PressAcademia

JBEF

Journal of Business, Economics & Finance

PressAcademia publishes journals, books, case studies, conference proceedings and organizes international conferences.

jbef@pressacademia.org

ISSN 2146-7943

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

ABOUT THE JOURNAL

Journal of Business, Economics and Finance (JBEF) is a scientific, academic, double-blind peer-reviewed, quarterly and open-access journal. The publication language is English. The journal publishes four issues a year. The issuing months are March, June, September and December. The journal aims to provide a research source for all practitioners, policy makers and researchers working in the areas of business, economics and finance. The Editor of JBEF invites all manuscripts that that cover theoretical and/or applied research on topics related to the interest areas of the Journal.

JBEF is currently indexed/archived by

Ulrich's Directiroy, Open J-Gate, New Jour, Princeton University Library, International Scientific Indexing, Directory of Research Journals Indexing (DRJI), International Society for Research Activity (ISRA), InfoBaseIndex, Scientific Indexing Services (SIS), Google Scholar, Root Indexing, Journal Factor Indexing, International Institute of Organized Research (I2OR), ASOS, Cabell's Directory, SOBIAD, EuroPub.

Ethics Policy

JBEF applies the standards of Committee on Publication Ethics (COPE). JBEF is committed to the academic community ensuring ethics and quality of manuscripts in publications. Plagiarism is strictly forbidden and the manuscripts found to be plagiarised will not be accepted or if published will be removed from the publication.

Author Guidelines

All manuscripts must use the journal format for submissions.
Visit www.pressacademia.org/journals/jbef/guidelines for details.

CALL FOR PAPERS
The next issue of JBEF will be published in December, 2023.
Submit manuscripts to
jbef@pressacademia.org or
http://www.pressacademia.org/submit-manuscript/
Web: www.pressacademia.org/journals/jbef

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

EDITORIAL BOARD

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

CONTENT

Title and Author/s **Page**

1. **The validity of technical analysis in the cryptocurrency market: evidence from machine learning methods**
   Ersin Kanat.. *102 - 109*
   DOI: 10.17261/Pressacademia.2023.
   JBEF-V.12-ISS.3-2023(1)-p.102-109

2. **Impact of work overload as a job stressor on employees' intention to leave: The mediating effect of work-family conflict in a Sri Lankan apparel sector organisation**
   Ganewatta G.K.H, Hiroshima N.L.D.H .... *110 - 117*
   DOI: 10.17261/Pressacademia.2023.
   JBEF-V.12-ISS.3-2023(2)-p.

3. **An examiner of China commercial banks' loans through credit channel prior COVID-19**
   Mohammad Farajnezhad.. *118 - 130*
   DOI: 10.17261/Pressacademia.2023.
   JBEF-V.12-ISS.3-2023(3)-p.118-130

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

THE VALIDITY OF TECHNICAL ANALYSIS IN THE CRYPTOCURRENCY MARKET: EVIDENCE FROM MACHINE LEARNING METHODS

DOI: 10.17261/Pressacademia.2023.1821
JBEF- V.12-ISS.3-2023(1)-p.102-109

Ersin Kanat
Zonguldak Bülent Ecevit University, Department of Finance and Banking, Devrek Campus, Zonguldak, Turkiye.
ersinkanat@beun.edu.tr , ORCID: 0000-0002-9361-4495

Date Received: August 3, 2023 **Date Accepted:** September 22, 2023

To cite this document
Kanat, E., (2023). The validity of technical analysis in the cryptocurrency market: evidence from machine learning methods. Journal of Business, Economics and Finance (JBEF), 12(3), 102-109.
Permament link to this document: http://doi.org/10.17261/Pressacademia.2023.1821

ABSTRACT

Purpose- This study aims to assess the effectiveness of technical analysis indicators used by investors in the cryptocurrency market for making informed decisions. Emphasizing the importance of accurate decision-making methods in financial markets, this research particularly focuses on the cryptocurrency market, which has gained significant attention among investors in recent years.
Methodology- The study specifically examines technical analysis, a widely employed method in various financial markets, with a focus on its predictive capabilities concerning Bitcoin price forecasts. Leveraging advanced technologies, such as big data analysis and machine learning, the research utilizes daily trading data from January 1, 2017, to June 30, 2022, presenting technical indicators and their associated error margins.
Findings- The study highlights the significance of using Weighted Moving Average (WMA) and Stochastic Oscillator (STO) indicators in combination, demonstrating that multiple indicators outperform individual ones. This research underscores the effectiveness of technical analysis methods in the cryptocurrency market, aiding the development of enhanced investment strategies.
Conclusion- In conclusion, this study delves into the potency of technical analysis techniques employed by investors in cryptocurrency markets. The insights indicate that combining indicators and technical analysis methods holds promise for future investment strategies. It is essential to note that even the best method can lead to losses, as evidenced by the presence of error margins, and absolute profitability cannot be guaranteed through technical analysis methods.

Keywords: Cryptocurrency, technical analysis, machine-learning, classification algorithms, investment.
JEL Codes: C38, C55, G17

1. INTRODUCTION

Investing in a market creates the need to have a strong predictive power. One of the most important features that distinguishes investments from games of chance is that they involve rational and predictable decisions. When trading with any investment instrument, taking a position with a random decision is not much different from playing games of chance. Undoubtedly, the motivation that drives people to invest is their desire to increase their money and keep it safe. For this reason, when everyone wants to trade, they want to get important information about important elements such as the market, products and demands, today and the future. This has led to constant research for forecasting methods. As a result of these research, various methods have emerged and have been applied in financial forecasts.

Analysis methods have been developed on many issues such as foreign exchange, stock market and commodity prices. These methods are classified as fundamental and technical analysis and have been the subject of many studies (Abuselidze & Slobodianyk, 2021; Lee, 2020; Pu & Zulauf, 2021; Venkatesh et al., 2021). Studies on fundamental analysis have been examined with a large number of macroeconomic, global, country-specific and political developments (Stevenson, 2001; Spilioti, 2022; Lam, 2004). Similarly, studies on technical analysis have focused on many calculations using historical data (Maknickienė, Stankevičienė, & Maknickas, 2020; Chou & Lin, 2019). Whether technical analysis is really useful or not has been a subject that has been constantly wondered and researched. In the past, some researchers have argued that technical analysis cannot be useful, and that past data cannot affect future prices (Fama, 1970). However, there are important studies showing that technical analysis is an important tool for price predictions. Especially with the development of behavioral finance, some calculations in technical analysis can be put forward logically.

The proliferation of investment products over time has led to the necessity of testing analysis methods on more instruments. One of these products is cryptocurrencies. In recent years, a lot of research has also been carried out on cryptocurrencies (Patel et al., 2020: 2). In addition, many cryptocurrency traders also benefit from technical indicators. However, in relation to cryptocurrencies, it is not easy to put forward a clear conclusion regarding the performance of technical indicators. Measuring the performance of past technical indicators separately and together becomes easier with big data analysis. Today, thanks to the development of computer systems, it is possible to conduct clearer research on the subject. Calculations can be applied to larger data, statistical analyses can be performed on big data, and various inferences and rules can be obtained. Although machine learning is considered as a competitor to technical analysis in some studies (Anghel, 2021), they can also be used to reveal relationships from past knowledge such as regression methods. In this study, the reliability of technical analysis methods, which are most accepted and used by investors and researchers, is tried to be revealed by machine learning methods. Thus, it is aimed to ensure that investors and fund managers follow the right strategies in their buying-selling decisions. In addition, academically it is tried to determine whether technical analysis works in crypto markets or how effective it is. It is thought that this research will provide significant concrete evidence on the opinions in the literature and will contribute to the literature.

The most commonly used and pioneering cryptocurrency, Bitcoin, constitutes a substantial portion of the overall cryptocurrency market (BlockChain 2022). Bitcoin boasts a Market Cap of approximately 402.84 billion dollars, underscoring its significant dominance within the market (Yahoo Finance 2022). Consequently, this study employs machine learning algorithms, with the assistance of Bitcoin, to investigate the validity of technical analysis in cryptocurrency markets.

2. LITERATURE REVIEW

Technical analysis is frequently used in price predictions of all kinds of financial instruments. For this reason, different technical analysis methods have been developed for many markets. However, it is known that not all of these methods are common. In addition, behavioral finance can explain the logic behind some methods, but some methods cannot reveal any logic. For these reasons, in this research, the most used methods in previous academic studies and the most preferred by investors in the markets were used.

Agrawal et al. (2019) conducted a study employing various technical indicators, including Moving Averages (MA), Exponential Moving Averages (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Stochastic Oscillator (STO), and Regression Analysis (R). Researchers conducted a study to predict stock prices. The research was conducted on the National Stock Exchange of India. As a result of the study, an accuracy of over 60% was observed.

Bustos et al. (2018) explored the effectiveness of Simple Moving Averages (SMA), Weighted Moving Averages (WMA), Momentum (MOM), MACD, RSI, Commodity Channel Index (CCI), STO, and Regression Analysis (R). The study focuses on the Colombian Stock Exchange. In this research, in which machine learning was used, the mentioned technical indicators were used as input. Up and down movements are used as output. Their study uncovered that the performance of support vector machines is better than artificial neural networks.

In Wang et al.'s (2018) investigation, they considered SMA, WMA, MOM, MACD, RSI, CCI, Regression Analysis (R), and STO. In their study examining the relationship between public sentiment and stock price movements and demonstrating the influence of public opinions on investment decisions, a new framework for financial market prediction was designed. This framework combines the wisdom of crowds and technical analysis. Based on real-world data collected, experimental results have shown that the proposed method outperforms baseline models by at least 14.2% in terms of the AUC value, indicating the effectiveness of DRSE as a viable mechanism for financial market prediction. This study emphasizes the importance of effectively integrating information sources in predicting financial markets and utilizing deep learning and ensemble learning techniques.

Labiad et al. (2016) focused on SMA, WMA, RSI, Rate of Change (ROC), and STO. Accurate prediction of very short-term fluctuations (up to 10 minutes ahead) in the Moroccan stock market has been the focus of this study, employing three distinct machine learning techniques: Random Forest (RF), Gradient Boosted Trees (GBT), and Support Vector Machine (SVM). In this investigation, a curated set of technical indicators served as input variables, with the objective of enhancing prediction accuracy and reducing training time through feature selection and sample selection processes. The experimental dataset encompassed an eight-year span of intraday tick-by-tick data from Maroc Telecom (IAM) stocks. The experimental results have unequivocally demonstrated the superior performance of RF and GBT over SVM. Furthermore, the computational simplicity and reduced training time of RF and

GBT have proven to be particularly suitable for short-term forecasting. This study aims to contribute to the ongoing efforts to predict nonlinear and non-stationary price movements in financial markets using machine learning techniques.

Ghanavati et al. (2016) analyzed SMA, WMA, MOM, RSI, CCI, STO, and Regression Analysis (R). Researchers have gone beyond the proposed forecasting approaches with this study, offering a framework that enables users to engage in stock market prediction using a broader array of tools.

Patel et al. (2015) examined SMA, WMA, MOM, MACD, RSI, CCI, STO, and Regression Analysis (R). This study deals with the problem of predicting the direction of stock price indexes and stock prices in the Indian stock markets. Using two distinct m ethods for data entry, four prediction models were examined. One of the strategies focuses on portraying these technical factors as trend-determining data, while the other data input approach employs stock trading data to calculate 10 technical parameters. For ea ch of the two data input procedures, the accuracy of each prediction model was assessed. Reliance Industries and Infosys Ltd. stock history data from 2003 to 2012, as well as stock price indices CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex, were used to conduct the evaluation. The experimental results show that Random Forest beat the other three prediction models in terms of overall performance for the first data input technique, where the ten technical parameters are represented as continuous valu es. The experimental findings also show that when these technical factors are represented as trend-determining data, the performance of all prediction models increases.

Shynkevich et al. (2014) used SMA, WMA, MOM, MACD, RSI, CCI, STO, and Regression Analysis (R)in their research. This study has looked into the connection between one-step-ahead (varying steps) forecasting accuracy and the size of the window utilized to calculate technical indicators. With the help of machine learning algorithms and technical analysis, future price movements h ave been forecasted in their general directions. For the Support Vector Machines approach, the results have shown a correlation between the window size and forecasting step size, but other approaches have not shown such a correlation. In conclusion, the study investigates the use of technical analysis, machine learning, and the optimization of technical indicator parameters in financial forecasting.

Examining earlier studies reveals that in recent years, research on the topic has regularly incorporated a va riety of artificial intelligence and machine learning algorithms and techniques. Support Vector Machines, Deep Learning, Artificial Neural Networks, Fuzzy logic, Genetic Algorithms, and Decision Trees are a few examples of these techniques (Chakraborty et al., 2018, Coyne et al., 2018, Di Persio & Honchar, 2018, Fischer & Krauss, 2018, Kia et al., 2018, Dingli & Fournier, 2017, Dang & Duong, 2016, Chai et al. The ability to draw conclusions about financial matters has increased with the growth of computer t echnologies. This gives researchers the chance to use huge data to generate more accurate observations. Particularly when applied to historical data, classification algorithms produce precise results. In particular, classification algorithms provide clear findings based on past data. For these reasons, in order to measure the validity of technical analysis in crypto markets, SMA, WMA, MACD, MOM, RSI, STO and CCI indicators have been tested with CHAID, C5.0 and CART algorithms, which are machine learning alg orithms.

3. DATA AND METHODOLOGY

In the study, the most used methods in the literature were preferred to test the technical analysis indicators. Daily data of Bitcoin covering the dates 01/01/2017 – 06/30/2022 were used. The prices used in the study were obtained from the Yahoo Finance web page. In addition, the effectiveness of the methods was analyzed with three different classification algorithms. Through thes e methods, not only the individual efficiency of technical indicators, but also their best-matched uses together were observed for the historical process. While examining past observations, daily trading transactions were applied for profit and loss situat ions. Inferences were made, considering that every day purchase is made according to the results of the indicator at the opening price, and the sale is made according to the closing prices. In this section, brief information about all these methods and their us es is given.

3.1. Technical Indicators

Input variables used in the research were SMA, WMA, MACD, MOM, RSI, STO and CCI indicators, respectively. Buy, Sell and Hold signal results were used as output. Technical indicators were calculated as shown in Table 1.

Table 1: Mathematical Equations of Technical Indicators

Indicators	Equation
SMA	$\frac{\sum_{i=1}^{12} P_i}{n}$
WMA	$\frac{P_t \ x \, n + P_{t-1} \ x \ (n-1) + \cdots + P_{t-11}}{[n \ x \ (n+1)]/2}$
MACD	$EMA12_t - EMA26_t$
MOM	$\left(\frac{P_t}{P_{t-9}}\right) x100$
RSI	$RS = \frac{APH_n}{APL_n}$ $100 - (\frac{100}{1+RS})$
STO	$\%K = \ 100 \ x \ \frac{P_t - L_x}{H_x - L_x}$ $\%D = MA_n \ of \ \%K$
CCI	$\frac{TP_t - STP_t}{0{,}015 \ x \ D_t}$

In Table 1; P represents the price of Bitcoin. Also in equations, APH is the average of the prices on the bullish days, APL is the average of the prices on the days of the decline, L_x is lowest price in x days, H_x is the highest price in x days, TP typical price, STP average of typical price, and D deviation. The 12 and 26-day EMAs are preferred for the MACD. STO 9 and RSI, CCI 14 days calculated. The SMA gives the average of prices for a given period. Thus, it is possible to have an idea about the direction of the trend. WMA is also a trend indicator. However, the weight of the last days in the period determined in WMA is more. The MACD provides buy-sell signals from the relationship of two moving averages. After the MACD is found, the signal (trigger) line must be found. In the study, the 9-day exponential moving average of the obtained MACD was calculated. If the MACD rises above this trigger line, a buy signal is obtained, if it falls below the trigger line, a sell signal is obtained. On the other hand, Momentum, examines past price movements and provides information about the rate of decline and rise in prices. The RSI takes a value between 0 and 100. This indicator helps to understand whether a financial product is overvalued or undervalued. The STO indicator measures prices over a period of time by their highest and lowest levels and indicates the turning points of prices. The basic assumption of this indicator is that during periods when prices are in an upward trend, the Price will tend to move towards the highest price within the selected period. Likewise, if prices are falling, prices are expected to tend to go to the lowest price within the selected period. Finally, CCI, like many indicators, indicates whether prices are overvalued or undervalued. It shows how much equity prices deviate from the average.

Table 3: VAR Lag Length Result

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	-2548.646	NA	6.69e+13	37.50950	37.55233	37.52690
1	-2363.036	363.0312	4.63e+12	34.83876	34.96726*	34.89098*
2	-2357.930	9.835301	4.55e+12	34.82251	35.03667	34.90954
3	-2352.959	9.430811	4.49e+12*	34.80822*	35.10805	34.93007
4	-2351.778	2.206269	4.68e+12	34.84967	35.23517	35.00633
5	-2348.858	5.366714	4.76e+12	34.86556	35.33673	35.05703
6	-2345.379	6.292966	4.80e+12	34.87322	35.43006	35.09951
7	-2341.005	7.782772	4.77e+12	34.86773	35.51023	35.12882
8	-2338.504	4.378226	4.88e+12	34.88976	35.61792	35.18567
9	-2334.361	7.127720	4.88e+12	34.88766	35.70149	35.21838
10	-2333.444	1.550396	5.11e+12	34.93300	35.83250	35.29854
11	-2331.456	3.303459	5.27e+12	34.96259	35.94776	35.36294
12	-2324.716	11.00270*	5.07e+12	34.92229	35.99312	35.35745

Note: LR: Likelihood Rate Test Statistics; FPE: Final Prediction-Error Criteria; AIC: Akaike Information Criteria; SIC: Schwarz Information Criteria; HQ: Hannan-Quinn Information Criteria.

3.2. Classification Algorithms

Classification methods are basically the process of estimating the class value and level according to certain characteristics. In this sense, it resembles classical statistical methods. However, there are a lot of assumptions in statistical methods. In classification methods, most assumptions such as constant variance or independence between variables are not required. In this study, Chaid, Cart and C5.0 algorithms, which are widely used classification methods, were used. R programming language was used for the implementation of classification methods.

The Chaid algorithm was developed by Kass (1980). It is preferred for situations where features are categorical. Branching operations are performed based on the chi-square statistic. It tries to reveal other variables and related data that explain the dependent variable as sparingly as possible. In order to best calculate the branching, it investigates whether the predictor variables have a statistically significant relationship with the target variables. In short, CHAID analysis uses chi-square statistics, Bonferronni approach, and category merging algorithm to enable the researcher to obtain the most important explanatory variables and interactions with the dependent variable. The method, which can work with both categorical and continuous variables, can branch more than 2 subgroups.

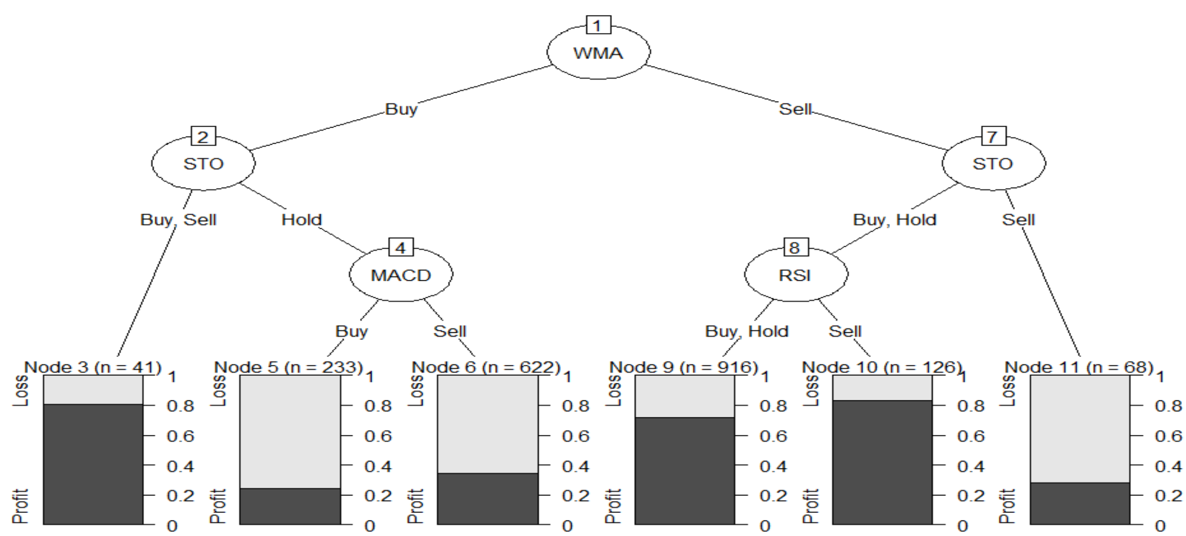
The Cart algorithm was developed by Breiman, Friedman, Olshen, and Stone (1984). It can only do double branching. In other words, it makes a branching process with yes or no answers on each question. The CART algorithm is based on entropy and uses Twoing and Gini techniques to calculate the branching criterion.

The C5.0 algorithm was created by Quinlan with the development of the C4.5 algorithm and was released in 1994. Its advantages over the C4.5 algorithm are that it is faster, uses less memory, creates more precise rules, can weight variables and types of misclassifications, and can exclude variables that do not contribute to the formation of the tree. The C5.0 algorithm can create smaller decision trees and is more effective at parsing data and improving dirty data (Quinlan, 1993; Quinlan, 1996). Unlike other methods, it grows the tree with the criterion of information gain. C5.0 can provide fairly robust predictions in data sets with lost data and a large number of independent variables.

4. FINDINGS AND DISCUSSIONS

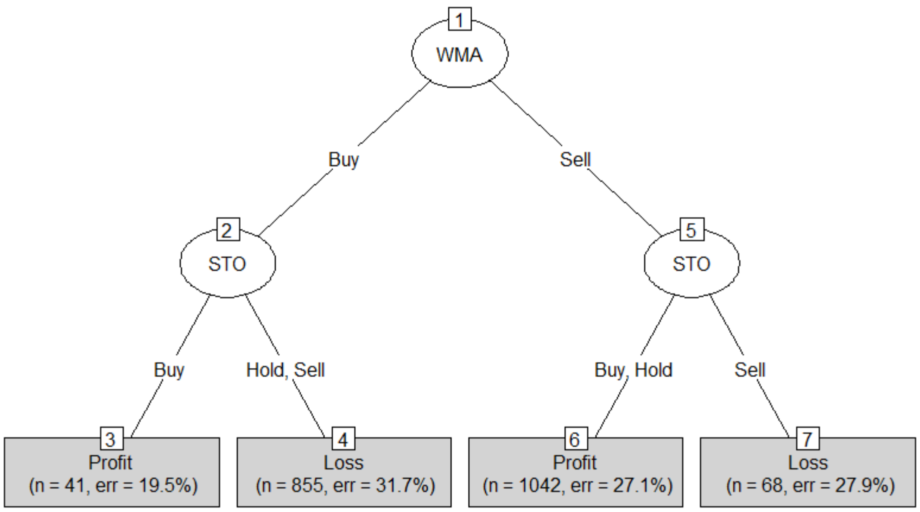
Each algorithm can produce different results for testing and classifying indicators together and alone to provide the best performance. Figure 1 shows the classification made by the Chaid algorithm. According to this algorithm, The WMA indicator signaling buy and the STO indicator signaling buy or sell occurred 41 times, which resulted in a significant profit. But after the WMA indicator, the wait signal in the STO generally indicated a loss. In addition, WMA's sell and STO's buy or wait signals often resulted in profit. This situation occurred 1042 times in total. It appeared with the buy or wait signal of the RSI 916 times and the sell signal of the RSI 126 times.

Figure 1: Result of the Chaid Algorithm



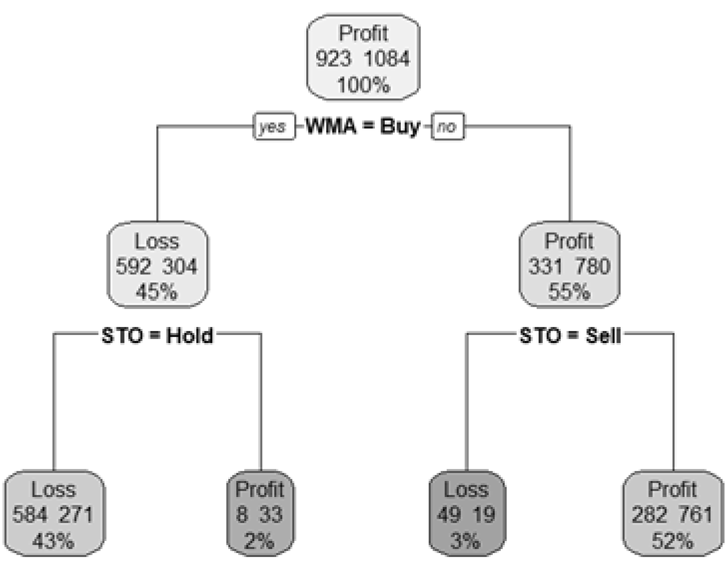
On the other hand, when Figure 2 is examined, the C5.0 algorithm also shows that a profit can be obtained with a 19.5% margin of error with the buy signal of WMA and the buy signal of STO. It states that, unlike the Chaid algorithm, both the wait and sell signals of the WMA cause losses with an error of approximately 31% after the buy signal. This state of the indicators has been observed 855 times. After WMA's sell signal, STO's signals also produced similar results to the Chaid algorithm.

Figure 2: Result of the C5.0 Algorithm



In also the Cart algorithm, WMA and STO indicators came to the prominence as important indicators. In this algorithm, it is understood that after WMA's buy signal, it is important whether only the STO has a wait signal or not. If there is a wai t signal, loss is possible, otherwise, there is the possibility of profit. It is stated that if the WMA does not give a buy signal, it is necessary to check whether the STO gives a sell signal.

Figure 3: Result of the Cart Algorithm



In all these observations, margins of error can be perceived as high or low for the decision maker. In addition, no single indicator can be deduced that it will be significantly beneficial. However, it is understood from the observations obtained from the past data that the use of the indicators of the WMA and STO indicators together can significantly increase the predictive power.

5. CONCLUSION

In this study, it is aimed to obtain information about the importance and importance level of technical analysis indicators in the cryptocurrency market. However, instead of investigating the importance levels of technical indicators as singles, it was thought that it was more important to evaluate them both individually and multiple. Therefore, the daily data between 01/01/2017-06/30/2022 were tested with machine learning methods. Due to the fact that the cryptocurrency market is dominated by Bitcoin and the Bitcoin market cap has a very high share in the market, the research was carried out on Bitcoin prices. It is a very difficult process to apply the indicators in long data sets and to compare each observation by examining them with both single and multiple indicators, and then to evaluate these results. However, with machine learning methods, the implementation of these processes can be done much easier and more reliably. Chaid, C5.0 and Cart methods were used in the study.

Findings from the analyses showed that using two or more indicators together produces better results than using them individually. In addition, it can be said that the main indicator according to all three methods is the WMA indicator. All three methods showed that the WMA indicator should be evaluated with the STO indicator. Only the Chaid algorithm has shown that after WMA and STO, MACD and RSI can also be considered. However, to generalize according to three methods, it can be said that profits can be made after WMA and STO give a buy signal. In addition, after both indicators give a sell signal, it is necessary not to buy, otherwise, it is understood from the past data observations that the probability of loss is high. When the STO gives a buy or hold signal after the WMA gives a sell signal, it usually results in a profit.

The main motivation for the study is that investment advice, especially in media such as websites and social media, are usually given by using technical analysis. This situation has led to the necessity of investigating whether technical analysis will really be a reliable method in the cryptocurrency market. The results show that a single indicator cannot be highly reliable. In addition, it has been shown in the analyses that technical indicators used together have margins of error. Therefore, when past performances are analyzed, technical indicators can be used by considering the performance of the indicators and the margins of error obtained. This situation shows that other useful strategies can be found with the help of different indicators and analyses made at different periods. For this reason, it is very important to conduct new research on different crypto coins, different indicators, and different periods, and also to give the necessary importance to the subject by researchers.

REFERENCES

Abuselidze, G. D., Slobodianyk, A. N. (2021), Value Assessment of Shares of Corporate Issuers by Applying the Methods of Fundamental Analysis in the Stock Exchange Market. In A. V. Bogoviz (Ed.), The Challenge of Sustainability in Agricultural Systems. Cham: Springer, 25-39, ISBN: 978-3-030-72109-1.

Agrawal, M., Khan, A. U., Shukla, P. K. (2019). Stock price prediction using technical indicators: a predictive model using optimal deep learning. International Journal of Recent Technology and Engineering, 8(2), 2297-2305.

Anghel, D. G. (2021). A reality check on trading rule performance in the cryptocurrency market: Machine learning vs. technical analysis. Finance Research Letters, 39(C), 1-8.

BlockChain. (2022, September 9). Retrieved from https://www.blockchain.com/charts/trade-volume

Breiman, L., Friedman, J., Olshen, R. A., Stone, C. J. (1984). Classification and Regression Trees. Florida: Chapman and Hall/CRC, ISBN 978-0-412-04841-8.

Bustos, O., Pomares, A., Gonzales, E. (2017). A Comparison between SVM and Multilayer Perceptron in Predicting an Emerging Financial Market: Colombian Stock Market. Congreso Internacional de Innovaciony Tendencias en Ingenieria (CONIITI 2017), Colombia: Institute of Electrical and Electronics Engineers Inc,. 1-6.

Chai, J., Du, J., Lai, K., Lee, Y. (2015). A hybrid least square support vector machine model with parameters optimization for stock forecasting. Mathematical Problems in Engineering, 20(S), 1-7.

Chakraborty P., Pria U., Rony M., Majumdar M. (2018). Predicting Stock Movement Using Sentiment Analysis of Twitter Feed. 2017 6th International Conference on Informatics, Electronics and Vision And 2017 7th International Symposium in Computational Medical and Health Technology, Iciev-Iscmht 2017, Institute of Electrical and Electronics Engineers Inc. (2018), Himeji: IEEE, 1-6.

Chou, C. C., Lin, K. S. (2019). A fuzzy neural network combined with technical indicators and its application to Baltic Dry Index forecasting. Journal of Marine Engineering & Technology, 18(2), 82-91.

Coyne S., Madiraju P., Coelho J. (2018). Forecasting Stock Prices Using Social Media Analysis. Proceedings - 2017 IEEE 15th International Conference on Dependable, Autonomic and Secure Computing, Institute of Electrical and Electronics Engineers Inc. (2018), Orlando: IEEE, 1031-1038.

Dang M., Duong D. (2016). Improvement Methods for Stock Market Prediction Using Financial News Articles. NICS 2016 - Proceedings of 2016 3rd National Foundation for Science and Technology Development Conference on Information and Computer Science, Institute of Electrical and Electronics Engineers Inc. (2016), Danang: IEEE, 125-129.

Di Persio L., Honchar O. (2016). Artificial neural networks architectures for stock price prediction: comparisons and applications. International Journal of Circuits, Systems and Signal Processing, 10(1), 403-413.

Dingli A., Fournier K. (2017). Financial time series forecasting – a deep learning approach. International Journal of Machine Learning and Computing, 7(5), 118-122.

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. The Journal of Finance, 25(2), 383-417.

Fischer T., Krauss C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270 (2), 654-669.

Ghanavati, M., Wong, R., Chen, F., Wang, Y., Fong, S. (2016). A Generic Service Framework for Stock Market Prediction. 2016 IEEE international conference on services computing (SCC 2016), San Francisco: IEEE, 283-290.

Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. Journal of the Royal Statistical Society, 29(2), 119-127.

Kia A., Haratizadeh S., Shouraki S. (2018). A hybrid supervised semi supervised graph-based model to predict one-day ahead movement of global stock markets and commodity prices. Expert Systems with Applications, 105, 159-173.

Labiad, B., Berrado, A., Benabbou, L. (2016). Machine Learning Techniques for Short Term Stock Movements Classification for Moroccan Stock Exchange. 11th International Conference on Intelligent Systems: Theories and Applications, Morocco: IEEE, 1-6.

Lam, M. (2004). Neural network techniques for financial performance prediction: integrating fundamental and technical analysis. Decision Support Systems, 37(4), 567-581.

Lee, C. F. (2020). Fundamental Analysis, Technical Analysis, and Mutual Fund Performance. In Lee C. F. and Lee J. C. (Ed.), Handbook of Financial Econometrics, Mathematics, Statistics, and Machine Learning. London: World Scientific Pub Co Inc., 3001–3058, ISBN: 978-9-811-20238-4.

Maknickien˙e, N., Stankeviˇcien˙e, J., Maknickas, A. (2020). Comparison of forex market forecasting tools based on evolino ensemble and technical analysis indicators. Romanian Journal of Economic Forecasting, 23(3), 134-148.

Patel, J., Shah, S., Thakkar, P., Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications, 42(1). 259-268.

Patel, M. M., Tanwar, S., Gupta, R., Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. Journal of Information Security and Applications, 55(2), 1-12.

Pu, Y., Zulauf, C. (2021). Where are the fundamental traders? A model application based on the Shanghai Stock Exchange. Emerging Markets Review, 49(C), 1-14.

Quinlan, J. R. (1993). C4.5: Programs for Machine Learning. Los Altos: Morgan Kaufmann, ISBN: 1-55860-238-0.

Quinlan, J. (1996). Improved use of continuous attributes in C4.5. Journal of Artificial Intelligence Research, 4(1), 77-99.

Shynkevich, Y., McGinnity, T., Coleman, S., Li, Y., Belatreche, A. (2014). Forecasting Stock Price Directional Movements Using Technical Indicators: Investigating Window Size Effects on One-Step-Ahead Forecasting. IEEE/IAFE Conference on computational intelligence for financial engineering, proceedings (CIFER), London: IEEE, 341-348.

Spilioti, S. N. (2022). Market share-prices versus their fundamental values: the case of the New York stock exchange. Applied Economics, 54(50), 1-8.

Stevenson, R. T. (2001). The economy and policy mood: a fundamental dynamic of democratic politics? American Journal of Political Science, 45(3), 620-633.

Venkatesh, P., Sudheer, K., Paramasivan, S. (2021). A study on technical analysis using candlestick pattern of selected large cap stocks listed in National Stock Exchange (NSE), India with reference to steel sector. GSI Journals Serie B: Advancements in Business and Economics, 3(2), 62-71.

Wang, Q., Xu, W., Zheng, H. (2018). Combining the wisdom of crowds and technical analysis for financial market prediction using deep random subspace ensembles. Neurocomputing, 299, 51-61.

Yahoo Finance. (2022, September 9). Retrieved from https://finance.yahoo.com.

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

IMPACT OF WORK OVERLOAD AS A JOB STRESSOR ON EMPLOYEES' INTENTION TO LEAVE: THE MEDIATING EFFECT OF WORK-FAMILY CONFLICT IN A SRI LANKAN APPAREL SECTOR ORGANISATION

DOI: 10.17261/Pressacademia.2023.1822
JBEF- V.12-ISS.3-2023(2)-p.110-117

Ganewatta G.K.H[1], Hiroshima N.L.D.H[2]
[1]University of Ruhuna, Department of Human Resource Management, Matara, Sri Lanka.
hemamali@badm.ruh.ac.lk , ORCID: 0000-0002-3817-6293
[2]University of Ruhuna, Department of Human Resource Management, Matara, Sri Lanka.
harshihiroshima96@gmail.com , ORCID: 0009-0001-0629-405X

Date Received: July 7, 2023 **Date Accepted:** September 12, 2023

To cite this document
Ganewatta G.K.H., Hiroshima N.L.D.H., (2023). Impact of work overload as a job stressor on employees' intention to leave: The mediating effect of work-family conflict in a Sri Lankan apparel sector organisation. Journal of Business, Economics and Finance (JBEF), 12(3), 110-117.
Permemant link to this document: http://doi.org/10.17261/Pressacademia.2023.1822

ABSTRACT

Purpose- This article investigates the impact of work overload and work-family conflict as job stressors on employees' intention to leave in the Sri Lankan apparel sector, focusing on the mediating effect of work-family conflict. The study addresses concerns over high employee turnover rates among machine operators in the sector.

Methodology- The study collected primary data through a self-administered questionnaire from a sample of 106 machine operators working in a selected factory in the western province of Sri Lanka. The research adopted a cross-sectional quantitative survey design, and data analysis was performed using the SPSS PROCESS macro.

Findings- The study revealed that work overload positively influenced work-family conflict, indicating challenges in balancing work and family responsibilities. Further, work overload increased employees' intention to leave, suggesting its detrimental effects on employee motivation and job satisfaction. Work-family conflict serves as a partial mediator in the relationship between work overload and turnover intentions, playing a crucial role in transmitting adverse effects, leading to increased turnover intentions.

Conclusion- This research demonstrates the combined effects of work overload and work-family conflict on employee turnover intentions within the Sri Lankan apparel sector context. The findings highlight the importance of addressing work-related demands and resources to enhance job outcomes, such as employee turnover, in compliance with the Job Demands-Resources model. These insights provide practical implications for implementing strategies that promote work-life balance, reduce turnover intentions and enhance both employee and organisational performance.

Keywords: Work overload, work-family conflict, employee turnover intentions, job stressor, Sri Lankan apparel sector.
JEL Codes: J28, J63, J81

1. INTRODUCTION

In today's fast-paced world, characterized by deadlines, technological advancements, and numerous demands, stress has become an increasingly prevalent aspect of people's lives. Stress, in general, and job stress, in particular, is a prevalent aspect of modern life that appears to be growing more. Even though a certain level of stress can motivate people to perform better, excessive stress can have detrimental effects on people’s health(Jamal, 2007). Stress is a highly subjective experience, varying from person to person based on their perceptions and circumstances (Baqutayan, 2015). Stress occurs when employees’ capabilities and resources are inadequate to meet the demands of their jobs. Job stress can be defined as “the harmful physical and emotional responses that occur when the requirements of the job do not match the capabilities, resources, or needs of the worker” (Malik, 2011, p. 3063). Job stress is caused by various factors, also known as job stressors, including high workload, time pressure, lack of motivation, Work-Family conflicts, role ambiguity, poor work relationships and job insecurity in the workplace (Basit & Hassan, 2017).

Job stress results in many negative consequences for both employees and organisations. Employees who are burned out, exhausted or stressed cannot generate desired results, since they lose their energy, accuracy and innovative thinking. The negative consequences can include reduced job satisfaction, decreased motivation, poor quality of work, high absenteeism, high turnover, increased healthcare costs, reduced performance, and reduced productivity(Lakshani & Weerasinghe, 2020; Welmilla, 2020). Employees can leave the stressful working environment or organisation, resulting in a high employee turnover rate. High employee turnover has always been a concern for organisations. Since employee turnover affects an organisation's cost, profitability, and operations, significant attention is required to understand why individuals leave their jobs. Employee Turnover Intention is the willingness of employees to leave an organisation. Research has shown that turnover intentions are a significant predictor of actual turnover in an organisation (Rasheed, Okumus, Weng, Hameed, & Nawaz, 2020). Hence, understanding the factors influencing Turnover intentions is helpful for searching for strategies that encourage employee retention.

The apparel industry of Sri Lanka is vital in strengthening the country's economy. It generates many employment opportunities and provides quality products for international markets. According to the Export Development Board (2021), the apparel sector contributed 45% of the country's total export earnings in 2019. This industry provides direct employment opportunities for more than 300,000 employees in Sri Lanka (Export Development Board, 2021). As stated by Rajapakshe (2018), the apparel industry employs approximately 15% of the workforce, with women comprising 85% of this workforce. Even though the apparel sector provides many benefits, it is confronted with numerous challenges, such as dealing with the problem of high employee turnover rates.

Sewing machine operators are the most demanded occupation in the Sri Lankan apparel sector, representing more than 40 percent of total demand (Rajapakshe, 2018). This high demand shows one aspect of the existing labour shortage problem in the apparel industry. In addition, organisations in the apparel industry suffer from a high labour turnover rate, requiring frequent recruitment and training. High employee turnover leads to many other problems. Organisations fail to complete planned production on time without interruption, adversely affecting the organisation's image. Therefore, many organisations work long hours to meet project deadlines and eliminate work delays. Employees who work longer hours are typically expected to work harder, even more strenuously in order to keep up with growing demands. Extended working hours and heavy workloads are common issues that lead to work-family conflicts among machine operators in Sri Lankan apparel sector organisations (Nishanthi & Thalgaspitiya, 2015).

The employee turnover rate in the apparel industry has been high in recent years (Rajapakshe, 2018). Even though several studies have examined the relationship between job stress on turnover intentions of employees in the apparel industry in Sri Lanka (Lakshani & Weerasinghe, 2020; Liyanage et al., 2014), there is still a dearth of research in this area (Sewwandi & Perera, 2016). In particular, there is a limited understanding of how various stressors predict employee turnover. Some researchers acknowledge that work-family conflict as the most powerful stress causing factor for both men and women (Vickovic & Morrow, 2020), although its impact may vary depending on the context. Some other researchers acknowledge that heavy workload (Jayaratne, 2020; Liyanage, Madhumini, & Galhena, 2014) as a significant stressor among machine operators in apparel sector organisations. Despite some empirical studies focusing on the impact of numerous stressors on the turnover intentions of employees in the apparel sector in Sri Lanka (Lakshani & Weerasinghe, 2020; Nanayakkara & Chandrika, 2018), none of them have comprehensively examined the influence of both work overload and work-family conflict on employee turnover in a single study. According to the author's knowledge, there is no empirical research that investigates work-family conflict as a mediator between the relationship between work overload and employee turnover in the Sri Lankan apparel sector. In this context, this study aims to address the following research questions.

- What is the impact of work overload on work-family conflict among employees in the apparel sector in Sri Lanka?
- What is the impact of work-family conflict on employee turnover intention in the apparel sector in Sri Lanka?
- What is the impact of work overload and employee turnover intention in the apparel sector in Sri Lanka?
- Does work-family conflict mediate the relationship between work overload and employee turnover intentions among employees in the apparel sector in Sri Lanka?

By addressing the above research questions, this study attempts to understand the dynamics between work overload, work-family conflict, and employee turnover in the Sri Lankan apparel sector.

2. LITERATURE REVIEW

2.1. Job Stress

Job stress can be defined as “an individual’s reactions to characteristics of the work environment that seem emotionally and physically threatening” (Jamal, 2007, p. 177). It can also be described as an emotional experience which is associated with anxiety, strain, and tension that originates from a job or occupation(Radzali, Ahmad, & Omar, 2013). Job stress occurs when there is a disparity between the expectations of a job and an individual's capacity to fulfil and meet those demands(Malik, 2011). Job stress is caused by various factors such as excessive workload, work-family conflict, strained work relationships with peers and supervisors, unstable employment conditions, lack of autonomy, lack of opportunities for career development, workplace harassment, bullying and poor working conditions (Mustafa et al., 2015; Radzali et al., 2013; Zeb et al., 2015). Job stress and stressors result in many negative influences on the organisation, including employee turnover.

2.2. Employee Turnover Intention

Turnover intention refers to the conscious and intentional readiness to voluntarily leave the organisation(Qureshi et al., 2013). It is an employee's subjective assessment of the likelihood that he or she will leave his/her company in the near future(Carmeli & Weisberg, 2006). It is the final step in the chain of perceived withdrawals leading to actual turnover, most probably within the next six months(Yanchus, Periard, Moore, Carle, & Osatuke, 2015). It is well accepted that employee turnover intentions directly predict employee turnover in an organisation (Carmeli & Weisberg, 2006; Liyanage, Madhumini, & Galhena, 2014). Employee turnover can be explained as the ratio of the employees who departed from the organisation within a specific timeframe to the average number of employees in the organisation during that same period(Rajapakshe, 2018). Numerous researchers have made efforts to address the question of what influences employees' intention to quit their jobs by studying potential antecedents and found that job-related stress as a key factor(Ongori, 2007).

2.3. Work Overload and Work-Family Conflict as Job Stressors

Work overload occurs when an employee is assigned excessive work demands such as tasks, duties and responsibilities which exceed the capacity and resources to complete tasks within a specified time frame. Heavy Workload is one of the primary reasons for increased job demands (Baker, Hakanen, Demerouti, & Xanthopoulou, 2007). The workload can be categorized into two forms as Quantitative workload, which refers to the volume or amount of work involved in a task, while qualitative workload, which pertains to the complexity of tasks associated with a given workload (Glaser, Tatum, Nebeker, Sorenson, & Aiello, 1999). Work overload can reduce job satisfaction, performance, increase stress, turnover, and negatively impact employees' overall well-being (Glaser et al., 1999; Radzali, Ahmad, & Omar, 2013)

On the other hand, work-family conflict is characterized as a form of interrole conflict, which arises when the obligations and demands of one domain (either work or family) hinder an individual's capacity to fulfill responsibilities in the other domain(Radzali et al., 2013). Work-family conflict can manifest in various forms: time-based conflict occurs when the time dedicated to one role impedes fulfilling responsibilities in the other, while strain-based conflict arises from the psychological stress experienced by one role interfering with duties in the other. Additionally, behaviour-based conflict occurs when the behavioural expectations of one role are not compatible with the other (Barriga Medina, Campoverde Aguirre, Coello-Montecel, Ochoa Pacheco, & Paredes-Aguirre, 2021; Radzali et al., 2013). Many researchers acknowledge that work-family conflict is a significant predictor of job stress (Vickovic & Morrow, 2020).

Moreover, Work-family conflict and workload overload are logically related. When employees experience high levels of work overload, they often face challenges in fulfilling their work obligations while also meeting their family responsibilities. Due to the increased workload, they may need to allocate more time and effort to their jobs, leaving little time and energy for their personal lives. As a result, employees may struggle to allocate sufficient time and attention to their families which could result in conflicts between the domains of work and family(Adil & Baig, 2018). Some Researchers have also found a positive relationship between Work overload and work-family conflict(Hong, Liu, & Zhang, 2021). Work overload is a crucial factor which can influence Work-family conflict among machine operators in Sri Lanka (Nishanthi & Thalgaspitiya, 2015). In this context, the following hypothesis was created.

Hypothesis 1: There is a positive association between work overload and work-family conflict among machine operators in the apparel sector.

2.4. Work-Family Conflict and Turnover Intention

Work-Family Conflict adversely affects individuals, families, and organisations (Chrisangika Perera & Kailasapathy, 2020) . Numerous researchers recognize that the conflict between work and family responsibilities is a major predictor of job stress(Vickovic & Morrow, 2020). Work-family conflict can lead to feelings of frustration, emotional exhaustion, and reduced satisfaction in both work and family domains(Chrisangika Perera & Kailasapathy, 2020). As a result, employees may develop a desire to leave their current job. Research investigations have revealed that the presence of work-family conflict acts as a stressor in job settings, subsequently increasing employees' intention to leave their positions (Dodanwala, Santoso, & Yukongdi, 2022). As suggested by the existing literature, Employees who experience higher levels of work-family conflict are more inclined to report a higher intention to leave their jobs. Therefore, it is possible to formulate the following hypothesis.

Hypothesis 2: Work-family conflict is positively associated with machine operators' turnover intentions in the apparel sector.

2.5. Work overload and Turnover Intention

Excessive workload can have detrimental effects on employees and their organisations. There is evidence that employees become demotivated and quit their jobs when their workloads become intolerable(Bakker, Demerouti, & Verbeke, 2004). In the apparel sector in Sri Lanka, machine operators face demanding workloads that can be physically and mentally challenging. Given the nature of the job and the work demands placed on machine operators, it is reasonable to expect that Work overload may affect their turnover intentions. Some of the scholars found a strong positive association between work overload and employees' intention to leave their positions within the apparel sector of Sri Lanka (Liyanage et al., 2014; Sewwandi & Perera, 2016). Hence, the following hypothesis can be formulated.

Hypothesis 3: Work overload is positively associated with employee turnover intentions among machine operators in apparel sector organisations.

2.6. Work-Family Conflict as a Mediator between Work Overload and Turnover Intention

Past studies have found that work overload and work-family conflict are job stressors which predict employee intention to leave(Dodanwala et al., 2022). Further, some researchers have found a positive relationship between Work overload and work-family conflict (Hong, Liu, & Zhang, 2021). When employees experience high work demands, it often leads to difficulties in balancing work and family responsibilities, resulting in conflicts which can contribute to their intention to leave the organisation. Previous research has also demonstrated the positive effect of work-family conflict on employee turnover intention. Hence, there is a logical rationale to consider work-family conflict as a mediator between Work overload and Turnover Intention. In view of the above arguments, the following hypothesis is formulated.

Hypothesis 4: Work-Family Conflict mediates the effect of work overload on employee turnover intentions.

3. DATA AND METHODOLOGY

3.1. Sample and Procedure

The study was designed as a cross-sectional quantitative survey research. It collected primary data through a self-administered questionnaire. The target population of this study comprises machine operators working in a selected factory located in the western province of Sri Lanka. The factory employs a total of 1200 individuals, both men and women, who serve as machine operators. Out of this population, a sample of 120 machine operators was randomly selected to participate in the study. The questionnaire was designed to collect information related to work overload, work-family conflict, turnover intention, and demographic characteristics. The questionnaire was originally developed in English and then backtranslated to Sinhala. Rigorous efforts were made to ensure the questionnaire's clarity, reliability, validity, and overall quality. Pilot testing was conducted using five machine operators to identify any issues with the questionnaire, and necessary adjustments were made before the main data collection. Machine operators were given clear instructions on how to complete the questionnaire and were given sufficient time to complete the questionnaire. A total of 106 usable questionnaires were returned, resulting in a response rate of 88%.

3.2. Measurements of Variables

To ensure the reliability and validity of the measurements, the study adopted a questionnaire that had been previously tested in similar research. All the measures described below are rated on a scale of 1 (strongly disagree) to 7 (strongly agree). Turnover intentions were assessed using a four-item scale adapted from Jensen, Patel, and Messersmith (2013). The items included: (a) "I often think of quitting this job," (b) "I am always on the lookout for a better job," (c) "It is likely that I will look for another job during the next year," and (d) "There isn't much to be gained by staying in this job." The Cronbach's alpha coefficient for this scale for this scale was .89, indicating high internal consistency.

Work overload was measured using an eight-item scale adapted from Gould-Williams et al. (2014), based on Cousins et al.'s (2004) work. The items included: (a) "I am pressured to work long hours," (b) "I have unachievable deadlines," (c) "I have to work very fast," (d) "I have to work very intensively," (e) "I have to neglect some tasks because I have too much to do," (f) "Different groups at work demand things from me that are hard to combine," (g) "I am unable to take sufficient breaks," and (h) "I have unrealistic time pressures." The Cronbach's alpha coefficient for this scale was calculated as .91, indicating high internal consistency.

The measurement of work-family conflict (WFC) was carried out using a ten-item scale derived from Netemeyer, Boles, and McMurrian (1996). This scale encompassed two subscales: Work-Family Conflict and Family-Work Conflict. The Work-Family Conflict scale consisted of five items, including (a) "The demands of my work interfere with my home and family life," (b) "The amount of time my job takes up makes it difficult to fulfill family responsibilities," (c) "Things I want to do at home do not get done because of the demands my job puts on me," (d) "My job produces strain that makes it difficult to fulfill family duties," and (e) "Due to work-related duties, I have to make changes to my plans for family activities." The Family-Work Conflict scale also consisted of five items, including: (a) "The demands of my family or spouse/partner interfere with work-related activities," (b) "I have to put off doing things at work because of demands on my time at home," (c) "Things I want to do at work don't get done because of the demands of my family or spouse/partner," (d) "My home life interferes with my responsibilities at work such as getting to work on time, accomplishing daily tasks, and working overtime," and (e) "Family-related strain interferes with my ability to perform job-related duties." The Cronbach's alpha coefficient for this scale was calculated as .91, indicating high internal consistency.

3.3. Respondent Characteristics

The respondent characteristics provide an overview of the sample. Out of 106 respondents, the majority (59.4%) were female machine operators. More than half of the machine operators (54.7%) belonged to the age group of 18-25 years, while 33% were within the age range of 26-35 years. Additionally, 7% were between the ages of 36-45, and the remaining 6% were between 46-55 years old. In terms of marital status, the majority (75%) were unmarried. Regarding education level, 48% of respondents had up to Advanced Level education, 18.9% had passed the Ordinary Level, and 7.5% had completed up to Grade ten education. When it comes to working experience, the majority (52.8%) had 2-5 years of experience, while 33% had less than one year. Additionally, 8.5% had 6-9 years of experience, and only 6% had been working for more than ten years.

4. FINDINGS AND DISCUSSIONS

In the research, descriptive statistics, correlation analysis were conducted with the SPSS 22 program.

4.1. Descriptive Statistics

Table1: Means, Standard Deviations, and Pearson correlations among the Study Variables in the Measurement Model

	Mean	SD	WOL	WFC	TI	Tolerance	VIF
Work overload (WOL)	3.90	.593	(0.901)			0.52	1.522
Work-Family Conflict (WFC)	3.89	.689	.693	(0.924)		0.52	1.522
Turnover Intention (TI)	3.81	.738	.662	.693	(0.876)		

Notes: ** Correlation is significant at the 0.01 level (2-tailed)
Values in parenthesis along the diagonal are reliability values (Cronbach's alpha)

Table 1 presents the correlations, means, standard deviations, and scale reliabilities of the study variables. The mean and standard deviation values provide information on the average and variation of the study variables. Work overload has a mean of 3.9, with a standard deviation of 0.593, while work-family conflict has a mean of 3.89. The turnover intention had a mean of 3.81 with a standard deviation of 0.738. The Pearson correlation coefficients indicate the strength and direction of the relationships between the variables. Work overload and work-family conflict show positive correlations with turnover intention, aligning with the expected relationships. The reliability analysis indicates that all scales are reliable since their Cronbach alpha values reached more than 0.70 (Nunnally, 1978). The tolerance values are less than 0.10 and the Variance Inflation Factor > 10 is often considered to be an indication of multicollinearity (Tabachnick, Fidell, & Osterlind, 2001). The results indicate that multicollinearity does not exist among all independent variables as the values for tolerance are greater than 0.10, and the VIF is less than 10.

4.2. Testing Hypotheses

Simple Mediation Analysis was carried out using the SPSS PROCESS macro developed by Hayes (2013) in order to test the research hypotheses. The PROCESS macro developed by Hayes (2013)is often considered a more advanced and desirable method for conducting mediation analysis. The mediation analysis, specifically Model 4 of the PROCESS macro, was performed using the bootstrapping method as suggested by Hayes (2013) with a 95% confidence interval (CI) and 5000 bootstrapping samples.

4.2.1. Direct Effects

The result of the analysis is presented below. The first three hypotheses were examined by analyzing the direct effect results for Path a, b, and c, respectively.

The first model summary which examined work overload as the predictor variable and work-family conflict as the outcome variable and was highly significant ($F(1, 104) = 95.91$, $p < .001$), explaining 47.98% of the variance in work-family conflict. Furthermore, the results in Table 2 indicate that Path "a", representing the effect of the independent variable on the mediator variable, was found to be significant ($\beta = .86$, $p < .001$). Hence, Hypothesis 1, which states that work overload is positively associated with Work-Family Conflict, is supported. It suggests that employees who experience high work demands are more likely to face difficulties in balancing their work and family responsibilities, leading to conflicts between the two domains. Similar findings have been reported in previous research conducted with samples from other settings (Baş & Güney, 2022; Nasurdin & O'Driscoll, 2012).

The next model summary assessed turnover Intention as the outcome variable, with work overload as the predictor variable and work-family conflict as the mediator variable. This model was also statistically significant ($F(2, 103) = 61.40$, $p < .001$) and explained 54.38% of the variance in Turnover Intention. As shown in Table 2, Path "b," describing the effect of the mediating variable (Work-family conflict) on the dependent variable (Turnover), was significant ($\beta = .419$; $p<.001$). It implies a positive effect of work-family conflict on Turnover Intention, supporting hypothesis 2. The findings indicate that when employees experience conflicts between their work and family domains, they are more inclined to develop a desire to leave their current jobs. These findings are consistent with previous research, which highlights the adverse effects of work-family conflicts (Dodanwala et al., 2022).

Subsequently, the model summary for the total effect model, which examines the total effect of the predictor variable (work overload) on the outcome variable turnover intention, was also a significant relationship ($F(1, 104) = 81.28$, $p < .001$), indicating that 43.87% of the variance in the outcome variable. Further, Table 2 shows Path "c," which depicts the direct effect of the independent variable (Work overload) on the dependent variable (Turnover Intention), was significant as well ($\beta = .407$; $p < .001$). It suggests a positive effect of work overload on turnover intention and supports Hypothesis 3. This indicates that when employees face excessive work demands, it can have detrimental effects on their motivation, job satisfaction, and overall well-being, increasing their intention to leave the organisation, in line with previous research (Sewwandi & Perera, 2016).

4.2.2. The Mediating Effect

The fourth hypothesis was tested by analyzing the coefficients for the total effect, direct effect, and indirect effect obtained from the mediation analysis using the PROCESS Macro. This analysis aimed to understand how work-family conflict functions as a mediator between work overload and turnover Intension.

Table 2: Path Estimates

	Path	β	SE	95% Confidence Interval		t	p
				Lower	Upper		
WOL → WFC	a	.8611	0879	.6867	1.0354	9.793	.0000
WFC → TI	b	.4196	.0861	.2488	.5904	4.872	.0000
WOL → TI	c’	.4072	.1071	.1949	.6195	3.803	.0002

WOL: Work Overload ; WFC: Work-family Conflict; TI Turnover Intention

Table 3: Direct Effect, Indirect Effect and Total Effect

Effect	Estimate.	SE	95% Confidence Interval		t	P
			Lower	Upper		
Indirect Effect	.3613	.0825	.2047	.5257	-	-
Direct Effect	.4072	.1071	.6195	.3510	3.8038	.0002
Total Effect	.7685	.0852	.5995	.9376	9.0157	.0000

The mediation results are summarized in Table 3, which presents the estimates for the indirect effect, the direct effect and the total effect. The indirect effect was found to be significant (Estimate = 0.3613, SE = 0.0825, 95% CI [0.2047, 0.5257]). This finding highlights the role of work-family conflict as a mediator in the relationship between work overload and turnover intention, offering strong support for H4. Moreover, the direct effect was also significant (Estimate = 0.4072, SE = 0.1071, 95% CI [0.6195, 0.3510]), suggesting a direct relationship between work overload and employee turnover Intention supporting H3. These results suggest work-family conflict partially mediated the relationship between work overload and Turnover Intention. As shown in Table 3, the total effect, which combines direct and indirect effects, was highly significant (Estimate = 0.7685, SE = 0.0852, 95% CI [0.5995, 0.9376]). According to the Job Demands-Resources model(Bakker & Demerouti, 2007), high work demands without sufficient resources can lead to burnout, increased stress, and a higher likelihood of intending to leave the organisation. It suggests that work-related demands (such as work overload) and resources (such as work-family balance) play a crucial role in determining employees' well-being and job outcomes. By examining the impact of work overload and work-family conflict on employee turnover intentions, this study aligns with the Job Demands-Resources model's focus on understanding the relationship between job demands, resources, and employee well-being and outcomes.

5. CONCLUSION AND IMPLICATIONS

This study examined the influence of Work overload on employee turnover intentions in the Sri Lankan apparel sector, considering work-family conflict as a mediator. The results revealed positive relationships between work overload, work-family conflict, and turnover intentions. The study also found that work-family conflict partially mediates the relationship between work overload and turnover intentions. These findings emphasize the significance of addressing both work overload and work-family conflict in organisations to reduce turnover intentions and enhance employee retention.

Theoretical implications arise from our study align with the Job Demands-Resources model, which suggests that high work demands without sufficient resources can lead to increased stress and a higher likelihood of intending to leave the organisation. Furthermore, this research enhances our theoretical knowledge regarding the factors influencing employee turnover. It emphasizes the importance of considering both job-related (work overload) and personal factors (work-family conflict) when studying job stress and its consequences. Additionally, this study contributes to the existing empirical literature by examining the combined effects of work overload and work-family conflict on employee turnover intentions within the Sri Lankan apparel sector context.

The practical implications of this study extend beyond the apparel sector. Organisations in various industries can benefit from recognizing and addressing the negative effects of work overload and work-family conflict on employee retention. Organisations can use strategies that promote work-life balance and provide support for employees in managing work demands and family responsibilities, such as flexible work arrangements, employee assistance programs, and training on stress management and work-life integration. By acknowledging the importance of work-family conflict as a mediator between work overload and turnover intentions, organisations can proactively address these factors to reduce employees' turnover intentions, leading to a healthier and more productive work environment, ultimately benefiting both employees and organisations.

REFERENCES

Adil, M. S., & Baig, M. (2018). Impact of job demands-resources model on burnout and employee's well-being: Evidence from the pharmaceutical organisations of Karachi. IIMB Management Review, 30(2), 119-133.

Baker, A. B., Hakanen, J. J., Demerouti, E., & Xanthopoulou, D. (2007). Job resources boost work engagement, particularly when job demands are high. Journal of Educational Psychology, 99(2), 274.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. Journal of Managerial Psychology, 22(3), 309-328.

Bakker, A. B., Demerouti, E., & Verbeke, W. (2004). Using the job demands-resources model to predict burnout and performance. Human Resource Management, 43(1), 83-104.

Baqutayan, S. M. S. (2015). Stress and coping mechanisms: A historical overview. Mediterranean Journal of Social Sciences, 6(2 S1), 479-479.

Barriga Medina, H. R., Campoverde Aguirre, R., Coello-Montecel, D., Ochoa Pacheco, P., & Paredes-Aguirre, M. I. (2021). The influence of work–family conflict on burnout during the COVID-19 pandemic: The effect of teleworking overload. International Journal of Environmental Research And Public Health, 18(19), 10302.

Baş, M., & Güney, S. (2022). The mediating role of work-family conflict in the relationship between work overload perception and job satisfaction. Journal of Information and Organisational Sciences, 46(2), 345-360.

Basit, A., & Hassan, Z. (2017). Impact of job stress on employee performance. International Journal of Accounting and Business Management, 5(2), 13-33.

Chrisangika Perera, J., & Kailasapathy, P. (2020). Individual, spousal factors and work–family conflict: A study from Sri Lanka. South Asian Journal of Human Resources Management, 7(1), 91-120.

Dodanwala, T. C., Santoso, D. S., & Yukongdi, V. (2022). Examining work role stressors, job satisfaction, job stress, and turnover intention of Sri Lanka's construction industry. International Journal of Construction Management, 8, 1-10.

Glaser, D. N., Tatum, B. C., Nebeker, D. M., Sorenson, R. C., & Aiello, J. R. (1999). Workload and social support: Effects on performance and stress. Human Performance, 12(2), 155-176.

Gould-Williams, J. S., Bottomley, P., Redman, T., Snape, E., Bishop, D. J., Limpanitgul, T., & Mostafa, A. M. S. (2014). Civic duty and employee outcomes: Do high commitment human resource practices and work overload matter? Public Administration, 92(4), 937-953.

Hong, X., Liu, Q., & Zhang, M. (2021). Dual stressors and female pre-school teachers' job satisfaction during the COVID-19: the mediation of work-family conflict. Frontiers in Psychology, 12, 691498.

Jamal, M. (2007). Job stress and job performance controversy revisited: An empirical examination in two countries. International Journal of Stress Management, 14(2), 175-186.

Jensen, J. M., Patel, P. C., & Messersmith, J. G. (2013). High-performance work systems and job control: Consequences for anxiety, role overload, and turnover intentions. Journal of Management, 39(6), 1699-1724.

Lakshani, K., & Weerasinghe, T. (2020). Nexus between work stress and employee turnover intention: Study of non-managerial female employees in apparel industry of Sri Lanka. In Proceedings of the International Conference on Business & Information (ICBI).

Malik, N. (2011). A study on occupational stress experienced by private and public banks employees in Quetta City. African Journal of Business Management, 5(8), 3063-3081.

Nanayakkara, A., & Chandrika, K. (2018). Impact of occupational stress on turnover intention of machine operators in selected apparel manufacturing companies in Sri Lanka. Human Resource Management Journal, 6(1), 12-21.

Nasurdin, A. M., & O'Driscoll, M. P. (2012). Work overload, parental demand, perceived organisational support, family support, and work-family conflict among New Zealand and Malaysian academics. New Zealand Journal of Psychology (Online), 41(1), 38-49.

Netemeyer, R. G., Boles, J. S., & McMurrian, R. (1996). Development and validation of work–family conflict and family–work conflict scales. Journal of Applied Psychology, 81(4), 400-412.

Nishanthi, H., & Thalgaspitiya, U. (2015). Impact of work and family life balance on job engagement of machine operators of the apparel sector in Dehiowita Divisional Sector, Kegalle District in Sri Lanka. In Proceedings of International HR Conference.

Radzali, F. M., Ahmad, A., & Omar, Z. (2013). Workload, job stress, family-to-work conflict and deviant workplace behavior. International Journal of Academic Research in Business and Social Sciences, 3(12), 109-123.

Rajapakshe, W. (2018). An analysis of major factors affecting labor turnover in the apparel industry in Sri Lanka: Policy alternations for solving the problem. International Journal of Academic Research in Economics and Management Sciences, 7(3), 214-231.

Rasheed, M. I., Okumus, F., Weng, Q., Hameed, Z., & Nawaz, M. S. (2020). Career adaptability and employee turnover intentions: The role of perceived career opportunities and orientation to happiness in the hospitality industry. Journal of Hospitality and Tourism Management, 44, 98-107.

Sewwandi, D.V.S., & Perera, G. D.N.(2016). The impact of job stress on turnover intention: A study of reputed apparel firm in Sri Lanka. 3rd International HRM Conference.

Tabachnick, B. G., Fidell, L. S., & Osterlind, S. J. (2001). Using multivariate statistics. Allyn and Bacon, Boston.

Vickovic, S. G., & Morrow, W. J. (2020). Examining the influence of work–family conflict on job stress, job satisfaction, and organisational commitment among correctional officers. Criminal Justice Review, 45(1), 5-25.

Welmilla, I. (2020). Human Resources challenges in apparel industry in Sri Lanka. Global Journal of Management and Business Research, 20(2), 45-55.

PressAcademia
www.pressacademia.org/journals/jbef
JBEF
ISSN 2146-7943
Journal of Business, Economics and Finance YEAR 2023 VOLUME 12 ISSUE 3

AN EXAMINER OF CHINA COMMERCIAL BANKS' LOANS THROUGH CREDIT CHANNEL PRIOR COVID-19

DOI: 10.17261/Pressacademia.2023.1823
JBEF- V.12-ISS.3-2023(3)-p.118-130

Mohammad Farajnezhad
Universiti Teknologi Malaysia, Azman Hashim International Business School, Kuala Lumpur, Malaysia.
taban1010@gmail.com , ORCID: 0000-0002-2086-9294

Date Received: June 28, 2023 **Date Accepted:** August 29, 2023

To cite this document
Farajnezhad, M., (20XX). An examiner of China commercial banks' loans through credit channel prior COVID-19. Journal of Business, Economics and Finance (JBEF), 12(3), 118-130.
Permament link to this document: http://doi.org/10.17261/Pressacademia.2023.1823

ABSTRACT

Purpose- China's economy has greatly developed in the last few decades, catapulting the nation to the second-biggest economy in the world. Financial growth took off over the last couple of decades because of the nation's expansion into the world economy and support for monetary policy. The purpose of this study is to analyse commercial bank-level data to examine a credit channel of the monetary policy transmission mechanism in emerging economies, such as China, from BRICS countries. Among the important questions that central banks, economists, and policymakers have raised in this area are: Does the impact of bank characteristics and macroeconomic variables affect the amount of loans in China? Do interacting bank characteristics and macroeconomic elements affect the amount of a loan in China?
Methodology- Data analysis is achieved using static panel data with a random-effect model. 216 commercial banks in China were used as a sample, and the study was conducted from 2009 to 2018. The statistical software Stata is utilised for data analysis.
Findings- According to findings from China's statistics, the capital ratio, GDP, inflation, and ROA interactions have a statistically significant but negative impact on the loan amount. The hypothesis is that capital ratio, total assets, and return on assets have a statistically significant and positive effect on the amount of the loan. The robust standard error coefficient showing a probable causal relationship between the variables was positive. Also,the results demonstrate that macroeconomic factors like interest rates, GDP, and inflation have a statistically insignificant positive impact on loan amounts. Hence, this study found enough evidence to accept the hypothesis that the loan amount had an insignificant effect.
Conclusion- The authors contribute to the existing literature by identifying the key determinants of monetary policy transmission channels through credit in China and, furthermore, through a country-level data analysis and disaggregation at the commercial bank level, as well as economic conditions.
Keywords: Panel Data, Banks, Monetary Policy Transmission Mechanism, Credit Channel, China economy.
JEL Codes: C23; E51; E52

1. INTRODUCTION

In macroeconomic literature, the monetary policy transmission mechanism (MPTM) is a complicated and fascinating topic. The MPTM concept predicts that a rise in the money supply will increase prices, which should theoretically lead to a rise in real GDP. MPTM is transmitted through several channels, involving the asset price channel, exchange rate channel, interest rate channel, and credit channel (Mishkin, 2006). The most crucial channel is credit, and it may contribute a significant amount to resolving the MPTM issue. There are two sub-channels comprising the credit channel: the bank lending channel (BLC) and the balance sheet channel (BSC). The capacity of the bank lending channel to provide bank loans to a firm is affected. Instead, the balance sheet channel represents firms' and individuals' financial conditions plus their capacity to approach the market of credit (Bernanke and Gertler, 1995). Consequently, credit channels demonstrate a crucial function in the investigation of macroeconomic trends.

The macroeconomic parameters for the MPTM use the credit channel as a major instrument. Further, a country's economic performance can be directly impacted by monetary policy transmission. The channel acts as an analytical method that explains the effect of money-related methods by applying loan supply in the country (Mishkin, 1996). Moreover, a new general credit channel manifests that credit itself depends upon the level of monetary activity. This infers the presence of a giant representative group in the country that depends on money correlated with various nations for market activities. It implies that the essential responsibility of financial markets and loans of banks in bank developments and money market developments creates critical consequences for the safe banking area and credit marketplaces (Singh et al., 2008; Altunbas et al., 2009). As a consequence, it is important to realise the routes over which MPTM is conveyed in a country.

Giving to (Farajnezhad et al., 2022) to examine a credit channel of the monetary policy transmission mechanism in India. According to the data, the bank's features have a large and negative liquidity ratio compared to the loan amount. Furthermore, there is a significant but negative relationship between the interaction of inflation and interest rates with the liquidity ratio and loan amount in India. Equally, with the line of research (Farajnezhad and Suresh, 2019), according to a Malaysian study, there is a credit channel.

The following concerns are addressed in this research: (a) What is the impact of the characteristics of banks and macroeconomic factors on the amount of loans in the Chinese economy? (b) Do the interacting features of a bank and macroeconomic elements affect credit supply in China's economy? The influence of this research is its contribution to the credit channel concerning the MPTM that influences the lending behaviour of China. The conclusion of this study has been shown in China that, according to empirical results, the author of this research has established that in China. Only a considerable and positive association exists between the interaction interest rate, capital ratio, and loan amount. The capital ratio, total assets, and return on assets hypothesis all have a statistically significant and positive impact on the loan amount. Additionally, the liquidity ratio influences the loan amount in a statistically meaningful but negative way. According to the findings, macroeconomic factors (interest rate, GDP, and inflation) have a statistically irrelevant positive impact on loan amounts. Hence, this research noticed enough proof to accept the hypothesis of the insignificant effect of the loan amount.

A sample of 216 commercial banks from China was included in this empirical investigation from 2009 to 2018. The choice of country enables analysis of the impact of loan bank supply responsiveness to MPTM through the credit channel while removing the prejudice created by changing monetary rules. Also, the dataset used for this study includes all the times when the central bank of a developing nation operated a single monetary policy in the Chinese economy. For data analysis, STATA, a statistical package, is utilized. The study is achieved using the random effect model method for panel data. This methodology enables employing methods to regulate both unobservable variability and the issues of endogeneity concerning MPTM and bank characteristics. This method creates accurate and fair assessments of the correlations between macroeconomic factors and bank features.

The remainder of the study is organised as follows: The concerned literature is examined in Section 2. Section 3: Data and methodology Section 4 presents empirical results. The further discussions on the random effect model in China in Sections 5 and 6 are the conclusion of the research.

2. LITERATURE REVIEW

China's economy has greatly developed; it has catapulted in recent years the nation to the second-biggest market in the world. China recently became the second-biggest market and is gradually playing a significant role in the global economy. Financial growth took off over the last couple of decades because of the nation's expansion into the world economy and the administration's striking support for monetary policy. The People's Bank of China (PBOC) expresses and controls MPTM, stops and resolves financial risks, and protects economic steadiness.

In 1978, China experienced a financial change. Several achievements from this shift originated at the start of the 21st century, particularly from 1996 to 2006. This denotes China's coordination with the globe. This change significantly affects Chinese and global history. In Chinese economics, monetary policy has assumed a significant role in steadying the economy, which has stimulated many theoretical discussions on the effect of MPTM in China (Sun, Ford, et al., 2010).

The most important part of China's monetary transmission system is made up of credit channels. Due to the lack of interest rate liberalisation, the stock and bond markets in China need development. Reserved income and bank loans are the most significant sources of funding for businesses in China, whereas interest rate channels and other asset price channels are negligible in contrast to credit channels. The bank lending channel of the MPTM views bank deposits and other sources of bank funding as insufficient replacements. Following the strengthening of credit supply by the central bank, banks cannot completely replace declining deposits with another financial resource. Therefore, the banks should deal with loaning, which will decrease the firm's assets as well as production, while restraining credit accessibility (Li and Lee, 2015a). Little progress has been made in the study of China's monetary policy direction. Ping (2004) utilises total statistics and finds that cash is unbiased with respect to growth in the long term, which is linked to inflation. Qin et al. (2005) research the influence of various MPTM instruments on aggregates of monetary and price levels. Liu, Waggoner, et al. (2009) study the long-run connection between inflation and deposit rates. Yet, all of the aforementioned research applies collective information and the Granger causality assessment to study the connection among credit supply and macroeconomic factors, focusing primarily on the influence of China's monetary policy. Sun, Ford, et al. (2010), based on a VECM model, explored whether bank lending could be used to transmit MPTM in China. In the long term, bank lending channel activity in China impacts MPTM, which is negatively related to necessary reserve ratios and the one-year lending rate.

According to Gunji and Yuan (2010), applying a general method of moments demonstrated that banks with less productivity tend to have a subtler MPTM. The impact of MPTM exists more on the stocks of small companies' business banks than on those of vast country-held business banks. Banks with greater liquidity tend to be susceptible to MPTM because the impact of MPTM on banks is uncertain. The study by Zhaohui (2006) studied MPTM with macroeconomic features such as GDP, CPI, interest rates, and total foreign trade. To analyse the impact of MPTM on economic activity from 1994 to 2004, Granger causality tests were used. The findings indicate that the monetary aggregate could affect price levels, but interest rates could not. Price is the greater cause of interest rates. The credit channel is a significant channel of MPTM. Like the exchange rate channel, which is low in this case owing to the fixed exchange rate and the limited stock market, the interest rate channel also has a meaningful impact.

China's growth continues today. In China, monetary policy is contrasted with that of more nations as far as accessible policy tools and policy conditions. The policy administration is transferring to a marketplace, and the national bank utilises a combination of established and cost-established devices (Tsang, 2011). As discussed by Fernald and Jones (2014), to assess the effects of Chinese MPTM in China, factor-augmented vector auto-regression (FAVAR) was used to integrate economic activity and inflation. The outcome of this research is that rising bank reserve provisions decrease economic activity and inflation. Likewise, shifting interest rates have a considerable impact on those factors through the different scale of the shift in credit situations, for instance, a shock to M2 or in different credit situations, such as when there is a shock to the money supply. Nguyen and Boateng (2013) evaluated bank loans and the impact of bank features on credit supply in reaction to monetary policy variations in China through an overall method of instants. The results show that involuntary excess reserves, bank measurements, and liquidity are essential in assessing the effect of monetary policy on credit development.

The work of He and Wang (2012) explained that financial experts determine lending rates, deposits, and window directions for lending in China's double-rate framework, while markets determine security rates. According to Liu and Zhang (2010), as part of China's mixed MPTM, both interest rates and money supply are set under a new Keynesian model. Consequently, consolidating the outcome illustrates the effectiveness of monetary policy regarding the largest welfare improvements evaluated by strength in inflation and production. Monetary policy operations involve both interest rates and the amount of money.

There have been numerous empirical investigations in China about monetary policy transmission mechanisms, in particular credit channels, since 2000 (Jiang et al., 2005; Wang and Wang, 2000). Yang and Shao (2016) found that commercial banks with low market capacity while increasing the growth of loans are less exposed to monetary policy shocks. So, increased banks of challenge in China are reducing the effect of MPTM through the credit channel. Consequently, improved competition among Chinese banks decreases the efficacy of MPTM in the bank lending channel. Furthermore, this effect is strong for well-capitalised banks, liquid banks, and city-commercial banks. Another study demonstrated that credit channels are incessantly adjusting for MPTM's impact on the economy in China (Fan and Jianzhou, 2011).

China's economy has had remarkable structural changes in recent years. This structure might change the effectiveness of counter-cyclical monetary policy for Chinese economic elements and inflation (Fernald et al., 2014). In China, financial stability and development are an extremely significant indicator of their economies in Asia and even in the world. Although the interpretation of MPTM in China is not simply due to the fact that the People's Bank of China (PBOC) uses more than one mechanism to perform monetary policy transmission, Certainly, for the People's Bank of China (PBOC) to set policy, the Fed usually uses a variety of tools, ranging from required reserve percentage-determined lending rates to deposit rates (McMahon et al., 2018).

Recently, China's MPTM has been investigated by numerous academics. For instance, Zhensheng (2002) assumed that the credit channel is a regulating part of the MPTM in China. According to Jiang and Zeng (2008), the bank lending channel shows the extremely essential responsibility of achieving the final objectives of monetary policy. Sun, Ford, et al. (2010) argued that credit, interest rate, and asset price channels all play a role in the MPTM in China, and the part of the bank lending channel looks mostly essential. According to Sun and Ma (2004), China's MPTM uses its influence on the country over money channels rather than credit channels.

Chen et al. (2016) found that the MPTM is more important in deficiency situations than in regular times, and monetary policy transmission has an unbalanced impact on the loan of the bank. Fernald et al. (2014) In general, the result has shown that the MPTM channels have encouraged development in developed countries. But, according to Geiger (2008), Ping (2004), and Xia and Liao (2001) considered, there is an unconstrained relationship between monetary aggregate and real economic activity due to a control issue with monetary aggregate in PBC. Also, Geiger (2008) and Rudebusch and Wu (2008) examined the interest rate channel, which does not have any impact on the MPTM Chinese economy.

In the examination of the evolution of monetary policy (Koivu et al., 2008; Laurens and Maino, 2007; Liu and Zhang, 2010; Pan and Tao, 2006), opposite to the West, China aims to achieve its financial objectives through a range of tools. As an alternative, a variant of the instrument is accepted. (Liu and Zhang, 2010; Porter and Xu, 2009) argued that acceptance of a combination of MPTM tools in China had a possible extra impact on maintaining inflation below the mechanism. More significantly, according to Fang et al. (2018), the relationship between MPTM and bank loans is unimportant in banks with official-and-director (OAD), indicating monetary policy is channelled through lending, which is missing when studying the OAD. Others generally empirical results on monetary policy transmission are: (Berkelmans et al., 2016; Chen et al., 2013; Chen et al., 2017; Chen et al., 2016; Chen and Hu, 2011; Chengping and Xu, 2012; Chuang and Xuwen, 2013; Fungáčová et al., 2016; Funke et al., 2015; He et al., 2013; Leeper and Zhou, 2013; Li and Lee, 2015b; Liu, Margaritis, et al., 2009; Lombardi et al., 2018; Nagai and Wang, 2007; Poon and Wong, 2011; Qin et al., 2005; Shaoping et al., 2012; Sheng and Wu, 2009; Sun, Ford, et al., 2010; Sun, Gan, et al., 2010; Wang and Wang, 2000; Yao et al., 2013; Yi, 2007; Yue and Zhou, 2007; Zhang and Clovis, 2009; Zhang et al., 2018).

Those findings mostly concentrate on the practical evaluation of the pertinence of money supply as a middle goal and excavate our knowledge of the MPTM. Achieving China's monetary policy goals consists of mostly two elements: monetary aggregates and exchange rates. China is essentially depending on credit to execute monetary policy. Monetary policy through loan cost and wealth channels assumes a generally reduced role in ordinary circumstances.

This study attempts to examine the factors related to credit channels in monetary policy transmission mechanisms among banks in China, focusing on credit supply (amount of loan) and policy transmission mechanisms. Additionally, the research objectives are to estimate banks and macroeconomic variables that are affected by the credit channel of MPTM and their effect on bank lending and the balance sheet channel. Due to a lack of literature on China, the aim of this study is to compare elements that define credit channels and balance sheets in MPTM across China.

3. DATA AND METHODOLOGY

This study makes use of Fitch's International Bank Database and bank scope. Just commercial banks were chosen for the sample, which spans the years 2009 to 2018. There are 216 commercial banks in the final panel sample. Data on macroeconomics is provided by the World Bank Development Indicators and the International Monetary Fund (IMF).

This study examines the bank credit channel using balance sheet data to determine the cross-sectional relevance of loan availability following the financial crisis. (Kashyap and Stein, 2000) with relation to the bank lending channel (Bernanke et al., 1996). These academic efforts are presented in the following (Bernanke et al., 1999; Holmstrom and Tirole, 1997). The capital ratios of banks are the focus of this study. Instead of Kashyap and Stein (2000) and Bernanke et al. (1996), liquidity ratios of banks are similarly examined in this study (Mar´ ıa Cantero Saiz and errez, 2017; Jimenéz et al., 2014; Jiménez et al., 2012; Juurikkala et al., 2011; Gunji and Yuan, 2010; Gambacorta, 2005; Ehrmann et al., 2003).

This research investigates the relationship between the MPTM and bank characteristics such as capital, liquidity, and size to examine the effect of these parameters on lending reactions to the MPTM. Lastly, this study shows three macroeconomic pointers as control variables: The factor controlling the demand for loans is the GDP growth rate. The increasing economic condition is affecting profitable investment plans, which is why the demand for bank loans is rising. The variables described below are listed in Table 1. They are also listed in the previous section according to their notation.

Table 1: Description of Variables

Variables	Units	Definition
Dependent variable		
Ln Δ amount loan it	00.00.00	Growth rate of loans lagged one year
Independent variables		
Macroeconomics condition (t)		
Δ IR t interest rate	%	Annual change of the country 3 -month interbank interest rate. Calculated as the nominal interest rate minus inflation in country j at time t.
Δ GDP	%	Gross domestic product growth rate

Δ Inflation rate	%	Measures the annual percentage change in the general price level during a period in an economy
Bank characteristic(b)		
Δ Bank capital it	%	The ratio of equity over total assets
Δ Bank liquidity it	%	The ratio of cash and securities over total assets
Ln total assets it	-	The log of the total assets of the bank
ROA it	%	The total net income over assets of the bank

The evaluation of this research strategy is based on the contributions of Mar' ıa Cantero Saiz and Errez (2017), Jimenéz et al. (2014), Jiménez et al. (2012), Juurikkala et al. (2011), Gunji and Yuan (2010), Gambacorta (2005), and Ehrmann et al. (2003). These investigators point out the significance of a few forms of heterogeneity issues for the MPTM, and this is found in presenting an interaction term between the policy method and the candidate source of heterogeneity. The empirical analyses for the MPTM by banks method emphasise the response of the credit supply to monetary shocks. Ultimately, it is important to determine whether some types of banks experience a big drop in lending after a monetary tightening. Numerous bank characteristics are connected to the examination of how sensitive banks are to the lending channel, according to bank-lending channel research.

To account for macroeconomic growth and the different reactions of different styles of banks to such growth, use factors are added to the model. Real GDP growth, interest rate, and inflation are contained in the regressors as control variables. To raise knowledge of the impact of MPTM on the loan supply, the focus is on the supply of the lending across several bank categories. That is the reason for the previously stated category elements included in the model, i.e., size, liquidity, and capitalization. For the purpose of describing the influence that these characteristics have on MP fluctuations, this study involves interaction terms between MPTM components and the bank-particular feature (size, LIQ, and CAP).

This work only examines the applications that are recognised and gives a pointer for applications submitted by firms at the time that are approved (the amount of the loan). The practical model of this research investigates the main factors of credit expansion with banks by various categories of ownership. In this research, the model is like those employed by the researchers previously described. We estimate a linear model to examine the correlation among MPTM and extensive margin amounts of loans (Mar´ ıa Cantero Saiz errez, 2017; Nguyen and Boateng, 2013; Jimenéz et al., 2012; Gunji and Yuan, 2010) that is used to investigate if banks respond to shocks in MPTM differently. The model utilises the equation, which uses expressions of interaction derived from the showing of monetary policy and a particular trait of the bank. Based on the static linear panel data, the following equation can be used to define the model:

Ln $\Delta amount\ loan\ it = \beta 1 \Delta IRt + \beta 2 \Delta\ GDPt + \Delta INF\ \beta 4\ capital\ ratioit{-}1 + \beta 5 liquidityit{-}1 + \beta 6\ Ln\ total\ assest\ it{-}1 + \beta 7\ ROA\ it{-}1 + \beta 8(\Delta IRt \times CAPit{-}1) + \beta 9(\Delta IRt \times LIQit{-}1) + \beta 10(\Delta GDPt \times CAPit{-}1) + \beta 11(\Delta GDPt \times LIQit{-}1) + \beta 12(\Delta INFt \times CAPit{-}1) + \beta 13(\Delta INFt \times LIQit{-}1) + \beta 14(\Delta GDPt \times Ln\ Total\ assetsit{-}1) + \beta 15(\Delta GDPt \times ROA\ it{-}1) + \beta 16(\Delta INFt \times Ln\ Total\ assetsit{-}1) + \beta 17(\Delta INFt \times ROAit{-}1) + \beta 18(\Delta IRt \times Total\ assetsit{-}1) + \beta 19(\Delta IRt \times ROA\ it{-}1) + \varepsilon it\ (1)$

4. EMPIRICAL RESULTS

4.1. Variables Correlation Matrix

Table 2 shows a correlation matrix based on unbalanced data from 216 Chinese-listed commercial banks.

Table 2 Variables Correlation Matrix in China

	AL	TA	ROA	LIQ	CAP	GDP	INF	IR	GDP x LIQ	GDP x CAP	INF x LIQ
AL	1										
TA	**0.9762*****	1									
ROA	0.1821***	0.1564***	1								
LIQ	-0.5664***	.0 4941***	-0.1515***	1							
CAP	-0.5897***	-0.5023***	-0.3109***	0.4824***	1						
GDP	0.0628	0.1008***	0.0514	-0.0325	-0.0041	1					
INF	0.0221	0.0388	0.0417	-0.0078	-0.0211	0.7441***	1				
IR	-0.0742**	-0.1172***	-0.0184	-0.673*	0.2171***	-0.9548***	-0.5666***	1			

GDP x LIQ	-0.2596***	-0.2003***	-0.0569**	0.4711***	0.6480***	0.3523***	0.27771***	-0.3169***	1		
GDP x CAP	-0.4177***	0.3462***	-0.2293***	0.3583***	0.6482***	0.2954***	0.2473***	-0.2775***	0.6299***	1	
INF x LIQ	0.0142	-0.0048	-0.0362	-0.0045	-0.0419	0.0575**	0.5948***	0.1239***	0.1802***	0.1385***	1
INF x CAP	-0.0074	0.0305	-0.0081	0.0214	-0.0193	0.0464	0.5205***	0.1163***	0.1224***	0.1793***	0.828***
IR x LIQ	0.0688	0.0355***	0.1215***	-0.0681*	-0.1356***	-0.1035***	0.2609***	0.3097***	-0.3857***	-0.2393***	0.5011***
IR x CAP	0.1351***	0.0840**	0.0964***	0.0516**	-0.2571	-0.067**	0.2312***	0.259***	-0.2006***	-0.277***	0.4279***
GDP x TA	0.0687***	0.1039***	0.0533***	-0.0508	-0.0106	**0.9819*** **	0.7290***	-0.9384***	0.3298***	0.2672***	0.0554
GDP x ROA	0.2236***	0.2310***	0.5544***	-0.1875***	-0.1877***	0.3294***	0.2044***	-0.3251***	0.1336***	-0.0198	0.0017
INF x TA	-0.0007***	0.0129	0.0316	0.0073	-0.0064	0.7184***	**0.9829*** **	-0.5412***	0.2690***	0.02359***	0.5881***
INF x ROA	-0.0062	-0.0036	0.0196	0.0029	-0.0435	0.0179	0.5123***	0.1455***	0.0383	0.0114	0.6744***
IR x TA	-0.0400***	-0.0786**	-0.0167	0.0653	-0.0209	0.9322***	-0.5475***	**0.9813*** **	-0.3000***	-0.2615***	0.1255***
IR x RQA	-0.0417	-0.0566**	-0.0474	0.0864	-0.018	-0.055	0.3018***	0.2864***	0.041	0.0121	0.4461***

Continue Table 2: Variables Correlation Matrix in China

AL	INF x CAP	IR x LIQ	IR x CAP	GDP x TA	GDP x RQA	INF x TA	INF x RQA	IR x TA	IR. ROA
TA									
RQA									
LIQ									
CAP									
GDP									
INF									
IR									
GDP x LIQ									
GDP x CAP									
INF x LIQ									
INF x CAP	1								
IR x LIQ	0.4645***	1							
IR x CAP	0.5718***	0.7888***	1						
GDP x TA	0.0426	-0.0958	-0.0597**	1					
GDP x RQA	-0.0543	-0.0269	-0.0145	0.3357***	1				
INF x TA	0.4975***	0.2615***	0.2212***	0.7299***	0.2029***	1			
INF x RQA	0.5155***	0.4109***	0.3021***	0.0187	0.0782***	0.5350***	1		
IR xTA	0.1129***	0.3024***	0.2475***	-0.9503***	-0.3193***	-0.5422***	0.1539***	1	
IR x RQA	0.3602***	0.5663***	0.4705***	-0.0557	-0.1412***	0.3190***	0.6572***	0.3004***	1

This table shows the correlation matrix between loan amount and bank-level determinants and economic determinants based on the unbalanced country sample (China). The sample consists of 216 commercial bank-year observations from 2009 to 2018. The independent variables are liquidity ratio, capital ratio, and Ln total assets. ROA, AGDP, A INF, and A IR AL: amount loan; LIQ: liquidity ratio; CAP: capital ratio; TA: total assets; LIQ: A GDP x liquidity ratio; GDP *CAP: A GDP x Capital Ratio; INF*LIQ: A INF x Liquidity Ratio; INF*CAP: A INF x Capital

Ratio; IR*LIQ: A IR x Liquidity Ratio; IR*CAP: A IR x Capital Ratio: GDP *LN TA: A GDP x total assets; INF*LNTA: A INF x total assets; INF*ROA: A INF x ROA; IR* Ln TA: A IR x total assets;

The table presents the Pearson correlation coefficients among variables with their significant *** Significant at the 1 percent level. ** Significant at the 5 percent level. Significant at the 10 percent level.

According to Table 2, the interest rate and the interaction between interest rate and size are highly correlated (r = 0.95), implying the existence of a multicollinearity problem. Nevertheless, in multicollinear regression, interest rate and its interaction with size would not be included in the same model, so the outcome would not be affected by multicollinearity. Similarity: both the interactions between inflation and capital ratio and the interactions between inflation and return on assets are statistically significant (r = 0.93 and r = 0.92, respectively), suggesting a potential multicollinearity problem. Both inflation-capital-ratio and inflation-return-on-assets interactions would not affect the outcome of the regression.

4.2 MULTICOLLINEARITY

As evident from Table 3, the result shows for China that the tolerance values for the main elements range between 0.221279 and 0.88505. Additionally, the value of VIF for the major variables ranges from 1.13 to 4.52. Besides, the tolerance values for main variables with interaction elements span from 0.100092 to 0.605912. Furthermore, the values of VIF for all elements span between 1.65 and 9.99. The results demonstrate that the tolerance for all factors is larger than 0.1, and so the VIF is smaller than the 10 recommended by Hair et al. (2011). As a result, the VIF tolerances of the variables in this study are within the recommended ranges.

Table 3: Variance Inflation Factor (VIF)

Δ INF	4.52	0.221279
Capital Ratio	1.58	0.632031
Total assets	1.51	0.661271
Liquidity Ratio	1.47	0.680090
ROA	1.13	0.885050
Mean VIF	**2.04**	
Δ IR× Liquidity Ratio-1	9.99	0.100092
Δ GDP × Liquidity Ratio-1	7.75	0.129056
Δ INF ×Capital Ratio -1	7.67	0.130422
Δ IR ×Capital Ratio -1	7.20	0.138971
Δ GDP ×Capital Ratio -1	6.32	0.158165
Capital Ratio	4.62	0.216538
Total assets	4.24	0.236018
Δ IR ×ROA -1	3.96	0.252580
Liquidity Ratio	2.97	0.3369720
Δ GDP ×ROA -1	1.79	0.560182
ROA	1.65	0.605912
Mean VIF	5.28	

4.3. Unıt Root Test

Table 4 depicts the unit root test in China. Based on the country sample, the dependent variable (Ln amount loan) does not have a unit root. The calculated ADF test value with lags (0) in the general sample is -89.354, and the PP test value with lags (0) is -208.09. The GDP, INF, IR GDP, IR, INF, capital ratio, total assets, liquidity ratio, and the interaction factors of the country of China do not have a unit root. There is a stationery as a result. Interestingly, none of the variables under evaluation have a unit root problem, as shown by table 4, and the data are stationary. Additionally, both the dependent and independent variables' p-values are significant. Thus, we disregard H0 and accept H1. This indicates that the data are steady and that none of the study's variables have a unit root issue.

Table 4: Unit Root Test

Variables	ADF*	Lags	PP**	Lags
Main variables				
Ln Δ amount Loan	-89.354	0	-208.09	0
Liquidity Ratio	-3.0122	0	-8.4701	0
Capital Ratio	-8.1641	0	-14.054	0
Ln total assets	-21.378	0	-33.864	0
ROA	18.9282	0	843.924	0
ΔGDP	-70.100	0	-157.48	0
Δ IN	-58.921	0	-101.75	0
Δ IR	-64.121	0	-147.12	0
Interaction variable				
Δ GDP × Liquidity Ratio-1	-35.001	0	-58.132	0
Δ GDP × Capital Ratio -1	-74.331	0	-154.57	0
Δ INF × Liquidity Ratio-1	-19.471	0	-22.178	0
Δ INF × Capital Ratio -1	-21.177	0	-25.027	0
Δ IR × Liquidity Ratio-1	-13.893	0	-15.755	0
Δ IR ×Capital Ratio -1	-12.797	0	-14.744	0
Δ GDP × Ln total assets-1	-67.567	0	-155.40	0
Δ GDP × ROA -1	-19.126	0	-26.283	0
Δ INF × Ln total assets-1	-56.181	0	-93.857	0
Δ INF × ROA-1	-21.263	0	-23.808	0
Δ IR × Ln total assets-1	-63.264	0	-144.48	0
Δ IR ×ROA -1	-13.644	0	-14.213	0

Note: *ADF (Augmented Dickey Fuller), **PP (Philip- Perron)

5. FURTHER DISCUSSIONS, FIXED EFFECT MODEL

In the bank scope of China, there are 216 commercial banks included, all of which have unbalanced panel data. The following equation calculates the correlation between the loan amount and the bank-level determinants using the pooled OLS and fixed effect analysis:

$Ln\ \Delta amount$ loan it= 1.04+0.018 ΔIRt-0.002Δ GDPt + 0.009ΔINF − 1.003 CAP − 1.05 LIQ + 0.83 size + 0.00.12(ΔIRt×CAPit−1) CAPit−1)+0.03(ΔIRt× LIQit−1)−0.006(ΔGDPt×CAPit−1)+ 0.006(ΔGDPt × LIQit−1)+ 0.085(ΔINFt× CAPit−1) - 0.027 (ΔINFt LIQit−1) -0.00042 (Δ GDP × 0.001+ 0 .001 (ΔGDP× ROA)+ 0.001 (ΔINF× Size) -0.018 (ΔINF× ROA) – 0.004 (ΔIR × Size) + 0.025 (Δ IR ×ROA)+ εit

Table 5: Fixed Effect Model

Variables	Fixed effects (within) regression	P-value	Robust Standard Error
TA	0.8327644	0.000***	0.0276766
Standard Error	0.0152172		
ROA	0.0944011	0.019**	0.0399401
Standard Error	0.0143111		
LIQ	-1.049879	0.000***	0.1074435
Standard Error	0 .0621728		
CAP	-1.003637	0.231	0.8347947

Standard Error	0 .1781264		
ΔGDP	-0.0020702	0.803	0.0083058
Standard Error	0 .008374		
Δ INF	0.0089159	0.791	0.0336248
Standard Error	0 .0319895		
Δ IR	0.0184682	0.817	0.0795965
Standard Error	0 .0831198		
Δ GDP x LIQ	0.0066523	0.518	0.0102651
Standard Error	0 .0067868		
Δ GDP x CAP	-0.0066739	0.848	0.0347033
Standard Error	0 .0195406		
Δ INF x LIQ	-0.0272305	0.349	0.0347033
Standard Error	0 .0279897		
Δ INF x CAP	0.0847229	0.512	0.0289914
Standard Error	0 .0674581		
Δ IR LIQ	0.0362019	0.679	0.1289585
Standard Error	0 .0715775		
Δ IR x CAP	0.1245168	0.527	0.0873792
Standard Error	0.1616176		
Δ GDP x TA	-2.27E-04	0.686	0.1962553
Standard Error	0.0007169		
Δ GDP x ROA	0.0013645	0.355	0.0005596
Standard Error	0.0014035		
Δ INF x TA	0.0010302	0.62	0.0014704
Standard Error	0 .0026983		
ΔINF x ROA	-0.0179056	0.017**	0.0020755
Standard Error	0.0068388		
Δ IR x TA	-0.0047882	0.434	0.0074285
Standard Error	0.0071479		
Δ IR x ROA	0.0246422	0.349	0.0061078
Standard Error	0.00211206		
Constant	1.040717	0.001	0.262581
Standard Error	0 .1687106		
R-sq:	within = 0.8907		
	between = 0.9655		
	overall = 0.9685		
chi2(19) = (b-B)'[(V b-V B)^(- 1)](b-B)	136.44	Hausman test	

Note: This table presents the relationship between variables based on unbalanced panel data. The dependent variable is the amount of the loan; the independent variable is the interest rate (AIR); gross domestic product (AGDP); inflation rate (AINF); capital rati o (CAP); liquidity ratio (LIQ); total assets (size); and return on assets (ROA). Tables shown are the coefficients of the variables, with the symbols ***, **, and * denoting the significance levels at 1%, 5%, and 10%, respectively, while the p-values shown in the parentheses are computed using panel-corrected standard errors. robust to heteroskedasticity and serial correlation. The DW statistic is the Durbin-Watson d test for autocorrelation. The asymptotic test statistic of the groupwise heteroskedasticity test shows Chi-square (n) scores, while the Wooldridge test for serial correlation shows the F statistic.

According to Table 5, a GLS regression with robust standard error correction in China was performed with a fixed effect model, and the p-values that were significant at 1,5 and 10 percent were accepted. The size (independent variable) is statistically significant and positively computed (coefficient = 0.83), with a p-value of 0.000p<0.01. According to the findings, hypothesis H0 is rejected and hypothesis H1 is not rejected. This shows that the variable of size determines the amount of loan in the Chinese economy from 2009 to 2018. Based on the liquidity ratio (an independent variable), it is statistically significant but negatively computed (coefficient = -1.04) with a p-value of 0.000 p < 0.01. According to the findings of this study, H0 is rejected and H1 is not rejected. This shows that the liquidity ratio variable influenced the amount of loan in the Chinese economy from 2009 to 2018. The return on assets (an independent variable) is statistically significant and positively computed (coefficient = 0.094) with a p-value of 0.019 p < 0.05. According to the findings of this study, the hypotheses H0 and H1 are rejected. This indicates that the variable of return on assets influenced the amount of loans in China's economy from 2009 to 2018. The interaction between inflation and return on assets (an independent variable) significantly but negatively affects the amount of loan (a dependent variable) computed (coefficient = 0.018) with a p-value of 0.017. According to the findings of this study, the hypotheses H0 and H1 are rejected. This indicates that the variable of interaction between Δ inflation and return on assets influences the amount of loans in China's economy from 2009 to 2018.

Other main and interaction variables such as ΔGDP, Δinflation rate, Δinterest rate, and interaction ΔGDP and liquidity ratio, interaction Δinflation rate and liquidity ratio, interaction Δinflation and capital ratio, interaction Δinterest rate and liquidity ratio, interaction Δinterest rate and capital ratio, interaction AGDP and size, interaction AGDP and return on assets, interaction Δinterest rate and size, interaction Δinterest rate and return on assets are insignificant. This means that these variables did not influence the amount of loan in China country from 2009 to 2018.

6. CONCLUSION

This work studied the credit channel of the monetary policy transmission mechanism MPTM in developing countries such as China, applying commercial banks from 2009 to 2018. The findings of the study have shown that, according to empirical results, the author of this research has established that in China.

The interaction between interest rate, capital ratio, and loan amount is only significantly and positively correlated in China. The capital ratio, total assets, and return on assets hypotheses all have a statistically significant and positive impact on the loan amount. The robust standard error coefficient was positive, indicating that there was a likely causal link between the variables. Additionally, the size of the loan is statistically significantly negatively affected by the liquidity ratio. The results demonstrate that macroeconomic factors like interest rates, GDP, and inflation have a statistically insignificant positive impact on loan amounts. Consequently, this study revealed sufficient support for the hypothesis that the size of the loan has no significant influence.

According to findings from China's statistics, the capital ratio, GDP, inflation, and ROA interactions have a statistically significant but negative impact on the loan amount. This study revealed sufficient data to disprove the notion that there is a significant and negative interaction between the size of the loan and GDP as well as bank capital. The amount of the loan is statistically influenced positively by the inflation-total-assets interaction hypothesis. According to findings from China's statistics, the capital ratio, GDP, inflation, and ROA interactions have a statistically significant but negative impact on the loan amount. A likely causal association between the components was shown by a robust standard error coefficient that was negative.

REFERENCES

Altunbas, Y., Gambacorta, L., & Marqués-Ibanez, D. (2009). An empirical assessment of the risk-taking channel. Available at SSRN 1459627.

Berkelmans, L., Kelly, G., & Sadeghian, D. (2016). Chinese monetary policy and the banking system. Journal of Asian Economics, 46, 38-55.

Bernanke, B. S., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. Journal of Economic perspectives, 9(4), 27-48.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1996). The flight to quality and the financial accelerator. Review of Economics and Statistics, 78(1), 1-15.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. Handbook of macroeconomics, 1, 1341-1393.

Chen, H., Chen, Q., & Gerlach, S. (2013). The implementation of monetary policy in China: The interbank market and bank lending. In Global banking, financial markets, and crises (pp. 31-69). Emerald Group Publishing Limited.

Chen, H., Chow, K., & Tillmann, P. (2017). The effectiveness of monetary policy in China: Evidence from a Qual VAR. China Economic Review, 43, 216-231.

Chen, K., Higgins, P., Waggoner, D. F., & Zha, T. (2016). China pro-growth monetary policy and its asymmetric transmission (No. 2016-9). Working Paper.

Chen, X. F., & Hu, C. (2011, June). Trade credit, traditional credit, and monetary policy transmissions: Evidence from Chinese firms. In ICSSSM11 (pp. 1-6). IEEE.

Chengping, C., & Xu, Z. (2012). An Empirical Study on the Effect of the Tight Monetary Policy to Control Inflation. Contemporary Economy & Management (2), 17-29.

Chuang, D., & Xu wen, X. (2013). A Study on Time-varying Characteristics of SinoUS Monetary Policy Spillover Effects. Studies of International Finance, 9(2), 45-57.

Ehrmann, M., Gambacorta, L., Martinez-Pagés, J., Sevestre, P., & Worms, A. (2003). The effects of monetary policy in the euro area. Oxford Review of Economic Policy, 19(1), 58-72.

Fan, Y., & Jianzhou, T. (2011). Studying on the monetary transmission mechanism in China in the presence of structural changes. China Finance Review International, 1(4), 334-357.

Fang, X., Liu, H., & Qian, X. (2018). Political incentives and the effectiveness of monetary policy: Evidence from China's city commercial banks. Applied Economics Letters, 25(2), 70-73.

Farajnezhad, M., Suresh, A. L. R., & Ramakrishnan, L. (2019). Effectiveness of credit channel of monetary policy transmission mechanism on commercial banks in Malaysia. International Journal of Recent Technology and Engineering, 8(1), 913-926.

Farajnezhad, M., Idrus, D., & Zadeh, M. S. K. (2022). New evidence on credit channel of monetary policy transmission in India. Future Technology, 1(1), 14-25.

Fernald, J. G., & Jones, C. I. (2014). The future of US economic growth. American Economic Review, 104(5), 44-49.

Fungáčová, Z., Nuutilainen, R., & Weill, L. (2016). Reserve requirements and the bank lending channel in China. Journal of Macroeconomics, 50, 37-50.

Gambacorta, L. (2005). Inside the bank lending channel. European Economic Review, 49(7), 1737-1759.

Geiger, M. (2008). Instruments of monetary policy in China and their effectiveness: 1994-2006.

Gunji, H., & Yuan, Y. (2010). Bank profitability and the bank lending channel: Evidence from China. Journal of Asian Economics, 21(2), 129-141.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing theory and Practice, 19(2), 139-152.

He, D., & Wang, H. (2012). Dual-track interest rates and the conduct of monetary policy in China. China Economic Review, 23(4), 928-947.

He, Q., Leung, P. H., & Chong, T. T. L. (2013). Factor-augmented VAR analysis of the monetary policy in China. China Economic Review, 25, 88-104.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. the Quarterly Journal of Economics, 112(3), 663-691.

Jiang, Q., & Zeng, L.-h. (2008). The Credit Channel of Monetary Policy in China: Theoretical Model and Empirical Analysis [J]. Collected Essays on Finance and Economics, 3, 132-145.

Jiang, Y., Liu, Y., & Zhao, Z. (2005). The empirical analysis of money channel and credit channel. Journal of Financial Research, 5, 234-246.

Jiménez, G., Ongena, S., Peydró, J. L., & Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? Econometrica, 82(2), 463-505.

Juurikkala, T., Karas, A., & Solanko, L. (2011). The role of banks in monetary policy transmission: Empirical evidence from Russia. Review of international economics, 19(1), 109-121.

Kashyap, A. K., & Stein, J. C. (1995, June). The impact of monetary policy on bank balance sheets. In Carnegie-rochester conference series on public policy (Vol. 42, pp. 151-195). North-Holland.

Kashyap, A. K., & Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? American Economic Review, 90(3), 407-428.

Kishan, R. P., & Opiela, T. P. (2000). Bank size, bank capital, and the bank lending channel. Journal of Money, Credit and Banking, 3, 121-141.

Leeper, E. M., & Zhou, X. (2013). Inflation's role in optimal monetary-fiscal policy (No. w19686). National Bureau of Economic Research.

Li, N., & Lee, Y. (2015). The bank-lending channel of monetary policy transmission in China: A comparison between Chinese and foreign banks. Korea and the World economy, 16(2), 167-193.

Li, N., & Lee, Y. (2015). The bank-lending channel of monetary policy transmission in China: A comparison between Chinese and foreign banks. Korea and the World economy, 16(2), 167-193.

Liu, L. G., & Zhang, W. (2010). A New Keynesian model for analysing monetary policy in Mainland China. Journal of Asian Economics, 21(6), 540-551.

Liu, M. H., Margaritis, D., & Tourani-Rad, A. (2009). Monetary policy and interest rate rigidity in China. Applied Financial Economics, 19(8), 647-657.

Liu, Z., Waggoner, D. F., & Zha, T. (2009). Asymmetric expectation effects of regime shift in monetary policy. Review of Economic Dynamics, 12(2), 284-303.

Lombardi, D., Siklos, P. L., & Xie, X. (2018). Monetary policy transmission in systemically important economies and China's i mpact. Journal of Asian Economics, 59, 61-79.

McMahon, M., Peiris, M. U., & Polemarchakis, H. (2018). Perils of unconventional monetary policy. Journal of Economic Dynamics and Control, 93, 92-114.

Mishkin, F. S. (1996). Understanding financial crises: a developing country perspective. National Bureau of Economic Research.

Mishkin, F. S. (2006). Monetary policy strategy: how did we get here? National Bureau of Economic Research.

Nagai, S., & Wang, H. (2007). Money Market Operations in China: Monetary Policy or FX Policy? (No. 07-E-13). Bank of Japan.

Nguyen, V. H. T., & Boateng, A. (2013). The impact of excess reserves beyond precautionary levels on bank lending channels in China. Journal of International Financial Markets, Institutions and Money, 26, 358-377.

Pan, L., & Tao, X. (2006). The monetary policy transmission in China:" Credit channel" and its limitations (No. 22). Working Paper.

Ping, X. (2004). China's monetary policy: 1998-2002. Stanford Center for International Development Working Paper, (No.217).

Poon, C. C., & Wong, F. K. (2011). China's monetary policy and its transmission mechanisms before and after the financial tsunami. Chinese economy, 44(3), 84-108.

Porter, N., & Xu, T. (2009). What drives China's interbank market? International Monetary Fund.

Qin, D., Quising, P., He, X., & Liu, S. (2005). Modeling monetary transmission and policy in China. Journal of Policy Modeling, 27(2), 157-175.

Rudebusch, G. D., & Wu, T. (2008). A macro-finance model of the term structure, monetary policy, and the economy. The Economic Journal, 118(530), 906-926.

Shaoping, W., Manzhou, Z., & Shuoshang, H. (2012). Macroeconomic Component and Macroeconomic Shocks of China's CPI Index [J]. Economic Research Journal, 12, 251-268.

Songcheng, S. H. E. N. G., & Peixin, W. U. (2009). The binary transmission mechanism of China's monetary policy—A research on the "two intermediaries, two targets" model. Frontiers of Economics in China, 4(3), 335-360.

Singh, S., Razi, A., Endut, N., & Ramlee, H. (2008). Impact of financial market developments on the monetary transmission mec hanism. BIS Papers, 39.

Sun, H., & Ma, Y. (2004). Money and price relationship in China. Journal of Chinese Economic and Business Studies, 2(3), 225-247.

Sun, L., Ford, J. L., & Dickinson, D. G. (2010). Bank loans and the effects of monetary policy in China: VAR/VECM approach. China Economic Review, 21(1), 65-97.

Sun, S., Gan, C., & Hu, B. (2010). Bank lending channel in China's monetary policy transmission mechanism: a VECM approach. Investment management and financial innovations, 7(2), 59-71.

Tsang, T. H. (2011). Monetary policy in China: autonomy, transmission mechanisms and its evaluation (Doctoral dissertation).

Wang, Z. S., & Wang, Z. Q. (2000). An empirical investigation of the channels of monetary transmission. Research on Financial and Economic Issues, 5, 19-22.

Xia, B., & Liao, Q. (2001). Money supply is no longer suitable to serve as intermediary target of China's current monetary policy. Journal of Economic Research, 8, 33-43.

Yang, J., & Shao, H. (2016). Impact of bank competition on the bank lending channel of monetary transmission: Evidence from China. International Review of Economics & Finance, 43, 468-481.

Yang, J., & Shao, H. (2016). Impact of bank competition on the bank lending channel of monetary transmission: Evidence from China. International Review of Economics & Finance, 43, 468-481.

Yao, S., Luo, D., & Loh, L. (2013). On China's monetary policy and asset prices. Applied Financial Economics, 23(5), 377-392.

Yue, Y.-D., & Zhou, S.-H. (2007). Empirical analysis of the monetary policy transmission through interest rate channel in China. Chinese Business Review, 6(3), 8-12.

Zhang, C., & Clovis, J. (2009). Modeling US inflation dynamics: persistence and monetary policy regimes. Empirical Economics, 36, 455-477.

Zhang, J. Q., Chen, T., Fan, F., & Wang, S. (2018). Empirical research on time-varying characteristics and efficiency of the Chinese economy and monetary policy: Evidence from the MI-TVP-VAR model. Applied Economics, 50(33), 3596-3613.

Zhaohui, S. (2006). On the effect of the transmission mechanism of monetary policy in China. Journal of Financial Research, 7 (3), 112-123.

Zhensheng, Z. Y. J. (2002). Monetary channel, credit channel and the effectiveness of monetary policy. Journal of Finance, 9(3), 99-112.