

Volatility Feedback and the State-Dependent Intertemporal Risk-Return Tradeoff: International Evidence from G7 Equity Markets

Osman Kilic,
Department of Finance
School of Business
Quinnipiac University
Hamden, CT 06518
Osman.Kilic@quinnipiac.edu

Kiseok Nam
Department of Finance
School of Business
Quinnipiac University
Hamden, CT 06518
Kiseok.Nam@quinnipiac.edu

Matthew L. O'Connor,
Department of Finance
School of Business
Quinnipiac University
Hamden, CT 06518
Matthew.O'Connor@quinnipiac.edu

Volatility Feedback and the State-Dependent Intertemporal Risk-Return Tradeoff: International Evidence from G7 Equity Markets

Abstract

This paper investigates whether the volatility feedback effect (VFE) is a localized anomaly or a pervasive international phenomenon that shapes the state-dependent intertemporal risk-return relation (IRRR). Using daily excess return data from G7 equity markets spanning several decades, we provide comprehensive evidence that the VFE is a central driver of intertemporal pricing of risk. While the influence of predictable volatility on expected returns is generally weak and inconsistent, the estimated VFE parameter is strongly positive and statistically significant across all G7 markets, indicating that unexpected volatility shocks dominate the pricing of volatility risk. Importantly, the VFE is highly state-dependent: it strengthens the positive risk-return tradeoff in adverse market conditions while weakening or eliminating the relation in favorable states. We further show that extreme levels of VFE, arising under the joint conditions of elevated volatility and negative market news, can serve as early indicators of crash risk even in the absence of identifiable macroeconomic shocks. These findings underscore the importance of systematic and persistent monitoring of extreme VFE by monetary authorities and market participants as part of volatility risk management strategies aimed at mitigating crash vulnerability in international equity markets.

JEL classification: G10; G12

Keywords: Intertemporal risk-return relation; Volatility feedback effect; State-dependent risk-return tradeoff; G7 equity markets; Market crash

1. Introduction

The intertemporal risk-return tradeoff is a fundamental principle in financial economics that captures how rational investors adjust their asset pricing decisions in response to changing risk over time. It is consistent with time-varying rationality, whereby risk-averse investors revise their expectations in response to changes in the volatility of asset returns. Recent studies suggest that rational investors adjust their expectations not only to predictable volatility but also to unanticipated volatility shocks, highlighting the importance of the volatility feedback effect (VFE) in shaping how investors perceive volatility risk and incorporate it into pricing decisions within the intertemporal risk-return relation (IRRR) framework.¹ These studies show that the VFE is a primary driver of the state-dependent IRRR in U.S. equity markets. Specifically, unexpected shocks to volatility heighten investors' perception of risk, causing an immediate negative adjustment in asset prices and higher required future returns. Thus, the VFE provides an explicit mechanism through which unanticipated volatility shocks shape the intertemporal pricing of risk, beyond the influence of predictable volatility alone.

¹ See Chelikani et al. (2023) and Kilic et al. (2024).

Originally defined as the negative correlation between asset prices and unexpected volatility, the volatility feedback effect has been widely recognized as a central factor behind the U.S. stock market crash of 1987. The panic triggered by internally generated volatility feedback—arising from extremely high levels of unexpected volatility shocks—precipitated the crash. The key lesson from 1987 is that any equity market is vulnerable to collapse when the risk-return tradeoff becomes excessively heightened due to volatility feedback, even in the absence of macroeconomic shocks. This underscores the importance of analyzing how rational, risk-averse investors respond to the VFE within the IRRR framework to better understand. Greater understanding of investor responses to the VFE may ultimately inform regulators and potentially help prevent crashes driven by unexpected volatility shocks.

The purpose of this study is to examine whether the VFE is a localized phenomenon affecting only U.S. equity markets, or a pervasive international phenomenon affecting global equity markets. Using daily excess-return data for G7 equity markets over several decades, we develop and test a state-dependent IRRR model that incorporates both expected volatility and unexpected volatility shocks. We assess whether the VFE is a critical risk factor in shaping the state-dependent IRRR in these markets and further explore how it interacts with market states—good versus bad news—and volatility regimes—high versus low.

Our analysis provides comprehensive evidence of volatility feedback effects existing across international equity markets. Our results also highlight several novel findings. First, while the effect of predictable volatility on expected returns is weak and often inconsistent, the VFE parameter is strongly positive and statistically significant across all G7 markets, implying that unexpected volatility shocks are a dominant driver of the intertemporal pricing of equity risk. Second, the VFE is highly state-dependent: it strengthens the positive risk-return tradeoff during bad market states but weakens or eliminates the relation during good states. Third, we show that extreme levels of VFE, arising under the joint conditions of high volatility and adverse market news, can serve as early indicators of crash risk—even in the absence of identifiable macroeconomic shocks.

This study makes four key contributions to the intertemporal risk-return literature. First, it demonstrates that incorporating the VFE resolves much of the ambiguity surrounding prior empirical evidence, offering a unified explanation for the asymmetric and regime-dependent nature of the IRRR. Second, it shows that the VFE is not market-specific but rather a stylized fact measurable across developed global equity markets. Third, the results have practical implications for risk management and asset allocation: ignoring the VFE biases estimates of the equity premium downward during bad states and upward during good states, potentially leading to risk mispricing and suboptimal portfolio strategies. Finally, the study highlights the need for systematic and ongoing monitoring of extreme VFE levels by

monetary authorities and market participants, as such oversight is essential for effective volatility risk management and for reducing the vulnerability of international equity markets to crash-like dynamics.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on the IRRR and VFE. Section 3 presents the theoretical framework and hypothesis development. Section 4 describes the data and methodology. Section 5 reports the empirical results. Section 6 provides robustness checks, and Section 7 concludes.

2. Related Literature

The intertemporal risk-return relation has long been a central idea in financial economics. At its core, the intertemporal risk-return relation (IRRR) posits that rational, risk-averse investors demand higher expected returns as compensation for increased risk, as measured by conditional volatility. Since the seminal contribution of Merton (1973), a substantial body of research has empirically examined and theoretically extended intertemporal risk-return models. Two dominant streams have emerged in the literature regarding the estimation of the Relative Risk Aversion (RRA) parameter: one assumes a constant RRA, while the other allows for time-varying RRA, typically linked to changes in economic or market conditions. Each approach offers a distinct perspective on the estimation and interpretation of the risk-return relation over time.

The constant RRA framework in the intertemporal risk-return relation posits that investors' degree of risk aversion remains fixed over time. Under this assumption, the sensitivity of expected asset returns to changes in conditional volatility is constant, implying a proportional but stable tradeoff between risk and return. This modeling approach simplifies empirical analysis and serves as a foundational benchmark for evaluating the risk-return tradeoff. Accordingly, many early empirical studies on the intertemporal risk-return relation adopt the constant RRA specification to examine the direction and significance of the relation. Studies that have empirically documented a positive risk-return tradeoff include Pindyck (1984), Haugen et al. (1991), Scruggs (1998), Ghysels et al. (2005), Ludvigson and Ng (2007), Bali and Peng (2006), Lundblad (2007), Bali (2008), Guo and Neely (2008), and Pastor et al. (2008), among others. In contrast, studies supporting a negative relationship between expected returns and volatility include Campbell (1987), Abel (1988), Glosten et al. (1993), Brandt and Kang (2004), Gennotte and Marsh (1993), Backus and Gregory (1993), Nelson (1991), Whitelaw (1994), and Ang et al. (2006). Additionally, a number of empirical studies have found the RRA relationship to be either unstable or statistically insignificant, indicating limited time variation in the expected risk premium. These include Poterba and Summers (1986), Baillie and DeGennaro (1990), Boudoukh et al. (1997), Whitelaw (2000), and Müller et al. (2011).

More recently, a second stream of research emphasizes that the intertemporal risk-return tradeoff is not constant but instead varies across different market regimes and investor environments. Whitelaw (1994), employing an instrumental variable approach to estimate the conditional mean and variance of returns, finds that the relationship between expected returns and conditional volatility is unstable, with its sign fluctuating over time. Yu and Yuan (2011) highlight the role of investor sentiment in shaping this relation, showing that the risk-return tradeoff is significantly positive during high-sentiment periods but becomes statistically insignificant when sentiment is low. They attribute this asymmetry to the influence of sentiment-driven trading in optimistic market environments, which can distort the expected risk-return dynamics. Extending this line of inquiry, Ghysels et al. (2014) apply a Markov-switching MIDAS (Mixed Data Sampling) model to show that the risk-return relation alternates between regimes with opposing signs, reinforcing the notion of time-varying dynamics.

Marks and Nam (2018) highlight the importance of accounting for lagged market returns in estimating the risk-return tradeoff. They find that the relation weakens in response to favorable market news but strengthens following adverse news. This asymmetry suggests that investor behavior, particularly in response to changing expectations, plays an important role in determining the risk premium. Wang (2018) extends this line of inquiry by incorporating institutional investor sentiment into the analysis. His findings reveal that the positive risk-return relation is significantly attenuated when institutional sentiment is bullish but remains intact during bearish sentiment periods, implying that even institutional investors are subject to sentiment-driven distortions. Chelikani et al. (2023) further investigate the state-dependent IRRR by examining how it responds to various market conditions. They document that the positive tradeoff between risk and return is significantly distorted during periods of extreme price changes, varying levels of investor sentiment, the introduction of stock options, and across different phases of the business cycle. Their findings highlight the importance of incorporating regime-specific dynamics and structural market shifts in modeling the intertemporal pricing of risk.

While much of the foundational work on the intertemporal risk-return relation was developed in the context of the U.S. market, an extensive body of research has tested the relation in international markets, uncovering variations in the strength, sign, and dynamics of the relation across countries, market types, and time periods.² Further developing this line of inquiry, several recent studies support for the view that the intertemporal risk-return relation is not constant but varies across market states. For example, using data from G7 equity markets, Kang et al. (2019) present robust evidence that the risk-return tradeoff is significantly positive during periods of negative market news but becomes statistically

² See Ferson and Harvey (1994), Bekaert and Harvey (1995), De Santis and Gerard (1997), Balaban and A. Bayar (2005), Hardouvelis et al. (2006), Guo (2006), Leon et al. (2007), Guo and Neely (2008), Ang et al. (2009), Bali and Cakici (2010), Chiang et al. (2015), Chen and Chiang (2016), and Savva and Theodossiou (2018).

insignificant or even absent following positive news. Examining the empirical relationship between risk and return for the 43 developed and emerging markets, Fifield et al. (2020) argue that the risk-return relation is switching in nature, driven primarily by changing risk preferences. They show that, when macroeconomic risk is high, a positive relation dominates; when it is low, or in optimistic bull markets, this pattern can invert. Similarly, Wang, Chen, and Lo (2021) examine the influence of economic states and investor behavior across a broad set of countries and find that the risk-return relation is both regime-dependent and asymmetric across bull and bear markets. Their results indicate that a positive risk-return relation is more likely to emerge during low-volatility, expansionary phases, while it tends to weaken or reverse during periods of economic contraction or elevated market uncertainty.

Much of the prior literature on the intertemporal risk-return relation has focused on its dynamic nature—whether constant or time-varying—and its pricing effect on expected returns. This study advances the field by identifying the volatility feedback effect as a central force in the global risk-return tradeoff. Specifically, we show that extreme VFE levels, arising under the joint conditions of heightened volatility and adverse market news, can serve as early warning signals of crash risk even in the absence of macroeconomic shocks. These results provide compelling evidence for why monetary authorities, regulators, and market participants should adopt systematic and continuous monitoring of extreme VFE as part of comprehensive volatility risk management. Overall, our findings help bridge the gap between the widely recognized role of equity market volatility and the often underappreciated link to potential crash vulnerability in international equity markets.

3. The Model for Volatility Feedback Effect and Hypotheses Development

3.1 Theoretical and Base Model for Intertemporal Risk-Return Relation

We model the intertemporal risk-return tradeoff driven incorporating both predictable and unpredictable volatility effects within a Slutsky-equation-based framework for equilibrium asset demand, first proposed by Marks and Nam (2018). Under a general portfolio model of two-period utility maximization, an investor chooses portfolio X from n risky assets subject to a wealth constraint. Let x_i be a quantity of asset i measured in shares and p_i be the price of asset i , such that the investor's net wealth is $\sum_{i=1}^n p_i x_i$, where $x_i > 0$ ($x_i < 0$) indicates a long (short) position. Let $\bar{x}_i$ be the initial quantity of asset i such that $W = \sum_{i=1}^n p_i \bar{x}_i$ is the initial net wealth. With a positive initial net wealth, the adjustment to the investor's portfolio is based on the following wealth constraint:

$$W - \sum_{i=1}^n p_i x_i = 0. \tag{1}$$

The investor attempts to maximize the following Lagrangian function (L):

$$L = U(x_1, \dots, x_n) + \lambda(W - \sum_{i=1}^n p_i x_i), \quad (2)$$

where λ is a Lagrangian multiplier for the continuous and at least twice differentiable utility function. The optimal portfolio X is found by solving the following first order conditions:

$$\partial U / \partial x_i - \lambda p_i = 0 \quad (3)$$

$$W - \sum_{i=1}^n p_i x_i = 0. \quad (4)$$

The second order condition for maximization is that the principal minors of the following bordered Hessian (H) alternate in sign, beginning positive:

$$H = \begin{bmatrix} \frac{\partial^2 L}{\partial x_i \partial x_j} & \frac{\partial^2 L}{\partial x_i \partial \lambda} \\ \frac{\partial^2 L}{\partial \lambda \partial x_j} & \frac{\partial^2 L}{\partial \lambda^2} \end{bmatrix}. \quad (5)$$

Consider a small change in p_i that induces changes in the optimal holdings of x_i . Differentiating the first order conditions with respect to p_i yields the following system of equations:

$$\begin{bmatrix} U_{11} & \dots & U_{1n} & p_1 & \partial x_1 / \partial p_i & 0 \\ \vdots & & \vdots & \vdots & \vdots & \vdots \\ U_{i1} & \dots & U_{in} & p_i & \partial x_i / \partial p_i & \lambda \\ \vdots & & \vdots & \vdots & \vdots & \vdots \\ U_{n1} & \dots & U_{nn} & p_n & \partial x_n / \partial p_i & 0 \\ p_1 & \dots & p_n & 0 & -\partial \lambda / \partial p_i & \bar{x}_i - x_i \end{bmatrix} = 0. \quad (6)$$

Solving this system yields the following Slutsky equation for the price changes:

$$\frac{\partial x_i}{\partial p_j} = \lambda \frac{|D_{ij}|}{|D|} + (\bar{x}_i - x_i) \frac{\partial x_i}{\partial W}, \quad (7)$$

where $|D_{ij}|$ is the cofactor of the ij^{th} element of the bordered Hessian, $|D|$ is the determinant of the bordered Hessian, and $(\bar{x}_i - x_i)$ is the investor's excess demand for the i^{th} asset. For the case of own price change, the Slutsky equation can be written as follows:

$$\frac{\partial x_i^*}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i} + (\bar{x}_i - x_i) \frac{\partial x_i^*}{\partial W}, \quad (8)$$

where $\frac{\partial x_i^*}{\partial p_i}$ is the response of the equilibrium asset demand to a change in its own price, $\frac{\partial x_i^U}{\partial p_i}$ is the response of x_i to a change in p_i along with the wealth compensated constraint maintaining the same level of the utility, and $\frac{\partial x_i^*}{\partial W}$ is the response of x_i to changes in portfolio wealth resulting from changes in p_i . The first term reflects a pure substitution effect, while the second term reflects a wealth effect.

Epps (1975) suggests that in equilibrium, an investor's excess demand for asset i , (i.e., $\bar{x}_i - x_i$) equals zero so that there is no wealth effect from price changes. Unless there is a sudden unexpected change in the investor's stocks of assets, $\bar{x}_i$ is always the same as the equilibrium quantity level of the i^{th} asset. In equilibrium, the excess demand for each of the assets is zero, so that changes in asset prices yield only substitution effects, which are not necessarily restricted in sign. For the compensation to maintain the same utility level to the variations in net wealth resulting from price changes, the substitution effect of asset demand is driven by the investor's expected asset price. Then, aligning with the derivation presented in Epps (1975), the Slutsky equation can be expressed as:

$$\frac{\partial x_i^*}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i^e} \cdot \frac{\partial p_i^e}{\partial p_i}, \quad (9)$$

where p_i^e is the expected price of the i^{th} asset with $\frac{\partial x_i^U}{\partial p_i^e} > 0$, which implies that the investor holds more (fewer) shares of the i^{th} asset when its expected price increases (decreases).

In equilibrium asset pricing, the term $\frac{\partial p_i^e}{\partial p_i}$ is primarily driven by investors' revisions in their expectations about future asset prices. Marks and Nam (2018) suggest that the responsiveness of expected price changes to current price changes is determined not only by the intertemporal risk-return relation but also by the price adjustments resulting from investor behavior to correct their prior mispricing. Recently, Chelikani et al. (2023) and Kilic et al. (2024) further expand the understanding of the intertemporal risk-return relationship by suggesting that it is affected by both expected volatility and unexpected volatility shocks. Based on these studies, the determination of $\frac{\partial p_i^e}{\partial p_i}$ involves three pricing channels: predictable volatility, unanticipated volatility shocks, and the correction of prior mispricing. Thus, the equation (9) can be rewritten as follows:

$$\frac{\partial x_i^*}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i^e} \left[\frac{\partial p_i^e}{\partial r_i^e} \frac{\partial r_i^e}{\partial \sigma_i^2} \frac{\partial \sigma_i^2}{\partial p_i} + \frac{\partial p_i^e}{\partial r_i^e} \frac{\partial r_i^e}{\partial v_i^2} \frac{\partial v_i^2}{\partial p_i} + \frac{\partial p_i^e}{\partial r_i^e} \frac{\partial r_i^e}{\partial p_i} \right]. \quad (10)$$

Let r_i denote the expected risk premium of the i^{th} asset, σ_i^2 its variance, and v_i^2 an anticipated variance shock. We incorporate asset price dynamics exogenously into the above Slutsky equation to reflect the idea that changes in asset prices lead rational, risk-averse investors to revise their expectations in response to time-varying volatility. Specifically, we replace p_i^e with $p_{i,t}^e = E_t(p_{i,t+1}|\Omega_t)$, denoting the expected price of the i^{th} asset in the next period under the assumption of rational expectations, given the information set Ω_t available at time t . Moreover, because true volatility is not directly observable, rational, risk-averse investors form expectations about the future volatility of the i^{th} asset, denoted $\hat{\sigma}_{i,t}^2 = E_t(\sigma_{i,t+1}^2|\Omega_t)$, using the same information set. We also define the unanticipated volatility shock as the volatility forecast error, i.e., $\hat{v}_{i,t}^2 = \sigma_{i,t}^2 - \hat{\sigma}_{i,t}^2$, where $\sigma_{i,t}^2$ is defined as the realized volatility. Accordingly, we rewrite Equation (10) as follows:

$$\frac{\partial x_{i,t+1}^*}{\partial p_{i,t}} = \frac{\partial x_{i,t}^U}{\partial p_{i,t}^e} \frac{\partial p_{i,t}^e}{\partial r_{i,t}^e} \left[\frac{\partial r_{i,t}^e}{\partial \hat{\sigma}_{i,t}^2} \frac{\partial \hat{\sigma}_{i,t}^2}{\partial p_{i,t}} + \frac{\partial r_{i,t}^e}{\partial \hat{v}_{i,t}^2} \frac{\partial \hat{v}_{i,t}^2}{\partial p_{i,t}} + \frac{\partial r_{i,t}^e}{\partial p_{i,t}} \right], \quad (11)$$

where $\frac{\partial x_{i,t+1}^*}{\partial p_{i,t}}$ is the risk-averse investor's response to the own price change in the equilibrium demand of the

i^{th} asset, and $\frac{\partial x_{i,t}^U}{\partial p_{i,t}^e} > 0$ is the responses of the i^{th} asset to the change in $p_{i,t}^e$ along with the wealth

compensated constraint while maintaining the same level of the utility. The concept of time-varying

rationality implies that $\frac{\partial p_{i,t}^e}{\partial r_{i,t}^e} < 0$, indicating that the expected risk premium negatively affects the expected

price. Note that the idea of the inverse relationship between risk-premium and the contemporaneous price change arises from the condition $\frac{\partial p_{i,t}^e}{\partial r_{i,t}^e} < 0$. To reflect the fact that both upward and downward price

movements can generate volatility, we define $\frac{\partial \hat{\sigma}_{i,t}^2}{\partial p_{i,t}} > 0$ for $\Delta p_{i,t} > 0$ and $\frac{\partial \hat{\sigma}_{i,t}^2}{\partial p_{i,t}} < 0$ for $\Delta p_{i,t} < 0$.

The term $\frac{\partial r_{i,t}^e}{\partial \hat{\sigma}_{i,t}^2}$ captures the effect of predictable volatility, while the term $\frac{\partial r_{i,t}^e}{\partial \hat{v}_{i,t}^2}$ captures the effect of an unanticipated volatility shock, which serves as the source of the volatility feedback effect. We propose that the complete intertemporal risk-return relationship is determined jointly by $\frac{\partial r_{i,t}^e}{\partial \hat{\sigma}_{i,t}^2}$ and $\frac{\partial r_{i,t}^e}{\partial \hat{v}_{i,t}^2}$.

Note that although $\frac{\partial r_{i,t}^e}{\partial \hat{\sigma}_{i,t}^2}$ is typically assumed to be positive, we do not impose this restriction in order to

reflect empirical evidence showing that the sign is not always positive. Lastly, $\frac{\partial r_{i,t}^e}{\partial p_{i,t}}$ represents price adjustments stemming from investors' tendency to correct prior mispricing. Specifically, $\frac{\partial r_{i,t}^e}{\partial p_{i,t}} > 0$ indicates return persistence, while $\frac{\partial r_{i,t}^e}{\partial p_{i,t}} < 0$ reflects return reversal. In estimation, we incorporate an AR(1) term to capture this adjustment process.

Given the positive monotonic functional relationship between the expected price and expected return, Equation (11) provides the rationale for proposing an empirical model in which the expected returns of each country's equity index are jointly determined by three pricing factors, as specified in the following baseline model of the intemporal risk-return relation with the constant RRA parameter:

$$E_t(r_{t+1} - rf | \Omega_t) = c + \tau \hat{\sigma}_t + \delta \hat{v}_t + \phi r_{t-1}, \quad (12)$$

where $E_t(r_{t+1} - rf | \Omega_t)$ represents the expected market risk premium available at time t for each index. $\hat{\sigma}_t^2$ and $\hat{v}_t^2$ denote the conditional forecast of the predictable component of return volatility and the forecast error, respectively, with the latter interpreted as an unanticipated volatility shock. For each country's index return, τ and δ represent constant RRA parameters associated with the intertemporal risk-return tradeoff. Specifically, τ captures the RRA associated with predictable volatility, while δ reflects the RRA linked to unanticipated volatility shocks; hence, δ is referred to as the constant VFE parameter. The parameter ϕ is the first-order autoregressive coefficient, capturing the price adjustment process resulting from investor behavior in response to correcting prior mispricing.

3.2 Hypotheses Development

We propose that the VFE constitutes a significant risk factor, implying that the full intertemporal risk-return tradeoff is driven by both expected and unexpected changes in volatility. Specifically, we introduce the following state-dependent model of the risk-return relationship, in which asymmetric RRA parameters are governed by positive and negative states of the equity market for each country.

$$E_t(r_{t+1} - rf | \Omega_t) = c + (\tau_P P + \tau_N N) \hat{\sigma}_t + (\delta_P P + \delta_N N) \hat{v}_t + \phi r_{t-1}, \quad (13)$$

where P and N are the dummies that represent the good and bad market states, respectively. τ_P and τ_N are the RRA parameters associated with expected volatility in good and bad market states, respectively, and δ_P and δ_N are the RRA parameters associated with unexpected volatility in good and bad market states,

respectively. We conjecture that under a bad market state, the VFE increases investors' perceived risk, thereby strengthening the risk-return tradeoff. Furthermore, we posit that this effect is not market-specific but rather a pervasive international phenomenon. Accordingly, our first hypothesis is that for each country's index, the RRA parameter under a bad market state is positive and statistically significant—specifically, $\delta_N > 0$ with $\delta_N > \delta_P$.

We further conjecture that the degree of asymmetry in the risk-return tradeoff between good and bad market states becomes more pronounced when the VFE is taken into account. Thus, given $0 < \delta_N > \delta_P \leq 0$, our second hypothesis is that for each country's index, the VFE amplifies the positive risk-return relationship under adverse market conditions, while weakening it under favorable conditions—specifically, $\tau_N + \delta_N > 0$ and $\tau_N + \delta_N > \tau_P + \delta_P$.

As mentioned earlier, the 1987 stock market crash illustrates that an extremely heightened risk-return tradeoff—driven by a very high level of the volatility feedback effect during bad market states—can trigger panic among risk-averse investors, potentially leading to a market crash. In this paper, we explore this possibility empirically by examining whether, and how, the VFE is influenced by the interaction of market conditions defined by combinations of unexpectedly high or low volatility and good or bad market states. To this end, we analyze the state-dependent VFE under four possible market scenarios, using the following model specification:

$$E_t(r_{t+1} - rf|\Omega_t) = c + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N] \cdot \hat{v}_t + \phi R_{t-1}, \quad (14)$$

where P (N) is a dummy variable indicating a good (bad) market state, and L (H) is a dummy variable indicating unexpectedly low (high) market volatility. The asymmetric VFE parameters are represented by δ_L^P and δ_H^N under low volatility conditions, and δ_H^P and δ_L^N under high volatility conditions.

During periods of heightened volatility, risk-averse investors tend to respond strongly to negative market news by demanding a higher risk premium, which can lead to sharp declines in asset prices. We therefore conjecture that the VFE is amplified by bad market news during high volatility periods. Accordingly, our third hypothesis is that the VFE parameter under the combined condition of high volatility and a bad market state is both economically and statistically significant and positive—that is, $\delta_H^N > 0$. Notably, an extremely high value of δ_H^N may serve as an indicator of a potential market crash.

4. Data and Methodology

To investigate whether the volatility feedback effect contributes to the asymmetric intertemporal risk-return relation as a common feature in global equity markets, we analyze daily returns of U.S. dollar-

denominated stock indices from the G7 countries. We use the S&P/TSX Composite index (Jan. 05, 1970 – Dec. 31, 2019) for Canada, the CAC (Jul 10, 1987 – Dec. 31, 2019) for France, the DAX30 (Jan. 04, 1965 – Dec. 31, 2019) for Germany, MSCI index (Sep 2, 1971 – Dec. 31, 2019) for Italy, the Nikkei 225 index (Jan. 04, 1965 – Dec. 31, 2019) for Japan, the FTSE 100 index (Feb. 1, 1978 – Dec. 31, 2019) for United Kingdom (UK), and the S&P500 (July 3, 1963 – Dec 31, 2019) for US. The daily excess return is computed as the difference between the nominal daily index return and the daily U.S. one-month T-bill rate reported by Ibbotson Associates.³

To estimate the intertemporal risk-return relation, we first generate conditional forecasts of market volatility by applying Nelson’s (1992) EGARCH (1,1) model to the daily excess returns of each index. The resulting forecast errors are used as proxies for unexpected volatility shocks. We then estimate the RRA parameters by running OLS regressions of daily excess returns on both the expected and unexpected components of market volatility.

Panel A of Table 1 presents the descriptive statistics for the G7 index returns. All daily excess returns exhibit negative skewness and excess kurtosis—stylized features commonly observed in short-horizon stock returns, which contribute to the presence of return heteroskedasticity. Panel B of Table 1 reports the estimated constant Relative Risk Aversion (RRA) parameters from the benchmark model of the constant intertemporal risk-return model: $R_t = c + \tau \hat{\sigma}_t + \delta \hat{v}_t + \phi R_{t-1} + \varepsilon_t$, where $R_t = r_t - rf$ and $\hat{\sigma}_t$ and $\hat{v}_t$ represent the expected and unexpected components of market volatility, respectively. In this specification, τ captures the RRA associated with predictable volatility, while δ measures the RRA corresponding to the volatility feedback effect. Note that the endogeneity issue in estimating the volatility feedback effect arises because the contemporaneous unexpected volatility shock perceived by the representative investor is unobservable to the econometrician. To resolve this issue, we use $\hat{v}_{t-1}$ as the best available forecast of $\hat{v}_t$.

Consistent with prior studies,⁴ the estimation results from the constant RRA model of the intertemporal risk-return relation fail to capture the time-varying nature of the intertemporal risk-return tradeoff. Nevertheless, a notable finding emerges; although the estimated sign of τ (the coefficient on predictable volatility) is inconsistent across indices, the volatility feedback effect parameter δ is positive for all seven indices, with five out of them statistically significant at the 10% level or better. This suggests that the VFE may serve as a dominant component in shaping the intertemporal risk-return relation.

³ Since the risk-free rate is available only at a monthly frequency, we construct a daily risk-free rate by assuming it remains constant throughout each month.

⁴ Whitelaw (1994), Yu and Yuan (2011), Ghysels et al. (2014), Marks and Nam (2018), Wang (2018), Chelikani, Marks, and Nam (2024), and Kilic, Nam, and O'Connor (2024).

[Insert Table 1 about here]

5. Empirical Work

5.1 Volatility Feedback Effect

To test our hypothesis that the volatility feedback effect is a significant risk factor in shaping the intertemporal risk-return tradeoff—and that this VFE is not market-specific but rather a pervasive international phenomenon—we estimate the following state-dependent IRRR model using data from the G7 equity indexes.

$$R_t = (c_P P + c_N N) + (\tau_P P + \tau_N N)\hat{\sigma}_t + (\delta_P P + \delta_N N)\hat{v}_t + (\phi_P P + \phi_N N)R_{t-1} + \varepsilon_t, \quad (15)$$

where $R_t = r_t - rf$. The dummy variables P and N represent good and bad market states, respectively. The parameters τ_P and τ_N capture the asymmetric relative risk aversion associated with expected volatility in good and bad market states, respectively, while δ_P and δ_N represent the asymmetric relative risk aversion associated with unexpected volatility in those market states. The effective RRA parameter is given by $\tau_P + \delta_P$ under good market state and by $\tau_N + \delta_N$ under bad market state. We conjecture that in a bad market state, the VFE amplifies perceived risk, thereby intensifying the risk-return tradeoff. Accordingly, we test whether the effective RRA is both economically and statistically significant and stronger under bad market conditions, that is, $0 < \delta_N > \delta_P$ and $0 < \tau_N + \delta_N > \tau_P + \delta_P$.

Table 2 shows the estimation results. Note that the numbers in parentheses are the Newey and West (1987) adjusted t -statistics, and $AdjR^2(\%)$ is the percentage adjusted R^2 . Panel A presents the estimation results for the asymmetric intertemporal risk-return relation, where the dummy variables are defined based on prior return shocks: $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$, with e_t denoting the mean-deviated excess return of each index. Panel B presents the results of diagnostic tests. We conduct a Wald F -test for the null hypothesis of no VFE, i.e., $H_0: \delta_P = \delta_N = 0$, and one-sided t -tests for the alternative hypotheses $H_1: \tau_N + \delta_N > 0$ and $H_1: \tau_P + \delta_P \leq 0$, respectively. The notable findings are as follows. First, for all seven indexes, the estimates of δ_N are positive and statistically significant at the 5% or 1% level, whereas the estimates of δ_P are non-positive.⁵ The average estimated values of δ_N and δ_P (Newey-West t -value) across the seven indexes are 2.328 (2.86) and -0.741 (-0.41), respectively. The results suggest that the volatility feedback RRA parameter is asymmetric—significantly positive in bad market states but non-positive in good market states. Canada exhibits the largest magnitude, with $\delta_N =$

⁵ Note that “non-positive” here refers to the lack of statistical significance in the positive direction.

4.423, which is more than twice the average of the estimates for the other six indexes. Furthermore, the Wald test on the null hypothesis $H_0: \delta_P = \delta_N = 0$ confirms the importance of the VFE in shaping the intertemporal risk-return relation in global stock markets. For all indexes, the null of no VFE is strongly rejected at the 1% significance level. Second, while the estimates of τ_P are non-positive, those of τ_N are weakly positive. Only Japan and the U.S. exhibit statistically significant positive values at the 5% level, while Germany and the U.K. show significance at the 10% level. Third, for all indexes, the estimates of $\tau_N + \delta_N$ are strongly positive, whereas those of $\tau_P + \delta_P$ are non-positive. The t-tests confirm that the asymmetric RRA parameters are economically and statistically significant. The average estimated values of $\tau_N + \delta_N$ and $\tau_P + \delta_P$ (t-value) across the seven indexes are 6.436 (5.71) and -1.978 (-1.75), respectively. These results support our hypothesis that the complete intertemporal risk-return relation is characterized by a strong positive RRA during bad market states and a non-positive RRA during good market states. Lastly, the findings reveal that the asymmetric VFE is an important risk factor in explaining the intertemporal risk-return relation across global stock markets.

[Insert Table 2 about here]

Table 3 shows the estimation results with the dummy variables defined by prior two consecutive return shocks: $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. The estimation results reveal patterns consistent with those presented in Table 2, with one notable addition: a statistically significant positive value of τ_N . First, the estimates of both τ_N and δ_N are strongly positive and statistically significant at the 5% level, except for the estimate of τ_N for the U.S., which is significant at the 10% level. The average estimated values of τ_N and δ_N (t-value) across the seven indexes are 8.511 (2.78) and 2.033 (2.40), respectively. Second, the estimates of both τ_P and δ_P are negative across all indexes, except for the estimate of δ_P for the U.K. The average estimated values of τ_P and δ_P (t-value) across the seven indexes are -5.160 (-1.88) and -2.554 (-1.53), respectively. These results suggest that two consecutive prior return shocks deepen the asymmetry in the magnitude of the RRA parameters between good and bad market states. The average estimated values of $\tau_N + \delta_N$ and $\tau_P + \delta_P$ (t-value) are 10.544 (6.88) and -7.714 (-3.48), respectively. Third, the statistically significant positive value of δ_N , along with the results of the Wald F -tests across all indexes, further confirm that the VFE is an important risk factor in the intertemporal risk-return tradeoff.

[Insert Table 3 about here]

Furthermore, we examine whether the significant results of the asymmetric VFE remain robust to extreme return shocks. Table 4 presents the estimation results using dummy variables defined by prior extreme return shocks: $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. The results provide robust evidence of a significant VFE under bad market states. The estimation results are presented in Table 4, which shows robust evidence of significant VFE under bad market states. The average estimated value of δ_N (t-value) across the seven indexes is 2.022 (1.97). Diagnostic tests further confirm that the volatility feedback RRA is a key driver of the asymmetric risk-return tradeoff. The average estimated values of $\tau_N + \delta_N$ and $\tau_P + \delta_P$ (t-value) are 6.254 (3.89) and -0.131 (-1.42), respectively.

[Insert Table 4 about here]

In summary, the findings of $\tau_N + \delta_N > 0$ and $\delta_N > 0$ indicate that the VFE is a key risk factor in shaping the complete risk-return tradeoff, and that volatility feedback parameters play a central role in determining the state-dependent intertemporal risk-return relation. The VFE reinforces the positive risk-return relation following negative return shocks, while it dampens the relation following positive return shocks. Accordingly, rational risk-averse investors demand a higher risk premium during bad market states but reduce their risk premium in good market states. Thus, ignoring the VFE leads to a downward bias in the estimated risk premium during bad market conditions and an upward bias during good market conditions. More importantly, the findings of this study provide strong evidence that the significant asymmetric VFE is not a localized phenomenon, but rather a robust and stylized fact across global stock markets.

5.2 Volatility Feedback Effect under Combined Market States

In this section, we test our third hypothesis that the VFE is amplified by bad market news during periods of high volatility. Specifically, we examine the extent to which the VFE is influenced by the interaction of market conditions, defined by combinations of unexpectedly high or low volatility and good or bad market states. To do so, we analyze the state-dependent VFE across four possible market scenarios using the following model specification:

$$R_t = (c_L L + c_H H) + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N] \hat{v}_t^2 + (\phi_L L + \phi_H H) R_{t-1} + \varepsilon_t, \quad (16)$$

where P (N) is a dummy variable indicating a good (bad) market state, and L (H) is a dummy variable indicating unexpectedly low (high) market volatility. The four cases of market conditions to consider are defined as L/P , L/N , H/P , and H/N . The volatility feedback RRA parameters are represented by δ_L^P and δ_L^N under low volatility conditions, and δ_H^P and δ_H^N under high volatility conditions. We test whether the estimate of δ_H^N is significantly positive. Note that an extremely high value of δ_H^N may serve as an indicator of a potential market crash.

Table 5 presents the estimation results of the state-dependent VFE model where the dummy variable L and H are defined based on prior unexpected volatility shocks: $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $H = 1$ when $\hat{v}_{t-1}^2 > 0$. Panel A presents the estimation results of the case in which $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$. Panel B presents the estimation results of the case in which $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C presents the estimation results of the case in which $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of index returns. $AVG \delta_H^N$ denotes the average estimated value of δ_H^N across the three panels, along with its corresponding average Newey-West t-value for each index. The results indicate that for all three specifications (Table 5 Panels A, B, and C) the estimates of δ_H^N are positive and significant across the seven indexes, with significance at the 1% level in most cases and at the 5% level in two instances. The average estimated values of δ_H^N (t-value) across the seven indexes is 2.326 (3.20) in Panel A, 2.529 (2.77) for Panel B, and 2.312 (3.24) for Panel C. The overall average of δ_H^N (t-value) across all three panels is 2.389 (3.07). Recall that positive, significant values for δ_H^N are signals of potential market crashes and thus an important indicator for market authorities, regulators and other market participants.

[Insert Table 5 about here]

Table 6 reports the estimation results of the state-dependent VFE model, where the dummy variables L and H are defined based on two consecutive unexpected volatility shocks: $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $\hat{v}_{t-2}^2 < 0$, and $H = 1$ when $\hat{v}_{t-1}^2 > 0$ and $\hat{v}_{t-2}^2 > 0$. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B considers $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C defines $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. The results show that 18 out of 21 estimates of δ_H^N across the three panels are significantly positive at the 5% level. $AVG \delta_H^N$ shows that all countries except Italy exhibit significantly positive estimates at the 5% level across all three panels. The average estimated values of δ_H^N (t-values) across the seven indexes are 2.603 (2.81) in

Panel A, 3.154 (3.96) in Panel B, and 1.644 (2.63) in Panel C. The overall average across all panels is 2.467 (3.13). Overall, these results suggest that volatility feedback effects persist over multiple periods.

[Insert Table 6 about here]

To further investigate the dynamics of the VFE, Table 7 presents the estimation results of the state-dependent VFE model, where the dummy variables L and H are defined based on prior extreme volatility shocks: $L = 1$ when $\hat{v}_{t-1}^2 < SDV$ and $H = 1$ when $\hat{v}_{t-1}^2 > SDV$, where SDV denotes one standard deviation of $\hat{v}_t^2$. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B considers $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C defines $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. The results show that 20 out of 21 estimates of δ_H^N across the three panels are significantly positive at the 5% level. The average values reported in AVG δ_H^N indicate that all countries, except Italy, exhibit significantly positive estimates at the 5% level across the three panels. The average estimated values of δ_H^N (t-values) across the seven indexes are 2.299 (2.48) in Panel A, 2.280 (2.43) in Panel B, and 2.342 (2.72) in Panel C. The overall average across all panels is 2.307 (2.55). As expected, the VFE is robust to extreme periods of market volatility.

[Insert Table 7 about here]

In summary, the estimation results of the state-dependent VFE model presented in Tables 5–7 show that the estimated value of δ_H^N is both economically and statistically significant and positive. The overall average estimated values of δ_H^N (Newey-West t-values) across all three panels is 2.389 (3.07) in Table 5, 2.467 (3.13) in Table 6, and 2.307 (2.55) in Table 7. These findings indicate that during periods of high volatility, risk-averse investors respond more sensitively to bad market news by demanding a higher risk premium, thereby supporting our third hypothesis: the VFE parameter (δ_H^N) under the combined market condition of high volatility and a bad market state is both economically and statistically significant and positive. Given that a significantly positive δ_H^N may serve as an indicator of a potential market crash, our results suggest that all G7 stock markets are substantially exposed to crash risk arising from internally generated high levels of VFE, even in the absence of specific macroeconomic shocks. This constitutes one of the key contributions of our study.

6. Robustness Checks

6.1 Sub-period Analysis

We conduct a sub-period analysis as a robustness check to assess the stability of our empirical models. For each index, the sample is divided into two sub-periods with an equal number of observations. The two models considered in this analysis are the complete asymmetric IRRR model and the state-dependent VFE model. Table 8 presents the estimation results of the complete asymmetric IRRR model, where prior positive and negative return shocks are used as dummy variables to represent good and bad market states, respectively. Table 9 reports the estimation results of the state-dependent VFE model, in which the combined dummy variables are defined based on both volatility shocks and return shocks. Panels A and B of Table 8 present the estimation results of the complete asymmetric IRRR model for the first and second sub-periods, respectively. The results for the first sub-period show that all countries, except Canada, exhibit significantly positive estimates of δ_N at the 1% or 5% level. In the second sub-period, all countries except Italy show significantly positive estimates of δ_N at the 5% or 10% level. Notably, Canada and Italy exhibit a statistically significant positive value at the 1% level for the second and first sub-period, respectively. The average estimated values of δ_N (Newey-West t-values) across the seven indexes are 2.163 (3.83) in Panel A and 2.779 (2.80) in Panel B. In sum, the sub-periods results provide robust evidence that the VFE is an important risk factor in shaping the state-dependent risk-return tradeoff—strengthening the positive risk-return relation under bad market states while weakening the relation under good market states.

[Insert Table 8 about here]

Panels A and B of Table 9 present the estimation results of the state-dependent VFE model for the first and second sub-periods, respectively. The results show a pattern similar to that reported in Table 8. For the first sub-period, all countries except Canada exhibit significantly positive estimates of δ_H^N at the 1% level. In the second sub-period, all countries except Italy show significantly positive estimates at the 1% or 5% levels, with the U.K. significant at the 10% level. Notably, Canada and Italy exhibit statistically significant positive values at the 1% level in the second and first sub-periods, respectively. The average estimated values of δ_H^N (Newey-West t-values) across the seven indexes are 2.312 (5.09) in Panel A and 2.637 (3.60) in Panel B. These sub-period results provide strong support for our third hypothesis: the VFE is amplified by bad market news during periods of high volatility. They also reinforce our argument that G7 stock markets are substantially exposed to crash risk stemming from internally generated high levels of volatility feedback effect.

[Insert Table 9 about here]

6.2 The Complete Intertemporal Risk-Return Relation under Combined Market Conditions

The empirical analysis demonstrates that the volatility feedback effect is a key risk component in shaping the intertemporal risk-return tradeoff. In this section, we examine the robustness of this finding by estimating the following complete asymmetric IRRR model under four combined market conditions:

$$R_t = (c_L L + c_H H) + [(\tau_L^P L + \tau_H^P H)P + (\tau_L^N L + \tau_H^N H)N]\hat{\sigma}_t^2 + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t, \quad (17)$$

where $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $H = 1$ when $\hat{v}_{t-1}^2 > 0$, indicating low and high unexpected volatility, respectively. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B defines $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. The asymmetric RRA parameters associated with predictable volatility are τ_L^P and τ_L^N under low volatility conditions, and τ_H^P and τ_H^N under high volatility conditions. The volatility feedback RRA parameters are δ_L^P and δ_L^N under low volatility conditions, and δ_H^P and δ_H^N under high volatility conditions. Our primary focus is to test whether the estimate of δ_H^N is significantly positive. The estimation results are presented in Table 10, with only the RRA parameter estimates reported. Panel A presents the estimation results of the case in which $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$. Panel B presents the estimation results of the case in which $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of index returns. $AVG \delta_H^N$ denotes the average estimated value of δ_H^N across the two panels, along with its corresponding average Newey-West t-value for each index. The table reveals a striking result: among all the RRA parameters defined under various market conditions, only δ_H^N consistently shows significantly positive estimates at the 1% or 5% level for all seven indexes across both panels. In other words, δ_H^N is the only RRA parameter that satisfies both economic and statistical significance criteria. The average values reported in $AVG \delta_H^N$ further confirm this robustness, showing significantly positive estimates at the 1% or 5% level for all indexes. The average estimated values of $AVG \delta_H^N$ (t-values) across the seven indexes are 2.241 (2.50) in Panel A and 2.236 (2.49) in Panel B. The overall average across all indexes and both panels is 2.238 (2.50). These results provide strong evidence that the volatility feedback effect is a critical and consistent risk factor in the intertemporal risk-return tradeoff, supporting its role as a stylized fact in global stock markets.⁶

⁶ As an additional robustness check, we re-estimated all models using conditional volatility forecasts generated from a Threshold-GARCH (1,1) specification. The resulting parameter estimates are highly consistent with those reported in the main tables, with only minor variations in magnitude. For brevity, these results are not tabulated here but are available from the authors upon request.

[Insert Table 10 about here]

7. Concluding Remarks

This paper provides comprehensive international evidence that the volatility feedback effect is a fundamental driver of the intertemporal risk-return tradeoff. Using several decades of data from G7 equity markets, we show that the volatility feedback effect consistently reinforces the positive risk-return relation during adverse states, while weakening or nullifying it during favorable states. These findings indicate that the return dynamics associated with volatility feedback effect are not a U.S.-specific anomaly but a robust and pervasive phenomenon across major developed economies.

Our results are highly consistent across countries, models, and market conditions. In nearly all cases, the estimated RRA parameters of the volatility feedback effect are positive and statistically significant, with robustness tests confirming their reliability. This consistency demonstrates that international investors, much like those in the U.S., systematically incorporate unexpected volatility shocks into asset pricing decisions. Importantly, we also find that extreme levels of the volatility feedback effect, arising from the joint conditions of heightened volatility and negative market news, can amplify risk perceptions and trigger crash-like dynamics even without macroeconomic shocks.

Recognizing the volatility feedback effect as a stylized fact offers a unified perspective on global asset pricing and carries significant implications for portfolio management, financial stability, and regulatory policy. In particular, our study emphasizes the need for systematic and continuous monitoring of extreme volatility feedback by monetary authorities and market participants as an essential tool for volatility risk management and for mitigating crash vulnerability in international equity markets.

References

- Abel, A. B. (1988). Stock prices under time-varying dividend risk: An exact solution in an infinite-horizon general equilibrium model, *Journal of Monetary Economics* 22: 373-393.
- Ang, A., Hodrick, R., Xing, Y. and Zhang, X. (2006). The cross-section of volatility and expected returns, *Journal of Finance* 61: 259-299.
- Backus, D. and Gregory, A. W. (1993). Theoretical relations between risk premiums and conditional variances, *Journal of Business and Economic Statistics* 11: 177-185.
- Baillie, R. and DeGennaro, R. P. (1990). Stock returns and volatility, *Journal of Financial and Quantitative Analysis* 25: 203-214.
- Balaban, E., and Bayar, A. (2005). Stock returns and volatility: empirical evidence from fourteen countries. *Applied Economics Letters* 12: 603-611.
- Bali, T. G. (2008). The intertemporal relation between expected returns and risk, *Journal of Financial Economics* 87: 101-131.
- Bali, T.G. and Cakici, N. (2010). World market risk, country-specific risk and expected returns in international stock markets, *Journal of Banking and Finance*, 34: 1152-1165.
- Bali, T. G. and Peng, L. (2006). Is there a risk-return trade-off? Evidence from high-frequency data, *Journal of Applied Econometrics* 21: 1169-1198.
- G. Bekaert, C.R. Harvey, C.R., 1995. Time-varying world market integration. *Journal of Finance*, 50, pp. 403-444
- Boudoukh, J., Richardson, M. and Whitelaw, R. F. (1997). Nonlinearities in the relation between the equity risk premium and the term structure, *Management Science* 43: 371-385.
- Brandt, M. W. and Kang, Q. (2004). On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach, *Journal of Financial Economics* 72: 217-257.
- Campbell, J. Y. (1987). Stock returns and the term structure, *Journal Financial Economics* 18: 373-399.
- Campbell, J. Y. and Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns, *Journal Financial Economics* 31: 281-318.
- Chelikani, S., Marks, J. M. and Nam, K. (2023). Volatility feedback effect and risk-return tradeoff. *Quarterly Review of Economics and Finance* 92: 49-65.
- Chen, C.Y.H. and Chiang, T.C. (2016). Empirical analysis of the intertemporal relationship between downside risk and expected returns: Evidence from time-varying transition probability models, *European Financial Management* 22: 749-796.

- Chiang, T.C., Li, H. and Zheng, D. (2015). The intertemporal risk-return relationship: Evidence from international markets, *Journal of International Financial Markets, Institutions and Money* 39: 156-180.
- De Santis, G., and Gerard, B. (1997). International asset pricing and portfolio diversification with time-varying risk. *Journal of Finance* 52: 1881-1912.
- Epps, T. W. (1975). Security price changes and transaction volumes: Theory and evidence, *American Economic Review* 65: 586-597.
- Ferson, W. E., and Harvey, C. R. (1994). Sources of risk and expected returns in global equity markets. *Journal of Banking and Finance* 18: 775-803.
- Fifield, S.G., McMillan, D.G. and McMillan, F.J. (2020). Is there a risk and return relation?. *The European Journal of Finance* 26: 1075-1101.
- Gennotte, G. and Marsh, T. A. (1993). Variations in economic uncertainty and risk premiums on capital assets, *European Economic Review* 37: 1021-1041.
- Ghysels, E., Guérin, P. and Marcellino, M. (2014). Regime switches in the risk-return trade-off, *Journal of Empirical Finance* 28: 118-138.
- Ghysels, E., Santa-Clara, P. and Valkanov, R. (2005). There is a risk return trade-off after all, *Journal of Financial Economics* 76: 509-548.
- Glosten, L., Jagannathan, R. and Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48: 1779-1801.
- Guo, H., 2006. The risk-return relation in international stock markets, *Financial Review* 41: 565-587.
- Guo, H. and Neely, C. J. (2008). Investigating the intertemporal risk-return relation in international stock markets with the component GARCH model, *Economics Letters* 99: 371-374.
- Hardouvelis, G.A., Malliaropulos, D. and Priestley, R. (2006). EMU and European stock market integration. *Journal of Business* 79: 365-392.
- Haugen, R. A., Talmor, E. and Torous, W. N. (1991). The effect of volatility changes on the level of stock prices and subsequent expected returns, *Journal of Finance* 46: 985-1007.
- Kang, M., Krausz, J. and Nam, K. (2019). The Intertemporal Risk-Return Relation, Investor Behavior, and Technical Trading Profits: Evidence from the G-7 Countries, *European Journal of Finance* 48: 780-798.
- Kilic, O., Nam, K. and O'Connor, M.L. (2024). State-dependent volatility feedback effect in the ICAPM, *Finance Research Letters* 59: 104700.
- León, A., Nave, J.M. and Rubio, G. (2007). The relationship between risk and expected return in Europe, *Journal of Banking & Finance* 31: 495-512.

- Ludvigson, S. C. and Ng, S. (2007). The empirical risk return relation: A factor analysis approach, *Journal of Financial Economics* 83: 171-222.
- Lundblad, C. (2007). The risk return tradeoff in the long run: 1836-2003, *Journal of Financial Economics* 85: 123-150.
- Marks, J. M. and Nam, K. (2018). Intertemporal risk-return tradeoff in the short-run, *Economics Letters* 172: 81-84.
- Merton, R. C. (1973). An intertemporal asset pricing model, *Econometrica* 41: 867-888.
- Müller, G., Durand, R. B. and Maller, R. A. (2011). The risk-return tradeoff: A COGARCH analysis of Merton's hypothesis, *Journal of Empirical Finance* 18: 306-320.
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach, *Econometrica* 59: 347-370.
- Newey, W. and West, K. (1987). Hypothesis testing with efficient method of moments estimation, *International Economic Review* 28: 777-787.
- Pástor, L., Sinha, M. and Swaminathan, B. (2008). Estimating the intertemporal risk-return tradeoff using the implied cost of capital, *Journal of Finance* 63: 2859-2897.
- Pindyck, R. S. (1984). Risk, inflation, and the stock market, *American Economic Review* 74: 335-351.
- Poterba, J. M. and Summers, L. H. (1986). The persistence of volatility and stock market fluctuations, *American Economic Review* 76: 1142-1151.
- Savva, C.S. and Theodossiou, P. (2018). The risk and return conundrum explained: International evidence, *Journal of Financial Econometrics* 16: 486-521.
- Scruggs, J. T. (1998). Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: A two-factor approach, *Journal of Finance* 52: 575-603.
- Wang, C. S., Chen, Y. C. and Lo, H. Y. (2021). A fresh look at the risk-return tradeoff, *Pacific-Basin Finance Journal* 68: 101546.
- Wang, W. (2018). The mean-variance relation and the role of institutional investor sentiment, *Economics Letters* 168: 61-64.
- Whitelaw, R. F. (1994). Time variations and covariations in the expectation and volatility of stock market returns, *Journal of Finance* 49: 515-541.
- Whitelaw, R. F. (2000). Stock market risk and return: An equilibrium approach, *Review of Financial Studies* 13: 521-547.
- Yu, J. and Yuan, Y. (2011). Investor sentiment and the mean-variance relation, *Journal of Financial Economics* 100: 367-381.

Table 1.
Descriptive Statistics of Daily Excess Returns of G7 Equity Indices

Panel A: Summary statistics							
	Canada	France	Germany	Italy	Japan	UK	US
Mean ($\times 100$)	0.020	0.020	0.030	0.012	0.029	0.022	0.034
Std. Dev.	0.011	0.014	0.013	0.016	0.014	0.012	0.010
Skewness	-0.949	-0.180	-0.151	-0.381	-0.232	-0.399	-0.614
Kurtosis	21.617	10.375	10.389	16.763	11.983	19.470	22.791
Observations	14,202	9,707	15,549	13,864	15,447	12,132	15,731
Panel B. Estimation results of the base model with the constant RRA parameters							
	Canada	France	Germany	Italy	Japan	UK	US
$c(\times 100)$	0.023	0.000	0.014	-0.009	-0.006	0.016	0.019
	(1.92)	(0.02)	(0.76)	(-0.40)	(-0.48)	(0.76)	(1.60)
τ	-0.536	0.980	0.873	0.811	1.972 ***	0.360	1.495
	(-0.43)	(0.69)	(0.68)	(1.03)	(3.42)	(0.21)	(1.33)
δ	1.184	1.062 **	0.837 *	0.387 *	0.892 **	0.561	0.976 ***
	(1.11)	(2.08)	(1.80)	(1.67)	(2.07)	(1.22)	(3.43)
ϕ	0.085 ***	0.008	0.017 *	0.041 ***	-0.013	0.022 **	-0.001
	(4.16)	(0.60)	(1.82)	(4.10)	(-1.16)	(1.87)	(-0.05)
$AdjR^2(\%)$	0.74	0.19	0.13	0.20	0.31	0.10	0.28

Note: Panel A presents the descriptive statistics for each index, while Panel B reports the estimation results of the baseline constant IRRR model for each index. The constant IRRR model is specified as $R_t = c + \tau \hat{\sigma}_t^2 + \delta \hat{v}_t^2 + \phi R_{t-1} + \varepsilon_t$, where R_t is the proxy for the expected market risk premium for each index, calculated as the difference between the nominal index return and the U.S. one-month risk-free rate. $\hat{\sigma}_t^2$ and $\hat{v}_t^2$ denote the conditional forecasts of predictable volatility and volatility forecast error, respectively. For each country's index return, τ and δ represent the constant relative risk aversion (RRA) parameters of the intertemporal risk-return tradeoff. Specifically, τ captures the RRA with respect to predictable volatility, while δ reflects the RRA associated with unanticipated volatility shocks—i.e., the constant volatility feedback effect (VFE) parameter. The parameter ϕ is the first-order autoregressive coefficient, capturing the price adjustment process driven by investor behavior in response to prior mispricing. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 2. The Complete Asymmetric Intertemporal Risk-Return Relation Based on Prior Return Shocks

Panel A: Estimation Results of the Complete IRRR.

	Canada	France	Germany	Italy	Japan	UK	US
$c_P(\times 100)$	0.022 (0.37)	0.070 (1.23)	0.075 ** (2.05)	-0.050 (-1.54)	0.017 (0.65)	0.066 (1.36)	0.017 (0.56)
$c_N(\times 100)$	0.069 * (1.83)	0.052 (1.13)	0.009 (0.22)	0.025 (0.68)	0.005 (0.18)	0.028 (0.73)	-0.008 (-0.43)
τ_P	-3.139 (-1.07)	1.550 (0.57)	-0.480 (-0.28)	-0.385 (-0.28)	0.221 (0.19)	-1.630 (-0.60)	-4.797 (-1.34)
τ_N	3.095 (0.70)	4.096 (1.45)	4.155 * (1.79)	1.704 (1.06)	3.923 *** (3.99)	5.250 * (1.92)	6.538 ** (2.03)
δ_P	-3.710 (-1.13)	1.657 (1.56)	0.457 (0.48)	-0.734 *** (-2.51)	-0.158 (-0.30)	0.884 (0.85)	-3.583 * (-1.84)
δ_N	4.423 *** (3.89)	2.865 *** (2.87)	2.311 *** (2.46)	1.314 ** (2.10)	1.966 *** (3.46)	1.327 *** (2.50)	2.088 *** (2.77)
ϕ_P	0.174 ** (2.24)	-0.062 (-1.62)	0.001 (0.02)	0.112 *** (3.57)	0.011 (0.36)	-0.006 (-0.17)	0.130 *** (2.76)
ϕ_N	0.280 *** (5.38)	0.140 *** (3.00)	0.104 *** (2.87)	0.101 ** (2.29)	0.061 * (1.80)	0.127 *** (3.72)	0.096 *** (2.63)
$AdjR^2(\%)$	2.31	0.33	0.29	0.31	0.45	0.26	1.31

Panel B: Diagnostics on the Complete IRRR.

Wald F -test	105.54 ***	15.12 ***	12.71 ***	11.03 ***	16.18 ***	9.19 ***	52.69 ***
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$H_1: \tau_N + \delta_N > 0$	7.518 ***	6.961 ***	6.466 ***	3.017 ***	5.888 ***	6.578 ***	8.626 ***
(t -value)	(7.98)	(4.53)	(4.97)	(2.48)	(6.01)	(4.57)	(9.43)
$H_1: \tau_P + \delta_P \leq 0$	-6.849 ***	3.207	-0.023	-1.118	0.063	-0.746	-8.380 ***
(t -value)	(-5.87)	(1.57)	(-0.02)	(-0.91)	(0.05)	(-0.47)	(-6.58)

Note: Panel A reports the estimation results of $R_t = (c_P P + c_N N) + (\tau_P P + \tau_N N)\hat{\sigma}_t^2 + (\delta_P P + \delta_N N)\hat{v}_t^2 + (\phi_P P + \phi_N N)R_{t-1} + \varepsilon_t$, where $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$, where e_t is the mean-deviated excess return of each index. δ_P and δ_N represent the volatility feedback RRA parameters following a prior positive and negative return shock, respectively. The overall risk-return RRA parameters are given by $\tau_P + \delta_P$ under good market states and $\tau_N + \delta_N$ under bad states. Panel B presents the results of diagnostic tests. We conduct a Wald F -test for the null hypothesis of no VFE ($H_0: \delta_P = \delta_N = 0$). We also perform one-sided t -tests for $H_1: \tau_N + \delta_N > 0$ and $H_1: \tau_P + \delta_P \leq 0$, respectively. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. The Complete Asymmetric Intertemporal Risk-Return Relation Based on Two Consecutive Same-Sign Return Shocks

Panel A: Estimation Results of the Complete IRRR.							
	Canada	France	Germany	Italy	Japan	UK	US
$c_P(\times 100)$	0.050 (1.46)	0.038 (0.70)	0.046 (1.04)	-0.090 * (-1.92)	0.101 *** (2.95)	0.125 *** (2.65)	-0.008 (-0.22)
$c_N(\times 100)$	-0.029 (-0.88)	0.002 (0.04)	-0.056 (-1.21)	-0.061 (-1.04)	-0.028 (-0.65)	-0.042 (-0.81)	-0.062 (-1.24)
τ_P	-6.121 * (-1.92)	-3.576 (-1.45)	-5.108 (-1.61)	-2.423 (-1.13)	-7.090 *** (-2.90)	-6.605 * (-1.70)	-5.199 *** (-2.46)
τ_N	11.578 *** (2.92)	8.057 *** (2.58)	7.625 *** (2.93)	5.200 *** (2.48)	5.686 *** (3.50)	11.006 *** (3.33)	10.427 * (1.73)
δ_P	-6.024 *** (-2.34)	-0.928 (-0.69)	-2.368 * (-1.86)	-2.779 *** (-3.34)	-0.371 (-0.48)	0.103 (0.18)	-5.513 ** (-2.21)
δ_N	3.350 *** (2.74)	2.710 ** (2.03)	2.041 ** (1.98)	1.611 ** (2.01)	1.876 *** (2.88)	1.368 ** (1.97)	1.273 *** (3.16)
ϕ_P	0.177 ** (2.28)	0.049 (0.84)	0.087 * (1.77)	0.205 *** (4.07)	0.056 (1.17)	0.001 ** (0.03)	0.148 *** (3.07)
ϕ_N	0.240 *** (3.55)	0.131 * (1.66)	0.078 (1.46)	0.097 * (1.71)	0.085 * (1.83)	0.122 ** (2.30)	0.068 (1.56)
$AdjR^2(\%)$	2.00	0.39	0.39	0.29	0.56	0.39	0.97
Panel B: Diagnostics on the Complete IRRR.							
Wald F -test	56.70 ***	6.51 ***	9.83 ***	12.34 ***	11.01 ***	3.50 **	18.39 ***
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
$H_1: \tau_N + \delta_N > 0$	14.949 ***	10.774 ***	9.666 ***	6.811 ***	7.562 ***	12.374 ***	11.669 ***
(t -value)	(11.50)	(5.26)	(5.82)	(3.95)	(6.22)	(6.11)	(9.32)
$H_1: \tau_P + \delta_P \leq 0$	-12.145 ***	-4.50 *	-7.476 ***	-5.202 ***	-7.461 ***	-6.502 ***	-10.711 ***
(t -value)	(-6.65)	(-1.71)	(-2.91)	(-2.38)	(-3.87)	(-2.72)	(-4.11)

Note: Panel A reports the estimation results of $R_t = (c_P P + c_N N) + (\tau_P P + \tau_N N)\hat{\sigma}_t^2 + (\delta_P P + \delta_N N)\hat{v}_t^2 + (\phi_P P + \phi_N N)R_{t-1} + \varepsilon_t$, where $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. δ_P and δ_N represent the volatility feedback RRA parameters following a prior positive and negative return shock, respectively. The overall risk-return RRA parameters are given by $\tau_P + \delta_P$ under good market states and $\tau_N + \delta_N$ under bad states. Panel B presents the results of diagnostic tests. We conduct a Wald F -test for the null hypothesis of no VFE ($H_0: \delta_P = \delta_N = 0$). We also perform one-sided t -tests for $H_1: \tau_N + \delta_N > 0$ and $H_1: \tau_P + \delta_P \leq 0$, respectively. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. The Complete Asymmetric Intertemporal Risk-Return Relation Based on One Standard Deviation of Return Shocks

Panel A: Estimation Results of the Complete IRRR.							
	Canada	France	Germany	Italy	Japan	UK	US
$c_P(\times 100)$	0.250 (0.96)	0.005 (0.02)	0.310 * (1.84)	0.260 (1.61)	-0.091 (-0.88)	0.326 ** (2.25)	-0.030 (-0.18)
$c_N(\times 100)$	0.018 (0.08)	0.020 (0.08)	0.167 (0.98)	-0.222 (-0.98)	0.072 (0.76)	0.051 (0.30)	-0.197 * (-1.83)
τ_P	-0.234 (-0.05)	2.630 (0.70)	-1.525 (-0.60)	-0.037 (-0.49)	-0.415 (-0.32)	1.731 (0.44)	-2.955 (-1.00)
τ_N	2.692 (0.53)	5.929 (1.15)	4.095 (1.54)	-0.026 (-0.20)	4.586 *** (3.26)	6.320 (0.90)	6.027 *** (2.77)
δ_P	-2.615 (-0.58)	1.333 (1.23)	2.237 (1.57)	1.513 (0.63)	-0.739 (-1.00)	2.411 ** (2.17)	-4.254 (-1.50)
δ_N	4.208 ** (2.17)	2.588 ** (1.99)	2.861 ** (2.14)	-0.556 (-0.21)	2.180 *** (3.10)	1.480 ** (2.01)	1.391 *** (2.61)
ϕ_P	0.012 (0.06)	-0.047 (-0.38)	-0.130 (-1.22)	0.172 (0.38)	0.074 (1.02)	-0.187 * (-1.93)	0.140 (1.09)
ϕ_N	0.249 (1.58)	0.149 (1.03)	0.168 (1.58)	0.514 (0.46)	0.103 (1.62)	0.156 (1.23)	-0.015 (-0.20)
$AdjR^2(\%)$	1.74	0.31	0.21	0.34	0.45	0.21	1.19
Panel B: Diagnostics on the Complete IRRR.							
Wald F -test	33.90 ***	4.05 **	10.59 ***	0.55	12.341 ***	8.99 **	20.61 ***
(p-value)	(0.00)	(0.02)	(0.00)	(0.58)	(0.00)	(0.03)	(0.00)
$H_1: \tau_N + \delta_N > 0$	6.900 ***	8.518 ***	6.956 ***	-0.582	6.766 ***	7.799 ***	7.418 ***
(t -value)	(4.83)	(3.27)	(3.34)	(-0.35)	(5.50)	(3.90)	(6.01)
$H_1: \tau_P + \delta_P \leq 0$	-2.849	3.963	0.712	1.475	-1.154	4.143	-7.209 ***
(t -value)	(-1.48)	(1.39)	(0.31)	(0.94)	(-0.64)	(1.60)	(-3.60)

Note: Panel A reports the estimation results of $R_t = (c_P P + c_N N) + (\tau_P P + \tau_N N)\hat{\sigma}_t^2 + (\delta_P P + \delta_N N)\hat{v}_t^2 + (\phi_P P + \phi_N N)R_{t-1} + \varepsilon_t$, where $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of index returns. δ_P and δ_N represent the volatility feedback RRA parameters following a prior positive and negative return shock, respectively. The overall risk-return RRA parameters are given by $\tau_P + \delta_P$ under good market states and $\tau_N + \delta_N$ under bad states. Panel B presents the results of diagnostic tests. We conduct a Wald F -test for the null hypothesis of no VFE ($H_0: \delta_P = \delta_N = 0$). We also perform one-sided t -tests for $H_1: \tau_N + \delta_N > 0$ and $H_1: \tau_P + \delta_P \leq 0$, respectively. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5. State-Dependent Volatility Feedback Effect Based on Prior Volatility ShocksPanel A: $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$.

	Canada	France	Germany	Italy	Japan	UK	US
$c_L(\times 100)$	0.041 ** (2.06)	0.032 (0.77)	-0.003 (-0.10)	-0.025 (-0.98)	0.003 (0.14)	0.051 ** (2.20)	0.024 * (1.75)
$c_H(\times 100)$	-0.006 (-0.26)	-0.052 * (-1.79)	0.005 (0.25)	0.029 (0.84)	0.014 (0.59)	-0.037 (-1.51)	0.018 (1.14)
δ_L^P	1.941 (0.50)	0.520 (0.19)	-0.047 (-0.02)	-0.314 (-0.21)	-0.699 (-0.33)	3.359 (1.12)	1.864 (0.60)
δ_H^P	-5.651 *** (-2.69)	0.697 (1.09)	-0.179 (-0.24)	-0.450 * (-1.86)	-0.496 (-0.96)	0.266 (0.42)	-3.373 ** (-2.28)
δ_L^N	2.804 (0.86)	0.390 (0.07)	-3.964 (-1.23)	-2.211 (-1.22)	-1.792 (-1.40)	0.067 (0.02)	-4.938 (-1.10)
δ_H^N	4.121 *** (4.33)	2.351 *** (3.10)	2.382 *** (3.21)	1.139 *** (2.50)	2.518 *** (4.02)	1.041 *** (2.75)	2.720 *** (2.48)
ϕ_L	0.164 *** (5.87)	0.006 (0.12)	0.080 *** (2.67)	0.085 *** (3.05)	-0.001 (-0.04)	0.021 (0.52)	0.107 *** (2.81)
ϕ_H	0.198 *** (6.45)	0.031 * (1.66)	0.045 *** (2.57)	0.071 *** (4.13)	0.031 * (1.71)	0.041 *** (2.49)	0.058 *** (3.70)
$AdjR^2(\%)$	2.40	0.26	0.33	0.33	0.46	0.19	1.15

Panel B: $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$.

$c_L(\times 100)$	0.018 (1.31)	0.021 (0.92)	0.010 (0.54)	-0.017 (-1.03)	0.023 * (1.67)	0.038 *** (2.62)	0.026 (1.58)
$c_H(\times 100)$	-0.007 (-0.32)	-0.021 (-0.72)	0.029 (1.37)	0.040 (1.22)	0.034 (1.41)	-0.027 (-1.06)	0.012 (0.66)
δ_L^P	-1.374 (-0.38)	1.155 (0.37)	1.607 (0.68)	-0.848 (-0.50)	3.890 * (1.89)	3.492 (1.30)	-1.673 (-0.40)
δ_H^P	-7.042 *** (-2.94)	-1.073 (-1.28)	-2.423 *** (-2.61)	-0.990 * (-1.85)	-0.445 (-0.56)	-0.599 *** (-2.54)	-1.695 (-0.77)
δ_L^N	-1.355 (-0.33)	-2.565 (-0.53)	-5.497 (-1.25)	-2.555 (-1.19)	-2.241 (-1.16)	-1.858 (-0.39)	-4.536 (-0.61)

δ_H^N	4.279 *** (3.71)	3.163 ** (2.16)	2.899 *** (3.20)	1.432 *** (2.37)	2.194 *** (3.34)	1.718 ** (1.98)	2.021 *** (2.62)
ϕ_L	0.167 *** (3.67)	0.019 (0.45)	0.079 *** (2.80)	0.075 *** (2.86)	0.012 (0.48)	0.016 (0.52)	0.071 ** (2.15)
ϕ_H	0.153 *** (5.65)	0.038 ** (1.98)	0.049 *** (3.20)	0.060 *** (3.86)	0.008 (0.55)	0.048 *** (3.18)	0.005 (0.21)
$AdjR^2(\%)$	2.48	0.31	0.51	0.34	0.43	0.23	0.60
Panel C: $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$.							
$c_L(\times 100)$	0.026 *** (2.63)	0.022 (1.45)	0.021 * (1.73)	-0.006 (-0.40)	0.015 (1.20)	0.036 *** (3.20)	0.030 *** (3.52)
$c_H(\times 100)$	-0.007 (-0.32)	-0.049 * (-1.75)	0.007 (0.32)	0.029 (0.84)	0.014 (0.59)	-0.036 (-1.45)	0.018 (1.07)
δ_L^P	2.111 (0.21)	-1.004 (-0.13)	12.002 ** (2.15)	0.236 (0.14)	0.297 (0.12)	0.945 (0.14)	-2.805 (-0.73)
δ_H^P	-5.596 *** (-2.54)	0.691 (1.10)	-0.198 (-0.26)	-0.450 * (-1.82)	-0.496 (-0.96)	0.255 (0.44)	-3.363 ** (-2.11)
δ_L^N	4.602 (0.76)	-6.603 (-0.38)	-10.708 (-1.13)	-1.415 (-0.55)	-5.007 * (-1.92)	1.913 (0.14)	-10.575 *** (-2.46)
δ_H^N	4.075 *** (4.40)	2.316 *** (3.09)	2.376 *** (3.24)	1.139 *** (2.48)	2.517 *** (4.05)	1.043 *** (2.78)	2.721 *** (2.61)
ϕ_L	0.164 *** (6.31)	0.012 (0.31)	0.097 *** (3.85)	0.079 *** (2.46)	0.006 (0.25)	-0.003 (-0.09)	0.083 *** (3.16)
ϕ_H	0.195 *** (6.34)	0.030 * (1.67)	0.045 *** (2.68)	0.071 *** (4.11)	0.031 * (1.72)	0.041 *** (2.60)	0.057 *** (3.85)
$AdjR^2(\%)$	2.40	0.28	0.54	0.30	0.50	0.15	1.26
AVG δ_H^N	4.158 ***	2.610 ***	2.552 ***	1.237 ***	2.410 ***	1.267 ***	2.487 ***
(t-value)	(4.15)	(2.78)	(3.22)	(2.45)	(3.80)	(2.50)	(2.57)

Note: Table 5 reports the estimation results of the state-dependent VFE model: $R_t = (c_L L + c_H H) + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t$, where $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $H = 1$ when $\hat{v}_{t-1}^2 > 0$, indicating low and high unexpected volatility, respectively. The asymmetric volatility feedback parameters are δ_L^P and δ_L^N under low volatility conditions and δ_H^P and δ_H^N under high volatility conditions. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B considers $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C defines $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. AVG δ_H^N denotes the average value of δ_H^N across the three panels, along with its corresponding average t-value for each index. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 6. State-Dependent Volatility Feedback Effect Based on Two Consecutive Same-sign Volatility Shocks

Panel A: $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$.							
	Canada	France	Germany	Italy	Japan	UK	US
$c_L(\times 100)$	0.018 (1.15)	0.023 (0.58)	-0.001 (-0.04)	-0.016 (-0.66)	0.023 (1.26)	-0.024 (-0.72)	0.026 (1.17)
$c_H(\times 100)$	0.036 (1.08)	-0.011 (-0.19)	0.003 (0.08)	0.057 (0.61)	0.038 (0.73)	-0.067 (-1.25)	0.048 (1.30)
δ_L^P	-2.825 (-1.04)	-0.381 (-0.09)	-1.498 (-0.53)	2.692 (1.50)	2.041 (1.16)	-2.298 (-0.51)	7.366 (1.29)
δ_H^P	-3.275 (-1.50)	1.308 (1.27)	-0.186 (-0.14)	0.792 (0.58)	-2.228 *** (-2.56)	1.574 (0.80)	-9.889 * (-1.92)
δ_L^N	1.977 (0.50)	1.834 (0.38)	-2.207 (-0.59)	-2.622 (-1.48)	-0.858 (-0.62)	-9.689 *** (-2.55)	-6.679 (-0.87)
δ_H^N	3.890 *** (2.80)	2.562 ** (2.08)	2.295 *** (2.90)	1.205 (0.74)	3.011 *** (5.10)	2.957 *** (3.01)	2.304 *** (3.02)
ϕ_L	0.152 *** (3.63)	0.019 (0.41)	0.099 *** (3.25)	0.112 *** (3.80)	0.004 (0.16)	0.049 (1.25)	0.142 ** (2.01)
ϕ_H	0.182 *** (3.67)	0.064 (1.58)	0.040 (1.33)	0.040 (0.84)	0.048 (1.63)	0.069 (1.64)	0.107 *** (2.72)
$AdjR^2(\%)$	1.17	0.13	0.13	0.20	0.42	0.48	1.01
Panel B: $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$.							
$c_L(\times 100)$	0.000 (-0.02)	0.008 (0.34)	0.012 (0.66)	-0.029 (-1.57)	0.022 (1.44)	0.038 ** (2.31)	0.033 ** (1.99)
$c_H(\times 100)$	0.007 (0.19)	-0.014 (-0.27)	0.031 (0.77)	0.021 (0.29)	0.040 (0.79)	-0.019 (-0.39)	-0.050 (-1.01)
δ_L^P	-3.766 (-0.81)	3.612 (1.05)	1.896 (0.45)	0.988 (0.49)	4.314 ** (2.25)	6.588 * (1.78)	5.675 (0.70)
δ_H^P	1.641 (0.53)	3.619 (1.49)	-2.481 (-1.30)	-0.113 (-0.07)	-2.374 ** (-2.26)	-2.279 (-1.29)	4.223 (0.81)
δ_L^N	-7.893 ** (-2.26)	-5.715 (-1.24)	-4.508 (-1.16)	-3.908 * (-1.83)	-2.036 (-0.81)	-3.658 (-1.08)	-1.455 (-0.14)

δ_H^N	3.456 *** (2.37)	4.325 *** (2.93)	2.315 *** (2.91)	3.811 *** (2.92)	2.921 *** (5.27)	3.918 *** (7.33)	1.329 *** (4.00)
ϕ_L	0.195 *** (4.15)	0.068 * (1.67)	0.116 *** (3.70)	0.085 *** (3.07)	0.006 (0.20)	0.038 (1.03)	0.074 (1.48)
ϕ_H	0.097 * (1.84)	0.077 ** (2.22)	0.041 (1.49)	0.086 *** (2.46)	0.018 (0.70)	0.099 *** (2.71)	-0.033 (-0.39)
$AdjR^2(\%)$	1.19	0.30	0.17	0.38	0.50	0.46	0.26
Panel C: $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$.							
$c_L(\times 100)$	0.022 ** (2.00)	0.011 (0.61)	0.019 (1.37)	-0.023 (-1.30)	0.012 (0.88)	0.033 *** (2.50)	0.021 ** (2.08)
$c_H(\times 100)$	0.058 (1.47)	0.016 (0.31)	0.003 (0.07)	0.106 (1.44)	0.014 (0.26)	-0.004 (-0.09)	-0.032 (-0.99)
δ_L^P	0.832 (0.08)	-1.000 (-0.13)	10.491 (1.75)	-0.897 (-0.59)	0.026 (0.01)	0.887 (0.16)	-4.181 (-0.95)
δ_H^P	-2.839 *** (-2.47)	0.709 (1.38)	0.555 (0.98)	0.239 (1.10)	0.149 (0.35)	0.620 (1.51)	-2.133 * (-1.74)
δ_L^N	5.325 (0.81)	-7.251 (-0.41)	-9.874 (-1.24)	-0.816 (-0.35)	-4.917 * (-1.85)	1.340 (0.10)	-9.839 ** (-1.99)
δ_H^N	2.298 *** (2.42)	1.918 *** (3.31)	1.737 *** (2.72)	0.445 (1.40)	2.052 *** (3.45)	0.624 * (1.83)	2.433 *** (3.28)
ϕ_L	0.176 *** (5.19)	0.042 (1.00)	0.124 *** (4.24)	0.062 ** (1.97)	-0.004 (-0.17)	0.007 (0.23)	0.071 *** (2.47)
ϕ_H	0.124 *** (2.40)	0.061 * (1.95)	0.021 (0.76)	0.027 (1.03)	-0.011 (-0.39)	0.034 (0.80)	0.040 (0.81)
$AdjR^2(\%)$	1.05	0.29	0.49	0.11	0.46	0.37	1.04
AVG δ_H^N	3.215 ***	2.935 ***	2.116 ***	1.820 *	2.661 ***	2.500 ***	2.022 ***
(t-value)	(2.53)	(2.77)	(2.84)	(1.69)	(4.61)	(4.06)	(3.43)

Note: Table 6 reports the estimation results of the state-dependent VFE model: $R_t = (c_L L + c_H H) + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t$, where $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $\hat{v}_{t-2}^2 < 0$, and $H = 1$ when $\hat{v}_{t-1}^2 > 0$ and $\hat{v}_{t-2}^2 > 0$, indicating low and high unexpected volatility, respectively. The asymmetric volatility feedback parameters are δ_L^P and δ_L^N under low volatility conditions and δ_H^P and δ_H^N under high volatility conditions. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B considers $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C defines $P = 1$ if $e_{t-1} > SD$ and $N = 1$ if $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. AVG δ_H^N denotes the average value of δ_H^N across the three panels, along with its corresponding average t-value for each index. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 7. State-Dependent Volatility Feedback Effect under Prior Extreme Volatility Shocks as Based Dummy Variables

Panel A: $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$.							
	Canada	France	Germany	Italy	Japan	UK	US
$c_L(\times 100)$	0.664 (0.95)	1.051 (1.50)	0.304 (0.57)	1.666 (1.25)	0.395 (1.03)	1.022 (0.79)	0.283 (0.45)
$c_H(\times 100)$	-0.024 (-0.17)	-0.073 (-0.71)	-0.108 (-1.28)	-0.040 (-0.29)	-0.034 (-0.30)	-0.136 (-1.60)	0.038 (0.31)
δ_L^P	6.474 (1.03)	7.440 (1.08)	-1.022 (-0.13)	11.622 (1.29)	6.721 *** (4.31)	12.928 (1.59)	3.569 (1.04)
δ_H^P	-5.451 ** (-2.01)	0.483 (0.66)	0.604 (0.64)	-0.234 (-0.76)	-0.299 (-0.37)	0.591 (0.68)	-2.851 (-1.43)
δ_L^N	9.141 (1.43)	18.632 (1.43)	3.178 (0.40)	11.101 (0.96)	-5.967 (-1.49)	17.140 (0.77)	-2.414 (-0.27)
δ_H^N	4.089 *** (2.65)	2.730 *** (3.08)	2.253 ** (2.27)	1.007 * (1.80)	2.531 *** (3.30)	1.131 ** (2.01)	2.351 ** (2.28)
ϕ_L	0.197 (0.41)	-0.579 * (-1.75)	-0.468 (-1.59)	0.359 (0.84)	0.861 *** (3.49)	-0.247 (-0.30)	-0.015 (-0.09)
ϕ_H	0.189 ** (2.10)	0.051 (1.60)	0.017 (0.44)	0.050 (1.23)	0.021 (0.54)	0.033 (0.86)	0.016 (0.41)
$AdjR^2(\%)$	1.12	0.62	0.32	0.09	0.78	0.24	0.90
Panel B: $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$.							
$c_L(\times 100)$	-0.214 (-0.49)	0.192 (0.52)	0.102 (0.34)	0.019 (0.15)	0.453 * (1.89)	-0.230 (-0.51)	-0.047 (-0.10)
$c_H(\times 100)$	-0.071 (-0.73)	0.091 (0.75)	0.043 (0.53)	0.064 (0.79)	0.064 (0.70)	-0.056 (-0.60)	-0.054 (-0.39)
δ_L^P	-0.840 (-0.13)	3.352 (0.57)	-1.314 (-0.27)	-2.819 (-0.80)	10.456 *** (2.94)	8.421 ** (2.13)	-7.682 (-1.24)
δ_H^P	-5.954 *** (-2.63)	-1.633 * (-1.79)	-2.332 ** (-2.11)	-1.075 * (-1.95)	-0.367 (-0.46)	-0.547 * (-1.84)	0.452 (0.14)
δ_L^N	-1.734 (-0.18)	5.394 (0.47)	-4.378 (-0.46)	-3.937 (-1.05)	-5.419 (-1.37)	-5.255 (-0.36)	-5.223 (-0.38)

δ_H^N	3.818 *** (2.82)	2.910 *** (2.35)	2.667 *** (2.51)	1.324 ** (1.97)	1.982 *** (2.77)	1.796 ** (2.15)	1.466 *** (2.43)
ϕ_L	0.271 (0.41)	-0.367 (-0.83)	-0.308 (-1.26)	0.025 (0.15)	0.618 *** (3.49)	0.009 (0.02)	-0.176 (-0.82)
ϕ_H	0.098 (1.40)	0.053 * (1.87)	0.042 (1.48)	0.054 *** (2.48)	-0.014 (-0.53)	0.052 * (1.76)	-0.082 (-1.60)
$AdjR^2(\%)$	1.16	0.41	0.42	0.18	0.84	0.21	0.74
Panel C: $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$.							
$c_L(\times 100)$	0.002 (0.00)	-0.018 (-0.06)	0.249 (1.05)	0.304 * (1.74)	0.216 * (1.87)	-0.301 (-1.05)	-0.140 (-0.32)
$c_H(\times 100)$	-0.024 (-0.14)	-0.073 (-0.71)	-0.108 (-1.19)	0.031 (0.35)	-0.022 (-0.30)	-0.136 (-1.59)	0.038 (0.29)
δ_L^P	3.431 (0.27)	-10.090 (-1.23)	13.522 (1.64)	4.249 (1.05)	0.445 (0.10)	-22.905 * (-1.86)	-2.612 (-0.33)
δ_H^P	-5.451 * (-1.75)	0.483 (0.65)	0.604 (0.68)	-0.482 * (-1.95)	-0.538 (-0.80)	0.591 (0.76)	-2.851 (-1.36)
δ_L^N	3.479 (0.59)	8.019 (0.48)	-7.216 (-0.81)	2.487 (0.42)	-4.959 (-1.62)	27.705 (1.45)	-13.345 (-1.45)
δ_H^N	4.089 *** (3.45)	2.730 *** (3.22)	2.253 ** (2.29)	1.135 ** (2.06)	2.704 *** (3.82)	1.131 ** (1.99)	2.351 ** (2.24)
ϕ_L	0.285 (1.13)	-0.586 * (-1.72)	-0.020 (-0.09)	0.067 (0.28)	0.144 (0.60)	-1.255 *** (-2.38)	0.042 (0.09)
ϕ_H	0.189 ** (2.21)	0.051 * (1.66)	0.017 (0.49)	0.073 *** (2.47)	0.038 (1.21)	0.033 (0.86)	0.016 (0.40)
$AdjR^2(\%)$	0.96	0.46	0.40	0.16	0.57	0.39	1.04
AVG δ_H^N	3.999 ***	2.790 ***	2.391 ***	1.155 *	2.406 ***	1.353 **	2.056 **
(t-value)	(2.97)	(2.88)	(2.36)	(1.94)	(3.30)	(2.05)	(2.32)

Note: Table 7 reports the estimation results of the asymmetric VFE model: $R_t = (c_L L + c_H H) + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t$, where $L = 1$ when $\hat{v}_{t-1}^2 < -SDV$ and $H = 1$ when $\hat{v}_{t-1}^2 > SDV$, where SDV denotes one standard deviation of $\hat{v}_t^2$. The asymmetric volatility feedback parameters are represented by δ_L^P and δ_L^N under low volatility conditions, and δ_H^P and δ_H^N under high volatility conditions. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B considers $P = 1$ when $e_{t-1} > 0$ and $e_{t-2} > 0$, and $N = 1$ when $e_{t-1} < 0$ and $e_{t-2} < 0$. Panel C defines $P = 1$ if $e_{t-1} > SD$ and $N = 1$ if $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. AVG δ_H^N denotes the average value of δ_H^N across the three panels, along with its corresponding average t-value for each index. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 8. Sub-period Analysis on Complete Asymmetric Intertemporal Risk-Return Relation

Panel A: Estimation Results for the 1 st Sub-period							
	Canada	France	Germany	Italy	Japan	UK	US
$c_P(\times 100)$	-0.049 (-1.61)	0.122 (1.45)	0.028 (0.48)	-0.105 ** (-2.26)	0.040 *** (1.34)	0.041 (0.68)	-0.008 (-0.20)
$c_N(\times 100)$	-0.019 (-0.53)	-0.040 (-0.57)	-0.058 (-1.33)	0.078 * (1.67)	0.034 (1.26)	0.029 (0.73)	0.042 (1.09)
τ_P	-8.610 *** (-3.56)	1.346 (0.35)	-4.440 (-0.79)	0.523 (0.43)	-0.129 (-0.12)	-2.758 (-0.55)	2.424 (1.02)
τ_N	2.259 (0.99)	7.137 (1.43)	5.057 (1.59)	0.361 (0.26)	1.973 ** (1.97)	8.903 *** (3.00)	1.047 (0.39)
δ_P	-12.163 *** (-4.53)	3.307 (1.54)	-2.554 *** (-3.10)	-1.522 *** (-3.77)	-0.351 (-0.61)	-1.444 * (-1.77)	-3.486 (-1.29)
δ_N	1.096 (0.60)	2.915 ** (2.26)	3.097 *** (2.70)	1.967 *** (2.90)	2.234 *** (4.34)	1.587 *** (6.18)	2.244 *** (7.86)
ϕ_P	0.438 *** (8.23)	-0.064 (-0.99)	0.173 *** (4.14)	0.223 *** (5.31)	0.094 *** (2.70)	0.093 ** (2.12)	0.191 *** (3.61)
ϕ_N	0.198 *** (3.23)	0.128 * (1.90)	0.082 * (1.95)	0.184 *** (3.75)	0.106 *** (2.89)	0.209 *** (5.56)	0.212 *** (4.04)
$AdjR^2(\%)$	4.87	0.49	1.29	1.69	1.11	0.64	2.93
Wald F -test (p-value)	60.05 *** (0.00)	6.68 *** (0.00)	18.38 *** (0.00)	19.33 *** (0.00)	16.66 *** (0.00)	10.28 *** (0.00)	42.53 *** (0.00)
$H_1: \tau_N + \delta_N > 0$ (t-value)	3.359 (1.59)	10.052 *** (3.22)	8.154 *** (3.43)	2.328 (1.46)	4.206 *** (4.97)	10.489 *** (2.73)	3.291 ** (2.04)
$H_1: \tau_P + \delta_P \leq 0$ (t-value)	-20.774 *** (-7.58)	4.653 (1.29)	-6.994 *** (-2.46)	-0.999 (-0.64)	-0.480 (-0.31)	-4.202 (-0.91)	-1.062 (-0.43)
Panel B: Estimation Results for the 2 nd Sub-period							
$c_P(\times 100)$	0.002 (0.03)	0.054 (1.13)	0.074 (1.50)	0.015 (0.27)	-0.046 (-1.04)	0.062 (1.12)	0.024 (0.64)
$c_N(\times 100)$	0.161 *** (2.84)	0.121 (1.64)	0.075 (1.40)	-0.018 (-0.29)	-0.025 (-0.47)	0.043 (0.67)	0.064 * (1.91)

τ_P	-1.610 (-0.53)	2.297 (1.23)	1.750 (0.71)	1.016 (0.36)	0.828 (0.36)	0.069 (0.03)	-7.900 *** (-2.40)
τ_N	2.976 (0.67)	3.525 (1.03)	3.946 * (1.95)	2.096 (0.87)	6.366 ** (2.06)	3.346 (1.30)	9.250 *** (3.72)
δ_P	-2.650 (-0.89)	1.807 ** (2.18)	1.603 (1.61)	1.012 (1.06)	-0.201 (-0.22)	2.912 * (1.85)	-2.558 (-1.23)
δ_N	5.368 *** (5.80)	3.048 ** (2.07)	1.707 * (1.69)	0.509 (0.40)	2.010 ** (1.97)	1.865 * (1.80)	4.943 *** (5.86)
ϕ_P	0.117 (1.44)	-0.107 ** (-2.02)	-0.087 ** (-2.06)	-0.044 (-0.82)	-0.024 (-0.51)	-0.081 (-1.53)	0.086 (1.36)
ϕ_N	0.324 *** (5.41)	0.171 *** (3.02)	0.124 *** (2.53)	0.029 (0.35)	0.056 (0.66)	0.093 (1.44)	0.175 *** (4.19)
$AdjR^2(\%)$	2.12	0.40	0.12	0.00	0.56	0.50	2.52
Wald F -test	70.72 ***	11.05 ***	5.45 ***	1.52	3.76 ***	12.64 ***	35.47 ***
(p-value)	(0.00)	(0.00)	(0.00)	(0.22)	(0.00)	(0.00)	(0.00)
$H_1: \tau_N + \delta_N > 0$	8.344 ***	6.573 ***	5.653 ***	2.605 *	8.377 ***	5.211 ***	14.193 ***
(t-value)	(7.24)	(3.73)	(3.21)	(1.76)	(4.23)	(3.22)	(9.74)
$H_1: \tau_P + \delta_P \leq 0$	-4.260 ***	4.104 **	3.354 *	2.028	0.627	2.982 *	-10.458 ***
(t-value)	(-2.76)	(2.08)	(1.86)	(1.09)	(0.29)	(1.68)	(-5.80)

Note: Panels A and B report the estimation results for the first and second sub-periods, respectively. The complete asymmetric IRRR is estimated using the following model specification: $R_t = (c_P P + c_N N) + (\tau_P P + \tau_N N)\hat{\sigma}_t^2 + (\delta_P P + \delta_N N)\hat{v}_t^2 + (\phi_P P + \phi_N N)R_{t-1} + \varepsilon_t$, where $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$, where e_t is the mean-deviated excess return of each index. The effective RRA parameter is represented by $\tau_P + \delta_P$ following a prior positive return shock and by $\tau_N + \delta_N$ following a prior negative return shock. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 9. Sub-period Analysis on State-Dependent Volatility Feedback Effect

Panel A: Estimation Results for the 1 st Sub-period							
	Canada	France	Germany	Italy	Japan	UK	US
$c_L(\times 100)$	0.054 *** (2.87)	-0.011 (-0.28)	0.021 (0.82)	-0.009 (-0.31)	0.050 *** (3.00)	0.084 ** (2.12)	0.044 *** (2.65)
$c_H(\times 100)$	0.064 *** (3.20)	-0.026 (-0.58)	0.054 ** (2.15)	0.121 *** (2.38)	0.014 (0.46)	-0.027 (-0.91)	0.020 (1.09)
δ_L^P	4.372 * (1.67)	0.047 (0.01)	2.447 (0.74)	1.291 (0.89)	0.923 (0.54)	4.909 (1.18)	-2.272 (-0.63)
δ_H^P	-11.198 *** (-4.74)	1.486 (1.07)	-1.953 *** (-2.45)	-1.126 *** (-3.90)	-0.321 (-0.59)	-1.747 *** (-2.57)	-4.659 (-1.39)
δ_L^N	11.025 (1.48)	-4.331 (-0.90)	0.751 (0.24)	-1.887 (-1.56)	0.337 (0.26)	1.835 (0.31)	6.123 (0.92)
δ_H^N	1.933 (0.97)	2.865 *** (2.96)	3.685 *** (3.93)	1.563 *** (3.73)	2.701 *** (3.95)	1.147 *** (6.22)	2.288 *** (13.87)
ϕ_L	0.252 *** (4.44)	0.089 ** (2.06)	0.155 *** (4.49)	0.244 *** (6.19)	0.132 *** (2.91)	0.051 (1.21)	0.115 * (1.89)
ϕ_H	0.266 *** (7.22)	0.051 ** (2.07)	0.103 *** (5.80)	0.143 *** (6.64)	0.087 *** (4.05)	0.118 *** (6.67)	0.211 *** (4.01)
$AdjR^2(\%)$	5.10	0.42	1.22	1.81	1.14	0.64	3.01
Panel B: Estimation Results for the 2 nd Sub-period							
$c_L(\times 100)$	0.050 * (1.86)	0.051 (1.06)	-0.001 (-0.02)	-0.015 (-0.38)	-0.071 *** (-2.45)	0.031 (0.67)	0.013 (0.44)
$c_H(\times 100)$	-0.054 * (-1.74)	-0.081 * (-2.09)	-0.029 (-0.87)	-0.034 (-0.77)	-0.003 (-0.07)	-0.056 (-1.49)	-0.014 (-0.52)
δ_L^P	1.191 (0.30)	0.183 (0.06)	-0.170 (-0.05)	-0.672 (-0.21)	-3.234 (-1.18)	3.937 (0.95)	5.217 (1.48)
δ_H^P	-4.637 * (-1.93)	0.997 (1.34)	0.707 (0.81)	0.618 (0.75)	-0.579 (-0.72)	2.116 * (1.71)	-3.429 (-1.59)
δ_L^N	2.059 (0.59)	2.466 (0.37)	-4.964 (-1.11)	-1.067 (-0.29)	-4.667 *** (-2.45)	-0.761 (-0.11)	-9.913 ** (-2.05)

δ_H^N	4.644 *** (8.92)	1.727 ** (2.03)	1.265 ** (1.98)	0.647 (0.58)	2.495 ** (2.14)	1.409 * (1.69)	6.273 *** (7.83)
ϕ_L	0.105 *** (2.40)	-0.048 (-0.81)	0.023 (0.53)	-0.036 (-0.67)	-0.081 *** (-2.59)	0.013 (0.25)	0.080 ** (2.06)
ϕ_H	0.172 *** (4.55)	-0.004 (-0.15)	0.004 (0.18)	0.002 (0.08)	-0.005 (-0.18)	-0.012 (-0.36)	0.034 (1.28)
$AdjR^2(\%)$	2.12	0.24	0.16	0.01	0.65	0.46	2.82

Note: Panels A and B report the estimation results of the state-dependent VFE model for the first and second sub-periods, respectively, using the following model specification: $R_t = (c_L L + c_H H) + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t$, where $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $H = 1$ when $\hat{v}_{t-1}^2 > 0$. The dummy variables for good and bad market states are defined as $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$, where e_t is the mean-deviated excess return of each index. The effective RRA parameter is represented by $\tau_P + \delta_P$ following a prior positive return shock, and by $\tau_N + \delta_N$ following a prior negative return shock. The asymmetric VFE parameters under good and bad market states are δ_L^P and δ_L^N under low volatility conditions ($L = 1$), and δ_H^P and δ_H^N under high volatility conditions ($H = 1$). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 10. Complete Intertemporal Risk-Return Relation under Combined Market States

Panel A: $P = 1$ when $e_{t-1} > 0$ and $N = 1$ when $e_{t-1} < 0$.							
	Canada	France	Germany	Italy	Japan	UK	US
τ_L^P	-3.485 (-0.25)	-6.231 (-0.74)	-12.748 * (-1.69)	5.034 (0.99)	1.355 (0.66)	-4.848 (-0.47)	11.160 (1.26)
τ_H^P	2.793 (0.95)	1.238 (0.38)	0.383 (0.13)	-2.029 (-0.71)	-1.724 (-0.47)	-1.931 (-0.44)	-9.934 (-1.60)
τ_L^N	5.805 (0.91)	7.508 (0.66)	9.240 (1.27)	-5.255 (-0.92)	5.092 (0.98)	9.980 (1.03)	3.022 (1.02)
τ_H^N	1.378 (0.18)	0.741 (0.22)	-3.109 (-0.92)	1.075 (0.29)	-0.439 (-0.12)	5.015 (1.02)	8.141 *** (2.56)
δ_L^P	-0.966 (-0.10)	-4.630 (-0.72)	-10.900 * (-1.67)	4.125 (0.97)	0.637 (0.19)	-0.620 (-0.07)	12.577 * (1.77)
δ_H^P	-6.459 *** (-3.87)	0.524 (0.65)	0.041 (0.06)	-0.547 (-1.68)	-0.374 (-0.73)	0.001 (0.00)	-2.260 (-1.65)
δ_L^N	7.887 (1.52)	6.701 (0.59)	3.582 (0.63)	-6.889 (-1.12)	2.821 (0.60)	9.127 (0.96)	-1.043 (-0.19)
δ_H^N	3.803 ** (2.42)	2.194 *** (2.40)	2.635 *** (3.08)	1.273 *** (2.35)	2.666 *** (3.01)	0.920 ** (2.10)	2.193 ** (2.16)
$AdjR^2(\%)$	2.45	0.26	0.41	0.33	0.48	0.25	1.63
Panel B: $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$.							
τ_L^P	0.484 (0.09)	-5.375 (-0.83)	-1.953 (-0.32)	-0.898 (-0.23)	1.204 (0.53)	-2.668 (-0.19)	9.972 (1.12)
τ_H^P	2.920 (1.04)	0.516 (0.19)	-1.015 (-0.38)	-1.845 (-0.75)	-1.610 (-0.47)	-2.389 (-0.58)	-9.777 ** (-2.02)
τ_L^N	6.541 ** (1.89)	5.037 (0.50)	-0.436 (-0.07)	-2.639 (-0.48)	2.974 (0.54)	11.143 (1.26)	-1.373 (-0.58)
τ_H^N	0.970 (0.13)	0.542 (0.22)	-1.999 (-0.66)	0.550 (0.17)	-0.496 (-0.14)	4.726 (0.95)	7.824 *** (2.46)
δ_L^P	2.990 (0.28)	-7.480 (-0.62)	9.132 (0.92)	-9.321 (-1.32)	1.714 (0.42)	-1.930 (-0.12)	9.452 (0.79)

δ_H^P	-6.448 *** (-3.53)	0.594 (0.79)	0.059 (0.07)	-0.497 * (-1.68)	-0.372 (-0.75)	0.052 (0.09)	-2.098 (-1.40)
δ_L^N	11.997 * (1.73)	1.306 (0.05)	-11.417 (-0.73)	-1.768 (-0.14)	-1.205 (-0.16)	18.358 (0.88)	-11.816 ** (-2.14)
δ_H^N	3.816 *** (2.52)	2.215 ** (2.17)	2.640 *** (3.05)	1.235 *** (2.38)	2.667 *** (3.01)	0.918 ** (2.23)	2.161 ** (2.10)
$AdjR^2(\%)$	2.47	0.28	0.53	0.36	0.49	0.23	1.68
AVG δ_H^N	3.810 ***	2.205 **	2.638 ***	1.254 ***	2.667 ***	0.919 **	2.177 **
(t-value)	(2.47)	(2.29)	(3.07)	(2.37)	(3.01)	(2.17)	(2.13)

Note: Table 10 reports the estimation results of the complete IRRR model under combined market states: $R_t = (c_L L + c_H H) + [(\tau_L^P L + \tau_H^P H)P + (\tau_L^N L + \tau_H^N H)N]\hat{\sigma}_t^2 + [(\delta_L^P L + \delta_H^P H)P + (\delta_L^N L + \delta_H^N H)N]\hat{v}_t^2 + (\phi_L L + \phi_H H)R_{t-1} + \varepsilon_t$, where $L = 1$ when $\hat{v}_{t-1}^2 < 0$ and $H = 1$ when $\hat{v}_{t-1}^2 > 0$, indicating low and high unexpected volatility, respectively. Panel A corresponds to the case where $P = 1$ if $e_{t-1} > 0$ and $N = 1$ if $e_{t-1} < 0$. Panel B defines $P = 1$ when $e_{t-1} > SD$ and $N = 1$ when $e_{t-1} < -SD$, where SD denotes one standard deviation of return shocks for each index. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.