Southeast Asian Journal of Economics Vol.12(1), April 2024: 35-76
Received: 17 May 2023
Revision: 2 June 2023
Accepted: 2 October 2023

From Troughs to Peaks: Uncovering the Effects of Shocks on Stock Market Conditions

Sapphasak Chatchawan
Faculty of Commerce and Accountancy, Thammasat University, Bangkok, Thailand
Corresponding author: sapphasak@tbs.tu.ac.th

Abstract

I classify stock market conditions into normal, bull, and bear markets and examine the impacts of various shocks on stock market conditions over the period from 2005 to 2020 on the Stock Exchange of Thailand. Inflation shocks cause bear market episodes, while shocks to dividend growth and real stock market returns drive the stock market into bull phases. Investors can benefit from adjusting their investment strategies based on current stock market conditions. In addition, inflation shocks are significant for capital market stability, especially during the Global Financial Crisis. Effectively implementing policies to control expected inflation is a promising approach to promoting capital market stability during financial crises.

Keywords: asset prices, inflation, stock market conditions.

1. Introduction

Stock market returns exhibit certain characteristics associated with stock market cycles. When stock market cycles are classified as bull and bear markets, a bull market displays high returns and low market volatility. In contrast, a bear market displays low returns and high market volatility (Maheu & McCurdy, 2000; Maheu et al., 2012). In light of these nonlinear features, the effects of various shocks on stock markets vary depending on stock market cycles. As a result, macroeconomic shocks do not have a uniform effect across different market phases, and stock market conditions serve as an indirect transmission mechanism of macroeconomic shocks (Bordo et al., 2008). Despite its influence, the concept of stock market conditions is inherently subjective. Because of the latent nature of stock market conditions and the difficulty of observing them ex-ante, the main objective of this study is to characterize stock market conditions and investigate the impact of various shocks on their dynamics.

Thailand's stock market conditions are classified into three distinctive categories: bull, bear, and normal market episodes, all of which are qualitative variables. To analyze the dynamics of stock market conditions, the qualitative variables were integrated into the vector autoregression (VAR) framework. The Qualitative VAR, or "QUAL VAR," proposed by Dueker (2005) and Dueker and Assenmacher-Wesche (2010), is employed to examine the dynamics of stock market conditions. One major challenge of dating stock market conditions is that the definitions and dating procedures heavily rely on the researcher's judgment, which can influence the shape of stock market conditions. To mitigate this subjectivity, the latent stock market conditions were resampled with the Metropolis-Hastings algorithm to align human judgment with real data. Furthermore, to complement the main findings, the stock market conditions were also reconstructed based on the concept of the hybrid latent-variable VAR from

Bordo et al. (2007, 2008), and the effects of shocks on the dynamics were analyzed in the robustness analysis. Another concern identified by Bordo et al. (2007, 2008) is that the selection and ordering of the variables in their VAR analysis are atheoretical. To address this concern, the selection and ordering of the variables was based on the VAR framework on an equity valuation criterion. This criterion exploits the relationship between the earnings-price ratio and the yield on Treasury bonds, offering a more theoretically sound foundation for the analysis.

The impulse response analysis reveals that inflation shocks lead to bear market episodes in the stock market, whereas shocks to dividend growth and stock market returns lead to bull market episodes. In contrast, shocks to long-term interest rates and foreign trading behavior are not statistically significant. These findings emphasize the importance of stock market conditions in equity investment. Investors should be aware that shocks to stock market fundamentals influence stock market conditions. Due to fundamental changes, stock market anomalies that exist in bull markets may not necessarily persist in bear markets. Thus, there is no one-size-fits-all investment strategy for different market conditions. Furthermore, additional analyses of stock market conditions provide insights into the implications for monetary policy. Variations in stock market conditions are largely determined by shocks to dividend growth, stock market returns, and inflation, as revealed by the variance decomposition analysis. The findings from the counterfactual analysis highlight the impact of inflation shocks on stock market conditions, particularly during the Global Financial Crisis. Therefore, effectively anchoring expected inflation enhances equity market stability during times of financial crisis.

2. Literature review

The United States witnessed stock market booms from 1994 to 2000, prompting investigations into the variables driving these boom episodes. Bordo et al. (2007) conducted a comprehensive event study, specifically focusing on the mid-1990s, and their findings revealed that stock market booms are associated with above-average levels of productivity, real output growth, and low inflation rates. Furthermore, Bordo et al. (2007) expanded their study beyond the United States, examining stock market booms in Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, the United Kingdom, and the United States since the 1970s. They observed similar patterns across these countries. One noteworthy observation from their research is that, although the median values of productivity and real output are higher than the long-term trend, the differences are not substantial, in contrast to the findings observed between 1996 and 2000. However, the association between booms and low inflation exhibits less variation than that with productivity and output growth. Additionally, Bordo et al. (2007) found that stock market booms are associated with low nominal and real money stock growth. Consequently, it can be inferred that increased liquidity levels did not play a significant role in triggering stock market booms.

Stock market booms are influenced by inflation and interest rates, according to empirical evidence from Bordo et al. (2007, 2008). They argued that central banks should adjust the policy rate in response to inflation and disinflation. Christiano et al. (2010) explained these empirical findings by introducing the news shock to the model in Clarida et al. (2000) and the medium-sized dynamic stochastic general equilibrium model. According to Christiano et al. (2010), stock market booms are driven purely by expectations. The news shock is modeled as a cost-saving technology that will be implemented in the near future. The price of a good is determined by both its current and expected future marginal costs. Therefore, the advent of such technology will reduce future marginal costs, prompting the central bank to lower the policy rate; this leads to higher aggregate demand for goods and services. The current marginal cost rises slightly, but the expected future marginal cost falls by a greater amount. As a result, the price level decreases during boom episodes. Using the medium-sized dynamic stochastic general equilibrium model, Christiano et al. (2010) also investigated the role of credit growth in booms and found that adding credit growth to the interest rate rule brings the economy to the Ramsey equilibrium.

In Thailand, Ahuja et al. (2003) examined the relationship between asset prices and monetary policy. They proposed a method for identifying and accommodating asset price bubbles under the inflation-targeting framework. Their findings suggest that asset prices are too volatile to be directly targeted by the central bank, but they still contain meaningful information that policymakers should not ignore. Asset prices also constitute one of the monetary policy transmission channels. Ahuja et al. (2003) concluded that good governance, strong regulations, and supervisory regimes are the most effective ways to deal with asset price bubbles. They also argued that inflation targeting and a managed float exchange rate regime are sufficient to contain asset price bubbles. In a related study of stock market conditions in Thailand, Thampanya and Pornpikul (2020) investigated the persistent and asymmetric volatility in stock market returns during bull and bear market phases in Thailand and other ASEAN-5 countries. Unlike Thampanya and Pornpikul (2020), this current study extracts the latent stock market conditions from the predetermined stock market dummy and analyzes the impacts of shocks on the dynamics of the stock market conditions.

The primary focus of this research is to examine the dynamic responses of stock market conditions to potential shocks to financial markets and the macroeconomy. At first glance, this study may appear to be closely related to that of Bordo et al. (2007, 2008). However, a closer look reveals that the study offers a different perspective. Bordo et al. (2007, 2008) selected variables that are likely to affect stock market conditions based on empirical evidence and prior literature. Their primary findings are the results of their analysis of the impacts of macroeconomic shocks, such as shocks to output, inflation, and short-term and long-term interest rates, on the real stock market index and stock market conditions. In contrast, this study is motivated by the empirical relationship between the earnings-price ratio and the 10-year government bond yields, known as the Fed model, which is well-documented in Campbell and Vuolteenaho (2004) and Bekaert and Engstrom (2010). However, this study extends the main argument in the literature that expected inflation is the component that gives rise to the robust positive correlation between the earnings-price ratio and the long-term government bond yields by incorporating stock market conditions into the analysis. The stock market condition is a latent variable that captures the cyclical characteristics of the stock market index. Thus, in contrast to Bordo et al. (2007, 2008), this study's analysis aims to complement the literature by providing a selection of potential variables that do not solely rely on empirical evidence from prior literature or observational data of empirical phenomena. Furthermore, the findings from the analysis have implications for investors and policymakers.

3. Theoretical background

3.1 The Yaari-Blanchard model and stock-wealth mechanism

In a standard New Keynesian model, incorporating stock market prices can induce sunspot-driven self-fulfilling expectations fluctuations, raising concerns about equilibrium determinacy (Bullard & Schaling, 2002; Carlstrom & Fuerst, 2007). Therefore, studies that rely on the standard New Keynesian model suggest that the central bank should respond adequately to inflationary pressures when dealing with swings in real stock market prices. This is due to the restriction of policy space. In other words, incorporating stock market prices becomes redundant since the dynamic path of aggregate consumption is sufficiently explained by the stochastic discount factor, and financial wealth fluctuations are smoothed out by infinitely-lived agents who remain the same in financial markets over time. Thus, using the infinitely-lived representative agent may not be appropriate when examining the interplay of stock market prices and monetary policy because it blocks off the demand-side transmission channel of financial shocks.

Another direction of the literature (Castelnuovo & Nisticò, 2010; Airaudo et al., 2015) explores whether the central bank should respond to stock market prices by introducing non-Ricardian households into a dynamic New Keynesian model. These studies contribute to the literature by shifting the focus from the supply side to the demand side, unlike previous studies. The perpetual youth model from Yaari (1965) and Blanchard (1985) is used to develop the underlying concept, which introduces heterogeneity among households. In this case, the stock market price, which is redundant in the standard setup with a representative agent, is no longer redundant.

The discrete-time stochastic perpetual youth model, or the discrete-time stochastic version of the Yaari-Blanchard model, is used to introduce household heterogeneity into a dynamic New Keynesian model. Let us consider the basic ideas of this model. In each period, the economy is populated by consumers who face a constant probability of replacement, γ, before the next period begins and a probability of survival, $1-\gamma$. A constant fraction of old consumers will be replaced by new consumers in the next period. Under this setup, consumers are no longer infinitely lived, and an old consumer who has survived a hundred years is no more likely to die in the next year than a consumer who was born last year. Thus, there are two types of consumers: old consumers and new consumers.

In each period, old consumers engage in financial transactions while newcomers have no financial assets. Old consumers have accumulated wealth and have a higher consumption capacity, while newcomers with zero financial assets consume less. This crucial feature creates a wedge between the stochastic discount factor and the average marginal rate of intertemporal substitution. The interaction between old and new consumers makes the aggregation of the individual Euler equations challenging due to the turnover of consumers. For instance, if stock prices increase today, old consumers who have accumulated financial assets over time anticipate an increase in financial wealth and consume more today. Tomorrow, a certain fraction of yesterday's consumers will be replaced by new consumers. New consumers consume up to their level of human wealth and cannot consume more than that since they do not hold any financial assets. The increase in stock prices does not influence the wealth of the newcomers because the increase occurred yesterday and the newcomers were not there yet. As a result, the increase in stock prices has a greater impact on current aggregate consumption than on expected future aggregate consumption. The increase in financial wealth increases the disparity in consumption between the old consumers and the newcomers. This is how the dynamics of asset prices affect real economic activities in the model with non-Ricardian agents on the demand side. Nisticò (2012) provides a comprehensive mathematical approach to the intuition of the discrete-time stochastic perpetual youth model, and Castelnuovo and Nisticò (2010) extend Nisticò (2012) to build a theoretical model and provide a meaningful interpretation of the model. Therefore, unlike the conventional wisdom from the supply-side analysis of the dynamic New Keynesian model, the demand-side analysis with non-Ricardian households suggests that the central bank should pay attention to and respond to changes in the stock-price gap if the shock is demand-driven. The movements of the stock-price gap are correlated with the stock market conditions, such as bull and bear markets. Policymakers should at least be concerned about the sources of the shocks to stock market variables.

3.2 The Fed model

The Fed model is a simple equity valuation criterion that exploits the association between the yield on Treasury bonds and the earnings-price ratio of stocks. Even though this simple valuation tool is named the 'Fed model,' the Federal Reserve might not have officially endorsed this model. It may have gained this name from Prudential Securities strategist Ed Yardeni, who noted that the Humphrey-Hawkins Report plotted the S&P500 earnings-price ratio against the yield of the 10-year real interest rate in July 1997 (Bekaert & Engstrom, 2010). Their chart shows that the earnings-price ratio and the bond yield exhibit a strong positive correlation. Investment professionals can exploit this correlation and use it as a simple equity valuation model. When the earnings per share, which is the inverse of the PE ratio, of the stock exceeds the 10-year bond yields, equity is attractive, and vice versa. The rationale behind the Fed model is that stocks and bonds are financial assets that compete for space in investors' portfolios. When bond yields increase, stock earnings also increase. This relationship implicitly suggests that the earnings yield of stocks should exhibit a strong positive correlation with expected inflation because the expectation of long-term inflation influences the long-term nominal interest rate.

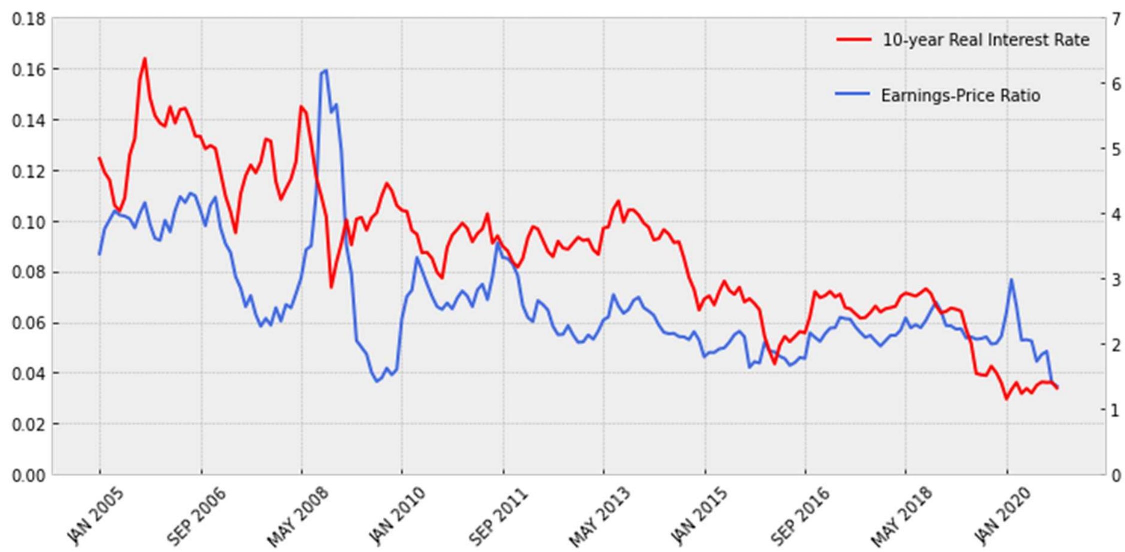
The issue with the Fed model is that it is successful in a behavioral description of equity prices but difficult to reconcile with a rational explanation. Among the seminal papers that analyze this correlation, Campbell and

Vuolteenaho (2004) found that investors are subject to inflation illusion, also known as money illusion. They found that stock market investors extrapolate the past nominal growth rate without incorporating inflation. Thus, almost 80 percent of the variation in stock market mispricing is explained by the level of inflation. This is why when inflation increases, the nominal discount rate of future nominal dividends also increases. The earnings-price ratio and the bond yield move together because investors do not adjust the nominal growth rate of dividends for inflation. In addition, their findings supported Modigliani and Cohn's (1979) hypothesis. By contrast, Bekaert and Engstrom (2010) found that the positive covariance between expected inflation and the dividend yield results from the positive relationship between expected inflation and the equity risk premium. Their empirical results show that the source of the highly positive correlation between expected inflation and the dividend yield is from the positive correlation between expected inflation and rational time-varying risk premiums. Thus, Bekaert and Engstrom (2010) demonstrate that the Fed model can be explained by a rational explanation, which differs from explanations grounded in inflation illusion.

The key difficulty can be demonstrated by the Gordon growth model. In the model, the long-term discount rate is influenced by the expected inflation. If the expected inflation increases, the long-term nominal interest rate also increases. Since the growth rate of the dividends is nominal, the increase in the expected inflation moves the growth rate of the dividends one-for-one (Campbell & Vuolteenaho, 2004). The effects of the expected inflation are eventually canceled out, and the dividend-price ratio remains constant. The search for the factors that explain the Fed model is beyond the scope of this paper. However, the model does roughly help narrow down the variables that can be incorporated into the modified QUAL VAR system.

In Thailand, the yield of the 10-year government bond against the earnings-price ratio reveals a persistent downward trend when plotted (Figure 1). These two variables exhibit a strong linear correlation of 57 percent, indicating a robust linear association between the bond yield and the earnings-price ratio. This presents compelling empirical evidence that aligns with the Fed model. Consequently, the earnings-price ratio should have a strong correlation with expected inflation. Thus, it is reasonable to assert that changes in expected inflation affect stock market prices.

Figure 1. 10-year government bond yield and the earnings-price ratio in Thailand



3.3 Yield decompositions

To represent the empirical observation of the Fed model in a dynamic system, the yield of the nominal interest rate was decomposed.

$$i_t \approx r_{int,t} + \pi_t^e \tag{1}$$

Based on equation (1), the sum of the real interest rate, $r_{int,t}$, and the expected inflation rate, π_t^e, approximates the nominal interest rate, i_t. In this study, the 10-

year bond yield is used as a proxy for the real interest rate, and inflation is used as a proxy for expected inflation in the modified QUAL VAR model.

To decompose the price-dividend ratio, the Campbell-Shiller decomposition was applied in a multi-period framework. From the definition of return, the return is expressed in terms of the price-dividend ratio and the dividend growth rate.

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = \frac{(P_{t+1} + D_{t+1})/D_t}{P_t/D_t} = \frac{\left(1 + \frac{P_{t+1}}{D_{t+1}}\right)\frac{D_{t+1}}{D_t}}{P_t/D_t} \tag{2}$$

Logarithms were applied to both sides of equation (2), with lowercase letters representing the logarithm of the corresponding uppercase letters.

$$r_{t+1} = ln(1 + e^{p_{t+1} - d_{t+1}}) + \Delta d_{t+1} - p_t + d_t \tag{3}$$

A 1st-order Taylor expansion was taken of the first term, $ln(1 + e^{p_{t+1} - d_{t+1}})$, about a point, e^{p-d}, in equation (3), $e^{p-d} = \frac{P}{D}$.

$$r_{t+1} \approx ln\left(1 + \frac{P}{D}\right) + \frac{\frac{P}{D}}{1 + \frac{P}{D}}\left((p_{t+1} - d_{t+1}) - (p - d)\right) + \Delta d_{t+1} - p_t + d_t \tag{4}$$

Equation (4) was then rearranged,

$$s_t \approx \gamma + \rho(s_{t+1}) + \Delta d_{t+1} - r_{t+1} \tag{5}$$

where

$$s_t = p_t - d_t \tag{6}$$

$$\gamma = ln\left(1 + \frac{P}{D}\right) - \rho(p - d) \tag{7}$$

$$\rho = \left(\frac{\frac{P}{D}}{1 + \frac{P}{D}} \right) \tag{8}$$

Since (5) is a difference equation, the equation was iterated forward. Without loss of generality, the constant term was omitted to show the *ex-ante* price-dividend ratio,

$$s_t \approx E_t \sum_{j=0}^{\infty} \rho^j (r_{t+1+j}) - E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+1+j}) \tag{9}$$

where

$$\lim_{j \to \infty} \rho^j (s_{t+j}) = 0 \tag{10}$$

In equation (9), the logarithmic difference in the real SET index was used as a proxy for the real return, and the growth rate of the dividend yield was used as a proxy for the real dividend growth.

As the change in expected inflation exerts a significant influence on stock market prices, it also has a consequential impact on the prevailing market conditions. Furthermore, the prevailing market conditions serve as an additional transmission mechanism through which macroeconomic shocks are propagated to stock market prices. Empirical findings in Bordo et al. (2008) show that the inclusion of stock market conditions in the dynamic multivariate system captures an indirect effect of macroeconomic shocks on stock market prices. However, the definition and filtering techniques employed to measure market conditions can introduce a degree of subjectivity into the analysis. To address this limitation, Bordo et al. (2008) employed a VAR system augmented by a latent variable to construct a more objective measure of stock market conditions. Finally, there is a growing body of literature that focuses on the impact of foreign trading behavior on the Thai stock market (Pavabutr & Yan, 2007; Gyntelberg et al, 2014). Foreign investors provide liquidity to the Thai stock market, and their equity flows do not appear to lead to excessive volatility. Therefore, the incorporation of foreign trading behavior into the analysis is likely to provide valuable insights into the dynamics of the Thai stock market.

4. Data and description

Inflation and 10-year government bond yields were obtained from Thailand's Integrated Database for Economics (TiDE), while the growth rate of dividends, stock market index, and net foreign trading volume were collected from SETSMART. Due to data availability constraints, the main dataset spans January 2005 to December 2020, comprising 192 monthly observations. Dividend growth and inflation were calculated as the difference in the logarithms of the market dividend yield and the consumer price index, respectively. The real interest rate was proxied by the yield on 10-year Treasury bonds. The real stock market index was obtained by dividing the stock market index by the CPI, and the real stock market return was calculated as the difference in the logarithms of the real stock market index. Net buying volume divided by market capitalization was a proxy for foreign trading behavior, and the ratio was scaled up by 10,000 due to its small magnitude. Additionally, this paper constructs the net investment flow of foreign investors. However, using either net buying volume or net investment flow does not significantly affect the impulse response functions and variance decomposition of stock market conditions. The QUAL VAR proposed in Dueker (2005) and Dueker and Assenmacher-Wesche (2010) was remodeled by resampling the latent stock market conditions with the Metropolis-Hastings algorithm and constructing the stock market conditions using the modified QUAL VAR. Following standard time-series procedures, all time-series data used are stationary. Table 1 presents the variables and their descriptions in detail.

Table 1. Variables and description

Variable	Description
Div	Dividend growth
Inf	Inflation
$GB10$	The yield of 10-year government bond rate
$Foreign$	Foreign trading behavior
SET	Real stock market return
$a^{\star}$	Stock market conditions

4.1 Identify boom, bust and normal episodes

The qualitative vector autoregressive model is the system that accounts for the discrete variables in the dynamic system; it allows for a nonlinear relationship, which is consistent with the definition of the stock market conditions in this study. The stock market conditions were predetermined by Pagan and Sossounov's (2003) framework, and the market conditions were drawn from the truncated normal distribution.

The algorithm proposed by Pagan and Sossounov (2003) is deployed to identify boom, bust, and normal episodes in the Stock Exchange of Thailand. One can think of this algorithm as a set of rules used to classify the dummy variables. When stock market conditions fell into bull/normal/bear categories, the dummy variable was set to +1/0/-1. Pagan and Sossounov's (2003) algorithm is defined as follows: 1) Identify peaks and troughs in a 25-month rolling window and eliminate all peaks except the highest one from the subsequent period of market troughs; this is to ensure that peaks and troughs alternate; peaks and troughs are reference points that were used in this paper to identify the bull, bear, and normal market phases, 2) Booms are defined as all periods of at least 36 months from a trough to a peak, with an average annual rate of stock market return of at least 10 percent, 3) Busts are defined as the 12-month period from the last market peak to the trough, with an average annual rate of stock market return that declines by at least 20 percent, and 4) Normal market episodes are those periods that do not meet the criteria for either booms or busts.

In addition to the above definitions, the periods from June 2009 to March 2020 were identified as a bust because the decline from the peak to the subsequent trough was approximately 35 percent, even though the periods lasted only 10 months instead of 12 months. This may seem subjective, but the Metropolis-Hastings algorithm was applied to the estimation procedure to reduce the degree of subjectivity involved in this step. Figure 2 plots the qualitative variable of stock market conditions and the stock market index. Stock market conditions are represented by a dummy variable that indicates the discrete changes in stock market regimes over time. There are three stock market categories: bull, bear, and normal markets. The dummy variable takes on the value 1 during bull market episodes, 0 during normal market episodes, and -1 during bear market episodes.

Figure 2. Stock market conditions (red) and SET index (blue) for 2005 to 2020

An examination of the full sample of the Thai stock market index from 1976 to 2020 reveals that there were 5 bull markets and 6 bear markets. However, Table 2 only presents the results for the period of the study, from 2005 to 2020, which includes 2 bull markets, 3 bear markets, and 4 normal markets. The duration of bull market phases, from trough to peak, was longer than the duration of bear market phases, from peak to trough. Bear market episodes in the Thai stock market typically lasted around 1 year. Notably, the sample period covers the Global Financial Crisis of 2007–2008, which was followed by a long bull market episode that lasted 53 months. The average monthly return during this long bull market episode was approximately 4.81 percent.

In November 2008, the Fed implemented the first Quantitative Easing (QE1) program, which may have caused the subsequent bull markets that immediately followed the bear markets of 2008. In 2011, Thailand experienced the worst floods in half a century. The stock index declined sharply, but the decline lasted only 3 months, which was too short for the dating algorithm to label the period as a bear market cycle. The bear market cycles of 2014–2015 may have been caused by the oil price decline, which was one of the three biggest oil price declines since World War II (World Bank, 2018). The COVID-19 pandemic likely had a major impact on the bear market phases from 2019 to 2020. Overall, the dummy variable for stock market conditions captures some significant events in the markets. The sample includes 4 normal market episodes but does not meet the criteria for either bull or bear markets in terms of duration or average monthly return; therefore, they are labeled as normal market conditions.

Table 2. Bull and bear market episodes in the Stock Exchange of Thailand from 2005–2020

Bull markets			
Bull start	Bull end	Average monthly percentage change	Duration (Month)
Dec-08	Apr-13	4.81	53
Jan-16	Feb-18	1.56	26
Bear markets			
Bear start	Bear end	Average monthly percentage change	Duration (Month)
Nov-07	Nov-08	-4.04	13
Dec-14	Dec-15	-1.08	13
June-19	Mar-20	-3.50	10
Normal markets			
Start	End	Average monthly percentage change	Duration (Month)
Jan-05	Oct-07	0.86	34
May-13	Nov-14	0.11	19
Mar-18	May-19	-0.58	15
Apr-20	Dec-20	1.26	9

4.2 Stock market conditions

Let a_t^* be the latent stock market conditions that cannot be directly observed from the data. The truncation limits, c_1 and c_2, were imposed. These cutoff values can be sampled from the uniform distribution, and then the mean of the posterior distribution of them was used.

Definition 1. Let the cutoff values follow this relation:

$$\mathrm{c}_2 > \mathrm{c}_1 \tag{11}$$

Stock market conditions are boom episodes *if and only if*

$$a_t^* > c_2 \tag{12}$$

Stock market conditions are normal episodes *if and only if*

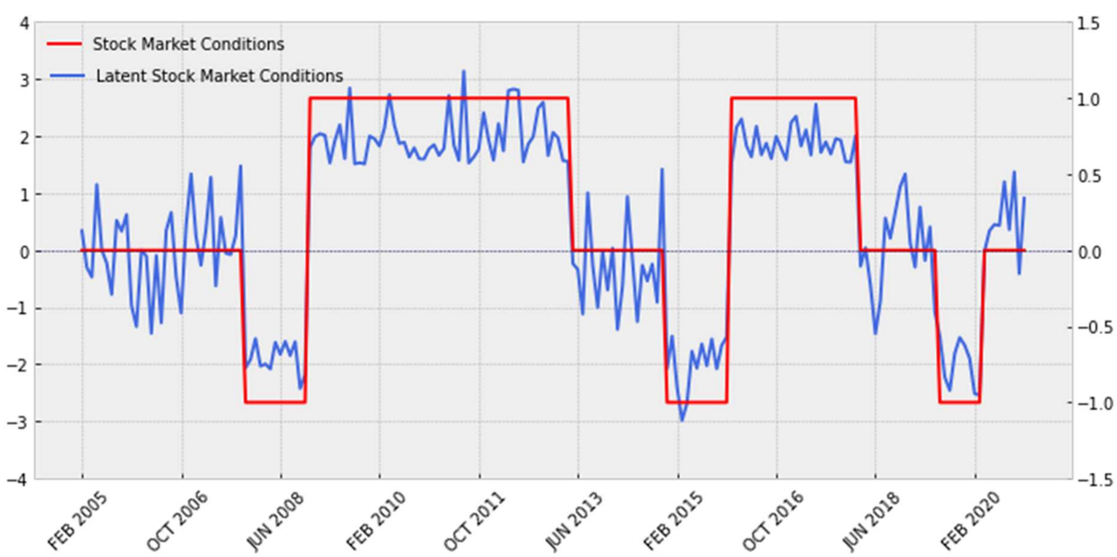
$$c_1 \leq a_t^* < c_2 \tag{13}$$

Stock market conditions are bust episodes *if and only if*

$$a_t^* < c_1 \tag{14}$$

The latent stock market condition is prescribed into three truncated regions demarcated by the cutoffs. Each cutoff value was set based on the value of the dummy variables. For example, if the dummy variable was set to +1, this is a boom. Thus, the latent stock market condition was sampled from $[2, \infty)$. When the dummy variable was equal to 0, the latent stock market condition is sampled from the interval $[-2,2)$, which is labeled as a normal condition. If the dummy was -1, the latent stock market condition is classified as a bust. Thus, the latent index was drawn from the interval $(-\infty, 2)$. Figure 3 shows the latent stock market condition that is drawn according to the concept.

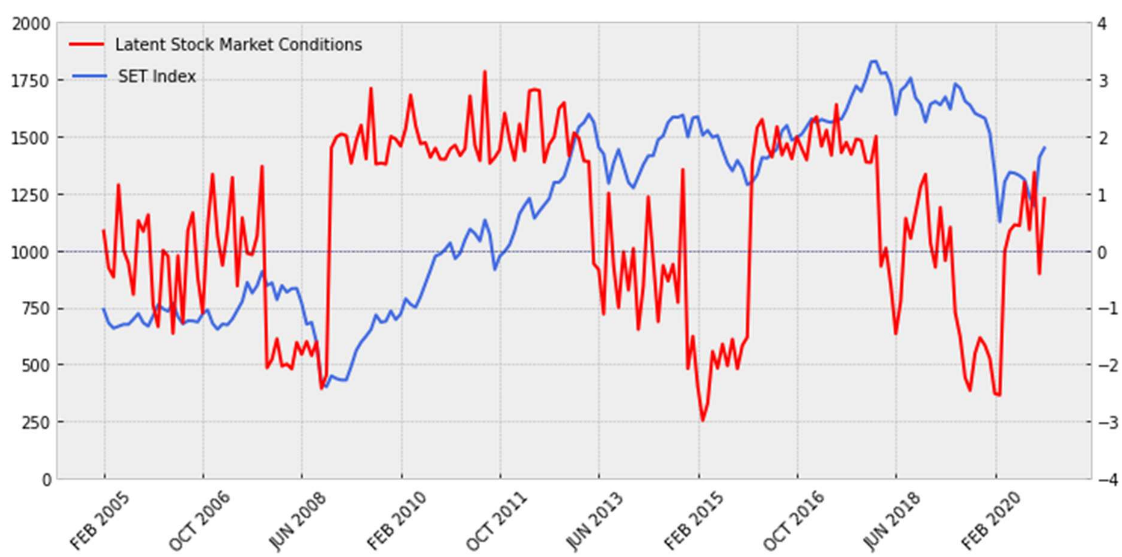
Figure 3. Model-implied latent stock market conditions for the Stock Exchange of Thailand from 2005–2020.



Note: The latent stock market condition variable (blue) appears to conform with the predetermined dummy variable.

Figure 3 depicts three states of stock market conditions: bull, bear, and normal. The values of the latent stock market conditions in Figure 3 are used as the initial values in Gibbs sampling. Figure 4 presents the latent stock market conditions alongside the SET index during 2005–2020. One may question the reliability of the sampled latent stock market conditions. After all, they are drawn based on dummy variables that are subjectively determined. As a result, bull markets for one person may not be bull markets for others. To mitigate this subjectivity, the Metropolis-Hastings algorithm was employed to draw the latent variable based on the forecast errors of the data; this may partially reduce the degree of subjectivity. Therefore, the latent stock market conditions after the Metropolis-Hastings algorithm are not necessarily constrained to the predetermined regions.

Figure 4. The latent stock market conditions and SET index from 2005–2020



4.3 Qualitative Vector Auto Regressive model (Qual VAR)

The estimation and the econometric model share the same spirit with the procedure elaborated in Bordo et al. (2007, 2008), Dueker (2005), and Dueker and Assenmacher-Wesche (2010). The qualitative variable was included in a dynamic system of the p-order vector autoregression model because the Qualitative VAR involves the latent variable. Thus, in order to capture the dynamics of latent stock market conditions, the system with the state space model is presented.

a_t^* is a latent variable that represents the unobserved stock market condition index behind the categorical variables of stock market conditions.

$$z_t = \begin{bmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{nt} \\ a_t^* \end{bmatrix}_{k\times 1} \tag{15}$$

z_t is a $k \times 1$ vector of macroeconomic and financial market variables and the latent stock market conditions. $k = n + 1$, where n is the number of observed variables in the dynamic ordered probit VAR system.

$$z_t = c_z + \sum_{i=1}^{p} \Psi_{k\times k}{}^{(i)} z_{t-i} + \varepsilon_t \tag{16}$$

Where Ψ^i is a $k \times k$ matrix of parameters of VAR and is defined as

$$\Psi^i = \begin{bmatrix} \Phi_{XX} & \Phi_{Xz} \\ \Phi_{zX} & \Phi_{zz} \end{bmatrix}^{(i)} \tag{17}$$

For each member in Ψ^i, the dimension of Φ_{XX} is $n \times n$ and Φ_{Xz} is n ×1 Φ_{zX} is $1 \times n$ and Φ_{zz} is 1×1.

$$z_t = c_z + \Psi^{(1)} z_{t-1} + \Psi^{(2)} z_{t-2} + \Psi^{(3)} z_{t-3} + \ldots + \Psi^{(p)} z_{t-p} + \varepsilon_t \tag{18}$$

The VAR system was rewritten with the state space model to obtain a measurement and a state equation. A vector of constant terms was not included in the following system:

The measurement equation.

$$X_t = \begin{bmatrix} I_{n-1} & 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} z_t \\ z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ \vdots \\ z_{t-p+1} \end{bmatrix} \tag{19}$$

The state equation.

$$\begin{bmatrix} z_t \\ z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ \vdots \\ z_{t-p+1} \end{bmatrix} = \tag{20}$$

$$\begin{bmatrix} \Psi^{(1)} & \Psi^{(2)} & \Psi^{(3)} & \Psi^{(4)} & \cdots & \Psi^{(p)} \\ I & 0 & 0 & 0 & \cdots & 0 \\ 0 & I & 0 & 0 & \cdots & 0 \\ 0 & 0 & I & 0 & \cdots & 0 \\ 0 & 0 & 0 & \ddots & \cdots & 0 \\ 0 & 0 & 0 & 0 & I & 0 \end{bmatrix} \begin{bmatrix} z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ z_{t-4} \\ \vdots \\ z_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

One special feature of the above state space is that it incorporates the non-linear latent variable into the system. Thus, the state space model was modified by allowing the sampling from the truncated normal as in Dueker (2005). The modified state space makes it possible to employ Bayesian Multi-move Gibbs sampling to sample the unobserved latent stock market conditions from the state space. Gibbs sampling allowed us to iteratively draw a marginal distribution from a joint distribution, and multi-move is more efficient than single-move sampling. "i" is the number of iterations in a Gibbs cycle. In this study, the burn-in phrase was the first 3,000 iterations, though 5,000 iterations were kept for the estimation and the calculation of the average values of posterior distributions.

$$g\left(\psi^{(i+1)}\middle|\left\{a_t^{*(i)}\right\}_{t=1}^{T}, \{X_t\}_{t=1}^{T}, \Sigma^{(i)}\right) \tag{21}$$

$$g\left(\Sigma^{(i+1)}\middle|\left\{a_t^{*(i)}\right\}_{t=1}^{T}, \{X_t\}_{t=1}^{T}, \psi^{(i+1)}\right) \tag{22}$$

$$g\left(a_t^{*(i+1)}\middle|\psi^{(i+1)}, \Sigma^{(i+1)}, \left\{a_j^{*(i+1)}\right\}_{j<t}, \left\{a_k^{*(i)}\right\}_{k>t}, \{X_t\}_{t=1}^{T}\right) \tag{23}$$

4.4 The conditional distribution of the latent variableUS

Latent variables are variables that cannot be directly observed from the data. To construct the latent stock market conditions, the latent index was sampled from the categorical variables, such as the dummy variables of stock market conditions produced by the dating algorithm; in other words, we can observe the discrete variables but not the latent variables. The latent stock market condition was sampled from the predetermined dummy variables and other relevant variables. To translate these ideas into algorithms, the full information conditional distribution was derived by using Gibbs sampling, beginning with the full conditional distribution.

$$f(a_t^*|\{z_{-t}\}, X_t) \propto f(z_t|\{z_{-t}\}) \tag{24}$$

The system of equations was expressed in the following form:

$$\varepsilon_t = z_t - c - \Psi_1 z_{t-1} - \Psi_2 z_{t-2} - \ldots - \Psi_p z_{t-p}$$

$$\varepsilon_{t+1} = z_{t+1} - c - \Psi_1 z_t - \Psi_2 z_{t-1} - \ldots - \Psi_p z_{t-p+1}$$

$$\vdots$$

$$\varepsilon_{t+p} = z_{t+p} - c - \Psi_1 z_{t-1+p} - \Psi_2 z_{t-2+p} - \ldots - \Psi_p z_t$$

Let

$$\omega_t = -c - \Psi_1 z_{t-1} - \Psi_2 z_{t-2} - \ldots - \Psi_p z_{t-p} \tag{25}$$

Then, rearrange the system.

$$\varepsilon_t = \omega_t + z_t$$

$$\varepsilon_{t+1} = \omega_{t+1} - \Psi_1 z_t$$

$$\vdots$$

$$\varepsilon_{t+p} = \omega_{t+p} - \Psi_p z_t$$

Densities of $\varepsilon_t, \varepsilon_{t+1}, \ldots, \varepsilon_{t+p}$ are below.

$$-\frac{1}{2}(\omega_t + z_t)'\Sigma^{-1}(\omega_t + z_t)$$

$$-\frac{1}{2}(\omega_{t+1} - \Psi_1 z_t)'\Sigma^{-1}(\omega_{t+1} - \Psi_1 z_t)$$

$$\vdots$$

$$-\frac{1}{2}\left(\omega_{t+p} - \Psi_p z_t\right)'\Sigma^{-1}(\omega_{t+p} - \Psi_p z_t)$$

Σ is the cross-equation variance-covariance matrix. They are uncorrelated across time, and what is calculated after collecting all cross-products is below.

$$z_t|\{z_{-t}\} \sim N(V^{-1}A, V^{-1}) \quad (26)$$

From the distribution,

$$V = \left(\Sigma^{-1} + \Psi_1'\Sigma^{-1}\Psi_1 + \ldots + \Psi_p'\Sigma^{-1}\Psi_p\right) \quad (27)$$

$$A = \left(-\Sigma^{-1}\omega_t + \Psi_1'\Sigma^{-1}\omega_{t+1} + \ldots + \Psi_p'\Sigma^{-1}\omega_{t+p}\right) \quad (28)$$

The equation $\widetilde{z_t} = z_t - V^{-1}A$ was defined and

$$f(\widetilde{z_t}) \propto e^{\left\{-\frac{1}{2}\widetilde{z_t}'V\widetilde{z_t}\right\}} \quad (29)$$

The last element of the vector z_t is the latent variable, and V is partitioned in this fashion.

$$V = \begin{bmatrix} V_{00} & V_{01} \\ V_{10} & V_{11} \end{bmatrix} \tag{30}$$

$$V_{10} = V_{01}' \tag{31}$$

As we can see, the last element in $V^{-1}A$ is a crucial part of drawing the latent variable.

$$\widetilde{a_t^*} | \widetilde{X_t} \sim N(-V_{11}^{-1} V_{01} \widetilde{X_t}, V_{11}^{-1}) \tag{32}$$

The conditional mean of a_t^* is the conditional mean of $\widetilde{a_t^*}$ plus the last element of $V^{-1}A$. We sampled a_t^* from the truncated normal distribution, which is truncated by the dummy of stock market conditions.

4.5 Metropolis-Hastings algorithm

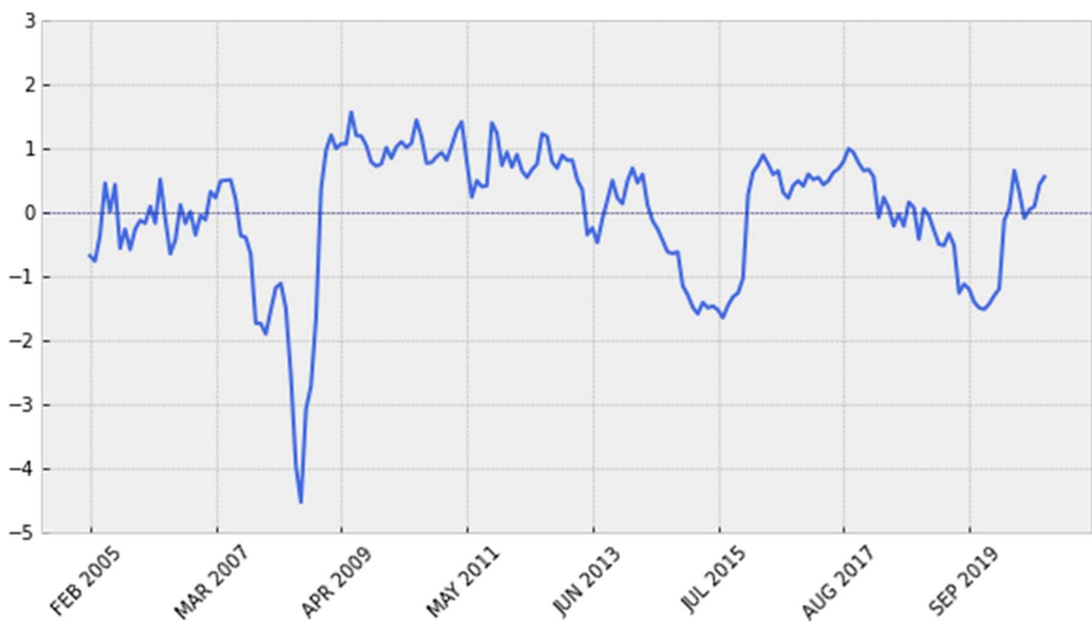
To reduce the researcher's subjective judgment in determining stock market conditions, the Metropolis-Hastings algorithm was employed to fit a latent stock market condition to the actual time series data. This allows the data to speak for itself rather than relying solely on human judgments. The resulting index may not fully conform to the predetermined categorical variables used to define stock market conditions. Therefore, in this study, the latent stock market condition index is partly endogenously determined by the model.

One may argue why the resampling procedure is not needed in forecasting the U.S. recession. The reason is that the NBER's dating committee provides a widely accepted chronology of U.S. business cycle turning points, making it unnecessary for individual researchers to date the recession dummy variable. Dueker (2005) shows the use of the Qual VAR in forecasting the U.S. recession. Equation (33) shows the Metropolis-Hastings algorithm employed in this paper.

$$\alpha(a^{new}) = \min\left\{1, \frac{g(a^{old})f(X|a^{new})}{g(a^{new})f(X|a^{old})}\right\} \tag{33}$$

The concept of the proportion presented here is that when the latent stock market conditions are drawn, the latent stock market condition may not be accepted if $\alpha(a^{new})$ is less than the value from the sampling of the uniform random distribution. If the series is not accepted, the procedure will resample the new series until $\alpha(a^{new})$ is greater than the value sampled from the uniform distribution. The procedure makes the latent stock market condition become endogenously determined to some extent. Figure 5 shows the stock market condition index, which is the outcome of the procedures.

Figure 5. Latent stock market condition index.



Note: The index is standardized and presented in units of standard deviation on the y-axis. The x-axis shows the monthly date. The index is categorized into bull, bear, and normal market episodes.

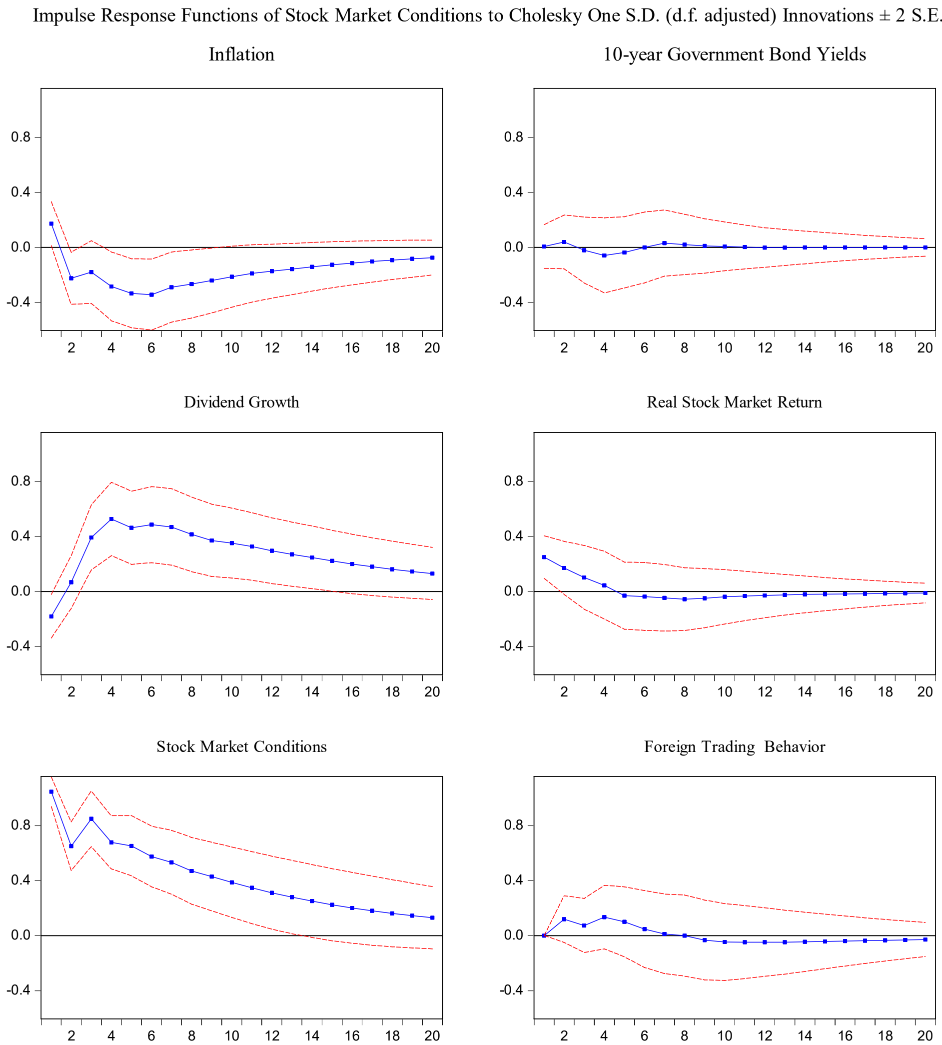
5. Empirical results and discussion

5.1 Impulse response functions

Variable selection and ordering in the modified QUAL VAR model are grounded in the theoretical derivation of the Fed model and relevant literature. The variables were ordered as follows: inflation, 10-year government bond yields, the growth rate of dividends, real stock market returns, stock market conditions, and foreign trading behavior. Foreign trading behavior was included in the model based on related literature, while inflation, 10-year government bond yields, the growth rate of dividends, and real stock market returns were included based on the Fed model. Additionally, different variable orderings were experimented with, such as placing foreign trading behavior before real stock market returns and stock market conditions and inserting the foreign trading variable between stock market returns and stock market conditions. Despite the reordering of the variables, the impulse response functions remained similar to the main results. The key contribution of this study is the use of the Fed model. In contrast, Bordo et al. (2007, 2008) ordered variables based on the degree of exogeneity, placing more exogenous variables before more endogenous ones. This was necessary because their model incorporated both stock market returns and stock market conditions, and there may not have been structural models at the time capable of separating these two shocks. Therefore, they employed variable ordering to achieve this separation.

The variable ordering in the modified QUAL VAR implies that isolated shocks to stock market conditions do not contemporaneously affect inflation, dividend growth, 10-year bond yields, or real stock market returns. In contrast, shocks to these variables do exert contemporaneous effects on stock market conditions. The lag length of the modified QUAL VAR model was determined based on the AIC and SBC criteria. The AIC suggested a lag length of 3 months, while the SBC recommended a lag length of 2 months. At first glance, the SBC might seem to be the preferred criterion for selecting the lag length, as it yields a more parsimonious model. However, the 3-month lag length was chosen based on the AIC because it captures the system's dynamics more effectively. Lag lengths of 1 month, 2 months, and 6 months were also explored, but the impulse response functions yielded qualitatively similar results, albeit with slight differences in dynamics. Typically, when estimating a VAR system, our primary interest lies not in the estimates themselves but in the dynamic responses of variables to shocks. However, in Figure 6, impulse response functions are presented along with point estimates and 2 standard deviation bounds. These functions illustrate the impulse responses of stock market conditions to shocks originating from inflation, dividend growth, the long-term interest rate, real stock market returns, and foreign trading behavior.

Figure 6. Impulse response functions of the stock market conditions to various shocks



The initial impact of the inflation shock on stock market conditions is statistically significant and positive (Figure 6). Specifically, stock market conditions contemporaneously increase only in the first month in response to the inflation shock. Subsequently, stock market conditions transition from the bull market and normal market phases to bear market episodes. The negative impact of the inflation shock on stock market conditions is persistent and statistically significant for month 2 and from months 4 to 9. The apparent puzzle lies in the positive response of stock market conditions in month 1, which remains unresolved even after incorporating forward-looking variables such as rubber prices, oil prices, exchange rate returns, and monetary aggregates and components. Inflation was recalculated from the whole kingdom CPI instead of the core CPI. However, the puzzle remained, even though subsequent restrictions were imposed on the modified QUAL VAR. One possible explanation of the short-term positive impact of the inflation shock on the stock market condition in month 1 is that investors may take the positive shock to inflation as a signal of economic prosperity since the impact is contemporaneous and, hence, investors raise the growth prospect of stocks. Then, the market briefly moves to the bull market phase. Over time, investors have accounted for the inflation shock by scaling up the required rate of return, and the discount factor of the stream of future cash flows has become bigger. As a result, the market has remained in bear market episodes ever since.

The impact of the shock to long-term yields on stock market conditions is not statistically significant and negatively affects stock market conditions only from months 3 to 5. The 3-month yields and the change in the policy rate were also incorporated into the modified QUAL VAR. Shocks to short-term yields and changes in the policy rate have negative impacts on market conditions from month 1, especially the shock to short-term yields. However, the impacts of both shocks on stock market conditions are not statistically significant. The shock to the dividend growth rate has a positive impact on stock market conditions. The market transitions to bull market episodes from month 2, and the shock's impact is statistically significant and persistent over time, particularly from months 3 to 15. The positive shock to the dividend growth rate causes investors to adjust the growth rate of dividends, resulting in a greater value for discounted cash flows. This shift brings the market into bull market phases even though the initial impact of the shock to the dividend growth rate on stock market conditions is negative and brief in month 1.

Stock market conditions contemporaneously respond to shocks to stock market returns. The initial impact of a shock on stock market conditions is positive and statistically significant. That is, a positive shock to real stock market returns drives the market into bull market states. However, the impacts of these shocks abate quickly. Bull market rallies are periods during which stock market returns increase. In this study, bull market phases are clearly defined as all periods of at least 36 months from a trough to a subsequent peak with an average annual rate of return of at least 10 percent. Thus, a positive shock raises the stock market return, which in turn causes the stock market to boom. In other words, the stock market condition positively responds to shocks to itself. In emerging financial markets, foreign trading behavior may affect stock market conditions. The impact of shocks to foreign trading behavior on stock market conditions is positive, and stock market conditions move to bull market phases in response to these shocks. When foreign investors buy more stocks, their net buying causes market rallies. However, the impact of foreign trading is not statistically significant.

5.2 Variance decomposition analysis

Forecast error variance decomposition (FEVD), or variance decomposition, is a technique used to quantify the importance of each shock in contributing to the variation in each of the variables within the system. The variance decomposition partitions the forecast error variance into components specific to each shock. It assists researchers in identifying the exogenous shock that contributes the most and in understanding the importance of these shocks in explaining the variation of the variable changes over time.

Figure 7. Stacked charts of the variance decomposition of the real stock market returns, the stock market conditions, and the foreign trading behavior

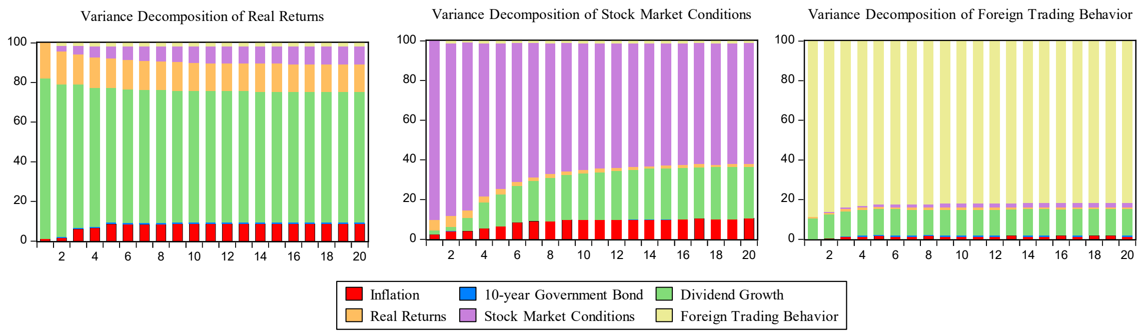


Figure 7 illustrates the sources of the variation in real stock market returns. The dividend growth rate is the most important source of variation, accounting for a significant portion of the total variation. Other important sources of variation include the real stock market return itself, stock market conditions, and the inflation rate. The variation of stock market conditions is driven by itself, the dividend growth rate, and the inflation rate. The stock market return has a relatively small impact on the variation in stock market conditions, while the inflation rate, which is not a financial market variable, contributes to the variation in both real returns and stock market conditions. The variation in foreign trading behavior is primarily driven by its own variation, with the second most important source of variation coming from shocks to dividend growth.

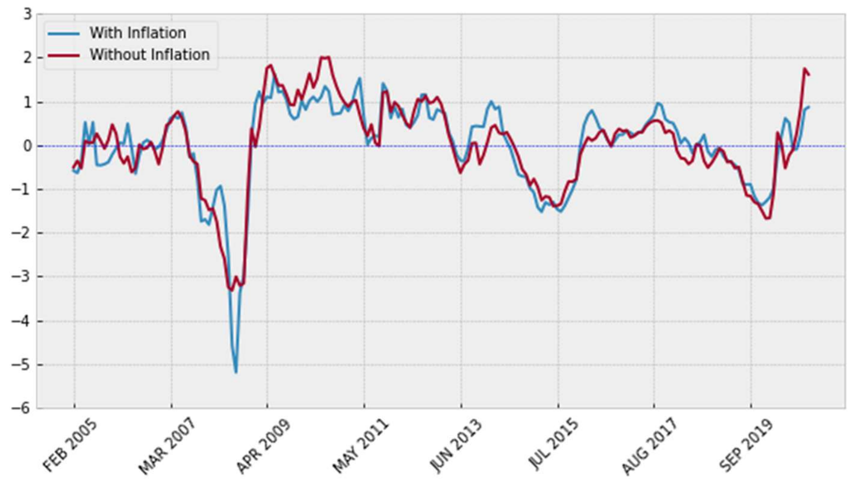
The shock to inflation seems to affect the variation in stock market returns and stock market conditions. Thus, anchoring the inflation rate may contribute to capital market stability to some degree. In addition, the shock to foreign trading behavior contributes to the variation in real stock market returns by around 2 percent and to the variation in stock market conditions by around 1 percent. On the contrary, the shock to dividend growth contributes to the variation in real stock market returns by more than 50 percent and to the variation in stock market conditions by more than 25 percent. Inflation is a macroeconomic variable such that shocks to inflation affect the total variation of real stock market returns and stock market conditions over time. Even though it accounts for only 8 percent of the total variation, the effects of inflation shocks seem to be persistent. The finding that stock market returns are partly driven by inflation is somewhat consistent with the theoretical prediction of the Fed model, which suggests that expected inflation drives stock market returns. However, in this study, expected inflation is proxied by *ex-post* inflation. Inflation shocks also influence stock market conditions over time. In the US, the stock-price gap, a measure of financial slack (Castelnuovo & Nisticò, 2010), is positive in bull market episodes and negative in bear market phases. Thus, even though this paper does not explicitly address the issue of stock market conditions and financial slack, one may infer potential results from the empirical findings, suggesting that expected inflation influences financial slack over time.

5.3 Counterfactual analysis

To emphasize the role of inflation shocks, the concept of counterfactual analysis is used to compare the stock market condition index with and without inflation shocks. In doing so, the stock market condition index was restructured by blocking inflation from the model (Figure 8).

The simple correlation between these two series is approximately 90 percent. Despite the high correlation between the two series, there are notable periods that deserve attention. During 2007–2008, the period of the Global Financial Crisis, Thai stock market conditions in both scenarios entered the bear market phases. In the absence of inflation shocks, the counterfactual diagram indicates that the Thai stock market conditions should have experienced weaker bear market episodes. That is, the stock market trough should have been shallower in 2008 if there were no inflation shocks. The analysis also shows that, without inflation shocks, the Thai stock market conditions might have been in stronger bull market phases during 2009–2010.

Figure 8. Simulated stock market conditions from the counterfactual analysis



From the variance decomposition of stock market conditions, inflation contributes 8 percent to the total variation. To highlight the role of inflation over time, the counterfactual path of stock market conditions was constructed by contrasting the simulated path with the actual one. Overall, the simulated path of stock market conditions is identical to the actual stock market conditions over time. From this analysis, inflation showed a pronounced impact on market conditions during the Global Financial Crisis.

5.4 Robustness analysis

The stock market condition index was reconstructed by using the exact definition in Bordo et al. (2008) and reexamined the impulse response functions of the newly constructed stock market conditions to the shocks. In equation (34), the stock market condition consists of two parts in this section. The first part, a_t^{Probit}, is the latent stock market conditions from the dynamic ordered probit VAR, and the second part, σ_t^{Factor} , comes from the dynamic factor model. e_t is a standard normal. In this specification, σ_t^{Factor} was scaled down to 1, which is the benchmark used in Bordo et al. (2008). σ_t^{Factor} represents the degree to which researchers rely on the predetermined categorical variables in a_t^{Probit}. If σ_t^{Factor} is less than 1, a_t relies more on a_t^{Probit} and vice versa.

$$a_t = a_t^{Probit} + \sigma_t^{Factor} e_t \tag{34}$$

The stock market conditions for the robustness analysis are presented in Figure 9. The notable feature of the newly constructed index is that it shows a sharp switch from one market state to another. The index still conforms to the predetermined stock market conditions. Figure 10 presents the impulse response functions of the new stock market conditions to shocks to inflation, the long-term interest rate, the dividend growth rate, the real stock market return, the market condition itself, and foreign trading behavior. The impulse response diagrams are qualitatively similar to those in 5.1. Thus, given the identification strategy, the main empirical findings are robust.

Figure 9. Stock market conditions with the scaling factor equal to 1

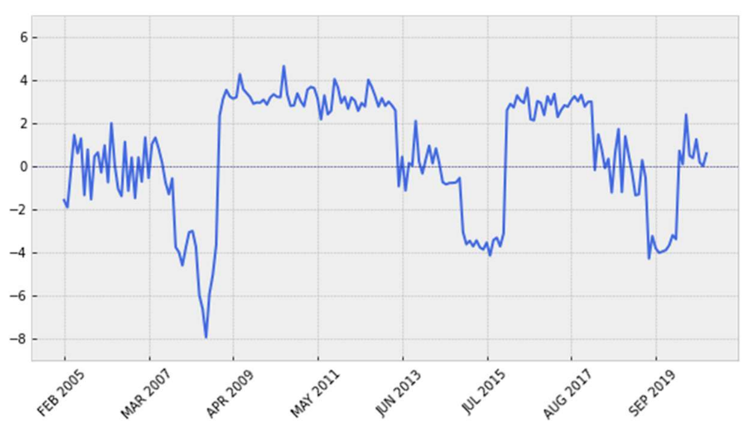
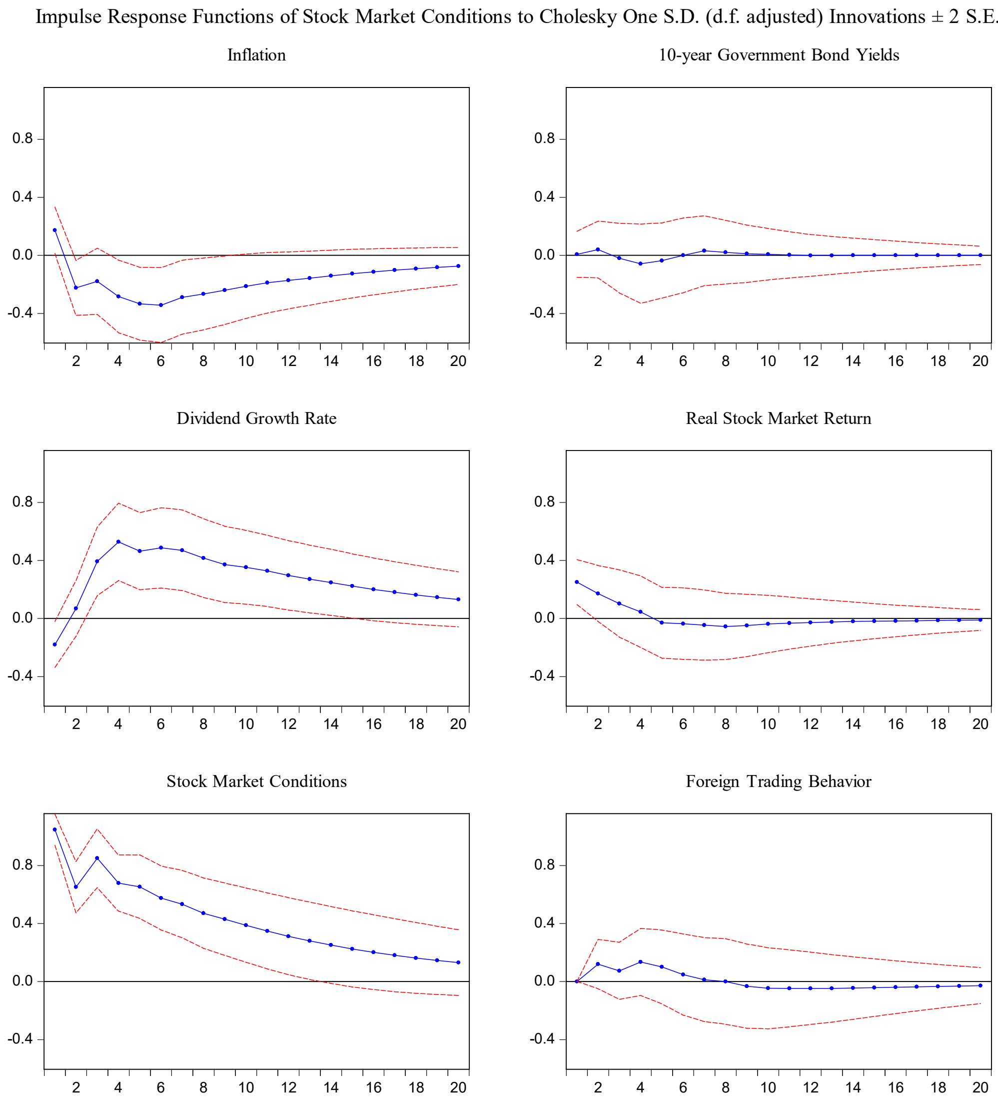


Figure 10. Impulse response functions of the newly constructed stock market conditions to various shocks



6. Conclusions

A multivariate dynamic ordered probit model, such as the QUAL VAR used in this study, allows the incorporation of lagged latent stock market conditions as autoregressive terms. These terms effectively capture the autocorrelation nature of qualitative stock market conditions. One potential limitation of the QUAL VAR model is that the categorical variables representing stock market conditions were derived from ad hoc dating rules. To mitigate this issue, the Metropolis-Hastings algorithm was employed to fit simulated data to the actual data. However, a persistent challenge in the literature is the absence of a sound theoretical foundation for identification and variable selection. This challenge was addressed by formally introducing the Fed model as the theoretical framework for guiding variable selection within the modified QUAL VAR model.

Shocks to stock market fundamentals affect stock market conditions. A positive shock to dividend growth and stock market returns leads to bull markets, while a positive shock to inflation leads to bear markets. These shocks also affect the presence of stock market anomalies. Some anomalies may be more prevalent in bull market episodes and vice versa. Investing in equity should be adapted to the conditions of the stock market because the presence of anomalies is not always consistent across market conditions. This implication is supported by the asset pricing literature. For example, a momentum strategy that involves buying past winners and selling past losers fails to generate strong positive average returns during extreme times. This phenomenon is referred to as a momentum crash. According to Daniel and Moskowitz (2016), in bear markets, the up-market betas of past loser stocks are very high and the down-market betas are very low; therefore, past losers have strong gains when the stock market recovers. Applying momentum strategies results in momentum crashes during these periods. However, this phenomenon is not the case for winning stocks during good times. In the local stock market, Dou et al. (2013) examined the hedge portfolio returns in different stock market regimes. They found that many anomalies are more likely to occur during bear markets than bull markets in the Australian stock market. In conclusion, it is essential that investors learn how to adapt and select the most appropriate investment strategy according to current market conditions. As a result, no single investment strategy can be applied to all market conditions.

The Global Financial Crisis, also known as the Great Recession, has posed several significant challenges to monetary policy and fiscal policy, and this study focuses on the discussion of the monetary policy and Thai capital market stability. Empirical evidence from the counterfactual analysis suggests that the absence of shocks to inflation can enhance capital market stability during extreme periods. In the Fed model employed in this study, inflation is a proxy for expected inflation. It appears that capital market stability is more sensitive to expected inflation shocks, and the effects of inflation shocks were more pronounced during the Global Financial Crisis. Therefore, anchoring expected inflation can help to enhance capital market stability during these extreme periods. However, an interesting question is whether this policy implication remains tenable if the underlying causes of crises are different. Given different circumstances, it is possible that one-size-fits-all solutions may not be appropriate. This is because, during the COVID-19 pandemic, the counterfactual simulation shows that, without the expected inflation shocks, the stock market condition in Thailand would have plunged even further. One possible explanation is that, during the pandemic, the economy suffered severely from the more extreme policies, such as containment policies and strict lockdowns, which depressed economic activities as a whole. The presence of shocks to expected inflation may signal economic recovery and bolster capital market stability rather than destabilize it, especially during times like the pandemic. Therefore, the underlying causes of crises are likely to determine not only the effects of monetary policy but also the effects of expected inflation shocks on capital markets.

In the stock market, certain sectors are more vulnerable to inflation shocks than others. By comparing the stock market conditions of the sectors that are highly inflation-sensitive to those that are less inflation-sensitive, we can see how inflation impacts each sector and how market conditions from different sectors can affect capital market stability during crises. Including only the stock market conditions from the highly inflation-sensitive sectors and analyzing the effects of inflation shocks during periods of asymmetric shocks, such as the COVID-19 pandemic, may provide additional insights into capital market stability. In addition, types of shocks may alter the analysis, especially during crises. During pandemic periods, the effects of a negative supply shock are uneven across economic sectors. That is, the contact-sensitive sectors are more vulnerable to a negative supply shock. These asymmetric shocks can lead to a permanent reallocation of resources among booming and declining economic sectors. If the effect of monetary policy on improving employment prospects in the declining sector is dominant, the process of reallocation is likely to slow down. If the effect of monetary policy on relative wages is sufficiently large, the process of reallocation is accelerated (Guerrieri et al., 2021). Accounting for certain sectors in the stock market and types of shocks, such as asymmetric shocks, on capital market stability is promising for future research.

7. Acknowledgement

The author thanks Thammasat Business School, Puey Ungphakorn Institute for Economic Research, the two anonymous referees, Vasileios Zikos, Anya Khanthavit, Manaschai, Nuansri, Rojana,and Anunyaporn. This work is not part of the author's doctoral study.

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