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Re-examining risk premiums in the Fama–French model: The role of investor sentiment



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ABSTRACT

This paper reconstructs the Fama–French three-factor (F–F) model as a panel smooth transition regression (PSTR) framework to investigate the differentiated effects of investor sentiment proxies—the volatility index (VIX), credit default swap (CDS), and TED spread—on the three risk premiums. Sample period spans from 2003: 1Q to 2013: 4Q. Sample objects are 58 semiconductor companies listed on Taiwan Security Exchange Corporation. The empirical results report that stock returns display a nonlinear path, and the three risk premiums are time-varying, depending on different proxies of investor sentiment in different regimes. Market premiums fall as investors in stock markets show extreme optimism or extreme pessimism. Except in rare situations, the size premium is significant and decreases with the increase in the VIX. Returns in holding growth stocks dominate holding value stocks when the investors show extreme pessimism or optimism. However, in normal sentiment of investment, value stocks earn more returns than growth stocks.

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1. Introduction

Equity valuation is important for investors to measure a firm's value and make investment strategies. The capital asset pricing model (CAPM), proposed by Sharpe (1964) and Lintner (1965), states that market risk has a positive effect on the risk premium of a financial asset. However, the model was found to be insufficient in explaining the expected stock returns (e.g., Reinganum, 1981; Rosenberg, Reid, & Lanstein, 1985). In 1993, Fama and French developed a well-known model to evaluate the asset return, named the Fama–French three-factor model (hereafter F–F model), by adding the firm size and book-to-market factors into the traditional CAPM. They find evidence in the US stock markets that small capitalization stocks and high book-to-market stocks have higher returns than those calculated by the CAPM. Since then, a substantial body of empirical work has examined the validity of the F–F model (e.g., Lawrence, Geppert, & Prakash, 2007; Simpson & Ramchander, 2008).

Several previous studies found that the F–F model leads to a low forecasting performance of asset returns (e.g., Aleati, Gottardo, & Murgia, 2000; Faff, 2004). To resolve this problem, a branch of research adds new factors into the F–F model. For example, Carhart (1997) adds a fourth factor – momentum and shows that the momentum factor makes a large contribution to the explanatory power of the factor model. More recently, Fama and French (2014) introduce a five-factor asset pricing model (beta, size, value, investment, and profitability) to investigate whether these new factors – profitability and investment – improve explanatory power.

Meese and Rogoff (1983) indicate that specifying a more appropriate model is another method to improve the forecasting performance of a specific estimation model. In practice, structural changes in stock returns (or stock prices) may occur as stock markets encounter considerable impacts originated from adjustments in economic environment and public policy. For example, the Subprime Mortgage Crisis in 2007 and the European sovereign debt crisis in 2008 have made stock prices display a non-linear dynamic process, which may further lead to non-linear risk premiums. The traditional F–F model describes a linear path of stock returns and constant risk premiums; therefore, it is unable to capture this regime-switching process. To resolve this problem, reconstructing the F–F model as a non-linear regime-switching one is necessary.

Several famous regime-switching models have been developed to describe the non-linear dynamics of economic variables, such as the Markov switching (MS) model, the threshold autoregressive (TAR) model, the smooth transition autoregressive (STAR) model, and the panel smooth transition regression (PSTR) model. In essence, the switching process of series in MS or TAR model is radical and discrete, which scarcely satisfies its actual movement. The estimation result of the STAR model ignores the heterogeneity among cross-sectional units. Taylor and Peel (2000) point out that transaction costs, policy disturbance, and non-synchronous adjustment by heterogeneous agents, all likely lead to series exhibits smooth regime switching, rather than discrete switching. In contrast, the PSTR model, recently developed by Fok, van Dijk, and Franses (2004) and González, Teräsvirta, and van Dijk (2005), considers the heterogeneity among cross-sectional units and allows for smooth rather than discrete switching between regimes, especially for low-frequency data.

This study rewrites the F–F model as a panel smooth transition regression (PSTR) one.² A simple PSTR model consists of two linear parts linked by a non-linear transition function, and it allows the series under investigation to change smoothly within two different regimes depending on the value of a transition variable. Bessec and Fouquau (2008) summarize the three main advantages of the PSTR model. First, it captures the heterogeneity in the dataset, since it allows for a smooth transition between the extreme regimes. Second, the threshold value of transition variable is not given a priori, but it is estimated in the model. Finally, it offers a parametric method to examine the individual heterogeneity and time variability of the effects of regressors on the dependent variable.

² Fouquau et al. (2008), Cheng and Wu (2013), and Wu, Liu, and Pan (2014) all verify that PSTR models can precisely capture the non-linear adjustment of economic variables within different regimes.

In a PSTR model, the transition variable plays a key role in influencing the dynamic path of the dependent variable and the marginal effects of regressors on the dependent variable. Thus, the choice of an appropriate transition variable is important. Investor sentiment is another potential source of stock return (or price) volatility. In general, investor sentiment may be reasonably defined as optimism or pessimism about stocks. The noise trader model of [De Long et al. \(1990\)](#) motivates many papers that explore the effect of noise trader risks on returns ([Baker & Wurgler, 2006](#); [Neal & Wheatley, 1998](#)). Some prior studies found that the time-series relationship between investor sentiment and market returns diverge substantially in terms of the direction, significance, sign and magnitude of the effects (e.g. [Brown & Cliff, 2005](#); [Qiu & Welch, 2006](#); [Wang, 2003](#)).

Volatility index (VIX), credit default swap (CDS), and treasury-Eurodollar (TED) spread are three popular proxies of investor sentiment. The VIX, developed by the Chicago Board Options Exchange in 1993, is a measure of the market expectations of stock return volatility over the next 30 calendar days, and is intended to provide a benchmark of expected short-term market volatility. [Padungsakasawasdi and Daigler \(2013\)](#) indicate that using VIX to examine the return-volatility nexus can eliminate statistical issues and can demonstrate the perception of risk by option traders in financial markets. A CDS is a contract that provides protection against credit loss on an underlying reference entity as a result of a specific credit event. Since the global financial crisis in 2008, default risk has been regarded as a serious issue, and the price of CDS has been deemed as a thermometer of investor panic level. [Dupuis, Jacquier, Papageorgiou, and Rémillard \(2009\)](#) show that stock returns and CDS spreads are negatively correlated, and the correlation is higher in the tails of the probability density functions. That is, there is an asymmetric relationship between CDS market and stock market. TED spread denotes the difference between the three-month LIBOR and the three-month T-bill interest rate, and is an indicator of perceived credit risk in the general economy. A rising TED spread often presages a downturn in the US stock market, as it indicates that liquidity is being withdrawn. Since the transition variable is individual-specific and time-varying, the regression coefficients (i.e., the three risk premiums in the F–F model) for each of the individual stocks in the panel are changing over time.

In sum, the aim of this paper is to employ PSTR models for investigating the time-varying risk premiums when three representative investor sentiment proxies are used as the transition variables. The empirical results provide useful information for investors in stock markets to evaluate stock returns and risk premiums more accurately; for financial institutions to apply appropriate products to hedge investment and loan risks, and for governments to adopt proper policies to stabilize financial markets. In conducting empirical estimation, we use 58 semiconductor firms listed on the Taiwan Security Exchange Corporation over the period 2003: 1Q to 2013: 4Q as sample objects.

This paper contributes to the existing literature in three distinct aspects. First, we provide an econometric approach in a non-linear and panel framework for the estimation of stock return, which can simultaneously deal with the non-linearity and heterogeneity problems; we trace the dynamic non-linear relationship between stock return and three risk premiums, and we determine whether stock return demonstrates a smoothly regime-switching process. Second, using the proxies of investor sentiment as the transition variable (also can be considered as the fourth factor in this study) in PSTR model, one can prove whether the proxies non-linearly cause the change in stock return. More importantly, estimating a PSTR model with the proxy of investor sentiment as the transition variable, we account for the differentiated marginal effects of the three factors on stock return, namely the time-varying risk premiums. This trait is especially useful for investors to make proper investment strategies.

The rest of this paper is organized as follows. Section 2 briefly introduces the PSTR specification of the FF model, with the aim of accounting for time-varying risk premiums when the proxies of investor sentiment (CDS, VIX, and TED spread) are considered as the transition variable and located in different regimes. Section 3 provides the estimation procedures for the PSTR models, including the panel unit root test, linearity test, and no remaining non-linearity test. Section 4 reports the data measurement and empirical results, and the final section gives a summary of estimation results and proposes some policy suggestions.

2. Empirical model

In the standard F–F model, the expected return of a stock portfolio in excess of a risk-free rate is a function of that portfolio's exposure to three risk factors, namely the market premium, size premium, and value premium. Following [Aleati et al. \(2000\)](#), the F–F model based on individual stock returns instead of portfolio returns can be expressed as follows:

$$R_{it} - R_{ft} = \alpha_{0i} + \alpha_1(R_{mt} - R_{ft}) + \alpha_2 R_{SMBt} + \alpha_3 R_{HMLt} + \varepsilon_{it} \quad (1)$$

where $i = 1, 2, \dots, N$ is the number of stocks and $t = 1, 2, \dots, T$ is the number of periods. R_{it} is the return on stock i at time t ; R_{ft} is the risk-free rate, and $(R_{it} - R_{ft})$ measures the excess return of stock i at time t . α_{0i} stands for a time-invariant individual effect. R_{mt} is the market return and $(R_{mt} - R_{ft})$ denotes the market premium. R_{SMBt} is the size premium, measured by the difference between the returns of a portfolio of small stocks and the returns of a portfolio of large stocks. R_{HMLt} is the value premium, measured by the difference between the returns of a portfolio of high book-to-market (value) stocks and the returns of a portfolio of low book-to-market (growth) stocks. ε_{it} is the residual. α_i , $i = 1, 2, 3$ are the estimated coefficients. In the F–F model, these coefficients are positive, implying that small stocks and value stocks are riskier than large stocks and growth stocks, and thus carry higher expected returns.

A basic PSTR model with two extreme regimes can be written as follows:

$$y_{it} = \mu_i + \beta'_0 x_{it} + \beta'_1 x_{it} F(z_{it}; \gamma, c) + \varepsilon_{it} \quad (2)$$

where y_{it} is a dependent variable, and x_{it} is a K -dimension vector regressors. μ_i is a time-invariant individual effect. $F(z_{it}; \gamma, c)$ is the transition function with value in the interval $[0, 1]$, depending on the transition variable z_{it} . [van Dijk, Terasvirta, and Franses \(2002\)](#) indicate that the transition variable can be an exogenous variable or a combination of the lagged endogenous one. γ is the transition parameter describing the transition speed between different regimes, and c is the threshold value of the transition variable. Following [González et al. \(2005\)](#), the logistic specification can be used for the transition function:

$$F(z_{it}; \gamma, c) = \frac{1}{1 + \exp\left(-\gamma \prod_{j=1}^m (z_{it} - c_j)\right)} \quad (3)$$

where $c_1 \leq c_2 \leq \dots \leq c_m$. m is the number of location parameters. When $\gamma \rightarrow \infty$, the PSTR converges towards a panel threshold regression (PTR) model. Conversely, when $\gamma \rightarrow 0$, the transition function is constant and the PSTR estimation becomes a panel with fixed effects. That is, PSTR model is a more generalized non-linear switching approach and can transform into a nearly linear model or an abrupt switching model. From the viewpoint of empirical estimation, [González et al. \(2005\)](#) and the followers suggest that it is generally sufficient to consider the case of $m = 1$ or $m = 2$ to capture the non-linearity due to regime switching. The case $m = 1$ refers to a logistic PSTR model, and $m = 2$ corresponds to a logistic quadratic PSTR specification. In addition, it is easy to extend the PSTR model (Eq. (2)) to more than two regimes:

$$y_{it} = \mu_i + \beta'_0 x_{it} + \sum_{j=1}^r \beta'_j x_{it} F_j(z_{it}; \gamma_j, c_j) + \varepsilon_{it} \quad (4)$$

where $F_j(z_{it}; \gamma_j, c_j)$, $j = 1, \dots, r$, are the transition functions and $r + 1$ is the number of regimes.

According to Eq. (4), we can rewrite the F–F model (Eq. (1)) as a PSTR framework:

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{10}(R_{mt} - R_{ft}) + \beta_{20} R_{SMBt} + \beta_{30} R_{HMLt} + \sum_{j=1}^r (\beta_{1j}(R_{mt} - R_{ft}) + \beta_{2j} R_{SMBt} + \beta_{3j} R_{HMLt}) \times F_j(z_{it-d}; \gamma_j, c_j) + \varepsilon_{it} \quad (5)$$

Notably, we replace current transition variable z_{it} with d -period lagged transition variable z_{it-d} to allow the lagged effect of transition variable on stock returns through regressors, especially for policy

variables or specific leading indicators. The transition variable z_{it-d} can be the VIX, CDS, or TED spread. We will explain it in more detail in the next section. In the case of one transition function (i.e., $r=1$), the marginal effect of $(R_{it} - R_{ft})$ in terms of the k th regressor is equal to $\beta_{k0} + \beta_{k1}F_1(z_{it-d}; \gamma_1, c_1)$, $k=1, 2, 3$. Obviously, the effect (i.e., the risk premium in this paper) varies with time and cross stocks. A positive (negative) value of β_{k1} indicates an increase (decrease) in the effect with the value of the transition variable.

Eq. (1) is the traditional F-F three-factor model, and the risk premiums in terms of market factor, size factor, and value factor are α_1 , α_2 , and α_3 , respectively. Apparently, the risk premiums are constant and irrespectively of the chosen proxies of investors sentiment. In practice, the proxies used in this paper can disturb stock prices through the three factors. Thus, specifying a PSTR model to estimate stock prices and assess the risk premiums is proper.

To conduct the estimation of Eq. (5), we have to employ a series of testing and estimation procedures. The procedures are introduced in detail in the next section.

3. Specification tests and estimation

Before performing the estimation of Eq. (5), we need to select the transition variable and determine the number of transition functions. Following Wu, Liu, and Pan (2013), a three-step procedure is adopted for estimating our constructed stock return model. First, we conduct the linearity test to check whether stock returns satisfy the linearity condition. Then, if linearity is rejected, we execute the no remaining non-linearity test to find out the number of transition functions (r) and location parameters (m). Finally, we remove individual-specific means and apply non-linear least squares to estimate the parameters of Eq. (5).

3.1. Selection of transition variable

Norden and Weber (2004) find that there is a lead-lag relationship between stock return and CDS, and CDS plays an important role in price discovery. Realdon (2008) estimates a CDS pricing model and confirms the validity of the linkage between firm's stock price and default intensity. Ramchander, Schiereck, and Trutwein (2011) investigate the impact of large changes in single-issuer CDS spreads on the underlying entity's equity prices. Their empirical evidence reports that the relationship between equity and credit markets is regime-dependent.

Whaley (2000) indicates that VIX is referred to as the investor fear gauge because high levels of VIX have coincided with high degrees of market turmoil in the US. Other studies evaluate the ability of implied volatility to predict future market returns (e.g., Diavatopoulos, Doran, & Peterson, 2008; Durand, Lim, & Zumwalt, 2011). For example, Fleming, Ostdiek, and Whaley (1995) find evidence that VIX index and stock index return has negative contemporaneous relationship. Giot (2005) finds that extremely high levels of VIX may signal attractive buying opportunities. Thus, there is a positive relationship between volatility changes and future stock market returns.

Pao (2010) finds that there are long-run equilibrium relationships between the CBOE VIX and the volatility indices in other countries (Belgium, Germany, the Netherlands, Japan, South Korea, Taiwan, UK, and Europe). Since the CBOE VIX is a well-known and representative fear index, and international investors in financial markets widely use it as a referenced index to measure relevant investment risks in the near future, we believe the results derived from this paper can provide valuable information.

The treasury Eurodollar (TED) spread measures the difference between 3-month London Interbank Offered Rate (LIBOR) and 3-month US Treasury bill (T-Bill). In general, T-Bill yield is considered as a risk-free rate of return while LIBOR measures the risk of lending to corporate borrowers. Thus, the TED spread reflects the risk premium that the market has assigned to corporate lending. Lashgari (2000) finds that TED spread has a negative effect on stock return and is able to explain 6% of change in stock return. Cheung, Fung, and Tsai (2010) indicate that the TED spread serves as a leading fear indicator and adjusts to new information rapidly.

In summary, CDS, VIX, and TED spread play an important role in influencing stock markets. They are not only the leading indicators to discover stock prices, but also the fear indicators. They can describe

the regime impact of investor sentiment on stock returns. Thus, this paper selects these three proxies of investor sentiment as the transition variables in the PSTR models.³

3.2. Linearity and no remaining non-linearity tests

To perform the linearity test of Eq. (5), van Dijk et al. (2002) propose to replace the transition function $F_j(z_{it-d}; \gamma, c)$ with its first-order Taylor expansion around $\gamma = 0$. Thus, we have the following auxiliary equation:

$$R_{it} - R_{ft} = \pi_i + \pi_{10}(R_{mt} - R_{ft}) + \pi_{20}R_{SMBt} + \pi_{30}R_{HMLt} + \pi_{11}(R_{mt} - R_{ft})z_{it-d} + \pi_{21}R_{SMBt}z_{it-d} + \pi_{31}R_{HMLt}z_{it-d} + \eta_{it} \quad (6)$$

The linearity test is conducted on $H_0: p_{11} = p_{21} = p_{31} = 0$. Previous studies provided three test methods i.e., the Fisher, Wald, and likelihood ratio tests, to execute the linearity test and no remaining non-linearity test (see, e.g., Fouquau, Hurlin, & Rabaud, 2008). However, van Dijk et al. (2002) suggest that the Fisher test statistics have better size properties in small samples than the other two tests. Thus, we use LM_F as the selection criterion for the number of transition functions.

The Fisher (LMF) test can be written as:

$$LM_F = \frac{[(SSR_0 - SSR_1)/mK]}{[SSR_0/(TN - N - m(K + 1))]} \quad (7)$$

where SSR_0 is the panel sum of squared residuals under H_0 (i.e., the linear panel model with individual effects, $r=0$) and SSR_1 is the panel sum of squared residuals under H_1 (i.e., the PSTR model with two regimes, $r=1$). K and m are the number of regressors and the number of location parameters, respectively. The LM_F statistic has an approximate $F[mK, TN - N - m(K + 1)]$ distribution.

As H_0 is rejected, a sequential approach is used to test the null hypothesis of no remaining non-linearity in the transition function. For instance, suppose that we want to test whether there is one transition function ($H_0: r=1$) against there are at least two transition functions ($H_1: r=2$). Then, we consider the following model:

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{10}(R_{mt} - R_{ft}) + \beta_{20}R_{SMBt} + \beta_{30}R_{HMLt} + (\beta_{11}(R_{mt} - R_{ft}) + \beta_{21}R_{SMBt} + \beta_{31}R_{HMLt}) \times F_1(z_{it-d}; g_1, c_1) + (b_{12}(R_{mt} - R_{ft}) + b_{22}R_{SMBt} + b_{32}R_{HMLt}) \times F_2(z_{it-d}; g_2, c_2) + \varepsilon_{it} \quad (8)$$

The null hypothesis of no remaining heterogeneity can be formulated as $\gamma_2 = 0$. As before, the test problem is solved by using a first-order Taylor approximation of $F_2(z_{it-d}; g_2, c_2)$, which leads to the following auxiliary regression:

$$R_{it} - R_{ft} = \pi_i + \pi_{10}(R_{mt} - R_{ft}) + \pi_{20}R_{SMBt} + \pi_{30}R_{HMLt} + (\pi_{11}(R_{mt} - R_{ft}) + \pi_{21}R_{SMBt} + \pi_{31}R_{HMLt}) \times F_1(z_{it-d}; g_1, c_1) + \pi_{12}(R_{mt} - R_{ft})z_{it-d} + \pi_{22}R_{SMBt}z_{it-d} + \pi_{32}R_{HMLt}z_{it-d} + \eta_{it} \quad (9)$$

³ This study attempts to compare the estimation results by using domestic and global VIX, CDS, or, TED spread as the transition variable. However, three constraints in Taiwan's financial markets force us to temporarily abandon this plan. First, Taiwan's financial markets are small ones relative to those in the US, China, UK, Japan, and German. Thus, investors in these markets are price takers. That is, the adjustment of stock prices, interest rates or exchange rates in Taiwan's financial markets is easily influenced by the policy changes of specific big countries, especially the US. Second, several new financial products are developed only in recent years; therefore, we have insufficient observations for implementing empirical estimation. Lastly, the trading volumes in these newly developed products are relatively limited, which causes unreliable estimation results and liquidity risks.

The null hypothesis of no remaining non-linearity can thus be defined as $H_0: \pi_{12} = \pi_{22} = \pi_{32} = 0$. The Fisher test can be computed as before. Then, we test the null hypothesis of no remaining non-linearity in this model. If it is rejected, estimate a three-regime model. The testing procedure continues until the first acceptance of the null hypothesis of no remaining heterogeneity.

4. Empirical results

4.1. Estimation results

In conducting the empirical estimation, this paper uses quarterly data of 58 semiconductor firms listed on TAIEX from 2003: 1Q to 2013: 4Q, gathered from the Taiwan Economic Journal databank. The data of CDS, VIX, and TED spread come from the Datastream database, Chicago Board Options Exchange, and Board of Governors of the Federal Reserve System, respectively.⁴ Thus, there are 2552 observations.⁵ The reason for choosing these firms is that currently Taiwan Semiconductor Industry Association represents approximately 70% of worldwide IC foundry revenue, around 55% of worldwide package revenue, around 76% of worldwide testing revenue, and around 20% of worldwide design revenue. Notably, these firms have different patterns of stock returns, which can satisfy the heterogeneity of cross-firm effects that influence stock returns differently.

CDS is measured by the five-year CDS index written by the Citibank. Market return is measured by the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). Risk-free rate is measured by the return on 1-month time deposit. Following Fama and French (1993), we can obtain the size factor (R_{SMB}) and book-to-market ratio factor (R_{HML}). First, we divide the semi-conductor firms into two groups based on market capitalization, i.e., small market capitalization (S) and big market capitalization (B). Second, we further divide each market capitalization group into three sub-groups based on break points for bottom 30% (L), middle 40% (M), and top 30% (H) of book-to-market ratios. Thus, we have six portfolios (SL, SM, SH, BL, BM, BH). Then the R_{SMB} and R_{HML} can be calculated from the following two formulas.

$$R_{SMB} = \frac{[(R_{SL} + R_{SM} + R_{SH}) - (R_{BL} + R_{BM} + R_{BH})]}{3}$$

$$R_{HMB} = \frac{[(R_{SH} + R_{BH}) - (R_{SL} + R_{BL})]}{2}$$

where R is the portfolio return of group indexed by the subscript letter. Thus, R_{SMB} is the average return of small market capitalization equity portfolio return minus big market capitalization equity portfolio return, and R_{HML} is the average return of the high book-to-market equity portfolio return minus low book-to-market equity return.

The results of descriptive statistics and panel unit root test for the variables under investigation are displayed in Tables A1 and A2. The results of the panel unit root tests show that all the variables satisfy the condition of stationarity.

To confirm whether using the reconstructed PSTR models are proper, we perform the linearity testing and no remaining non-linearity test. The linearity tests are executed for various PSTR models, formed by different specifications of transition variables (CDS, VIX, and TED), location parameters ($m = 1, 2$), and lag length of transition variables ($d = 0, 1, \dots, 6$), by using LMF testing statistic. The

⁴ The historical data of Taiwan's VIX and CDS began in 2007 and 2008, respectively. In addition, the trading volumes of these two products are relatively rare in the first three years. Based on the considerations of enough observations in the panel context or the liquidity of market, the usefulness of the VIX and CDS in Taiwan is doubtful. In addition, Pao (2010) finds that there are long-run equilibrium relationships between the CBOE VIX and the volatility indices in other countries (Belgium, Germany, the Netherlands, Japan, South Korea, Taiwan, UK, and Europe). Moreover, 80% of the trading volumes in global CDS concentrate on the US. Thus, we do not execute the estimation of the PSTR models with Taiwan's VIX or CDS as the transition variable and engage in the comparison of the results by employing domestic VIX (or CDS) and global VIX (i.e., the CBOE VIX) (or CDS) as the transition variable. However, we hope to fill the gap in the future as the data are reliable.

⁵ This sample of firms is dictated by data availability.

Table 1
Linearity test.

No. of location parameters (m)	$m = 1$		$m = 2$		$m = 1$		$m = 2$		$m = 1$		$m = 2$	
Lag length of transition variable	Transition variable				Transition variable				Transition variable			
	CDS				VIX				TED spread			
$d = 0$	11.12	[0.00]	9.713	[0.00]	13.31	[0.00]	8.928	[0.00]	9.626	[0.00]	8.636	[0.00]
$d = 1$	10.40	[0.00]	8.217	[0.00]	4.577	[0.00]	15.28	[0.00]	5.258	[0.00]	11.37	[0.00]
$d = 2$	9.747	[0.00]	7.638	[0.00]	7.406	[0.00]	8.266	[0.00]	3.163	[0.02]	14.61	[0.00]
$d = 3$	3.760	[0.00]	9.049	[0.00]	5.616	[0.00]	8.039	[0.00]	8.777	[0.00]	6.434	[0.00]
$d = 4$	3.987	[0.27]	6.695	[0.00]	1.869	[0.13]	9.763	[0.00]	7.048	[0.00]	4.979	[0.00]
$d = 5$	5.311	[0.00]	5.664	[0.00]	9.033	[0.00]	10.73	[0.00]	3.681	[0.01]	8.212	[0.00]
$d = 6$	4.046	[0.01]	6.127	[0.00]	13.77	[0.00]	7.731	[0.00]	10.06	[0.00]	12.62	[0.00]

Note: The test statistic is LM_F . The digits in brackets are the P -values. The significance level is specified at 5%.

testing results of linearity are shown in Table 1. Evidently, except for two cases of PSTR-CDS model with $d=4$ and $m=1$ and PSTR-VIX model with $d=4$ and $m=1$, the remaining cases significantly reject the null hypothesis of linearity. Thus, the stock returns display a non-linear dynamic path, and it is proper to adopt non-linear PSTR models to estimate stock returns and risk premiums.

Once the non-linearity of stock returns is verified, we can perform the no remaining non-linearity test to determine the optimal number of transition functions. The testing results are displayed in Table 2.⁶ Clearly, most PSTR models have at least two transition functions. However, this study uses the AIC and BIC to determine the optimal PSTR models for different transition variables. For CDS as the transition variable (i.e., the PSTR-CDS model), the optimal model that has minimum AIC is the PSTR-CDS model with $m=2$, $r=1$, and $d=6$. For the PSTR-VIX model (VIX as the transition variable), the optimal model is the one with $d=5$, $r=1$, and $m=2$, and for PSTR-TED model (i.e., TED spread as the transition variable), the optimal model is the one with $d=6$ and $r=m=1$.

Table 3 reports the estimation results of PSTR models with three proxies of investor sentiment as transition variables, and the standard F–F model. For the PSTR-CDS model, the transition parameter is 2.212 and two threshold parameters are 14.33 and 127.4. In terms of the PSTR-VIX model, the transition parameter is 225.7 and two threshold parameters are 12.82 and 14.70. Regarding the PSTR-TED model, the transition parameter and threshold parameter are 0.25% and 0.249, respectively. Evidently, the transition function in the PSTR-CDS and PSTR-VIX models is symmetric and in the PSTR-TED model is asymmetric.

5. Risk premiums

5.1. Market premium

The marginal effect of market return on stock return (i.e., the market premium) for the PSTR-CDS model is $1.446 - 0.091 \times F(CDS_{t-6}; 2.212, 14.33, 127.4) > 0$; for the PSTR-VIX model is $1.829 - 0.480 \times F(VIX_{t-5}; 225.7, 12.82, 14.70) > 0$, and for the PSTR-TED model is $1.067 + 0.336 \times F(TED_{t-6}; 0.30\%, 0.249) > 0$. In two extreme cases, i.e., the values of transition function $F(\cdot)$ are 0 and 1, the market premiums are 1.446 and 1.355 for the PSTR-CDS model; 1.829 and 1.349 for the PSTR-VIX model, and 1.067 and 1.403 for the PSTR-TED model. Obviously, the marginal effects depend on the value of the assigned transition variable. The value of the assigned transition variable varies in each period; therefore, the effects change with time.

There are several interesting findings in terms of the estimated market premiums. First, although the positive market premiums are consistent with the empirical results in the F–F model and most followers, the estimated market premiums vary with time, which cannot be obtained in the F–F model. Second, the market premiums in the three PSTR models are all greater than one, implying that the stock prices of semiconductor face higher volatile than the index of market portfolio.⁷ Third, the market premiums are the smallest as the values of CDS (or VIX) are at extremely high levels (over the second threshold) or extremely low levels (below the first threshold). That is, as investors in stock markets show extreme optimism (e.g., the announcement or spread of good news) or extreme pessimism (e.g., the announcement or spread of bad news), the market premiums fall. The phenomenon is especially obvious for the PSTR-VIX model. Fourth, for the PSTR-TED model, as the TED spread is over the threshold (0.249), the corresponding market premium increases. However, the TED spread in sample period is quite stable (see Table A1).

5.2. Size premium

The marginal effect of size factor on stock return (i.e., the size premium) for the PSTR-CDS model is $0.089 + 0.253 \times F(CDS_{t-6}; 2.212, 14.33, 127.4) > 0$; for the PSTR-VIX

⁶ To save space, we omit the results in the rest of no remaining non-linearity test. However, they are available upon request.

⁷ For the PSTR-CDS model, the market premium is statistically insignificant as the value of CDS over the threshold, implying that high CDS cannot significantly reduce the market premium.

Table 2

No-remaining nonlinearity test.

Null hypothesis	$r = 1$		$r = 1$		$r = 1$		$r = 1$		$r = 1$		$r = 1$	
Alternative hypothesis	$r = 2$		$r = 2$		$r = 2$		$r = 2$		$r = 2$		$r = 2$	
No. of location parameters (m)	$m = 1$		$m = 2$		$m = 1$		$m = 2$		$m = 1$		$m = 2$	
Lag length of transition variable	Transition variable CDS				Transition variable VIX				Transition variable TED spread			
$d = 0$	6.813	[0.00]	9.48	[0.00]	3.960	[0.01]	11.22	[0.00]	6.954	[0.00]	6.456	[0.00]
$d = 1$	2.349	[0.07]	12.06	[0.00]	14.00	[0.00]	13.84	[0.00]	0.072	[0.98]	6.728	[0.00]
$d = 2$	3.389	[0.02]	12.85	[0.00]	9.725	[0.00]	16.45	[0.00]	1.802	[0.15]	3.022	[0.01]
$d = 3$	8.517	[0.00]	10.26	[0.00]	12.08	[0.00]	7.397	[0.00]	4.04	[0.01]	8.268	[0.00]
$d = 4$	5.484	[0.00]	12.19	[0.00]	4.014	[0.01]	7.221	[0.00]	5.598	[0.00]	0.007	[1.00]
$d = 5$	4.557	[0.01]	3.988	[0.00]	5.406	[0.00]	21.52	[0.00]	8.759	[0.00]	10.32	[0.00]
$d = 6$	1.125	[0.34]	15.19	[0.00]	5.966	[0.00]	11.38	[0.00]	23.65	[0.00]	6.931	[0.00]

Note: The test statistic is LM_F . r denotes the number of transition functions. The digits in brackets are the P -values. The significance level is specified at 5%.

Table 3

Estimation of stock return of semiconductor industry.

Model	PSTR-CDS	PSTR-VIX	PSTR-TED	Linear
Transition variable	CDS	VIX	TED spread	–
Parameter	$r = 1, m = 2, d = 6$	$r = 1, m = 2, d = 5$	$r = m = 1, d = 6$	–
γ	2.212	225.7	0.003	–
c_1	14.33	12.82	0.249	–
c_2	127.4	14.70	–	–
$R_{mt} - R_{ft}$				
θ_1	1.446 (27.07)***	1.829 (19.3)***	1.067 (23.3)***	0.733 (28.8)***
$\theta_{1'}$	–0.09 (–1.442)	–0.48 (–4.87)**	0.336 (5.78)**	–
R_{SMBt}				
θ_2	0.089 (1.349)	0.743 (9.45)***	–0.078 (–1.34)	1.075 (33.0)***
$\theta_{2'}$	0.253 (2.910)**	–0.521 (–5.86)***	0.443 (5.65)***	–
R_{HMLt}				
θ_3	0.142 (3.375)**	0.243 (3.78)**	0.190 (4.47)***	0.113 (5.27)***
$\theta_{3'}$	–0.308 (–5.52)***	–0.367 (–5.25)**	–0.294 (–5.71)***	–
AIC	4.970	5.085	5.068	6.59
BIC	4.978	5.093	5.075	6.64
R-squared	–	–	–	0.263

Note: r and m denote the number of transition functions and location parameters, respectively. d is the lag length of transition variable. The digit in parenthesis is t -statistic. The three optimal models are chosen by employing minimum AIC and BIC.

*Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

model is $0.743 - 0.521 \times F(VIX_{t-5}; 225.7, 12.82, 14.70) > 0$, and for the PSTR-TED model is $-0.078 + 0.443 \times F(TED_{t-6}; 0.30\%, 0.249)$. In two extreme cases, the size premiums are 0.089 and 0.342 for the PSTR-CDS model; 0.743 and 0.222 for the PSTR-VIX model, and –0.078 and 0.365 for the PSTR-TED model.

The estimation results of size premium also have some crucial findings. First, the size premiums are positive for the three PSTR models, satisfying the argument in the F–F model that small capitalization stocks have higher returns than big capitalization stocks.⁸ Again, the estimated size premiums in this study are time-varying, not time-invariant. Second, the size premium is insignificant as the TED spread is smaller than the threshold (0.249) and the CDS is around the mean of the two thresholds (14.33 and 127.4). That is, in the situations of small TED spreads and moderate CDSs, the size premiums are statistically insignificant. In addition, small semiconductor firms get more size premium as the degree of investor panic deepens (i.e., the increase in CDS or TED spread). The probable reason is that in the face of a more panic market sentiment, small firms can adjust their operating strategies more motorized than large firms. Third, the size premium decreases with the increase in the VIX, revealing that extreme fear sentiment of investment makes size premium more ambiguous or the returns between small capitalization stocks and big capitalization stocks indifferent. This result is quite different from the finding of [Brown and Cliff \(2004\)](#) that investor sentiment has little predictive power for small stocks.

5.3. Value premium

The marginal effect of book-to-market ratio factor on stock return (i.e., the value premium) for the PSTR-CDS model is $0.142 - 0.308 \times F(CDS_{t-6}; 2.212, 14.33, 127.4)$; for the PSTR-VIX model is $0.243 - 0.367 \times F(VIX_{t-5}; 225.7, 12.82, 14.70)$, and for the PSTR-TED model is $0.190 - 0.294 \times F(TED_{t-6}; 0.30\%, 0.249)$. In two extreme cases, the value premiums are 0.142 and

⁸ Although size premium in the PSTR-TED model may be negative, the estimated size premium using historical data of TED spread is positive.

–0.166 for the PSTR-CDS model; 0.243 and –0.124 for the PSTR-VIX model, and 0.190 and –0.104 for the PSTR-TED model.

The estimation results give the following findings. First, the value premiums in the three PSTR models are statistically significant, but their signs are ambiguous. Notably, the value premiums are time-varying and may be negative, not constant and positive, obtained from the F–F model and most followers (e.g., Fama & French, 2006). Second, as the CDS and VIX are at extreme low levels (i.e., below the first threshold) or extreme high levels (i.e., above the second threshold), the value premiums are negative, implying that growth stocks get higher returns than value stocks. Thus, when the investors in stock markets show extreme pessimism or extreme optimism, the returns in holding growth stocks dominate holding value stocks. Contrarily, as the CDS (or VIX) locates around the mean of the two thresholds, the value premium is positive and the largest one. That is, in normal sentiment of investment, value stocks that have more completely operating framework and system earn more returns than growth stocks. The negative value premium is the same as those reported by previous studies. For example, Blazenko and Fu (2010) find that growth stocks with high profitability, high market/book, and non-dividend paying have high returns. However, the effect here varies with time and is not permanently constant, and the growth stocks gradually enlarge their advantage as the three proxies of investor sentiment becomes more panic. Third, the value premium increases as the TED spread is over the threshold (0.249). One of the probable reasons is that the TED spread is measured from two more safe assets (Treasury bill and bank's deposit rate), not specific derivatives used by CDS and VIX. Fourth, as the three proxies of investor sentiment are over their individual thresholds, the value premiums decrease.⁹ Clearly, in the situation of extreme fear of investment, the attraction of growth stocks broadens.

For comparison, we also report the estimation result of the F–F model. The F–F model is estimated using fixed effects with a cross-section seemingly unrelated regression (SUR) approach. The market premium, size premium, and value premium are statistically significant, i.e., 0.733, 1.075, and 0.113, consistent with the results in most previous studies (e.g., Perez-Quiros and Timmermann, 2009). Evidently, the size factor has the biggest effect on stock returns among the three factors. In addition, the three risk premiums are time invariant, not time-varying verified in this study. In addition, compared to the three PSTR models, the market premium is underestimated, and the size premium is overestimated.¹⁰

5.4. Simulation of time-varying risk premiums

This sub-section depicts the dynamic paths of the three estimated risk premiums based on the estimation results in Table 3. For the PSTR-CDS model (see Fig. 1), CDS is over its upper threshold (127.4) in the period 2006: Q1–2007: Q2 and under its lower threshold (14.33) in the period 2008: Q3–2012: Q3. Obviously, market and value risk premiums decrease and size premium increases, during these two periods. Since the investors are gradually familiar with the impact of high credit risk (i.e., CDS over the upper threshold) or low credit risk (i.e., CDS under the lower threshold) on stock prices; therefore, the premiums for stock market index and value stocks fall as the CDS locates in these two risk regions. However, worry about the continuity of default in high or low credit risk makes small stocks have higher risk premiums. For the remaining periods, the CDS locates within the two thresholds, which causes the increase in market and value premiums and the decrease in size premium.

Fig. 2 describes the processes of the three risk premiums, VIX and its thresholds using the PSTR-VIX model. As VIX is over the upper threshold, i.e., $VIX \geq 14.70$ (e.g., the periods of 2003: Q1–2003: Q4 and 2007: Q2–2012: Q3) or below the lower threshold, i.e., $VIX \leq 12.82$ (e.g., the period 2005: Q2–2007: Q1), the three risk premiums are decreasing and passivating. In other words, the three risk premiums reduce as market investors show extreme pessimism or extreme optimism. The reason is similar to

⁹ For the PSTR-CDS and PSTR-VIX models, the threshold means the second threshold.

¹⁰ The three PSTR models have lower AIC and BIC than the linear F–F model. This result also supports the use of the PSTR models to measure the risk premiums.

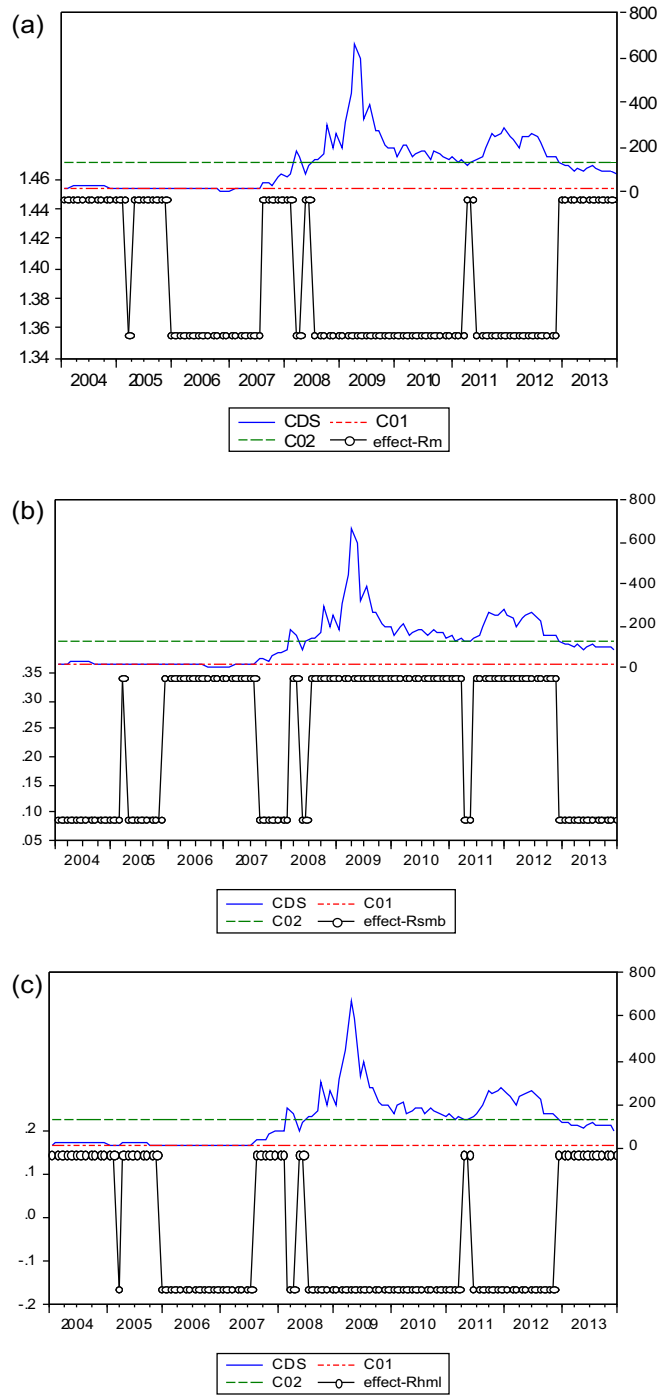


Fig. 1. (a) CDS, threshold and mark et premium, (b) CDS, threshold and size premium, (c) CDS, threshold and value premium. Note: CDS is the credit default spread. C01 and C02 are two thresholds 14.33 and 127.1. The premiums are measured in left vertical axis. effect-Rm, effect-Rsmb, and effect-Rhml are market premium, size premium, and value premium, respectively.

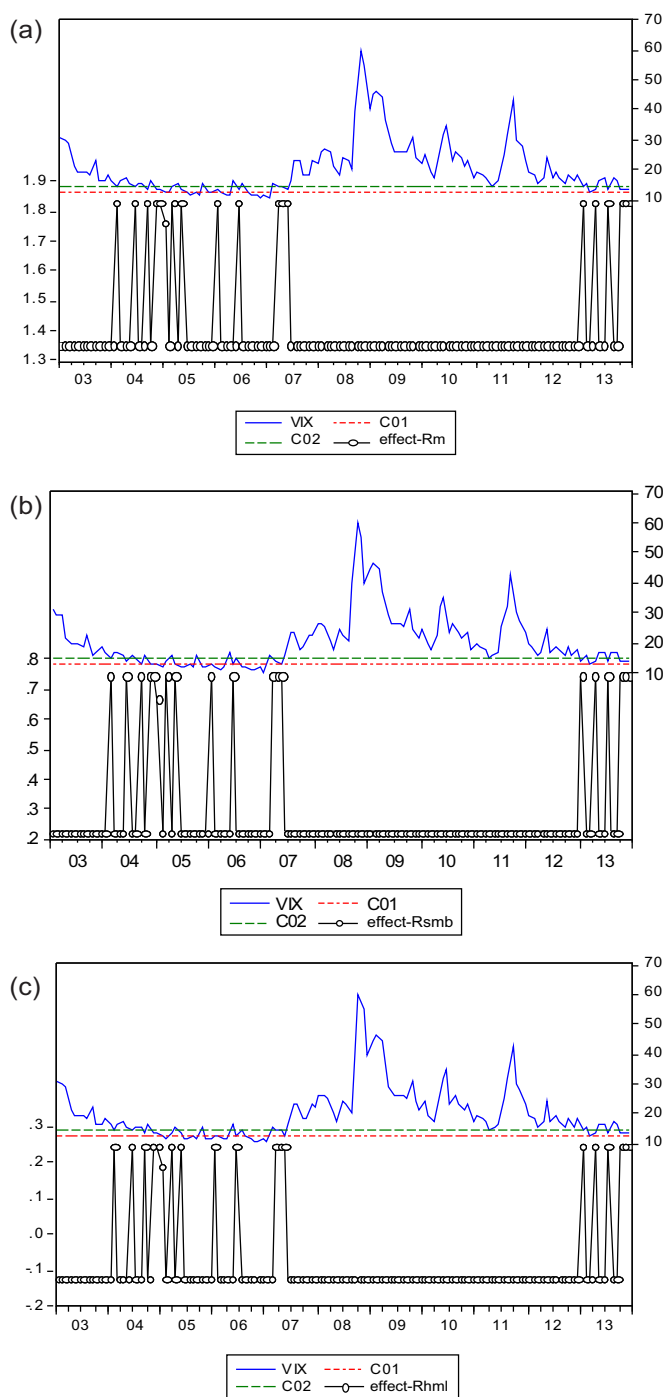


Fig. 2. (a) VIX, threshold and market premium, (b) VIX, threshold and size premium, (c) VIX, threshold and value premium. Note: VIX is the volatility index. C01 and C02 are two thresholds 12.82 and 14.70. The premiums are measured in right vertical axis. effect-Rm, effect-Rsmb, and effect-Rhml are market premium, size premium, and value premium, respectively

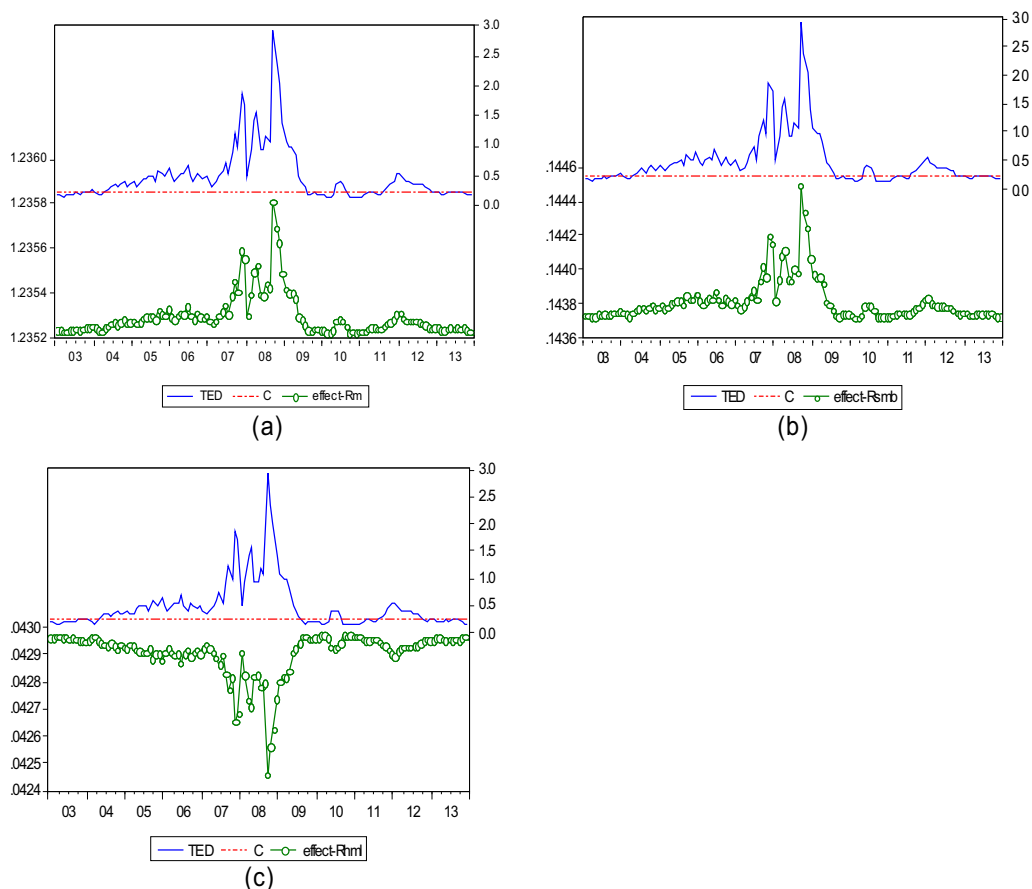


Fig. 3. (a) TED, threshold and market premium, (b) TED, threshold and size premium, (c) TED, threshold and value premium. Note: TED is the TED spread. C is the threshold 0.2492. effect-Rm, effect-Rsmb, and effect-Rhml are market premium, size premium, and value premium, respectively. The premiums are measured in left vertical axis.

that in the PSTR-CDS model that stock investors are gradually familiar with the high or low fear in stock markets as the VIX is larger or smaller than a specific threshold value; therefore, the required risk premiums for compensating the fear reduce. Under the circumstances, the dominance of small stocks over big stocks and value stocks over growth stocks worsens. It is worth mentioning that the events of the Severe Acute Respiratory Syndrome (2003: Q1) and the European sovereign debt crisis (2009: Q4–2100: Q2) have VIXs over the upper threshold, implying that financial crises weaken the three premiums or the excess returns of small stocks and value stocks deteriorate.¹¹

The dynamic paths of TED spread and the corresponding risk premiums are shown in Fig. 3. During the period of 2004: Q2–2009: Q1, the TED spread is over its threshold (0.249), and market and size risk premiums increase, and value premium decreases. The results in the changes of market and size risk premiums are quite different from those in PSTR-CDS and PSTR-VIX models. As indicated by Wu(2013), the reason may be that the correlation between TED spread and CDS fluctuates around zero prior to the Subprime Mortgage crisis (December 2007–June 2009), while moves notably higher during the crisis,

¹¹ While the processes of the risk premiums in Fig. 2 do not display a smooth regime switching, they are still the probable results derived from the PSTR model (see above in Section 2). The reason originates from the large volatility of the transition variables (VIX and CDS) in adjacent two periods.

and fell down to the levels between 0.05 and 0.1 after 2009. This unstable relationship between TED spread and CDS leads to different threshold effects of CDS or TED spread on the three risk premiums.¹²

According to the evidence in Figs. 1–3, we can obtain the following conclusions. First, the three risk premiums vary with the use of the proxies of investors sentiment, and the differential results can be investigated from the intrinsic characteristics of the proxies. The underlying assets in CDS, VIX, and TED spread are bonds, stock options, and a three-month LIBOR rate and a three-month US Treasury bill rate, respectively, which are highly associated with the volatilities in bond, option and, monetary markets. Previous studies have indicated that stock, bond, option, and money markets have close relationships, even though the relationships are ambiguous. Thus, we expect that these three proxies may cause differential impacts on risk premiums and stock returns. Second, CDS and VIX have similar results in the three risk premiums. That is, the sentiment of extreme pessimism or extreme optimism can generate symmetric influences on the three risk premiums. The stylized facts in Figs. 1 and 2 also support the finding in Ericsson, Reneby, and Wang (2006) that there is a positive relationship between CDS and VIX in the absence of variance risk premium. Third, for the three sentiment proxies, high sentiment proxies clearly lead to the decrease in the relevance of value stocks. Moreover, the impact directions of VIX on the three premiums are considerably consistent. Thus, the VIX is a more appropriate proxy for evaluating the consistent influence of high fear sentiment on risk premiums and stock prices.

6. Conclusion

This paper reconstructs the Fama and French's (1993) three-factor model as a PSTR framework. In the framework, we use three proxies of investor sentiment as the transition variables to investigate the threshold effects of the proxies on stock returns, and to evaluate three time-varying risk premiums. To execute empirical analysis, we use 58 semiconductor stocks listed on Taiwan Security Exchange Corporation as sample objects. The sample period spans from 2003 through 2013.

There are several interesting findings in terms of the estimated risk premiums, including: (1) the three risk premiums vary with time, which cannot be obtained in the standard F–F model; (2) the market premiums fall as investors in stock markets show extreme optimism or extreme pessimism; (3) except in the situation that the CDS spread is around the mean of the two thresholds (14.33 and 127.4), the size premium is significant for the semiconductor stocks, i.e., small capitalization stocks have higher returns than big capitalization stocks; (4) the size premium decreases with the increase in VIX, revealing that the returns between small capitalization stocks and big capitalization stocks become indifferent; (5) returns in holding growth stocks dominate holding value stocks when the investors show extreme pessimism or optimism. However, in normal sentiment of investment, value stocks earn more returns than growth stocks; (6) the value premium increases as the TED spread is over the threshold (0.249), and as the three proxies of investor sentiment are over their individual thresholds, the value premiums decrease. Clearly, in the situation of extreme fear of investment, the attraction of growth stocks widens.

Our results have the following implications of investment strategy. First, all the three risk premiums are time-varying; therefore, investors in stock markets need to adjust investment portfolio based on the estimated risk premiums for each period. Second, in normal sentiment of investment, investors need to hold value stocks to earn higher returns than growth stocks. Contrarily, in the situations of extreme pessimism and extreme optimism, they need to hold growth stocks. Third, holding small capitalization stocks cannot have extra returns than big capitalization stocks as the VIX becomes unusually large. Finally, the three proxies of investor sentiment have different impacts on the three risk premiums, derived from the complicated relationships among the CDS, VIX, and TED spread. Thus, using the indicator of investor sentiment to evaluate their impacts on risk premiums or stock returns, we need to carefully distinguish the individual proxies of investor sentiment.

¹² The testing result of linearity in Table 2 has indicated that using the PSTR-TED model to estimate the three premiums is proper. The main reason that the three risk premiums change within a narrow range is the tiny transition speed ($\gamma = 0.003$). That is, the series spends a longer time to return back its long run equilibrium. However, we are unable to deny the non-linear processes in the risk premiums.

Appendix A.

Table A1
Descriptive statistics.

Variable	R_{it}	R_M	R_{SML}	R_{HML}	CDS	VIX	TED
Mean	−0.995	−0.642	0.585	−3.910	123.9	20.20	0.520
Median	−2.597	−0.214	0.041	−3.990	110.3	17.12	0.355
Max	65.61	14.70	13.96	13.98	666.6	59.90	3.35
Min.	−33.74	−21.02	−10.31	−31.93	7	10.42	0.12
Std. Dev.	15.30	6.069	5.052	7.470	117.8	9.146	0.504
Skewness	1.419	−0.290	0.408	−0.491	1.611	1.928	2.643
Kurtosis	7.514	3.916	3.000	4.211	7.214	7.201	11.60
Jarque–Bera	7817	322.9	183.2	668.3	7738	8942	28,000
P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: R_{it} , R_M , R_{SML} , R_{HML} , CDS, VIX, and TED are the return of equity i , market return, size premium, value premium, credit default swap, volatility index, and TED spread, respectively.

Table A2
LLC panel unit root test.

Variable	R_{it}		R_M		R_{SML}	
Method	Statistic	P-value	Statistic	P-value	Statistic	P-value
LLC	−11.37	0.00	−9.826	0.00	−11.19	0.00
Variable	R_{HML}		CDS		VIX	
Method	Statistic	P-value	Statistic	P-value	Statistic	P-value
LLC	−10.84	0.00	−1.493	0.07	−1.522	0.06
Variable	TED					
Method	Statistic		P-value			
LLC	−2.058		0.02			

Note: R_{it} , R_M , R_{SML} , R_{HML} , CDS, VIX, and TED are the return of equity i , market return, size premium, value premium, credit default swap, volatility index, and TED spread, respectively. LLC performs well when N lies between 5 and 250 and T lies between 5 and 250. The N and T in this study are 58 and 132, respectively, so it is applicable to use the LLC test to confirm the stationarity.

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