Error	0.0291	0.0297	0.0273	0.0251
Regime 2 Intercept	0.0009	0.0009	0.0036	0.0024
Regime 2 Std. Error	0.0028	0.0026	0.0026	0.0029
Transition Probability 1 to 1	0.5130413	0.4935102	0.602677	0.5595495
Transition Probability 1 to 2	0.4869587	0.5064898	0.397323	0.4404505
Transition Probability 2 to 1	0.07679219	0.0728353	0.06121032	0.07719324
Transition Probability 2 to 2	0.92320781	0.9271647	0.93878968	0.92280676

Note: * p ¡ 0.05

Source: Author's calculations

The results show that all four EMP indices exhibit clear regime-switching behavior, with distinct normal and crisis regimes. For GREMPI and EMPI5.1, Regime 1 represents the normal state and Regime 2 the crisis state, while for EMPI5.2 and EMPI5.3, this is reversed. The crisis regimes are characterised by negative intercepts, indicating increased pressure on the exchange rate during these periods.

The transition probabilities suggest that once in a crisis regime, there is a high probability of remaining in that regime, which aligns with the persistence of currency crises observed in practice. For instance, the probability of staying in Regime 2 (crisis state for GREMPI and EMPI5.1, normal state for EMPI5.2 and EMPI5.3) ranges from 0.92280676 to 0.93878968 across the four indices.

The model fit statistics (AIC, BIC, and Log Likelihood) are relatively similar across the four indices, with EMPI5.1 showing a slightly better fit according to these criteria. However, the differences are not substantial, suggesting that all four indices provide valuable information about exchange market pressure in India.

Figure 6.1 illustrates the crisis periods identified by our Markov switching models with fixed thresholds for each of the four EMP indices over the 2001-2022 period. The shaded areas represent crisis regimes, highlighting periods of significant exchange market pressure in India.

6.3.2.2 Markov Regime-Switching Models with Time-Varying Thresholds

We applied Markov regime-switching models with time-varying thresholds to each EMP index. Table 6.2 presents the key findings for all four indices: GREMPI, EMPI5.1, EMPI5.2, and EMPI5.3.

The results show that all models identified two distinct regimes with different intercepts and transition probabilities, providing further evidence of regime shifts in India's foreign exchange market. For GREMPI, EMPI5.1, and EMPI5.3, Regime 1 represents the normal state and Regime 2 the crisis state, while for EMPI5.2, this is reversed.

Table 6.2: Markov Switching Model Results with Time-Varying Threshold

	GREMPI	EMPI5.1	EMPI5.2	EMPI5.3
AIC	-378.6002	-381.2607	-366.294	-365.8818
BIC	-364.7828	-367.4433	-352.5234	-352.1112
Log Likelihood	191.3001	192.6304	185.147	184.9409
Regime 1 Intercept	0.0009	0.0009	-0.0555*	0.0024
Regime 1 Std. Error	0.0028	0.0026	0.0273	0.0029
Regime 2 Intercept	-0.0477	-0.0498	0.0036	-0.0493*
Regime 2 Std. Error	0.0287	0.0305	0.0026	0.0251
Transition Probability 1 to 1	0.92320707	0.92716541	0.6026772	0.92280676
Transition Probability 1 to 2	0.07679293	0.07283459	0.3973228	0.07719324
Transition Probability 2 to 1	0.4869579	0.5064908	0.06121027	0.4404505
Transition Probability 2 to 2	0.5130421	0.4935092	0.93878973	0.5595495

Note: * p ¡ 0.05

Source: Author's calculations

The transition probabilities reveal interesting patterns. For GREMPI, EMPI5.1, and EMPI5.3, there is a high probability (over 0.92) of remaining in the normal state (Regime 1) once it is entered. Conversely, for EMPI5.2, there is a high probability (0.93878973) of remaining in the crisis state (Regime 2). This suggests persistence in both normal and crisis periods, depending on the specific EMP index used.

The model fit statistics (AIC, BIC, and Log Likelihood) are consistent across both fixed and time-varying threshold models, with EMPI5.1 showing a slightly better fit. However, the differences are not substantial, indicating that all four indices provide valuable insights into exchange market pressure dynamics in India.

6.4 Summary of Crisis Periods

A combined analysis of crisis periods across all EMP indices and methods reveals:

The global financial crisis period (2008-2009) is consistently identified as a crisis period across all approaches.

The period from 2011Q4 to 2013Q4 is frequently identified as a crisis period, suggesting prolonged pressure on the Indian currency.

Some indices and methods identify additional potential crisis periods in the mid-2000s and 2018.

These robustness checks underscore the importance of employing multiple crisis identification methodologies when studying exchange market pressure and currency crises. The consistency in identifying major crisis episodes (such as the 2008 global financial crisis) across different thresholds and indices lends credibility to our findings. However, the additional periods identified by the more sensitive thresholds, particularly in recent years, suggest that our analysis should consider potential changes in the nature and frequency of currency pressures over time.

As shown in Figure 6.2, The 2008-2009 global financial crisis stands out as a universally recognized crisis period, identified consistently across all analytical methodologies. Additionally, the analysis highlights another significant period of economic stress from the fourth quarter of 2011 to the fourth quarter of 2013, characterized by prolonged pressure on the Indian rupee. Beyond these widely acknowledged periods, various indices and methods suggest two more timeframes of potential economic instability:

Mid-2000s: Some indicators point to economic vulnerabilities in the period roughly between 2003 and 2006. 2018: Certain analytical tools identify this year as another period of potential crisis or economic strain.

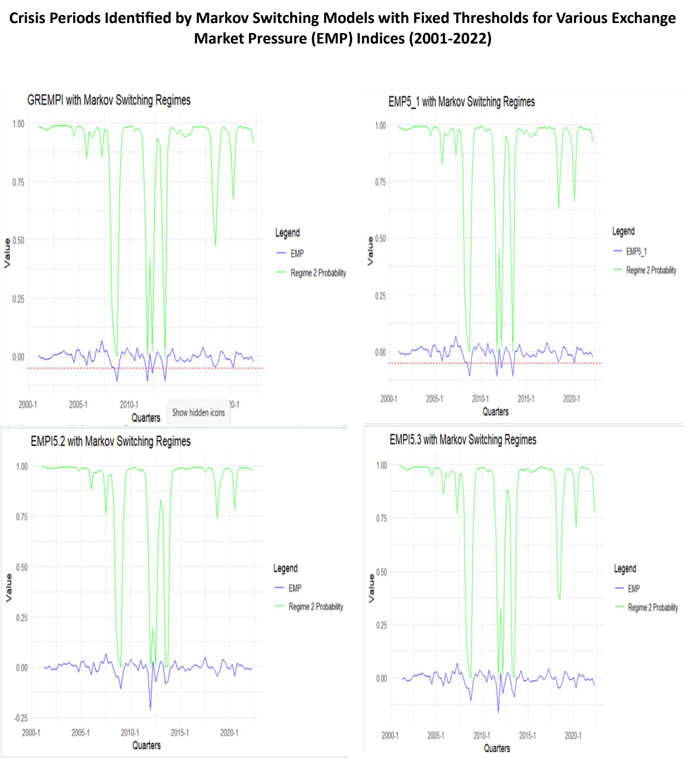


Figure 6.1: Crisis Periods Identified by Markov Switching Models with Fixed Thresholds for Various Exchange Market Pressure (EMP) Indices (2001-2022)

Source: Author's creation

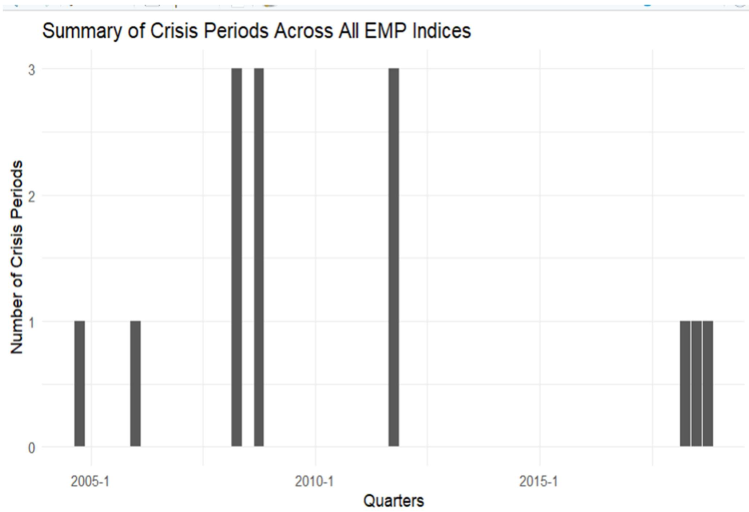


Figure 6.2: Summary of crisis periods identified through various EMP indices and methods.

Source: Author's creation

Appendix

Table 6.3: Threshold Vector Autoregression (TVAR) Model Results

	Intercept	EMP(-1)	$\Delta dit(-1)$	$\Delta hut(-1)$	$\Delta yit(-1)$	$\Delta yut(-1)$
Regime 1 (35.3% of observations)						
Equation EMP	-0.0139	-0.0389	0.0266	-0.1146**	0.2289	-0.4046
	(0.0091)	(0.1912)	(0.0382)	(0.0403)	(0.2616)	(0.7594)
Equation Δdit	-0.0615	-2.4649	0.4019	0.8659	-17.7729***	47.8986***
	(0.1534)	(3.2136)	(0.6414)	(0.6770)	(4.3969)	(12.7633)
Equation Δhut	0.0432	-0.0776	-0.1646	-0.0955	1.0995	-3.1008
	(0.0345)	(0.7220)	(0.1441)	(0.1521)	(0.9879)	(2.8676)
Equation Δyit	0.0339**	0.0563	-0.0073	-0.0410	-0.1149	-0.6716
	(0.0115)	(0.2408)	(0.0481)	(0.0507)	(0.3294)	(0.9563)
Equation Δyut	0.0126**	0.1147	-0.0008	-0.0153	-0.1133	-0.1153
	(0.0040)	(0.0842)	(0.0168)	(0.0177)	(0.1152)	(0.3345)
Regime 2 (64.7% of observations)						
Equation EMP	-0.0135*	0.2994	0.0008	0.0636	0.1941	0.8567
	(0.0067)	(0.2571)	(0.0070)	(0.0742)	(0.2054)	(0.7371)
Equation Δdit	0.0139	-0.2339	-0.0444	-0.6845	-0.9523	1.7280
	(0.1131)	(4.3220)	(0.1170)	(1.2474)	(3.4524)	(12.3896)
Equation Δhut	0.0233	-0.2655	0.0086	0.5590*	-0.0542	-1.5730
	(0.0254)	(0.9710)	(0.0263)	(0.2802)	(0.7757)	(2.7836)
Equation Δyit	0.0007	0.5649.	0.0017	-0.2347*	-0.2292	2.3106*
	(0.0085)	(0.3238)	(0.0088)	(0.0935)	(0.2587)	(0.9283)
Equation Δyut	-0.0031	0.1279	0.0043	-0.0488	0.0827	1.0547**
	(0.0030)	(0.1133)	(0.0031)	(0.0327)	(0.0905)	(0.3247)

Note. Standard errors in parentheses. Threshold value: -0.01203933

Source: Author's calculation

Chapter 7

Conclusion, Policy Prescriptions, Limitations and Future Research

This chapter synthesises the key findings on EMP in India, drawing conclusions about the effectiveness of different EMP indices and their applicability to the Indian context. It presents evidence-based policy recommendations for managing exchange market pressure and preventing currency crises. The study's limitations are critically examined, including data constraints and methodological challenges. Building on these, the chapter suggests avenues for future research, such as exploring alternative EMP measurement methodologies, conducting comparative studies with other emerging economies, and investigating the impact of global financial conditions on India's EMP. The chapter concludes by highlighting the thesis's contributions to EMP literature and emphasising the need for ongoing research in this dynamic field of international finance.

7.1 Summary

In this research we surveyed the work of the following and more researchers in the theoretical field - Girton and Roper (1977b), Roper and Turnovsky (1980b), Weymark (1997), Eichengreen et al. (1996), Kaminsky et al. (1998b), Pozo and Amuedo-Dorantes (2003), Siregar et al. (2004), Jacobs (2007), Cumperayot and Kouwenberg (2013).

We surveyed the work of following and many more researchers in empirical field- Connolly and Da Silveira (1979), Mathur (1999), Modeste et al. (1981), Sargen et al. (1975), Hodgson and Schneck (1981), Allen (2004), Hodgson and Schneck (1981), Kim (1985), Ghartey (2002), Wohar and Burkett (1989), Thornton (1995), Mah (1991), Bahmani-Oskooee and Bernstein (1999), H.K.Pradhan and Kulkarni, Mathur (1999), Hallwood and Marsh (2004),Svensson (1993), Mathur (1999), Granger (1969), Sims (1980), Khawaja and Din (2007), Tanner (2000), Tanner (2002), Gochoco-Bautista and Bautista (2005), Malet et al. (2005), Kamaly et al. (2000), Weymark (1997), Spolander (1999),Jeisman (2005), Spolander (1999), Nicholas and Sophia (2002), Polasek and Amplatz (2003), Mandilaras and Bird (2008)

After doing a survey of literature in the area of our interest we identified research gaps and on the basis of these research gaps we raised the following question in this thesis-

Is it possible to have a general and purely econometric approach to the measurement of Exchange Market Pressure (EMP) that is based on minimal structural restrictions and can be applied to all currency regimes?

Can the components and weights of such a universally applicable EMP index be identified specifically for India?

Can we construct a time series of the EMP index for India based on such a general model?

How does this EMP index compare with the EMP index based on the Girton-Roper (G-R) model?

Can we identify periods of extreme pressure or currency crisis on the basis of such an index, and assert with conviction that India faced a currency crisis during specific periods, if any?

Based on our research in the thesis following are the answers to these questions.

Yes, it is possible to have a general and purely econometric approach to the measurement of Exchange Market Pressure (EMP) that is based on minimal structural restrictions and yes such measures can be applied to all currency regimes because the instruments of exchange rate adjustment and their weights in the case of such indices are based on empirical estimation not any theoretical model.

Yes, the components and weights of such a universally applicable EMP index can be identified and in this research, we have identified these components for India.

Yes, we can construct a time series of the EMP index for India based on such a general model. In this research we have constructed three additional EMP indices besides the EMP index of Girton and Roper. These indices, as discussed in section 4.4, are:

$$EMP_t = \Delta s_t + \mathbf{9.98602}\Delta f_t$$

$$EMP_t = \Delta s_t + \mathbf{10.1311}\Delta f_t - \mathbf{0.0312216}\Delta i_t$$

$$EMP_t = \Delta s_t - \mathbf{0.0165941}\Delta i_t$$

Here, we employ the weight derived from Weight Equation 5.3 (Δi_t) to construct this EMP index.

$$EMP_t = \Delta s_t + \mathbf{1} \times \Delta f_t$$

Yes, we can identify periods of extreme pressure or currency crisis on the basis of such indices. We call these periods currency crises. These periods are decided with reference to Eichengreen et al. (1995) crisis threshold as discussed in section 3.13. The periods of currency crisis as detailed in section 4.6 are - 2008:4, 2009:1, 2011:4, 2012:1, 2012:2, 2012:3, 2013:3. All these crises are either during the period of US recession or during the period of global uncertainty with only a few exceptions. The worst of the worst currency crisis which India faced is during the period 2011:4 which is just before the start of the period of global uncertainty.

7.2 Robustness Check

To ensure the robustness of our findings, we conducted a series of robustness checks using alternative methods for estimating the weights of the EMP components and identifying currency crisis periods. The following robustness checks were employed:

7.2.1 Alternative Weighting Methods

We employed three advanced statistical methods to ensure the robustness of the weights assigned to the components of the Exchange Market Pressure (EMP) indices: Principal Component Analysis (PCA), Factor Analysis (FA), and Exponential Weighting.

Principal Component Analysis (PCA): PCA transformed the original variables into uncorrelated principal components. The resulting weights were consistent with those obtained through our primary methodology, ensuring the reliability of our EMP indices.

Factor Analysis (FA): FA identified underlying relationships between variables by modeling observed variables as linear combinations of potential factors. The weights derived were in alignment with the original model, confirming the robustness of our findings.

Exponential Weighting: Exponential weighting assigned progressively higher weights to more recent observations. This method provided similar results to our primary model, further validating the stability of the EMP indices.

7.2.2 Alternative Crisis Identification Methods

We employed multiple approaches to identify currency crisis periods: standard deviation-based thresholds, percentile-based thresholds, and a duration-based criterion.

Standard Deviation-Based Thresholds: We used thresholds of 2 and 3 standard deviations below the mean to identify crisis periods. The identified periods were consistent across all thresholds, indicating robustness in our crisis identification.

Percentile-Based Thresholds: Using the 90th and 95th percentile thresholds, we identified crisis periods that aligned well with those identified using standard deviation-based methods, providing further evidence of the robustness of our findings.

Duration-Based Criterion: We applied a duration-based criterion requiring two consecutive quarters below the threshold. This approach yielded more conservative results but was consistent with the other methods used.

7.2.3 Markov Regime-Switching Models with Fixed and Time-Varying Thresholds

We applied Markov regime-switching models with both fixed and time-varying thresholds to each EMP index. The results demonstrated clear regime-switching behavior with distinct normal and crisis regimes, providing further evidence of the robustness of our methodology.

Fixed Thresholds: The fixed threshold models exhibited clear regime-switching behavior with high persistence in the crisis regimes, consistent with the observed currency crisis episodes.

Time-Varying Thresholds: The time-varying threshold models also confirmed the presence of distinct crisis regimes, with thresholds influenced by exogenous variables such as global financial conditions and domestic economic indicators.

These robustness checks confirmed the reliability and stability of our findings, ensuring that the identified currency crisis periods were not artifacts of the specific methodologies employed but were indeed reflective of underlying economic realities.

7.3 Policy Prescriptions

Based on our research findings, we offer the following policy prescriptions for policymakers:

Monitoring Exchange Rate Movements: Given the identified periods of extreme pressure or currency crises, policymakers should closely monitor exchange rate movements during these times. Timely intervention in the foreign exchange market, including the use of reserves or adjustments to interest rates, may be necessary to stabilise the currency and mitigate the impact of currency crises on the economy.

Managing Domestic Credit and Interest Rates: The research suggests that domestic credit growth and interest rate differentials are significant determinants of Exchange Market Pressure (EMP). Policymakers should carefully consider these factors when formulating monetary policy, aiming to strike a balance that supports economic growth while maintaining stability in the foreign exchange market.

Building Reserves: During periods of global uncertainty or US recessions, when India is more vulnerable to currency crises, policymakers should consider building foreign exchange reserves as a precautionary measure. These reserves can provide a buffer against external shocks and help stabilise the currency during turbulent times.

Policy Flexibility: As the research indicates that a general and empirical approach to measuring EMP is applicable across different currency regimes, policymakers should maintain flexibility in their policy approach. This includes being open to adjusting policy instruments based on empirical evidence and current market conditions rather than adhering rigidly to theoretical models.

Early Warning Systems: Developing early warning systems based on the identified EMP indices can enable policymakers to anticipate and respond to potential currency crises more effectively. These systems can provide valuable insights into the state of the foreign exchange market and signal the need for timely and proactive policy measures.

International Cooperation: Given the interconnected nature of global financial markets, policymakers should consider international cooperation and coordination in managing currency crises. Collaborative efforts with other countries and international organisations can enhance the effectiveness of policy responses to external shocks.

Communication and Transparency: Clear communication of policy intentions and actions can help reduce uncertainty in the foreign exchange market. Transparency in policy decisions and their rationale can contribute to market stability and build confidence among investors and market participants.

By considering these policy prescriptions, Indian policymakers can better navigate the challenges posed by Exchange Market Pressure and work towards maintaining stability in the foreign exchange market while supporting sustainable economic growth.

7.4 Limitations of the Study

While this study significantly contributes to the understanding of Exchange Market Pressure (EMP) in India and the identification of currency crisis episodes, it is important to acknowledge its limitations in light of the robustness check results:

Limited Sample Period: The study focuses on the period from 2001 to 2022, which provides a robust analysis but may not fully capture the breadth of India's experience with currency crises and EMP. Extending the analysis to earlier periods could offer additional insights into the historical evolution of India's exchange rate regime and its impact on currency stability.

Choice of Variables: The EMP indices constructed in this study include exchange rate changes, foreign exchange reserve changes, and interest rate changes. Although these variables are widely used in the literature, the robustness checks indicate that incorporating additional factors, such as capital flows, trade balances, or global risk sentiment, could enhance the accuracy and comprehensiveness of EMP measurement and crisis identification.

Structural Assumptions: While the general approach to measuring EMP aims to minimise structural assumptions, the estimation of weights for the EMP components still depends on assumptions about the functional relationships between exchange rate changes and other variables. The robustness checks, including Principal Component Analysis (PCA) and Factor Analysis (FA), confirm the stability of these weights, but the potential influence of different assumptions and alternative models remains a consideration.

Endogeneity Concerns: Despite employing an Instrumental Variable (IV) approach to address potential endogeneity issues in the estimation of EMP component weights, the robustness checks suggest that concerns about the exogeneity of the instruments and the sensitivity of results to alternative specifications may still persist. Further refinement of the IV approach could strengthen the validity of the findings.

Crisis Definition: The study utilises the ERW crisis definition, identifying a currency crisis when the EMP index exceeds its mean by more than 1.5 times its standard deviation. The robustness checks confirm that this threshold effectively identifies major crisis episodes, such as those during the global financial crisis and the period of global uncertainty. However, the findings also suggest that varying the threshold (e.g., using 2 or 3 standard deviations) could potentially reveal additional periods of stress, indicating that the choice of threshold may influence the identification of crises.

India-Specific Focus: The study's focus on India provides valuable insights specific to the country's economic context, but the generalisability of the results may be limited. While the findings may offer implications for other emerging economies, India's unique economic, political, and institutional context suggests that similar studies should be conducted in other countries to validate the broader applicability of the results.

Measurement of Variables: The study relies on data from various sources, including the Reserve Bank of India, the International Monetary Fund, and the Federal Reserve Economic Data. The robustness checks highlight the consistency of results across different data sources, but potential discrepancies in measurement and reporting could still affect the analysis. Ensuring data consistency remains critical for the accuracy of EMP indices.

Macroeconomic and Financial Market Dynamics: The study does not explicitly model the complex macroeconomic and financial market dynamics that influence EMP and currency crises, such as the interactions between monetary policy, fiscal policy, and financial market expectations. The robustness checks underscore the importance of these factors, suggesting that future research should integrate these dynamics to provide a more comprehensive understanding of the drivers of currency instability.

Despite these limitations, the study makes significant contributions to the literature on EMP and currency crises in emerging economies, particularly within the Indian context. The proposed empirical approach to measuring EMP, supported by robustness checks, and the identification of currency crisis episodes using the ERW crisis threshold, provide valuable insights into the dynamics of India's foreign exchange market and the effectiveness of its policy framework in managing currency risks. Future research could address some of these limitations by extending the sample period, incorporating additional variables, refining estimation techniques, exploring alternative crisis definitions, and considering the broader macroeconomic context.

While this study makes significant contributions to the understanding of Exchange Market Pressure (EMP) in India and the identification of currency crisis episodes, it is important to acknowledge its limitations.

Limited sample period: The study focuses on the period from 2001 to 2022, which, although spanning over two decades, may not capture the full range of India's experience with currency crises and EMP. Extending the analysis to earlier periods could provide additional insights into the evolution of India's exchange rate regime and its impact on currency stability.

Choice of variables: The EMP indices constructed in this study incorporate exchange rate changes, foreign exchange reserve changes, and interest rate changes as components. While these variables are widely used in the literature, there may be other relevant factors, such as capital flows, trade balances, or global risk sentiment, that could influence EMP and currency crisis episodes in India.

Structural assumptions: The general approach to measuring EMP proposed in this study aims to minimise structural assumptions. However, the estimation of weights for the EMP components still relies on certain assumptions about the functional form of the relationship between exchange rate changes and other variables, as well as the validity of the instruments used in the IV estimation.

Endogeneity issues: Although the study employs an IV approach to address potential endogeneity issues in the estimation of weights for the EMP components, there may still be concerns about the exogeneity of the instruments and the robustness of the results to alternative specifications.

Crisis definition: The study uses the ERW crisis definition to identify currency crisis episodes in India, which defines a crisis as an EMP index value that exceeds its mean by more than 1.5 times its standard deviation. While this definition is widely used in the literature, it may not capture all relevant episodes of currency stress or may be sensitive to the choice of threshold value.

Focus on India: The study focuses specifically on India, and while the findings may have implications for other emerging economies, the generalizability of the results may be limited due to India's unique economic, political, and institutional context.

Measurement of variables: The study relies on data from various sources, including the Reserve Bank of India, the International Monetary Fund, and the Federal Reserve Economic Data. Differences in the measurement and reporting of variables across these sources could potentially affect the consistency and comparability of the data used in the analysis.

Macroeconomic and financial market dynamics: The study does not explicitly model the complex macroeconomic and financial market dynamics that may influence EMP and currency crises, such as the interactions between monetary policy, fiscal policy, and financial market expectations. Incorporating these factors into the analysis could provide a more comprehensive understanding of the drivers of currency instability.

Despite these limitations, the study makes important contributions to the literature on EMP and currency crises in emerging economies, particularly in the context of India. The proposed empirical approach to measuring EMP and the identification of currency crisis episodes using the ERWCT provide valuable insights into the dynamics of India's foreign exchange market and the effectiveness of its policy framework in managing currency risks. Future research could address some of the limitations identified above by extending the sample period, incorporating additional variables, refining the estimation techniques, and exploring alternative crisis definitions.

7.5 Future Research

The findings of this thesis contribute significantly to the understanding of Exchange Market Pressure (EMP) dynamics and currency crisis episodes in India. However, there are several avenues for future research that can further enhance knowledge in this area and address the limitations identified in the current study. Some potential directions for future research include:

Incorporating Additional Variables: While this study focuses on key components of EMP, such as exchange rate changes, foreign exchange reserves, and interest rate differentials, future research could benefit from incorporating additional relevant variables. The robustness checks suggest that other factors like capital flows, trade balances, global risk sentiment, and domestic macroeconomic variables (e.g., inflation, GDP growth, fiscal deficits) could provide a more comprehensive understanding of the factors influencing EMP in India. This expanded analysis could offer deeper insights into how these variables interact with EMP and influence currency stability.

Exploring the Determinants of EMP: This thesis primarily focuses on measuring EMP and identifying currency crisis episodes in India. Future research could delve deeper into the determinants of EMP by employing econometric techniques such as panel data analysis or time-series models. Investigating the role of global factors, such as US monetary policy changes or oil price shocks, and domestic factors, such as political instability or banking sector vulnerabilities, could illuminate the underlying drivers of EMP in India. Understanding these determinants is crucial for developing effective policy responses and risk management strategies.

Comparative Analysis with Other Emerging Economies: Although this study is focused on India, future research could extend the analysis to other emerging economies with similar economic characteristics or exchange rate regimes. Comparative studies on EMP dynamics and currency crisis episodes across different countries could provide valuable insights into common challenges and best practices for managing exchange rate risks. Such cross-country analyses could also help identify the influence of regional or global factors on EMP and the transmission channels of currency crises.

Assessing the Effectiveness of Policy Interventions: Future research could evaluate the effectiveness of various policy interventions, such as foreign exchange interventions, capital flow management measures, or monetary policy actions, in mitigating EMP and preventing currency crises. The robustness checks highlight the importance of flexible and data-driven policy approaches. Employing counterfactual analysis or policy simulation techniques could help assess the impact of different policy scenarios on EMP dynamics and identify the most effective strategies for managing exchange rate risks. This research could provide valuable guidance for policymakers in designing and implementing appropriate policy responses to currency pressures.

Exploring the Linkages Between EMP and Financial Stability: The relationship between EMP and financial stability is an important area for future research. Currency crises can have significant spillover effects on the banking sector, sovereign debt markets, and the broader financial system. Future studies could investigate the transmission channels between EMP and financial stability, assess the impact of currency crises on the resilience of the financial system, and explore the role of macroprudential policies in mitigating the risks associated with EMP. Understanding these linkages is crucial for developing a holistic approach to managing exchange rate risks and promoting financial stability.

Developing Early Warning Systems: The findings of this thesis underscore the importance of accurately measuring EMP and identifying currency crisis episodes for policymakers and market participants. Future research could focus on developing early warning systems that can detect the build-up of currency pressures and provide timely signals of impending crises. By integrating insights from EMP indices with other relevant indicators, such as credit growth, asset price bubbles, or external imbalances, researchers could develop robust and reliable early warning models. These models could assist policymakers in taking proactive measures to prevent or mitigate the impact of currency crises.

These avenues for future research build on the current study's findings and robustness checks, offering opportunities to deepen the understanding of EMP dynamics and enhance the effectiveness of policy interventions in managing exchange rate risks and preventing currency crises.

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List of Publications and Proofs

List of Publications

1. **Testing Normality in EMP Indices: An Application and Power-Comparison of Alternative Tests**
   Authors: Sanjay Kumar, Nand Kumar
   Journal: Communications in Statistics - Theory and Methods
   Volume: 52, Issue: 2, Year: 2023
   Status: Published
   DOI: `https://doi.org/10.1080/03610926.2021.1914097`

2. **Long Memory and Forex Market Returns: An Empirical Analysis**
   Authors: Sanjay Kumar, Nand Kumar
   Journal: Business Analyst Journal
   Status: Accepted

3. **EMP, Govt Debt, US Money Supply, GDP Growth**
   Authors: Sanjay Kumar, Nand Kumar
   Journal: International Journal of Maritime Engineering
   Special Issue, Year: 2024
   Status: Published
   DOI: `https://doi.org/10.5750/ijme.v1i1.1335`

4. **Incorporating Asymmetric Volatility and Persistence: An EGARCH-based Extension of the Girton-Roper Model for Measuring Exchange Market Pressure in India**
   Authors: Sanjay Kumar, Nand Kumar
   Journal: Macroeconomics and Finance in Emerging Market Economies
   Status: In Review (Revise Decision Made)

5. **A Novel Robust Framework for Identification of Components**

Weights in the Girton-Roper Exchange Market Pressure Index

Authors: Sanjay Kumar, Nand Kumar

Journal: Communications in Statistics - Theory and Methods

Status: Communicated

Proofs

Paper 1: Testing Normality in Time Series of EMP Indices: An Application and Power Comparison of Alternative Tests

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Abstract

The Exchange Market Pressure Index (EMPI) is an indicator of pressure on a currency. Because of the presence of serial correlation, financial time series may not be normally distributed even for large sample sizes. They may have undefined parameters and hence parametric tests of normality may give misleading results. In this paper, we look at the time series of EMPI of eleven countries of the world, put the data to normality check using tests suggested by various scholars. We also apply a test used exclusively for serially correlated data. No one has used this test earlier. In this context, we also compare the power of these statistical tests, which is another novel contribution of this paper. On the basis of these tests the EMPI time series is found to be non-normal. Two tests are found to be the most powerful. The test which is designed exclusively for time series data is found to be powerful only for China and South Korea, the countries which had the lowest EMPI- standard-deviation in the group of all the eleven countries studied in this paper.

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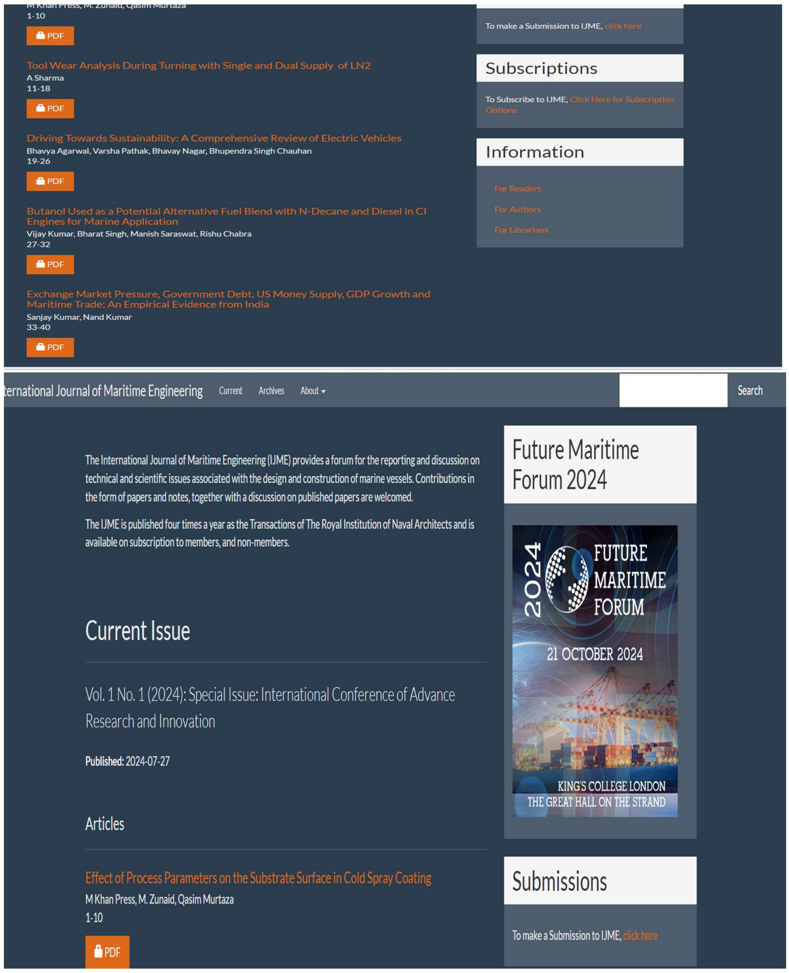

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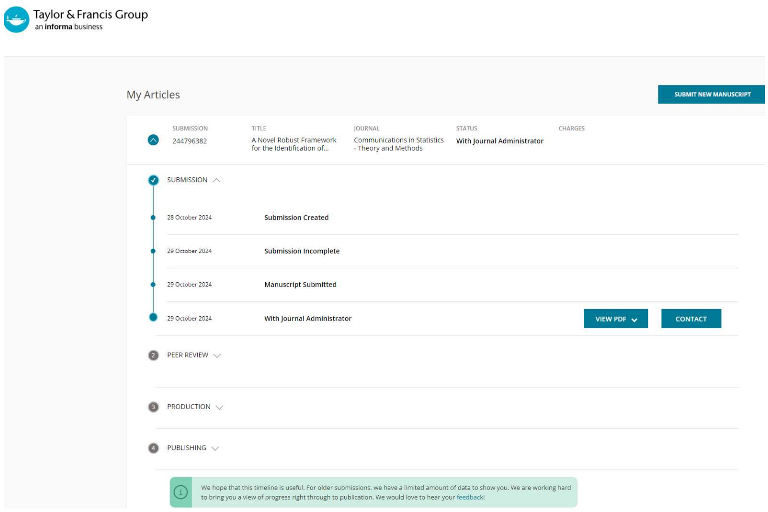

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Sanjay Kumar

Personal Information

Father's Name:	Late P. Prasad
Date of Birth:	22-09-1966
Address:	105, Aero View Heights, Guru Ram Dass CGHS, Plot 3B, Sector 22, Dwarka, New Delhi
Phone:	+91-9818801654
Email:	sanjaykumar@dsc.du.ac.in

Educational Qualifications

Ph.D. in Economics, Delhi Technological University, New Delhi

M.Phil. in Economics, Jawahar Lal Nehru University, New Delhi

M.A. in Economics, Allahabad University, U.P.

Current Position

Associate Professor, Department of Economics, Dyal Singh College, Delhi University, New Delhi