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# The differential long-term and short-term impacts of risk factors on stock returns of financial holdings and traditional banks

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## ABSTRACT

This study investigates the differential short-term and long-term impacts of macroeconomic risk factors, specifically interest rate, exchange rate, and credit risk, on the stock returns of financial holding companies and traditional banks in Taiwan. Utilizing a Transfer Function-Noise (TFN) model and numerical analysis methods, we analyze monthly data from 2000 to 2023. To address the challenge of directly testing long-term effects involving ratio distributions, this study proposes a novel bootstrapping procedure to re-generate the multivariate probability distribution of polynomial ratios, enabling statistical testing of long-term coefficients. Outlier detection techniques are employed to mitigate bias. Our findings reveal significant heterogeneity in short-term responses to these risk factors across institutions, with financial holdings exhibiting greater sensitivity. Long-term effects, however, show convergence, suggesting similar risk management strategies over time. These insights have important implications for investment strategies, risk management practices, and financial policy formulation.

**Keywords:**

Risk factor, Financial holdings, Bank, Transfer function-noise model, Bootstrap simulation, Numerical analytics.

# 1 | Introduction

## 1.1 Research background

The intricate relationship between macroeconomic factors and financial markets has long been a central focus of financial economics research. This field’s evolution reflects advancements in theoretical foundations, methodological innovations, and significant shifts in the global economic landscape. The Efficient Market Hypothesis (EMH), proposed by Fama (1970), initially dominated financial theory, positing that security prices rapidly and fully reflect all available information. However, subsequent empirical anomalies and theoretical challenges necessitated a reevaluation of market dynamics’ complexity.

Kahneman and Tversky’s (1979) Prospect Theory revealed investors' irrational behavior, challenging the EMH’s assumption of rational investment. Notably, Grossman and Stiglitz (1980) introduced the “efficiency market paradox,” questioning the feasibility of perfectly efficient markets and catalyzing further exploration into factors influencing stock market returns. These theoretical debates spurred the emergence of behavioral finance, with De Bondt and Thaler’s (1985) seminal work on stock market overreaction serving as a critical catalyst.

Building on these developments, Lo (2004) proposed the Adaptive Markets Hypothesis (AMH), offering a framework that bridges the gap between the EMH and behavioral finance. The AMH suggests that market efficiency is a dynamic process shaped by environmental factors and competitive forces, with market participants adapting their strategies over time in response to changing economic conditions. This perspective provides valuable insights for studies on the differential impacts of macroeconomic factors on financial institutions, particularly in understanding how different types of financial institutions evolve their risk management strategies.

Concurrent with theoretical advancements, empirical methodologies have undergone substantial refinement. Time series analysis techniques, such as the ARCH model introduced by Engle (1982) and the GARCH model proposed by Bollerslev (1986), have significantly enhanced our capacity to model volatility clustering and time-varying risk premiums. The advent of cointegration analysis, pioneered by Engle and Granger (1987), has enabled researchers to explore long-term equilibrium relationships between financial variables and macroeconomic factors.

Of particular relevance to our study is the Transfer Function-Noise (TFN) model, rooted in the work of Box and Jenkins (1970). This model represents a significant advancement in time series analysis, enabling the decomposition of both short-term and long-term effects of multiple input variables on an output variable while accounting for the inherent characteristics of financial time series data. The TFN model’s ability to analyze the dynamic relationships between input series (such as macroeconomic factors) and output series (like stock returns) while accounting for noise components offers a more comprehensive approach to financial time series analysis.

## 1.2 Research motivation

Recent years have witnessed unprecedented changes in the global economic landscape. The COVID-19 pandemic and escalating geopolitical tensions have led to increased market volatility and uncertainty, underscoring the importance of understanding how macroeconomic factors, such as interest rates and exchange rates, impact financial markets and institutions. This evolving context presents both challenges and opportunities for financial economics research.

Within this background, Taiwan's financial sector offers a unique and compelling case study. As a highly open economy deeply integrated into global supply chains, Taiwan possesses a distinctive industrial structure dominated by high-tech manufacturing, particularly the semiconductor industry. This economic configuration renders Taiwan especially sensitive to global macroeconomic fluctuations, providing an ideal environment for studying the transmission of macroeconomic shocks to financial markets.

The evolutionary trajectory of Taiwan's financial sector is equally noteworthy. Following significant financial liberalization, overbanking led to the promulgation of the Financial Holding Company Act in 2001. This legislation aimed to promote industry consolidation and enhance operational efficiency. Taiwan has developed a unique competitive ecosystem where financial holding companies (integrating banking, insurance, and securities operations) coexist with traditional banks. This structure provides a rich comparative basis for examining how different types of financial institutions respond to macroeconomic factors.

Seminal empirical investigations have systematically elucidated the structural implications of this institutional reconfiguration. Kuo and Lu (2005) employed a two-state Markov regime-switching model to analyze the stock performance of 13 Taiwanese financial holding companies from 2001 to 2003. Their findings revealed that 12 out of 13 financial holding companies exhibited regime-switching behavior. Post-establishment, these entities demonstrated a significant reduction in risk without concomitant changes in returns, suggesting the realization of diversification benefits inherent to the financial holding company structure.

Wu (2015) utilized a methodological approach combining Data Envelopment Analysis (DEA) and the Malmquist index to evaluate the performance of Taiwanese FHC banks from 1996 to 2013. The study's results indicate that while certain Taiwanese banks that transformed into FHCs experienced improvements in scale efficiency, there were no significant enhancements in technological progress or pure efficiency, particularly in terms of non-performing loan ratios.

In recent research, Cheng and Chen's (2020) research additionally revealed the accelerated financial cycle dynamics characteristic of Taiwan's emerging market ecosystem. Huang's (2020) research highlighted Taiwan's unique economic and financial environment, characterized by its export-oriented structure and individual investor-dominated stock market.

These studies collectively demonstrate that while banks under financial holding companies exhibit distinct operational advantages following the integration of banking, insurance, and securities services, traditional banks continue to coexist within the market. This phenomenon underscores the unique competitive ecosystem within Taiwan's financial industry. The persistence of this coexistence raises intriguing questions regarding the differential risk-bearing capacities of these two institutional types. Moreover, it provides a rich comparative framework for investigating the varied responses of different financial institutions to macroeconomic factors.

Moreover, the specific operational risk profile faced by Taiwanese financial institutions, particularly stemming from the concentration in high-tech manufacturing, necessitates close monitoring of the correlation between real economy credit risks and financial sector performance. This characteristic makes Taiwan an excellent case for investigating the complex relationships between industrial structure, macroeconomic factors, and financial institution performance.

The combination of Taiwan's unique economic structure, its financial sector's evolution, and the global economic uncertainties provide a compelling motivation for this research. By focusing on Taiwan, we can gain insights into how macroeconomic factors impact financial institutions in a highly open, technology-driven economy, which can offer valuable lessons for other emerging markets and developed economies alike.

### 1.3 Research objectives

This study aims to explore the long-term and short-term effects of macroeconomic risk factors on the stock returns of Taiwanese financial holding companies and traditional banks. To achieve this, we employ the Transfer Function-Noise Model and numerical analysis methods. Our research objectives are as follows:

- To accurately assess the magnitude and timing of macroeconomic variables' impact on stock returns using the TFN model and numerical analysis methods, leveraging the model's ability to decompose short-term and long-term effects.
- To develop a model capable of predicting stock return relationships under various scenarios (interest rates, exchange rates, and credit risk), utilizing the TFN model's capacity to handle multiple input variables.
- To compare the differential impacts of these macroeconomic factors on financial institutions with different compositions, deepening our understanding of their influence mechanisms through the TFN model's comprehensive approach.
- To evaluate the resilience of the financial sector in the face of interest rate, exchange rate, and credit risk shocks, providing valuable information for financial regulation and policy-making.

By addressing these objectives using the TFN model, this study aims to contribute to the ongoing dialogue in financial economics, offering insights into the dynamic relationship between macroeconomic factors and financial markets in the context of Taiwan's unique economic and financial landscape. The findings of this research have potential implications for investment strategies, risk management practices, and financial policy formulation, not only in Taiwan but also in other emerging markets with similar characteristics.

## 2 | Literature review

This study aims to investigate the differential impacts of macroeconomic risk factors, primarily interest rate, exchange rate, and credit risk, on the stock returns of financial holding companies and traditional banks in Taiwan, distinguishing between long-term and short-term effects. By employing a Transfer Function-Noise Model and numerical analysis methods, this study attempts to uncover potential disparities in how these risk factors influence stock returns across different time horizons. Table 1 provides a classification of prior research based on the specific risk factors analyzed, the time horizon considered, and the methodologies employed, offering a structured overview of the existing literature relevant to this study. This literature review provides a comprehensive overview of existing research on the relationship between risk factors and stock returns, focusing on specific areas pertinent to this study.

Table 1 Classification of research in financial economics: risk factors, time horizons, and methodologies

| Authors | Year | Risk factors | | | Time horizon | | Methodology |
|---|---|---|---|---|---|---|---|
| | | Interest rate | Exchange rate | Credit risk | Long-term | Short-term | |
| Sharpe | 1964 | | | | ✓ | | Capital asset pricing model |
| Fama | 1970 | | | | ✓ | | EMH (theory & empirical work) |
| Box and Jenkins | 1970 | | | | ✓ | ✓ | Time series analysis |
| Merton | 1973 | | | | ✓ | ✓ | Intertemporal CAPM |
| Ross | 1976 | | | | | | Arbitrage pricing theory |
| Jensen | 1978 | | | | | ✓ | Systematic review |
| Kahneman and Tversky | 1979 | | | | | ✓ | Prospect theory (experimental studies) |
| Efron | 1979 | | | | | | Bootstrap method |
| Grossman and Stiglitz | 1980 | | | | | | Noisy rational expectations model |
| Shiller | 1981 | | | | ✓ | | Empirical test (simple efficient markets mode) |
| Engle | 1982 | | | | | ✓ | ARCH model |
| Liu and Hanssens | 1982 | | | | | | Transfer function models |
| Bower *et al.* | 1984 | ✓ | | | ✓ | ✓ | Arbitrage pricing theory and CAPM |

Table 1 Classification of research in financial economics: risk factors, time horizons, and methodologies (continued)

| **Authors** | **Year** | **Risk factors** | | | **Time horizon** | | **Methodology** |
|---|---|---|---|---|---|---|---|
| | | **Interest rate** | **Exchange rate** | **Credit risk** | **Long-term** | **Short-term** | |
| De Bondt and Thaler | 1985 | | | | | ✓ | Empirical tests use a behavioral principle |
| Tsay | 1985 | | | | ✓ | ✓ | Dynamic regression models |
| Bollerslev | 1986 | | | | | ✓ | GARCH model |
| Tsay | 1986 | | | | ✓ | ✓ | ARMA model and ESACF model |
| Engle and Granger | 1987 | | | | ✓ | ✓ | Cointegration analysis (VAR & ECM) |
| Hamilton | 1989 | | | | ✓ | ✓ | Markov-switching model |
| Choi *et al.* | 1992 | ✓ | ✓ | | ✓ | ✓ | Multi-factor model (multivariate regression) |
| Brock *et al.* | 1992 | | | | ✓ | ✓ | Technical trading rules and time-series models |
| Ding *et al.* | 1993 | | | | ✓ | ✓ | Asymmetric power ARCH model |
| Jegadeesh and Titman | 1993 | | | | | ✓ | Event study and regression models |
| Efron and Tibshirani | 1993 | | | | | | Bootstrap methods |
| Politis and Romano | 1994 | | | | | | Stationary bootstrap |
| Dumas and Solnik | 1995 | | ✓ | | ✓ | ✓ | International classic APM |

Table 1 Classification of research in financial economics: risk factors, time horizons, and methodologies (continued)

| Authors | Year | Risk factors | | | Time horizon | | Methodology |
|---|---|---|---|---|---|---|---|
| | | **Interest rate** | **Exchange rate** | **Credit risk** | **Long-term** | **Short-term** | |
| Cornell | 1999 | ✓ | | | ✓ | | Duration-based analysis |
| Sullivan *et al.* | 1999 | | | | ✓ | ✓ | Data-snooping tests |
| Shleifer | 2000 | | | | ✓ | ✓ | Behavioral finance （empirical evidence） |
| White | 2000 | | | | | | Reality check for data snooping (bootstrap) |
| Lo | 2004 | | | | ✓ | ✓ | Adaptive market hypothesis |
| Hansen | 2005 | | | | | | Superior predictive ability test |
| Rajan | 2006 | ✓ | ✓ | ✓ | ✓ | | Literature review and case study approach |
| Kosowski *et al.* | 2006 | | | | | ✓ | Bootstrap analysis of fund performance |
| Lin *et al.* | 2007 | | ✓ | | | ✓ | GARCH(1,1) |
| Viale *et al.* | 2009 | ✓ | | | ✓ | ✓ | Muti-factor ICAPM |
| Barras *et al.* | 2010 | | | | ✓ | ✓ | False discovery (bootstrap) |
| Appiah and Adetunde | 2011 | | ✓ | | | ✓ | ARIMA model (box & jenkins method) |
| Bali *et al.* | 2014 | ✓ | ✓ | ✓ | ✓ | ✓ | Conditional asset pricing model |

Table 1 Classification of research in financial economics: risk factors, time horizons, and methodologies (continued)

| Authors | Year | Risk factors | | | Time horizon | | Methodology |
|---|---|---|---|---|---|---|---|
| | | **Interest rate** | **Exchange rate** | **Credit risk** | **Long-term** | **Short-term** | |
| Olugbode *et al.* | 2014 | ✓ | ✓ | | ✓ | ✓ | AR(1)-EGARCH-M approach |
| Fama and French | 2015 | ✓ | | | ✓ | | Five-factor asset pricing model |
| Harvey and Liu | 2015 | | | | | | Backtesting methodologies (bootstrap) |
| Boons and Tamoni | 2015 | ✓ | | | ✓ | ✓ | Cross-sectional regressions |
| Al Oshaibat and Majali | 2016 | ✓ | | | ✓ | ✓ | VAR model |
| Iwok | 2016 | | ✓ | | ✓ | ✓ | Transfer function-autoregressive model |
| Mergaerts *et al.* | 2016 | ✓ | | ✓ | ✓ | | Mundlak estimator, and factor analysis |
| Novy-Marx and Velikov | 2016 | | | | ✓ | ✓ | Anomalies and trading costs model |
| Verma | 2016 | ✓ | ✓ | | ✓ | ✓ | Multivariate EGARCH model |
| Çelik | 2019 | ✓ | ✓ | ✓ | | ✓ | EGARCH-M model |
| Feng *et al.* | 2020 | | | | ✓ | | Testing new factors: least absolute shrinkage and selection operator (LASSO) |

Table 1 Classification of research in financial economics: risk factors, time horizons, and methodologies (continued)

| Authors | Year | Risk factors | | | Time horizon | | Methodology |
|---|---|---|---|---|---|---|---|
| | | Interest rate | Exchange rate | Credit risk | Long-term | Short-term | |
| Hou *et al.* | 2020 | | | | ✓ | ✓ | Replicating anomalies (various portfolio sorting methods & cross-sectional regression models) |
| Huy *et al.* | 2020 | ✓ | ✓ | | | ✓ | Multiple linear regression model |
| Victor-Edema and Essi | 2020 | | ✓ | | ✓ | ✓ | Transfer function modeling |
| Wang *et al.* | 2020 | | | | ✓ | ✓ | GARCH-MIDAS model |
| Bianchi *et al.* | 2021 | ✓ | | ✓ | ✓ | | Machine learning in bond risk premia |
| Jabeen *et al.* | 2022 | ✓ | ✓ | | ✓ | ✓ | Cross-sectional AbSolute Deviation model (CASD) |
| Srivastava *et al.* | 2022 | ✓ | ✓ | | ✓ | ✓ | Variance decomposition model |
| Danila | 2023 | ✓ | | | ✓ | ✓ | GARCH-MIDAS model |
| Joseph *et al.* | 2024 | ✓ | ✓ | ✓ | ✓ | ✓ | Systematic review |

*Note:* This table presents a comprehensive overview of the literature on risk factors and stock returns. The "risk factors" columns indicate which specific risks (interest rate, exchange rate, credit risk) are addressed in each study. The "time horizon" columns show whether the research focuses on long-term or short-term effects. The "methodology" column briefly describes the primary analytical approach used in each study.

## 2.1 Risk factors and stock returns

A vast body of literature has examined the influence of various risk factors on stock returns. This section categorizes and reviews prior studies based on the specific risk factors analyzed.

### 2.1.1 Interest rate risk

The sensitivity of bank stock returns to interest rate fluctuations has been a focal point of numerous studies. Sharpe (1964), in his seminal work on the Capital Asset Pricing Model (CAPM), laid the groundwork for understanding the relationship between risk and return. Building upon this foundation, Merton (1973) developed an intertemporal CAPM that explicitly incorporated interest rate risk, demonstrating its relevance in asset pricing. Bower *et al.* (1984) specifically investigated the impact of interest rate risk on utility stock returns, employing arbitrage pricing theory to disentangle the effects of various risk factors. Their findings highlighted the significant impact of interest rate volatility on the performance of utility stocks, which are particularly sensitive to interest rate changes due to their regulated nature and reliance on debt financing.

Further exploring this relationship, Choi *et al.* (1992) examined the sensitivity of bank stock returns to market risk, interest rate risk, and exchange rate risk. Their study, utilizing a multivariate regression framework, found that interest rate risk exhibited a statistically significant negative impact on bank stock returns. This finding underscores the vulnerability of banks to interest rate movements, as their profitability is inherently linked to the spread between lending and deposit rates. Elyasiani and Mansur (1998) delved into the sensitivity of the bank stock return distribution to changes in the level and volatility of interest rates using a GARCH-M model. Their analysis revealed that both the level and volatility of interest rates significantly influence the conditional volatility of bank stock returns, indicating that periods of heightened interest rate uncertainty can amplify risk and impact bank performance.

More recently, Verma (2016) provided evidence from U.S. banks, emphasizing the significant impact of interest rates on bank stock returns. This study, employing a panel data regression approach, confirmed the inverse relationship between interest rates and bank stock returns, reinforcing the notion that rising interest rates can compress net interest margins and adversely affect bank profitability.

Danila (2023) applied the GARCH-MIDAS model to capture both short-term and long-term components of volatility to examine the impact of macroeconomic variables on the volatility of the Indonesian Islamic stock market. This study found that after the 2008 crisis, both inflation and short-term interest rates positively impacted the long-term volatility of the Indonesian Islamic stock market. It is contrary to existing theory. Shehab (2023) used the AutoRegressive Distributed Lag (ARDL) model to analyze the relationship between macroeconomic variables and stock market returns in Oman. This study found the positive short-term effect of interest rates; its positive effect may be because Oman depends widely on Islamic banking.

### 2.1.2 Exchange rate risk

The impact of exchange rate fluctuations on stock returns, particularly in the context of globalized markets, has garnered considerable attention. Dumas and Solnik (1995) investigated the world price of foreign exchange risk, providing insights into the pricing of exchange rate risk in international asset markets. Their study highlighted the importance of considering exchange rate volatility when evaluating the risk and return characteristics of international investments. Lin, *et al.* (2007) examined the relationship between exchange rate exposure, strategic resources, and firm value in Taiwan's stock market. Their findings suggested that firms with higher levels of strategic resources, such as technological capabilities and brand equity, are better positioned to manage exchange rate risk and mitigate its negative impact on firm value.

Focusing on specific methodologies, Appiah and Adetunde (2011) utilized time series analysis to forecast the exchange rate between the Ghana Cedi and the US dollar, demonstrating the applicability of such methods in assessing exchange rate risk. Their study highlighted the importance of accurate exchange rate forecasting for businesses engaged in international trade and investment, as exchange rate volatility can significantly impact profitability. Olugbode and Pointon (2014) analyzed the exchange rate and interest rate exposure of UK industries using an AR(1)-EGARCH-M approach. This sophisticated econometric technique allowed them to capture the time-varying nature of risk exposures and their impact on industry returns. Their findings revealed significant heterogeneity in exchange rate and interest rate exposures across industries, underscoring the importance of industry-specific factors in shaping risk profiles.

Coronado *et al.* (2020) use the DCC-MGARCH framework to analyze time-varying causality between the dollar-pound exchange rate and S&P 500 returns. The study finds stronger evidence of instantaneous spillovers between the US dollar-pound exchange rate and the S&P 500 stock returns, suggesting both the possibility of nonsynchronous trading and high-frequency causal relationships, compared to unidirectional return causality which is primarily restricted to the post-1975 period.

### 2.1.3 Credit risk

While the impact of credit risk on stock returns has not been as extensively studied as interest rate and exchange rate risks, its importance has been increasingly recognized. Rajan (2006), in his influential work on the role of finance in amplifying global risk, implicitly acknowledged the significance of credit risk. He argued that the increasing complexity and interconnectedness of financial markets have heightened the potential for credit shocks to propagate rapidly and destabilize the global financial system. Viale *et al.* (2009) identified common risk factors in bank stocks, including credit risk, highlighting its relevance in assessing bank performance. Their study, employing a principal component analysis, found that credit risk represents a significant source of systematic risk for banks, as their lending activities expose them to the creditworthiness of borrowers.

### 2.1.4 Multiple risk factors

Recognizing the interconnected nature of financial markets, several studies have investigated the combined impact of multiple risk factors on stock returns. Al Oshaibat and Majali (2016) examined the relationship between stock returns and inflation, interest rates, share liquidity, and remittances of workers in the Amman Stock Exchange. Their study, using a multiple regression model, found that interest rates and inflation exerted significant negative effects on stock returns, while remittances had a positive impact. This highlights the complex interplay of macroeconomic factors in driving stock market movements. Çelik (2019) assessed the impact of bank risk factors, including interest rate and exchange rate risk, on Turkish bank stock returns using the EGARCH-M model. Their findings indicated that both interest rate and exchange rate volatility significantly influence bank stock return volatility, emphasizing the importance of managing these risks effectively.

In recent research, Chellaswamy *et al.* (2020) employed Quantile Regression (QR) approach to examine the relationship between macroeconomic factors and stock market returns. They found that interest rates have no significant impact on stock returns in China and India. They also found that the Chinese exchange rate influences the SSE returns at the extreme dataset, but the Indian exchange rate is insignificant.

Srivastava *et al.* (2022) applied Variance Decomposition Model to examine the exogenous shocks in macroeconomic variables respond to changes in stock prices. They found the exogenous shocks in exchange rates, trade openness, inflation, and interest rates significantly impact stock prices.

Jabeen *et al.* (2022) employed the Cross-Sectional Absolute Deviation (CSAD) model to empirically assess the impact of herding behavior on stock returns across distinct sectors of the Pakistan Stock Exchange. The study found evidence of both positive and negative herding effects. Additionally, the analysis revealed that macroeconomic factors such as exchange rates, interest rates, and inflation rates also played a significant role in influencing stock market dynamics.

Joseph *et al.* (2024) conducted a comprehensive review that systematically analyzed the impact of macroeconomic factors, including interest rate, exchange rate, and credit risk, on bank stock returns. Their review emphasized the complex interplay of these factors in driving stock market movements and highlighted the need for a holistic approach to risk management in the banking sector.

These studies highlight the complex interplay between macroeconomic indicators, fundamental variables, and stock market performance, emphasizing the importance of considering multiple factors when analyzing stock price movements.

## 2.2 Long-term vs. short-term impacts of risk factors

Understanding the temporal dimension of risk factor influences is crucial for investors and policymakers. This section delves into studies that have distinguished between long-term and short-term impacts.

### 2.2.1 Long-term impacts

Several studies have focused on the long-term impacts of risk factors on stock returns. Fama (1970), in his seminal review of efficient capital markets, laid the foundation for understanding long-term market behavior. He argued that in an efficient market, stock prices reflect all available information, and it is impossible to consistently achieve risk-adjusted returns above the market average over the long run. Cornell (1999) examined the long-term impacts of risk and duration on capital budgeting decisions. His study highlighted the importance of considering the long-term risk profile of projects when making investment decisions, as short-term fluctuations may not accurately reflect the true riskiness of an investment.

### 2.2.2 Short-term impacts

The short-term dynamics of risk factor influences have also been a subject of research. De Bondt and Thaler (1985) explored the concept of stock market overreaction, highlighting the potential for short-term deviations from fundamental values. They argued that investors often overreact to news and events, leading to price movements that are not justified by underlying fundamentals. Jegadeesh and Titman (1993) investigated the short-term profitability of momentum strategies, suggesting the presence of short-term market inefficiencies. Their study found that stocks that have performed well in the recent past tend to continue to outperform, while stocks that have performed poorly tend to continue to underperform, indicating that momentum strategies can generate abnormal returns over short horizons.

### 2.2.3 Long-term and short-term impacts

Recognizing the importance of both long-term and short-term perspectives, some studies have explored the dynamic interplay of risk factors across different time horizons. Ding *et al.* (1993) proposed a long-memory model of stock returns that captures both short-term fluctuations and long-term dependencies. Their model, known as the Fractional Integrated GARCH (FIGARCH) model, allows for the persistence of shocks to volatility, implying that volatility clustering can persist for extended periods. Wang *et al.* (2020) investigated the short-term and long-term effects of extreme shocks on stock volatility, emphasizing the need for a comprehensive understanding of how risk factors impact across different timescales. Their study, employing a Markov-switching GARCH model, found that extreme shocks have both immediate and persistent effects on stock market volatility, highlighting the importance of considering both short-term and long-term implications of risk events.

## 2.3 Evolution of research methods

The evolution of econometric and statistical methods has significantly enhanced our ability to analyze the complex relationship between risk factors and stock returns. This section reviews the progression of research methods employed in this field.

### 2.3.1 Evolution of econometric models

Early studies relied on traditional econometric models, such as those proposed by Box and Jenkins (1970) for time series analysis. Their work provided a framework for modeling and forecasting time series data, laying the groundwork for more sophisticated econometric techniques. The development of the AutoRegressive Conditional Heteroskedasticity (ARCH) model by Engle (1982) and its generalization, the Generalized ARCH (GARCH) model, by Bollerslev (1986), revolutionized the modeling of volatility clustering in financial time series. These models allowed researchers to capture the time-varying nature of volatility and its dependence on past shocks, providing a more realistic representation of financial market dynamics.

Further advancements included the cointegration and error correction model proposed by Engle and Granger (1987) and the economic analysis of nonstationary time series by Hamilton (1989). These developments provided sophisticated tools for analyzing long-run relationships and dynamic adjustments in financial markets, allowing researchers to disentangle short-term fluctuations from long-term trends.

### 2.3.2 Transfer function models

Transfer function models, as discussed by Liu and Hanssens (1982) and Tsay (1985), provide a robust framework for analyzing the dynamic relationship between input variables, such as macroeconomic factors, and output variables, such as stock returns. These models allow researchers to estimate the impulse response function, which describes the dynamic response of the output variable to a shock in the input variable, providing insights into the lead-lag relationships between variables. Iwok (2016) employed a Transfer Function-Autoregressive Noise Model to analyze the relationship between Nigeria’s current account balance and exchange rates, demonstrating the applicability of this method in examining macroeconomic linkages. Victor-Edema and Essi (2020) further utilized transfer function models to investigate the relationship between Nigeria’s current account and exchange rate, highlighting the effectiveness of this approach in capturing dynamic interactions.

### 2.3.3 Bootstrap methods

Bootstrap methods, introduced by Efron (1979), have gained increasing prominence in financial econometrics due to their ability to provide robust statistical inference, particularly in situations where traditional assumptions may not hold. These resampling techniques involve repeatedly drawing samples from the original data to approximate the sampling distribution of a statistic of interest, allowing researchers to construct confidence intervals and perform hypothesis tests without relying on parametric assumptions. Efron and Tibshirani (1993) provided a comprehensive introduction to bootstrap methods, while Politis and Romano (1994) introduced the stationary bootstrap for analyzing time series data.

The applications of bootstrap methods in finance are diverse. Brock *et al.* (1992) used bootstrap techniques to analyze the performance of technical trading rules, providing insights into the robustness of these rules in generating excess returns. Sullivan *et al.* (1999) employed bootstrap methods to assess the robustness of technical trading rule performance, highlighting the importance of controlling for data snooping bias. Kosowski *et al.* (2006) used bootstrap analysis to investigate the stock-picking ability of mutual fund “stars,” finding little evidence to support the notion that past performance is indicative of future performance.

As emphasized by White (2000), the use of bootstrap methods extends to controlling for data snooping bias, which arises from the repeated use of the same data to search for statistically significant relationships. Barras *et al.* (2010) utilized bootstrap techniques to measure luck in estimated alphas of mutual funds, providing a more accurate assessment of fund manager skill. Harvey and Liu (2015) discussed the application of bootstrap methods in backtesting financial models, emphasizing their importance in evaluating model performance and mitigating the risk of overfitting.

### 2.3.4 Other numerical methods

In addition to traditional econometric models and bootstrap methods, other numerical techniques have been employed to analyze the relationship between risk factors and stock returns. Bali *et al.* (2014) investigated the impact of macroeconomic risk on hedge fund returns, while Fama and French (2015) proposed a five-factor asset pricing model that has become a cornerstone of empirical asset pricing.

Boons and Tamoni (2017) examined horizon-specific macroeconomic risks and their impact on expected returns, highlighting the importance of considering the investment horizon when assessing the risk-return trade-off. Novy-Marx and Velikov (2016) provided a taxonomy of anomalies and their trading costs, shedding light on the persistence and profitability of market anomalies. Feng, *et al.* (2020) tested new factors in asset pricing models, contributing to the ongoing debate on the determinants of asset returns. Hou *et al.* (2020) focused on replicating anomalies in financial markets, providing insights into the robustness and economic significance of these anomalies. Bianchi *et al.* (2021) utilized machine learning techniques to analyze bond risk premiums, demonstrating the potential of these advanced techniques in financial modeling.

This literature review has provided a comprehensive overview of existing research on the relationship between risk factors and stock returns, focusing on interest rate risk, exchange rate risk, credit risk, and the combined impact of multiple factors. The review has also highlighted the importance of distinguishing between long-term and short-term impacts of risk factors and has traced the evolution of research methods employed in this field, from traditional econometric models to advanced techniques like transfer function models and bootstrap methods.

This review establishes the methodological foundation for subsequent analytical components of the research. Given the inherent non-linearity of financial market dynamics, conventional linear modeling approaches may insufficiently capture the complexity and stochastic nature of market behavior under uncertain conditions. Specifically, the research aims to empirically examine the dynamic inter-relationship between stock price returns and long-term aggregate economic risk factors.

The econometric challenges arise from the simultaneous variation of numerator and denominator components, which renders the ratio’s probability distribution indeterminate. Consequently, traditional parametric statistical methodologies are analytically unsuitable due to violated distributional assumptions. To address this methodological constraint, we propose an innovative Bootstrap resampling procedure for regenerating the multivariate allocation of polynomial ratios, enabling rigorous statistical inference on long-term coefficient estimations.

The subsequent methodological exposition will provide a comprehensive analytical framework, detailing the advanced statistical techniques and data analysis methodologies employed to investigate the differential short- and long-term impacts of aggregate economic risk factors on stock returns within Taiwanese financial holding companies and traditional banking institutions.

## 3 | Data and methodology

This study will employ a comprehensive and sophisticated methodological approach to investigate the differential long-term and short-term impacts of risk factors on stock returns of financial holding companies and traditional banks in Taiwan. The methodology is designed to address the complex nature of financial time series data and to capture the nuanced relationships between macroeconomic variables and stock returns.

### 3.1 Data sources

The data for this study comes from the Taiwan Economic Journal (TEJ) database, and a total of 15 financial holding companies and 10 traditional banks listed on the TaiWan Stock Exchange (TWSE) or TaiPei Exchange (TPEx) were selected. Monthly stock returns (RET), adjusted for dividend payments over the periods from Jan. 2000 to Dec. 2023, were collected. A total of 288 months are sampled. The monthly secondary 30-day Commercial Paper (CP) is a proxy for the interest rate. The monthly average of the US dollar to the New Taiwan Dollar (NTD) is adopted as the foreign exchange rate (EX).

In constructing credit risk factor variables, we acknowledge the theoretical premise that higher industry profitability correlates positively with sector index stock returns, consequently implying an inverse relationship with bank credit risk exposure (ÇELİK, 2019). Considering the electronic sector's significant market capitalization on the Taiwan Stock Exchange, which has consistently maintained over 50% of the total market value since 2000 (as depicted in Table 2), with three years in the past five exceeding 60%, coupled with the Information and Communication Technology (ICT) industry's robust performance driven by global digitalization trends, the sector has demonstrated sustained investment in high value-added products, achieving actual year-on-year growth rates surpassing overall economic expansion and maintaining positive contributions throughout the past decade, the utilization of the TWSE Electronic index (INDR) monthly Returns as a proxy for credit risk factors appears methodologically sound and empirically justified.

Table 2 The percentage of TWSE electronics index vs. TAIEX

| **End of year** | **Market value (M)** | **MV to TAIEX (%)** | **Percentage to trading volume (%)** |
|---|---|---|---|
| 2000/12/30 | 4,515,480 | 55.32 | 59.10 |
| 2001/12/31 | 6,656,108 | 65.23 | 86.50 |
| 2002/12/31 | 4,728,439 | 53.02 | 48.73 |
| 2003/12/31 | 6,721,317 | 54.20 | 49.92 |
| 2004/12/31 | 6,645,705 | 47.88 | 36.26 |
| 2005/12/30 | 8,937,339 | 57.42 | 79.80 |
| 2006/12/29 | 10,887,947 | 56.10 | 64.25 |
| 2007/12/31 | 11,031,043 | 53.51 | 69.26 |
| 2008/12/31 | 6,020,930 | 51.53 | 69.52 |
| 2009/12/31 | 11,782,002 | 56.00 | 70.94 |
| 2010/12/31 | 12,219,004 | 51.79 | 41.75 |
| 2011/12/30 | 9,560,336 | 50.01 | 67.03 |
| 2012/12/28 | 10,765,590 | 50.76 | 65.09 |
| 2013/12/31 | 11,778,077 | 48.39 | 67.15 |

Table 2 The percentage of TWSE electronics index vs. TAIEX (continued)

| End of year | Market value (M) | MV to TAIEX (%) | Percentage to trading volume (%) |
|---|---|---|---|
| 2014/12/31 | 14,433,585 | 53.67 | 66.70 |
| 2015/12/31 | 12,913,852 | 52.90 | 58.97 |
| 2016/12/30 | 14,394,037 | 52.92 | 62.52 |
| 2017/12/29 | 17,444,493 | 54.92 | 68.19 |
| 2018/12/28 | 15,058,277 | 51.80 | 70.28 |
| 2019/12/31 | 20,676,991 | 57.16 | 80.05 |
| 2020/12/31 | 28,274,520 | 63.39 | 68.37 |
| 2021/12/30 | 34,752,946 | 62.23 | 66.83 |
| 2022/12/30 | 25,926,998 | 58.84 | 49.70 |
| 2023/12/29 | 36,314,586 | 64.72 | 74.84 |

### 3.2 Methodology

This study investigates the differential long-term and short-term impacts of risk factors on stock returns of financial holding companies and traditional banks in Taiwan. To effectively capture the complex dynamics of these relationships, we employ the Transfer-noise model as our primary analytical tool. This model is particularly well-suited to our research objectives due to its ability to capture non-linear relationships in financial systems, which are crucial for understanding the intricate interactions between macroeconomic variables and stock returns in the Taiwanese financial sector.

The Transfer-noise model offers several key advantages that align with our research goals. Its non-linear transfer function allows for more accurate modeling of real-world financial phenomena, such as market saturation effects and threshold responses, which are particularly relevant in the context of Taiwan's export-oriented, technology-driven economy. Furthermore, the model's adaptability to complex data patterns enables us to capture system behavior under diverse and often unpredictable market conditions, enhancing the robustness of our analysis. This capability is especially valuable for examining how financial holding companies and traditional banks respond differently to macroeconomic shocks over various time horizons. By leveraging these features, we aim to provide deeper, more nuanced insights into the dynamics of Taiwan's financial markets, potentially uncovering patterns and relationships that might be missed by more conventional approaches. Our modeling approach will consist of several stages:

#### 3.2.1 ARIMA modeling

Previous studies proposed that expected changes in variables would not have meaningful impacts on asset prices under an efficient market and only the unexpected changes of interest rate and exchange rate might have influences on stock returns (Choi *et al.*, 1992; Olugbode & Pointon, 2014; Çelik, 2019). In this study, the ARIMA model is adopted for the estimation of unexpected changes in interest rate and exchange rate.

We will first use ARIMA (AutoRegressive Integrated Moving Average) models to estimate unexpected changes in interest rates and exchange rates. The general form of an ARIMA(p,d,q) model is:

$$\emptyset(B)(1-B)^d Y_t = \theta(B)\varepsilon_t \quad (3.2.1\text{-}1)$$

Where $\emptyset(B)$ is the autoregressive operator of order $p$. $(1-B)^d$ is the differencing operator of order d. $\theta(B)$ is the moving average operator of order $q$. $\varepsilon_t$ is white noise.

We will estimate ARMA(0,0) to ARMA(p,q) models for CP (interest rate), EX (exchange rate), and IND (credit risk factor) resulting in a p x q grid of model specifications. The ARMA(p,q) model can be expressed as:

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} + \varepsilon_t \quad (3.2.1\text{-}2)$$

We will then conduct residual diagnostics to ensure a white noise process with appropriate ARMA orders. This can be done using the Ljung-Box test and examining the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) of the residuals.

The residual series of CP (defined as CPR), EX (defined as EXR) and credit risk factor (defined as INDR) will be used as independent variables in the subsequent transfer function model. The transfer function model can be expressed as:

$$Y_t = V(B)X_t + N_t \quad (3.2.1\text{-}3)$$

In this equation, $Y_t$. is the dependent variable (stock returns), and $X_t$ is the vector of independent variables (CPR, EXR, INDR). $V(B)$ is a polynomial that measures the dynamic relationship between $Y_t$ and $X_t$. $N_t$ is the noise component, which can be modeled as an ARIMA process.

This approach allows us to examine both the long-term and short-term impacts of risk factors on the stock returns of financial holding companies and traditional banks, potentially revealing differences in their sensitivity to these factors.

### 3.2.2 Transfer Function-Noise (TFN) model

The core of our analysis will be based on the empirical transfer function-noise model. This model is particularly suitable for our purposes as it allows us to capture both the short-term and long-term impacts of our independent variables on stock returns. The TFN model is defined as follows:

$$Y_t = V(B)X_{t-b} + C'Z_t + N_t \quad (3.2.2\text{-}1)$$

$$V(B) = \frac{W(B)}{\delta(B)}B^b = \frac{W_0 - W_1 B - W_2 B^2 - \cdots - W_S B^S}{1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r} B^b \quad (3.2.2\text{-}2)$$

$$N_t = \frac{\theta(B)}{\emptyset(B)} a_t \qquad (3.2.2\text{-}3)$$

Where $Y_t$ and $X_t$ are dependent and indpendent variables, respectively. $Z_t$ is a vector of dummy variables for outliers, the outlier indicators with a value of $1 = outlier$ or $0 = otherwise$. $V(B)$is a polynomial that measures the dynamic relationship between $Y_t$ and $X_t$. $N_t$ is a noise component and $a_t$ is a pure error. $B$ is the lag operator. $W(B)$ is a s-order moving average terms orders and $\delta(B)$ is an r-order autoregressive terms for the $X_t$ and b measures the delay effect. For simplicity, this study assumes $b = 0$. $C'$ is a vector of the outlier parameters. $a_t$ is a noise component. $\theta(B)$ are moving average terms and $\emptyset(B)$ are autoregressive terms of $a_t$.

### 3.2.3 Short-term and long-term impact measures

We will use the following measures to quantify the short-term and long-term impacts of our independent variables. The short-term impact index ($ST_j$) and the long-term impact index ( $LT_j$ ) are measured as follows: (Assuming b=0)

Short-term impact index:

$$ST_j = W_0 - W_1B - W_2B^2 - \dots. -W_sB^s \qquad (3.2.3\text{-}1)$$

Long-term impact index:

$$LT_j = \frac{W_0 - W_1B - W_2B^2 - \dots. - W_sB^s}{1 - \delta_1B - \delta_2B^2 - \dots. - \delta_rB^r} \qquad (3.2.3\text{-}2)$$

## 3.3 Model estimation and diagnostic checking

### 3.3.1 Likelihood Ratio (LR) tests

To ensure the appropriate lag structure for the TFN model, we will employ likelihood ratio tests.

### 3.3.2 Iterative estimation process

The detection and treatment of outliers is an important topic in statistics and data science. The existence of outliers will destroy the consistency of the entire sample, thus distorting the original statistical laws and leading to model setting errors. Tsay (1986) examines the impact of outliers on time series model specification. The research highlights the potential for outliers to significantly distort autocorrelation and partial autocorrelation functions, leading to misspecification of ARIMA models.

To enhance the reliability of modeling, the TFN estimation with outlier detection will be an iterative process, continued until all outliers are identified. We define outliers as standardized residuals with absolute values greater than or equal to 3 (Tsay, 1986):

$$\left|\frac{\hat{a}}{\hat{s}_a}\right| \geq 3 \qquad (3.3.2\text{-}1)$$

### 3.3.3 Joint coefficient ward test

After completing the TFN estimation and obtaining the final numerator and denominator coefficients, we will use the joint coefficient Ward test to examine the short-term effects of our three factors (CPR, EXR, INDR) on stock returns.

### 3.3.4 Bootstrap sampling

For the long-term effects, due to the unknown distribution of the ratio (or quotient), we cannot directly test the long-term impacts ($LT_j$). Since we are only interested in sampling from this ratio distribution, this study will adopt the bootstrapping of sampling distribution, by using estimated means and covariance matrix of regression coefficients derived from the TFN estimation. The equality of regression coefficients and covariance matrix would test between the initial TFN estimates and simulated estimates for validity. Then, the short-term and long-term impacts of the three factors on the financial holdings stock returns could be verified.

### 3.3.5 Validity check

We will test the equality of regression coefficients and covariance matrices between the initial TFN estimates and the simulated estimates to verify the validity of our approach.

### 3.4 Comparative analysis

We will conduct separate analyses for financial holding companies and traditional banks, allowing us to compare and contrast the impacts of our risk factors on these two types of financial institutions. This comparative approach will help us identify any systematic differences in how these institutions respond to macroeconomic shocks.

## 4 | Empirical results

This study investigates the impact of macroeconomic risk factors on the stock returns of 15 financial holding companies and 10 traditional banks listed on the Taiwan Stock Exchange or Taipei Exchange. We employ a Transfer Function-Noise (TFN) model, a robust time series approach particularly suitable for analyzing the dynamic relationship between input (macroeconomic) series and output (stock return) series, allowing for the identification of both short-term and long-term effects. To enhance the reliability of our analysis, we incorporate bootstrap simulations, a resampling technique that provides robust statistical inference by generating multiple datasets from the original sample. This approach is particularly valuable in addressing the heterogeneity in our sample, which arises from differences in establishment dates, merger processes, and data availability across financial institutions.

Before estimating the TFN model, we first identify the appropriate AutoRegressive Moving Average (ARMA) specifications for the interest rate (CP) and exchange rate (EX) series. This step is crucial to ensure the white noise property of the input series, a fundamental assumption of the TFN model. We estimate a 5x5 grid of ARMA models, ranging from (0,0) to (5,5), and select the optimal specifications based on residual diagnostics. The residual series from these optimal ARMA models, denoted as CPR (unexpected changes in interest Rates) and EXR (unexpected changes in exchange rates), serve as independent variables in the subsequent TFN model. Additionally, we include INDustry Risk (INDR) as a factor to capture the impact of industry-specific shocks on stock returns.

### 4.1 Sample observations

Table 3 presents the number of observations for each financial institution. The “holdings” column in Table 3 indicates that it is a financial holding company, while those not mentioned by the reporter indicate traditional banks. The sample sizes range from 63 to 288 observations, reflecting differences in establishment dates and merger processes. This heterogeneity is addressed through our bootstrap simulation approach, ensuring robust statistical inference despite the unbalanced panel.

Table 3 The sample size of each firm

| **Holdings** | **Code** | **Freq.** | **Cum. freq.** |
|---|---|---|---|
| | 2801 | 288 | 288 |
| | 2809 | 288 | 576 |
| | 2812 | 287 | 863 |
| | 2834 | 288 | 1,151 |
| | 2836 | 288 | 1,439 |
| | 2838 | 288 | 1,727 |
| | 2845 | 288 | 2,015 |
| | 2849 | 288 | 2,303 |
| | 2897 | 80 | 2,383 |
| | 5876 | 63 | 2,446 |
| ✓ | 2880 | 265 | 2,711 |
| ✓ | 2881 | 265 | 2,976 |
| ✓ | 2882 | 265 | 3,241 |
| ✓ | 2883 | 265 | 3,506 |
| ✓ | 2884 | 264 | 3,770 |
| ✓ | 2885 | 263 | 4,033 |
| ✓ | 2886 | 263 | 4,296 |
| ✓ | 2887 | 263 | 4,559 |
| ✓ | 2888 | 263 | 4,822 |
| ✓ | 2889 | 262 | 5,084 |
| ✓ | 2890 | 260 | 5,344 |

Table 3 The sample size of each firm (continued)

| Holdings | Code | Freq. | Cum. freq. |
|---|---|---|---|
| ✓ | 2891 | 260 | 5,604 |
| ✓ | 2892 | 252 | 5,856 |
| ✓ | 5820 | 249 | 6,105 |
| ✓ | 5880 | 145 | 6,250 |

## 4.2 ARMA model diagnostics

Tables 4(a) and 4(b) report the results of ARMA model specifications for the interest rate (CP) and exchange rate (EX) series. We estimate a 5x5 grid of ARMA models, from ARMA(0,0) to ARMA(5,5), and conduct residual diagnoses to ensure the white noise process. The optimal ARMA orders are determined to be CP(2,0) and EX(2,1), respectively. The residual series from these models, denoted as CPR and EXR, serve as independent variables in the subsequent TFN model.

Table 4(a) The residual diagnosis of the optimal ARMA(p,q) for CP

| LAG | MA 0 | MA 1 | MA 2 | MA 3 | MA 4 | MA 5 |
|---|---|---|---|---|---|---|
| AR 0 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| AR 1 | <.0001 | <.0001 | 0.0016 | 0.0291 | 0.0252 | 0.0096 |
| AR 2 | 0.2624 | 0.6166 | 0.9245 | 0.1838 | 0.6826 | 0.3895 |
| AR 3 | 0.5163 | 0.9345 | 0.6351 | 0.5350 | 0.3925 | 0.5062 |
| AR 4 | 0.7833 | 0.5734 | 0.5334 | 0.5861 | 0.8507 | 0.7632 |
| AR 5 | 0.1093 | 0.5473 | 0.5624 | 0.8046 | 0.7559 | 0.8052 |

Table 4(b) The residual diagnosis of the optimal ARMA(p,q) for EX

| LAG | MA 0 | MA 1 | MA 2 | MA 3 | MA 4 | MA 5 |
|---|---|---|---|---|---|---|
| AR 0 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| AR 1 | <.0001 | 0.1957 | 0.7669 | 0.9204 | 0.6420 | 0.8435 |
| AR 2 | 0.0490 | 0.9919 | 0.8094 | 0.6935 | 0.8626 | 0.8879 |
| AR 3 | 0.5986 | 0.8248 | 0.9305 | 0.7777 | 0.8848 | 0.9043 |
| AR 4 | 0.6766 | 0.6100 | 0.8042 | 0.8585 | 0.8217 | 0.8220 |
| AR 5 | 0.6183 | 0.6769 | 0.8781 | 0.8423 | 0.9911 | 0.6282 |

## 4.3 TFN model selection

Table 5 displays the likelihood ratio test results for determining the optimal lag structure of the TFN model. We evaluate lags from 1 to 5, with the 5-lag specification demonstrating the lowest weighted AICc (1752.59) and the highest log-likelihood value (-864.01). However, the improvement in log-likelihood from 4 lags to 5 lags is minimal, justifying the selection of a 4-lag specification for further analysis, balancing model fit and parsimony.

Table 5 The optimal lag of TFARIMA model fitting

| LAG | Wt_AICc | LN(L) | LRT | CHISQ_P |
|---|---|---|---|---|
| 1 | 1776.09 | -877.58 | | |
| 2 | 1771.40 | -874.92 | 5.32 | 0.1497 |
| 3 | 1767.59 | -872.61 | 4.62 | 0.2018 |
| 4 | 1754.98 | -865.80 | 13.61 | 0.0035 |
| 5 | 1752.59 | -864.01 | 3.59 | 0.3095 |

*Note:* i. Wt_AICc = sample size weighted AICc; ii. LNL = natural log of likelihood value. iii. LRT = likelihood ratio test between neighboring LnLs; iv. CHISQ_P = observed *p*-value of the Chi-square test.

## 4.4 TFN estimation results

Tables 6(a), 6(b), and 6(c) present the TFN estimation results for CPR, EXR, and INDR (INDustry Risk) factors, respectively. While individual numerators ($W_0$~$W_4$) show varied significance across firms, over 60% of the sample exhibits highly significant long-term parameters (Delta). The results show considerable heterogeneity across firms. It also suggests a more pronounced and consistent long-term impact of macroeconomic factors on stock returns, aligning with the gradual information incorporation hypothesis in semi-strong form market efficiency.

Table 6(a) The final estimate of TFARMA model for each firm - CPR effect

| Code | Item | CPR | | | | | |
|---|---|---|---|---|---|---|---|
| | | $W_0$ | $W_1$ | $W_2$ | $W_3$ | $W_4$ | Delta |
| 2801 | Est. | 2.418 | -10.393 * | -21.639 ** | -28.347 ** | -15.557 ** | -0.978 ** |
| | t | 0.428 | -1.293 | -2.676 | -3.540 | -2.789 | -20.561 |
| 2809 | Est. | -1.536 | 1.216 | -7.005 | -14.125 * | -6.630 | 0.107 |
| | t | -0.197 | 0.158 | -0.914 | -1.455 | -0.412 | 0.117 |
| 2812 | Est. | -2.814 | -6.831 | -4.915 | -3.290 | -2.883 | 0.094 |
| | t | -0.444 | -0.857 | -0.348 | -0.268 | -0.294 | 0.050 |
| 2834 | Est. | 4.755 | -10.449 | -16.028 * | -16.204 * | 0.724 | -0.714 * |
| | t | 0.737 | -1.278 | -1.909 | -1.810 | 0.082 | -1.979 |

Table 6(a) The final estimate of TFARMA model for each firm - CPR effect (continued)

| Code | Item | CPR | | | | | |
|---|---|---|---|---|---|---|---|
| | | $W_0$ | $W_1$ | $W_2$ | $W_3$ | $W_4$ | Delta |
| 2836 | Est. | -7.019 | -4.859 | -22.352 ** | 12.887 * | 11.489 * | 0.887 ** |
| | t | -1.144 | -0.614 | -2.828 | 1.608 | 1.824 | 10.998 |
| 2838 | Est. | -7.744 * | 6.398 | -1.158 | -10.428 * | -11.878 ** | -0.965 ** |
| | t | -1.384 | 0.831 | -0.154 | -1.377 | -2.125 | -14.644 |
| 2845 | Est. | -0.934 | -1.695 | -10.103 | -1.209 | 17.236 ** | 0.934 ** |
| | t | -0.140 | -0.190 | -1.126 | -0.136 | 2.554 | 24.310 |
| 2849 | Est. | -4.885 | 9.736 | -1.041 | -18.567 * | -16.121 ** | -0.963 ** |
| | t | -0.712 | 0.997 | -0.106 | -1.917 | -2.308 | -28.329 |
| 2897 | Est. | 12.683 | 47.915 ** | -24.411 | -8.675 | -9.836 | 0.992 ** |
| | t | 0.695 | 2.274 | -1.161 | -0.393 | -0.509 | 22.438 |
| 5876 | Est. | -5.242 | 59.735 * | -56.869 * | 10.767 | 6.239 | 0.956 ** |
| | t | -0.179 | 1.813 | -1.656 | 0.329 | 0.201 | 3.512 |
| 2880 | Est. | -0.183 | 2.763 | -15.071 ** | 0.526 | 9.430 * | 0.959 ** |
| | t | -0.036 | 0.423 | -2.300 | 0.077 | 1.604 | 6.363 |
| 2881 | Est. | -2.295 | -0.663 | -2.302 | 6.898 | 1.520 | 0.791 ** |
| | t | -0.426 | -0.103 | -0.358 | 1.084 | 0.238 | 3.554 |
| 2882 | Est. | -1.195 | -12.243 * | 7.404 | -0.007 | 7.463 | 0.773 ** |
| | t | -0.212 | -1.838 | 1.046 | -0.001 | 1.249 | 3.551 |
| 2883 | Est. | -0.376 | 1.758 | -8.306 | 5.660 | 4.863 | 0.915 ** |
| | t | -0.065 | 0.245 | -1.152 | 0.790 | 0.812 | 8.645 |
| 2884 | Est. | -3.323 | -2.991 | 0.758 | -2.922 | 6.448 | 0.951 ** |
| | t | -0.599 | -0.415 | 0.105 | -0.409 | 1.127 | 27.234 |
| 2885 | Est. | 0.820 | -13.167 * | 9.861 | 6.896 | -4.918 | 0.986 ** |
| | t | 0.139 | -1.710 | 1.274 | 0.892 | -0.829 | 94.073 |
| 2886 | Est. | -2.441 | -5.051 | 1.565 | 4.085 | 5.317 | 0.541 |
| | t | -0.422 | -0.797 | 0.247 | 0.663 | 0.773 | 1.088 |
| 2887 | Est. | 2.067 | 1.998 | -5.922 | -0.235 | 22.046 ** | 0.718 ** |
| | t | 0.337 | 0.288 | -0.848 | -0.034 | 3.440 | 5.987 |
| 2888 | Est. | -4.267 | -1.099 | -8.514 | -8.693 | 2.336 | -0.625 |
| | t | -0.570 | -0.112 | -0.865 | -0.825 | 0.225 | -0.990 |
| 2889 | Est. | -4.616 | -1.295 | 1.906 | -5.947 | 5.761 | 0.944 ** |
| | t | -0.881 | -0.196 | 0.288 | -0.897 | 1.069 | 23.065 |
| 2890 | Est. | 3.824 | -5.580 | 0.588 | 9.351 * | 7.015 | 0.756 ** |
| | t | 0.680 | -0.857 | 0.090 | 1.455 | 1.124 | 4.973 |

Table 6(a) The final estimate of TFARMA model for each firm - CPR effect (continued)

| Code | Item | CPR | | | | | |
|---|---|---|---|---|---|---|---|
| | | **$W_0$** | **$W_1$** | **$W_2$** | **$W_3$** | **$W_4$** | **Delta** |
| 2890 | Est. | 3.824 | -5.580 | 0.588 | 9.351 * | 7.015 | 0.756 ** |
| | t | 0.680 | -0.857 | 0.090 | 1.455 | 1.124 | 4.973 |
| 2891 | Est. | -4.596 | -3.031 | -7.899 | 6.780 | 13.996 * | 0.560 ** |
| | t | -0.683 | -0.416 | -1.116 | 0.926 | 1.976 | 2.159 |
| 2892 | Est. | 5.707 | -5.288 | -6.078 | 9.687 * | 6.263 | 0.574 * |
| | t | 1.160 | -0.948 | -1.007 | 1.505 | 1.088 | 1.615 |
| 5820 | Est. | -6.929 | -4.543 | -14.220 * | -7.737 | 19.605 ** | 0.262 |
| | t | -0.995 | -0.601 | -2.030 | -0.852 | 2.539 | 0.676 |
| 5880 | Est. | 0.268 | -2.422 | -10.160 | -1.633 | -5.473 | -0.225 |
| | t | 0.028 | -0.233 | -0.899 | -0.093 | -0.502 | -0.142 |

*Note:* **: $p<0.01$; *: $p<0.05$

Table 6(b) The final estimate of TFARMA model for each firm - EXR effect

| Code | Item | EXR | | | | | |
|---|---|---|---|---|---|---|---|
| | | **$W_0$** | **$W_1$** | **$W_2$** | **$W_3$** | **$W_4$** | **Delta** |
| 2801 | Est. | -2.552 * | -1.696 | -1.826 | -1.067 | 0.925 | 0.883 ** |
| | t | -1.859 | -0.901 | -0.986 | -0.586 | 0.591 | 7.423 |
| 2809 | Est. | -4.474 ** | 4.283 * | -4.227 * | -6.226 ** | -3.214 * | -0.905 ** |
| | t | -2.366 | 1.627 | -1.645 | -2.360 | -1.685 | -6.603 |
| 2812 | Est. | -2.867 * | 0.677 | -3.030 * | -2.729 | -1.706 | 0.235 |
| | t | -1.846 | 0.292 | -1.701 | -1.260 | -0.644 | 0.411 |
| 2834 | Est. | -3.563 ** | 0.465 | -0.022 | -2.885 * | -1.717 | 0.078 |
| | t | -2.262 | 0.143 | -0.013 | -1.843 | -0.609 | 0.100 |
| 2836 | Est. | -1.905 | 0.862 | -2.184 | -2.069 | 0.922 | 0.657 |
| | t | -1.273 | 0.352 | -0.878 | -1.115 | 0.288 | 0.770 |
| 2838 | Est. | -1.612 | 1.799 | -1.079 | -2.575 * | -1.835 * | -0.965 ** |
| | t | -1.153 | 0.953 | -0.578 | -1.364 | -1.335 | -10.216 |
| 2845 | Est. | -1.857 | 2.278 | -1.106 | -5.914 ** | -4.626 ** | -0.986 ** |
| | t | -1.147 | 1.012 | -0.490 | -2.590 | -2.899 | -34.961 |
| 2849 | Est. | -3.503 ** | -3.850 * | -2.261 | 1.014 | 2.023 | 0.728 * |
| | t | -2.085 | -1.422 | -1.050 | 0.382 | 1.214 | 1.474 |
| 2897 | Est. | -1.181 | 0.862 | 1.403 | 0.196 | -0.890 | 0.979 ** |
| | t | -0.480 | 0.255 | 0.449 | 0.070 | -0.389 | 19.736 |

Table 6(b) The final estimate of TFARMA model for each firm - EXR effect (continued)

| Code | Item | EXR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $W_0$ | | $W_1$ | | $W_2$ | | $W_3$ | | $W_4$ | | Delta | |
| 5876 | Est. | 0.388 | | -1.964 | | 2.502 | | 4.935 | | -2.796 | | 0.997 | ** |
| | t | 0.093 | | -0.373 | | 0.496 | | 1.114 | | -0.724 | | 15.476 | |
| 2880 | Est. | -2.547 | ** | -1.909 | | -1.316 | | -0.169 | | 0.201 | | 0.926 | ** |
| | t | -2.127 | | -1.183 | | -0.820 | | -0.105 | | 0.157 | | 10.897 | |
| 2881 | Est. | -3.971 | ** | -3.439 | * | -0.401 | | -0.875 | | 1.283 | | 0.942 | ** |
| | t | -3.148 | | -1.990 | | -0.234 | | -0.528 | | 1.031 | | 11.848 | |
| 2882 | Est. | -4.350 | ** | -2.088 | | -1.506 | | -2.808 | * | 2.054 | * | 0.977 | ** |
| | t | -3.292 | | -1.132 | | -0.824 | | -1.581 | | 1.556 | | 16.898 | |
| 2883 | Est. | -2.979 | ** | -2.991 | * | 1.349 | | -1.612 | | 1.103 | | 0.944 | ** |
| | t | -2.215 | | -1.651 | | 0.745 | | -0.921 | | 0.825 | | 19.196 | |
| 2884 | Est. | -2.473 | * | 5.046 | ** | 2.740 | * | -0.022 | | -0.725 | | -0.969 | ** |
| | t | -1.946 | | 2.800 | | 1.511 | | -0.012 | | -0.558 | | -26.821 | |
| 2885 | Est. | -3.670 | ** | -0.810 | | 1.355 | | -2.400 | * | -3.326 | * | 0.013 | |
| | t | -2.649 | | -0.395 | | 0.956 | | -1.549 | | -2.045 | | 0.031 | |
| 2886 | Est. | -2.893 | ** | 1.849 | | 2.255 | * | -1.156 | | -2.832 | * | -0.208 | |
| | t | -2.147 | | 0.926 | | 1.459 | | -0.647 | | -1.997 | | -0.422 | |
| 2887 | Est. | -5.065 | ** | 5.369 | ** | 1.919 | | -1.731 | | -3.218 | ** | -0.546 | * |
| | t | -3.572 | | 2.095 | | 0.965 | | -1.040 | | -2.297 | | -1.392 | |
| 2888 | Est. | -1.614 | | 1.807 | | 0.201 | | -3.879 | ** | -5.747 | ** | -0.348 | |
| | t | -0.921 | | 0.934 | | 0.104 | | -2.085 | | -3.127 | | -1.079 | |
| 2889 | Est. | -2.496 | * | -1.231 | | -0.525 | | -1.147 | | 1.088 | | 0.637 | |
| | t | -2.056 | | -0.188 | | -0.308 | | -0.729 | | 0.341 | | 0.249 | |
| 2890 | Est. | -3.335 | ** | -2.684 | * | -0.424 | | 0.187 | | 0.009 | | 0.997 | ** |
| | t | -2.483 | | -1.450 | | -0.237 | | 0.108 | | 0.007 | | 12.419 | |
| 2891 | Est. | -4.110 | ** | -2.531 | | -0.055 | | -1.506 | | 0.354 | | 0.965 | ** |
| | t | -2.592 | | -1.161 | | -0.026 | | -0.729 | | 0.232 | | 14.023 | |
| 2892 | Est. | -1.606 | * | 0.528 | | 0.690 | | -1.427 | | -1.869 | * | 0.778 | ** |
| | t | -1.408 | | 0.359 | | 0.479 | | -1.006 | | -1.567 | | 4.460 | |
| 5820 | Est. | -3.798 | ** | 2.716 | | -1.224 | | -2.758 | | -1.624 | | -0.330 | |
| | t | -2.264 | | 0.448 | | -0.416 | | -0.896 | | -0.488 | | -0.214 | |
| 5880 | Est. | -0.941 | | -1.253 | | 1.853 | * | -0.468 | | -0.024 | | 0.927 | ** |
| | t | -0.934 | | -0.900 | | 1.337 | | -0.340 | | -0.023 | | 12.088 | |

*Note:* **: $p$<0.01; *: $p$<0.05

Table 6(c) The final estimate of TFARMA model for each firm - EXR effect

| Code | Item | INDR | | | | | |
|---|---|---|---|---|---|---|---|
| | | $W_0$ | $W_1$ | $W_2$ | $W_3$ | $W_4$ | Delta |
| 2801 | Est. | 0.603 ** | -0.533 ** | 0.027 | 0.013 | 0.092 * | -0.977 ** |
| | t | 9.552 | -5.908 | 0.296 | 0.150 | 1.380 | -35.953 |
| 2809 | Est. | 0.612 ** | -0.658 ** | -0.195 * | -0.139 | 0.032 | -0.945 ** |
| | t | 7.058 | -5.097 | -1.573 | -1.134 | 0.342 | -12.777 |
| 2812 | Est. | 0.616 ** | 0.091 | 0.005 | -0.105 * | -0.096 | 0.169 |
| | t | 8.707 | 0.246 | 0.070 | -1.403 | -0.908 | 0.282 |
| 2834 | Est. | 0.576 ** | -0.530 ** | 0.047 | -0.021 | 0.047 | -0.988 ** |
| | t | 7.983 | -5.236 | 0.460 | -0.206 | 0.635 | -84.795 |
| 2836 | Est. | 0.511 ** | -0.536 ** | -0.001 | 0.169 * | 0.182 ** | -0.956 ** |
| | t | 7.457 | -5.421 | -0.012 | 1.689 | 2.497 | -23.426 |
| 2838 | Est. | 0.369 ** | -0.414 ** | 0.045 | 0.064 | -0.001 | -0.986 ** |
| | t | 5.826 | -4.531 | 0.502 | 0.726 | -0.022 | -13.949 |
| 2845 | Est. | 0.476 ** | -0.574 ** | 0.019 | 0.143 * | 0.100 | -0.970 ** |
| | t | 6.448 | -5.487 | 0.176 | 1.336 | 1.262 | -33.971 |
| 2849 | Est. | 0.520 ** | -0.414 ** | 0.023 | -0.068 | 0.065 | -0.964 ** |
| | t | 6.736 | -3.795 | 0.209 | -0.629 | 0.787 | -28.386 |
| 2897 | Est. | 0.361 ** | 0.349 * | 0.029 | -0.074 | 0.096 | 0.764 * |
| | t | 3.305 | 1.483 | 0.233 | -0.540 | 0.848 | 1.456 |
| 5876 | Est. | 0.414 ** | 0.502 ** | -0.020 | 0.030 | 0.009 | 0.929 ** |
| | t | 2.405 | 2.565 | -0.097 | 0.132 | 0.052 | 5.780 |
| 2880 | Est. | 0.562 ** | -0.287 | 0.060 | -0.057 | 0.018 | -0.718 * |
| | t | 8.931 | -1.144 | 0.610 | -0.691 | 0.221 | -1.700 |
| 2881 | Est. | 0.523 ** | 0.485 ** | -0.137 * | -0.027 | 0.002 | 0.787 ** |
| | t | 7.707 | 4.670 | -1.582 | -0.316 | 0.031 | 6.124 |
| 2882 | Est. | 0.573 ** | -0.451 ** | 0.072 | -0.231 ** | -0.177 ** | -0.984 ** |
| | t | 8.117 | -3.688 | 0.683 | -2.192 | -2.148 | -8.489 |
| 2883 | Est. | 0.742 ** | 0.684 ** | -0.032 | -0.074 | 0.014 | 0.875 ** |
| | t | 10.319 | 6.586 | -0.338 | -0.784 | 0.180 | 12.305 |
| 2884 | Est. | 0.521 ** | 0.466 | -0.114 | -0.030 | 0.048 | 0.594 |
| | t | 7.801 | 0.636 | -0.508 | -0.359 | 0.686 | 0.428 |
| 2885 | Est. | 0.764 ** | 0.105 | 0.046 | 0.028 | -0.103 * | 0.083 |
| | t | 10.401 | 0.189 | 0.555 | 0.355 | -1.352 | 0.115 |
| 2886 | Est. | 0.563 ** | 0.033 | 0.088 | -0.186 ** | -0.184 * | -0.133 |
| | t | 7.860 | 0.126 | 0.979 | -2.342 | -1.760 | -0.296 |

Table 6(c) The final estimate of TFARMA model for each firm - EXR effect (continued)

| Code | Item | INDR | | | | | |
|---|---|---|---|---|---|---|---|
| | | **$W_0$** | **$W_1$** | **$W_2$** | **$W_3$** | **$W_4$** | **Delta** |
| 2887 | Est. | 0.668 ** | 0.532 | -0.106 | -0.078 | 0.091 | 0.649 |
| | t | 8.845 | 0.589 | -0.685 | -0.731 | 0.713 | 0.482 |
| 2888 | Est. | 0.938 ** | 0.362 | -0.073 | -0.161 | 0.136 | 0.481 |
| | t | 10.043 | 0.210 | -0.358 | -0.692 | 0.373 | 0.263 |
| 2889 | Est. | 0.476 ** | 0.221 | -0.006 | -0.129 * | 0.172 ** | 0.590 * |
| | t | 7.328 | 1.105 | -0.074 | -1.683 | 2.532 | 1.544 |
| 2890 | Est. | 0.541 ** | 0.602 ** | -0.181 * | 0.090 | 0.015 | 0.996 ** |
| | t | 7.690 | 5.766 | -1.826 | 0.904 | 0.214 | 12.432 |
| 2891 | Est. | 0.566 ** | -0.476 ** | 0.079 | -0.067 | -0.044 | -0.950 ** |
| | t | 6.752 | -3.508 | 0.628 | -0.531 | -0.470 | -9.387 |
| 2892 | Est. | 0.528 ** | 0.580 ** | 0.033 | -0.119 * | -0.036 | 0.894 ** |
| | t | 8.665 | 6.090 | 0.390 | -1.408 | -0.544 | 9.317 |
| 5820 | Est. | 0.735 ** | -0.460 * | -0.148 * | -0.120 | 0.100 | -0.597 * |
| | t | 8.163 | -1.541 | -1.377 | -1.036 | 0.899 | -1.587 |
| 5880 | Est. | 0.383 ** | -0.008 | 0.067 | 0.078 | -0.034 | -0.008 |
| | t | 7.013 | -0.014 | 1.181 | 0.688 | -0.253 | -0.005 |

*Note:* **: $p$<0.01; *: $p$<0.05

## 4.5 Outlier detection

Table 6(d) reports the number of outliers identified for each firm during the TFN estimation process. The variation in outlier counts across firms provides insights into their differential exposure to extreme events or firm-specific shocks. This information is crucial for understanding the robustness of our estimates and identifying periods of abnormal market behavior.

Table 6(d) The outliers of TFARMA model in each firm

| Id | Code | Holdings | No. of outliers |
|---|---|---|---|
| 1 | 2801 | 0 | 25 |
| 2 | 2809 | 0 | 20 |
| 3 | 2812 | 0 | 20 |
| 4 | 2834 | 0 | 20 |
| 5 | 2836 | 0 | 20 |
| 6 | 2838 | 0 | 20 |
| 7 | 2845 | 0 | 20 |
| 8 | 2849 | 0 | 20 |
| 9 | 2897 | 0 | 8 |
| 10 | 5876 | 0 | 3 |

Table 6(d) The outliers of TFARMA model in each firm (continued)

| Id | Code | Holdings | No. of outliers |
|---|---|---|---|
| 11 | 2880 | 1 | 20 |
| 12 | 2881 | 1 | 14 |
| 13 | 2882 | 1 | 20 |
| 14 | 2883 | 1 | 20 |
| 15 | 2884 | 1 | 20 |
| 16 | 2885 | 1 | 5 |
| 17 | 2886 | 1 | 20 |
| 18 | 2887 | 1 | 20 |
| 19 | 2888 | 1 | 20 |
| 20 | 2889 | 1 | 20 |
| 21 | 2890 | 1 | 20 |
| 22 | 2891 | 1 | 20 |
| 23 | 2892 | 1 | 20 |
| 24 | 5820 | 1 | 20 |
| 25 | 5880 | 1 | 3 |

## 4.6 Simulation validation

Tables 7(a) and 7(b) demonstrate the equality of regression coefficients and covariance matrices between the TFN estimates and simulated estimates. The close alignment validates our bootstrap simulation approach, ensuring the reliability of our statistical inferences on short-term and long-term effects.

Table 7(a) The paired regression coefficients test between TFN and simulated series

| Var | Parms | Diff | t | *p* | N |
|---|---|---|---|---|---|
| CPR | $W_0$ | -0.0148 | -0.8345 | 0.4122 | 25 |
| | $W_1$ | -0.0074 | -0.6190 | 0.5417 | 25 |
| | $W_2$ | -0.0391 | -1.6109 | 0.1203 | 25 |
| | $W_3$ | 0.0085 | 0.2816 | 0.7807 | 25 |
| | $W_4$ | -0.0183 | -0.8297 | 0.4149 | 25 |
| | Delta | -0.0008 | -1.1307 | 0.2694 | 25 |
| EXR | $W_0$ | -0.0024 | -0.7464 | 0.4627 | 25 |
| | $W_1$ | -0.0028 | -0.4053 | 0.6888 | 25 |
| | $W_2$ | 0.0011 | 0.2745 | 0.7861 | 25 |
| | $W_3$ | 0.0029 | 0.6785 | 0.5039 | 25 |
| | W4 | -0.0066 | -1.7503 | 0.0928 | 25 |
| | Delta | -0.0020 | -0.9927 | 0.3308 | 25 |

Table 7(a) The paired regression coefficients test between TFN and simulated series (continued)

| **Var** | **Parms** | **Diff** | **t** | ***p*** | **N** |
|---|---|---|---|---|---|
| INDR | $W_0$ | 0.0002 | 1.3059 | 0.2040 | 25 |
| | $W_1$ | 0.0006 | 0.6417 | 0.5272 | 25 |
| | $W_2$ | -0.0002 | -0.8687 | 0.3936 | 25 |
| | $W_3$ | -0.0001 | -0.4959 | 0.6245 | 25 |
| | $W_4$ | 0.0000 | -0.1782 | 0.8600 | 25 |
| | Delta | 0.0007 | 0.7204 | 0.4782 | 25 |

Table 7(b) Covariance equality test between initial and simulated series across firms

| **Id** | **CHISQ** | **DF** | ***P*** |
|---|---|---|---|
| 1 | 83.26 | 171 | 1.0000000 |
| 2 | 91.11 | 171 | 0.9999999 |
| 3 | 82.67 | 171 | 1.0000000 |
| 4 | 69.58 | 171 | 1.0000000 |
| 5 | 79.27 | 171 | 1.0000000 |
| 6 | 81.49 | 171 | 1.0000000 |
| 7 | 90.45 | 171 | 0.9999999 |
| 8 | 92.90 | 171 | 0.9999998 |
| 9 | 87.16 | 171 | 1.0000000 |
| 10 | 88.18 | 171 | 1.0000000 |
| 11 | 87.43 | 171 | 1.0000000 |
| 12 | 74.56 | 171 | 1.0000000 |
| 13 | 68.95 | 171 | 1.0000000 |
| 14 | 88.12 | 171 | 1.0000000 |
| 15 | 95.85 | 171 | 0.9999994 |
| 16 | 89.98 | 171 | 0.9999999 |
| 17 | 103.12 | 171 | 0.9999905 |
| 18 | 80.35 | 171 | 1.0000000 |
| 19 | 92.75 | 171 | 0.9999998 |
| 20 | 65.14 | 171 | 1.0000000 |
| 21 | 94.79 | 171 | 0.9999996 |
| 22 | 74.72 | 171 | 1.0000000 |
| 23 | 73.62 | 171 | 1.0000000 |
| 24 | 79.21 | 171 | 1.0000000 |
| 25 | 84.75 | 171 | 1.0000000 |

## 4.7 Simulated effects on financial holdings and traditional banks

Table 8 presents the simulated short-term and long-term effects of CPR, EXR, and INDR on each financial institution. The results indicate significant impacts across all three factors, with notable heterogeneity in both direction and magnitude across firms. The key observations include:

- CPR effects vary widely, with some institutions showing strong positive short-term impacts (e.g., 2801 with 78.27) and others negative (e.g., 5876 with -25.11).
- EXR effects are generally smaller in magnitude but still significant for most institutions.
- Long-term effects often differ substantially from short-term effects, highlighting the importance of considering both time horizons in risk assessment.

This heterogeneity underscores the complex nature of risk transmission in the financial sector and the importance of firm-specific characteristics in determining market responses.

Table 8 The simulated short- and long-run impacts on bank's stock returns

| **Code** | **Item** | **CPR** | | | | **EXR** | | | | **INDR** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Short-term** | | **Long-term** | | **Short-term** | | **Long-term** | | **Short-term** | | **Long-term** | |
| 2801 | Coef. | 78.27 | ** | 39.58 | ** | 1.11 | ** | 16.47 | ** | 1.00 | ** | 0.51 | ** |
| | t | 338.21 | | 337.04 | | 115.42 | | 9.53 | | 431.25 | | 433.74 | |
| 2809 | Coef. | 24.89 | ** | 53.13 | ** | 4.89 | ** | 2.60 | ** | 1.57 | ** | 0.81 | ** |
| | t | 101.98 | | 6.58 | | 63.79 | | 63.93 | | 474.05 | | 487.36 | |
| 2812 | Coef. | 14.97 | ** | 18.65 | ** | 3.92 | ** | 9.60 | ** | 0.72 | ** | 1.04 | ** |
| | t | 51.18 | | 8.39 | | 118.51 | | 12.78 | | 151.98 | | 23.91 | |
| 2834 | Coef. | 47.11 | ** | 26.85 | ** | 0.63 | ** | 6.77 | ** | 1.03 | ** | 0.52 | ** |
| | t | 177.58 | | 184.00 | | 17.27 | | 4.51 | | 394.57 | | 395.04 | |
| 2836 | Coef. | -4.23 | ** | -101.30 | ** | 0.54 | ** | 7.74 | | 0.70 | ** | 0.36 | ** |
| | t | -143.73 | | -3.92 | | 32.10 | | 1.85 | | 264.19 | | 264.81 | |
| 2838 | Coef. | 8.93 | ** | 4.56 | ** | 2.06 | ** | 1.05 | ** | 0.67 | ** | 0.34 | ** |
| | t | 42.61 | | 42.66 | | 36.91 | | 36.99 | | 297.64 | | 299.45 | |
| 2845 | Coef. | -5.15 | ** | -162.08 | ** | 7.51 | ** | 3.78 | ** | 0.79 | ** | 0.40 | ** |
| | t | -244.51 | | -9.07 | | 112.31 | | 112.27 | | 285.53 | | 286.33 | |
| 2849 | Coef. | 21.31 | ** | 10.88 | ** | -0.44 | ** | -4.64 | ** | 0.91 | ** | 0.47 | ** |
| | t | 75.97 | | 75.99 | | -27.12 | | -4.10 | | 321.90 | | 323.09 | |
| 2897 | Coef. | 7.73 | ** | -2732.79 | | -2.74 | ** | -352.39 | ** | -0.04 | ** | -2.08 | * |
| | t | 44.05 | | -0.74 | | -161.38 | | -5.47 | | -19.20 | | -2.36 | |
| 5876 | Coef. | -25.11 | ** | -425.25 | ** | -2.28 | ** | 8.98 | | -0.11 | ** | -2.48 | 5876 |
| | t | -95.08 | | -5.37 | | -46.99 | | 0.03 | | -98.12 | | -9.68 | |

Table 8 The simulated short- and long-run impacts on bank's stock returns (continued)

| **Code** | **Item** | **CPR** | | **EXR** | | **INDR** | |
|---|---|---|---|---|---|---|---|
| | | **Short-term** | **Long-term** | **Short-term** | **Long-term** | **Short-term** | **Long-term** |
| 2880 | Coef. | 2.20** | 64.82** | 0.65** | 37.14** | 0.83** | 0.47** |
| | t | 46.27 | 4.06 | 95.69 | 2.88 | 253.29 | 314.07 |
| 2881 | Coef. | -7.82** | -73.13** | -0.54** | -10.57* | 0.20** | 1.11** |
| | t | -117.09 | -12.31 | -61.72 | -2.12 | 181.33 | 40.64 |
| 2882 | Coef. | -3.89** | -62.23** | 0.00 | -0.97 | 1.36** | 0.68** |
| | t | -82.58 | -4.70 | -1.19 | -1.14 | 467.44 | 485.99 |
| 2883 | Coef. | -4.39** | -166.70** | -0.83** | -19.56** | 0.15** | 1.58** |
| | t | -138.39 | -3.33 | -97.94 | -7.05 | 186.77 | 12.73 |
| 2884 | Coef. | -4.61** | -1416.75 | -9.49** | -4.81** | 0.15** | 0.38** |
| | t | -194.99 | -1.18 | -175.55 | -175.88 | 25.94 | 12.32 |
| 2885 | Coef. | 2.17** | 152.15** | 1.49** | 3.58** | 0.69** | 1.17** |
| | t | 102.64 | 10.43 | 42.41 | 12.97 | 137.30 | 8.18 |
| 2886 | Coef. | -8.49** | -42.05** | -3.09** | -1.17** | 0.81** | 0.81** |
| | t | -94.69 | -7.39 | -65.86 | -5.85 | 264.65 | 34.08 |
| 2887 | Coef. | -15.75** | -78.56** | -7.47** | -4.51** | 0.22** | 0.59** |
| | t | -219.87 | -14.12 | -126.52 | -111.96 | 23.16 | 14.75 |
| 2888 | Coef. | 11.18** | -3.03 | 5.94** | 4.85** | 0.70** | 1.26** |
| | t | 36.48 | -0.85 | 110.69 | 96.21 | 28.82 | 45.78 |
| 2889 | Coef. | -5.03** | -153.71** | -0.59** | -1.98** | 0.22** | -7.09 |
| | t | -192.36 | -15.45 | -15.12 | -2.70 | 82.63 | -0.96 |
| 2890 | Coef. | -7.54** | -76.33** | -0.41** | -51.64** | 0.01** | 4.88 |
| | t | -141.97 | -5.28 | -70.21 | -4.34 | 30.79 | 1.77 |
| 2891 | Coef. | -14.45** | -70.24** | -0.37** | -9.44** | 1.07** | 0.55** |
| | t | -156.92 | -6.41 | -42.35 | -6.69 | 307.31 | 312.32 |
| 2892 | Coef. | 1.05** | -15.97** | 0.49** | 12.28** | 0.07** | 0.77** |
| | t | 12.58 | -4.43 | 42.36 | 5.05 | 120.60 | 11.26 |
| 5820 | Coef. | -0.06 | -15.56** | -0.91** | 1.22 | 1.36** | 0.84** |
| | t | -0.42 | -7.34 | -15.69 | 1.50 | 288.00 | 414.55 |
| 5880 | Coef. | 19.84** | 20.19** | -1.05** | -37.95** | 0.28** | 0.87* |
| | t | 62.61 | 3.50294 | -162.469 | -7.679 | 71.388 | 2.26846 |

*Note:* The simulated sample size = 10,000.**: $p$<0.01; *: $p$<0.05

## 4.8 Comparative analysis of financial holdings vs. traditional banks

Table 9 provides a crucial comparative analysis of the simulated short-term and long-term effects on financial holdings and traditional banks. Key findings include:

- Short_CPR: Financial holdings show a negative mean response (-3.04) while traditional banks exhibit a positive mean (4.64), with the difference being highly significant (*p*<0.0001). This suggests divergent short-term sensitivities to interest rate changes.
- Long_CPR: Despite substantial mean differences (-20.53 for financial holdings vs. 14.91 for traditional banks), the long-term effect is not statistically significant (*p*>0.05), indicating potential convergence in long-term interest rate risk management.
- Short_EXR: Both groups demonstrate negative means, with financial holdings showing greater sensitivity (-9.10 vs. -3.79 for traditional banks). This significant difference (*p*<0.0001) implies higher short-term exchange rate risk exposure for financial holdings.
- Long_EXR: The long-term exchange rate effect shows no significant difference between the two groups (*p*>0.05), suggesting similar long-term foreign exchange risk management strategies.
- Short_INDR and Long_INDR: Both groups exhibit positive means for industry risk factors. The short-term effect differs significantly between the two groups (*p*<0.0001), while the long-term effect does not (*p*>0.05), indicating differential short-term responses to industry-specific risks.

Table 9 The t-tests of financial holdings vs. traditional banks on simulated short- and long-term effects

| **Variable** | **Financial holdings (N=150,000)** | **Traditional banks (N=100,000)** | **Variance assumption** | **t-test** | ***p*-val** | **sig.** |
|---|---|---|---|---|---|---|
| | **Mean** | **Mean** | | | | |
| Short_CPR | -3.04 | 4.64 | equal | 78.96 | <0.0001 | ** |
| | | | unequal | 70.30 | 0.0002 | ** |
| Long_CPR | -20.53 | 14.91 | equal | 1.21 | 0.2245 | |
| | | | unequal | 1.09 | 0.2738 | |
| Short_EXR | -9.10 | -3.79 | equal | 153.14 | <0.0001 | ** |
| | | | unequal | 160.98 | <0.0001 | ** |

Table 9 The t-tests of financial holdings vs. traditional banks on simulated short- and long-term effects (continued)

| **Variable** | **Financial holdings (N=150,000)** | **Traditional banks (N=100,000)** | **Variance assumption** | **t-test** | ***p*-val** | **sig.** |
|---|---|---|---|---|---|---|
| | **Mean** | **Mean** | | | | |
| Long_EXR | -7.39 | -13.56 | equal | -0.17 | 0.8633 | |
| | | | unequal | -0.17 | 0.8678 | |
| Short_INDR | 0.50 | 0.46 | equal | -9.39 | <0.0001 | ** |
| | | | unequal | -8.20 | <0.0001 | ** |
| Long_INDR | 0.60 | 0.62 | equal | 0.19 | 0.8474 | |
| | | | unequal | 0.18 | 0.8575 | |

*Note:* **: $p<0.01$; *: $p<0.05$

The empirical findings of this study reveal a nuanced and sophisticated landscape of institutional risk dynamics in Taiwan's financial sector, characterized by significant short-term differentials between financial holding companies and traditional banks. This observation underscores the critical role of institutional structure in mediating economic responsiveness and risk adaptation.

The regulatory framework established by Taiwan's Financial Holding Company Act mandates a complex organizational architecture wherein financial holding companies must integrate at least two subsidiaries from three core financial service domains: banking, securities, and insurance. This structural requirement generates a multifaceted risk management ecosystem characterized by inherent heterogeneity.

The variability in risk exposure emerges from two fundamental dimensions. First, the macroeconomic risk sensitivities of different subsidiary sectors-banking, securities, and insurance-demonstrate markedly distinct response patterns. These variations stem from sector-specific operational characteristics, regulatory environments, and structural vulnerabilities that collectively influence the financial holding company's overall risk profile.

Secondly, the compositional structure of the financial holding company-encompassing the specific subsidiary combinations and their relative market scales-plays a pivotal role in determining risk dynamics. The proportion, market positioning, and interdependence of these subsidiaries create a unique risk diversification mechanism intrinsic to each financial holding company's configuration.

Notably, while short-term empirical evidence highlights significant institutional differences, the long-term trajectory suggests a potential convergence of risk management strategies. This phenomenon indicates that over extended temporal horizons, financial holding companies and traditional banks may develop increasingly similar approaches to risk mitigation and economic adaptation.

The convergence observed in long-term risk management strategies suggests a sophisticated evolutionary process wherein institutional learning and market pressures gradually harmonize divergent approaches. This trend implies that initial structural differences may progressively diminish as institutions refine their risk management frameworks in response to complex and dynamic economic environments.

Such findings have profound implications for understanding institutional risk adaptation. They reveal that financial institutions are not static entities but dynamic systems capable of learning, evolving, and strategically responding to macroeconomic challenges. The research illuminates the complex interplay between institutional structure, risk sensitivity, and adaptive capacity in contemporary financial ecosystems.

The academic significance of these observations extends beyond Taiwan's financial landscape. By providing a granular analysis of how different institutional structures respond to economic fluctuations, this research contributes to a more nuanced understanding of financial system resilience, risk transformation mechanisms, and the evolutionary dynamics of financial institutions in emerging markets.

Moreover, the study highlights the importance of regulatory frameworks in shaping institutional risk management strategies. Taiwan's Financial Holding Company Act emerges not merely as a compliance mechanism but as a sophisticated policy instrument that encourages institutional diversity, risk diversification, and adaptive capacity in the financial sector.

In this study, the empirical results provide robust evidence of heterogeneous responses to macroeconomic factors across different financial institutions, particularly in the short term. This nuanced understanding is crucial for developing targeted financial policies, refining risk management strategies, and informing investment decisions in Taiwan's financial markets.

## 5 | Conclusions

This study examines the differential impacts of macroeconomic risk factors on the stock returns of financial holding companies and traditional banks in Taiwan, utilizing the Transfer Function-Noise (TFN) model and numerical analysis methods. Our findings highlight significant short-term heterogeneity in responses to macroeconomic shocks between financial holdings and traditional banks, while long-term effects exhibit convergence.

Our findings reveal significant short-term heterogeneity in responses to macroeconomic shocks. Notably, financial holding companies demonstrate a statistically significant negative short-term sensitivity to unexpected changes in interest rates (CPR), with a mean effect of -3.04, whereas traditional banks exhibit a positive response of 4.64 ($p < 0.0001$). This difference highlights potential disparities in risk exposure and the sensitivity of business models between the two types of institutions in response to changes in monetary policy. The conclusion drawn from the methodologies and models employed in this study aligns with observations in practice. Generally, traditional banks benefit more from rising interest rates, which contributes to an increase in their primary interest income. In contrast, the composition of financial holding companies, which includes securities and insurance subsidiaries, indicates that rising interest rates can negatively impact their operations and the valuation of existing bond portfolios. This results in divergences in short-term stock price responses between the two types of institutions when interest rates fluctuate.

In fact, the variability of risk exposure emerges from two critical dimensions. First, subsidiary sectors demonstrate markedly different macroeconomic risk sensitivities, stemming from distinct operational characteristics, regulatory environments, and structural vulnerabilities. Second, the compositional structure of financial holding companies-including the specific combination of subsidiaries and their relative market scales-significantly influences overall risk profiles.

Empirical evidence highlights significant short-term institutional differences, while long-term trajectories suggest a potential convergence of risk management strategies. This phenomenon indicates that financial institutions progressively develop more harmonized approaches to risk mitigation and economic adaptation as they navigate complex and dynamic market environments.

The study transcends descriptive analysis, offering profound insights into institutional learning, adaptive capacities, and the evolutionary dynamics of financial systems. By examining how different institutional structures respond to economic fluctuations, the study contributes to a more nuanced understanding of financial system resilience and risk transformation mechanisms.

Interestingly, the long-term effects of interest rate (CPR), exchange rate (EXR), and industry-specific risks (INDR) do not show significant differences between the two types of institutions ($p>0.05$). This convergence suggests that both financial holdings and traditional banks may gravitate towards similar risk management strategies over time. This long-term convergence could be driven by various factors, including regulatory pressures, competitive forces, and learning from past experiences. While this observation aligns with the notion of market participants adapting to persistent economic conditions as posited by the Adaptive Markets Hypothesis (AMH, Lo, 2004), further research directly examining the dynamic interplay between market efficiency, investor behavior, and institutional adaptation is needed to confirm the applicability of AMH in this context.

The TFN model, coupled with bootstrap simulations, proves valuable in capturing the dynamic relationships between macroeconomic factors and stock returns, effectively addressing the heterogeneity in our sample. The outlier detection process further strengthens the robustness of our findings by mitigating potential biases from extreme market events.

These results bear important implications for policymakers and market participants. The observed short-term heterogeneity underscores the need for regulators to consider institutional differences when designing policies to maintain financial stability. For investors, our findings highlight the potential diversification benefits of distinguishing between financial holdings and traditional banks, particularly during periods of heightened macroeconomic uncertainty.

While this study provides valuable insights into Taiwan's financial sector, the focus on a single market may limit the generalizability of our findings. Future research could explore cross-country comparisons or investigate the evolution of these relationships during periods of financial stress.

In conclusion, this study contributes to the understanding of risk transmission mechanisms in Taiwan's financial market, emphasizing the nuanced interplay between macroeconomic factors and stock returns across different financial institutions. Our findings underscore the importance of considering both short-term and long-term perspectives when assessing the impact of macroeconomic risks on financial institutions.

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# 風險因子對金融控股與傳統銀行股票收益的長期和短期影響差異

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**摘要**

本研究探討總體經濟風險因子（特別是利率、匯率和信用風險）對臺灣金融控股公司和傳統銀行股票收益之短期和長期影響的差異。透過傳遞函數-雜訊模型（TFN）和數值分析方法，我們分析了 2000 年至 2023 年間每月的月資料。為了解決直接測試涉及比率分佈的長期效應的挑戰，本研究提出了一種新穎的拔靴法的程序(bootstrapping procedure)來重新生成多項式比率的多元機率分佈，從而能夠對長期係數進行統計測試。採用異常值檢測技術來減輕偏差。我們的研究結果顯示，兩類金融機構對這些風險因素的短期影響部份存在顯著異質性，尤其金融控股公司表現出更高的敏感性。然而，在長期影響部份則呈現出收斂趨同的情形，顯示隨著時間推移，兩類金融機構逐漸採取類似的風險管理策略。這些見解對投資策略、風險管理實踐和金融政策制定具有重要意義。

**關鍵字:**

風險因子、金融控股公司、銀行、轉移函數-雜訊模型、拔靴法、數值分析