On the Intertemporal Risk-Return Tradeoff: Another Look

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Abstract

We find that the tendency for investors to mis-react to price changes in the short-term causes stocks to become overpriced (underpriced) in response to good (bad) news, thus inducing a weak or negative (strong positive) risk-return tradeoff. We verify this asymmetry through the indirect relation of a non-negative (a significantly negative) relation between excess market returns and contemporaneous volatility innovations conditional on good (bad) news. The distortion of the risk-return relation is strengthened in periods of high investor sentiment. Our results also demonstrate that inclusion of a price adjustment term is critical for reliable estimation of the intertemporal risk-return relation.

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JEL classification: G10; G12

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1. Introduction

The tradeoff between risk and return is one of the core tenets of financial economics. In particular, the intertemporal risk-return relation is vital for the time-varying rational expectations hypothesis which implies that rational risk-averse investors revise their expectations in response to changing volatility. For instance, Fama and French (1989) argue that systematic patterns in the predictable variation of expected returns are consistent with the intertemporal asset pricing models by Lucas (1978) and Breeden (1979), and the notion of consumption smoothing captured by Modigliani and Brumberg (1954) and Friedman (1957). Ferson and Harvey (1991) and Evans (1994) also document the importance of time-varying risk premia associated with conditional betas to explain predictable variation in expected returns.

Despite its importance in asset pricing theories, the actual sign of the intertemporal risk-return relation (hereafter IRRR) has been debated for decades, with empirical findings that are mixed and inconclusive. While a positive IRRR is consistent with theoretical predictions, some argue that in reality it can be close to zero or even negative. For example, French, Schwert and Stambaugh (1987), Campbell and Hentschel (1992), Ghysel, Santa-Clara and Valkanov (2005), and Bali (2008) present evidence that a substantial amount of intertemporal variation in expected market returns is determined by a positive risk-return tradeoff. However, Glosten et al. (1993) argue that the sign of the IRRR can be negative when investors are exceptionally optimistic about future stock price performance, thus not requiring a large premium for bearing risk. Abel (1988) argues that a negative relation between conditional risk and the risk premium can be consistent with a general equilibrium model when the coefficient of relative risk aversion (RRA) is less than one. Barsky (1989) also documents that the directional effect of an increase in risk on stock prices depends on the curvature of the utility function, which suggests the possibility of a negative risk-return relation.[1] On the contrary, Poterba and Summers (1986), Baillie and DeGennaro (1990), Boudoukh et al. (1997), Whitelaw (2000), and Müller et al. (2011) document that the IRRR is either close to zero or unstable, causing insignificant time variation in the expected market risk premium.[2]

The objective of this paper is to demonstrate that investors' mispricing could distort the risk-return tradeoff, such that the intertemporal mean-variance relation may not necessarily be positive. We suggest that the tendency for investors to mis-react to good and bad market news in the short-term causes overpricing and underpricing, respectively.[3] Mispricing is exploited by rational arbitrageurs' selling on good news and buying on bad news, which ultimately induces asymmetry in the intertemporal risk-return relation. We conjecture that due to arbitrage trading, overpricing (underpricing) under good (bad) news

[1] Studies that support a positive intertemporal risk return relation include French, Schwert and Stambaugh (1987), Fama and French (1988), Ball and Kothari (1989), Tuner, Startz and Nelson (1989), Harvey (1989), Cecchehtti, Lam and Mark (1990), Haugen, Talmor and Torous (1991), Campbell and Hentschel (1992), Scruggs (1998), Kim, Morley and Nelson (2001), Ghysel, Santa-Clara and Valkanov (2005), Ludvigson and Ng (2006), and Bali (2008). Studies that support a negative intertemporal risk return relation include Campbell (1987), Breen et al. (1989), Nelson (1991), Backus and Gregory (1993), Gennotte and Marsh (1993), Whitelaw (1994), Harvey (2001), Brandt and Kang (2004) and Ang et al. (2006).

[2] French et al. (1987) find a negative relation between ex-post excess market returns and the unpredictable component of conditional market volatility and use it as indirect evidence for a positive relation between ex-ante expected returns and predictable volatility.

[3] In contrast to earlier studies that capture periods of mispricing through the low frequency data of Baker and Wurgler (2006), we demonstrate that investors' mis-reaction to daily good and bad market news also significantly affects the intertemporal risk-return tradeoff in the same manner as does investor sentiment.

weakens (strengthens) the positive intertemporal risk-return relation, such that it is positive conditional on bad market news, but non-positive conditional on good market news.

Our main result is to demonstrate that using daily excess returns on the U.S. value-weighted market index during the period 1926-2015, the intertemporal mean-variance relation is negligible or negative conditional on a positive prior market return (i.e., good market news) but is significantly positive conditional on a negative prior market return (i.e., bad market news). This asymmetry in the ex-ante risk-return relation with respect to recent market news is further supported by the indirect relation between excess market returns and contemporaneous volatility innovations suggested by French, Schwert, and Stambaugh (1987); the indirect risk-return relation is weak or positive conditional on a positive prior return but is significantly negative conditional on a negative prior return.

Our study corroborates the results of Yu and Yuan (2011) and Stambaugh et al. (2015). Yu and Yuan (2011) provide important empirical evidence that supports the conclusion that the sign of the ex-ante mean-variance relation is not necessarily positive. They find that the IRRR is strongly positive during periods of low market sentiment, but is negligible when market sentiment is high. To explain their result, they argue that sentiment-driven traders have a greater effect on prices in periods of high sentiment due to their reluctance to act on low sentiment through short positions, and that sentiment-driven traders are also more likely to be naïve and mis-forecast the conditional volatility of returns. The result is that sentiment-driven traders undermine what would otherwise be a positive risk-return relation when sentiment is high. Extending this research, Stambaugh, Yu, and Yuan (2015) show that the combined effects of arbitrage risk (i.e., risk that deters arbitrage) and arbitrage asymmetry (i.e., relatively less arbitrage activity directed towards overpriced relative to underpriced stocks) can induce a negative relationship between aggregate idiosyncratic volatility and expected market return. They show that the effect of idiosyncratic volatility on expected return is strongly negative for overpriced stocks, but positive for underpriced stocks. In aggregate, the negative risk-return relation among overpriced stocks dominates the positive risk-return relation for underpriced stocks, which generates an overall negative risk-return relation.[4]

The empirical models for returns we study include both a measure intended to capture over- or underpricing, and also a process capturing price adjustments to prior mispricing as a control variable when estimating the intertemporal risk-return relation. Using a theoretical model, we derive this adjustment term as an important component to the Slutsky equation for equilibrium asset demand. The inclusion of this price adjustment term reflects the fact that even if market volatility remains unchanged, there is predictable variation in the expected market return induced by market reaction to prior prices which is not considered by the strictly rational models typically used to model the risk-return tradeoff. Some examples of investor behavior that can be captured by this adjustment process include negative or positive feedback trading (De Long, Shleifer, Summers, and Waldmann, 1990; Sentana and Wadhwani, 1992; and Nofsinger and Sias, 1999), underreaction (Jegadeesh and Titman, 1993), overreaction (De Bondt and Thaler, 1985, 1990), lead-lag effects in cross-autocorrelations (Lo and MacKinlay, 1990), delayed overreaction (De Long, Shleifer, Summers, and Waldmann, 1990), self-attribution bias (Daniel, Hirshleifer, and Subrahmanyam, 1998), newswatchers and momentum trading (Hong Stein, 1999), and liquidity trading (Campbell, Grossman, and Wang, 1993). One important contribution of this work is to show that this adjustment process is a critical control variable for reliable estimation of the intertemporal risk-return relation. Our empirical results show that the inclusion of the adjustment term significantly decreases (increases) the magnitude of the IRRR coefficient under a positive (negative) price change. This implies that ignoring the adjustment process constitutes a significant model misspecification problem, causing an upward (downward) bias in the IRRR coefficient conditional on good (bad) market news, which leads to mis-estimation of the expected market risk premium.

The outline of the paper is as follows. In Section 2, we develop testable hypotheses. In Section 3, using a theoretical utility maximization model for portfolio choice under uncertainty, we derive the

[4] They also show that high (low) sentiment strengthens the negative (positive) relation among overpriced (underpriced) stocks, thus inducing a weak or negative (positive) relation between idiosyncratic volatility and expected return during periods of high (low) market sentiment.

intertemporal risk-return relation and investors' adjustment behavior as the two main pricing factors. In Section 4, we present our empirical work and interpretation of the results. Section 5 presents empirical results for the ICAPM using size decile portfolios. Section 6 concludes the paper.

2. Hypothesis Development

Our hypothesis begins with the notion that investors tend to mis-react to market news in the short-term, which can lead to the mispricing of stocks, such as overpricing conditional on good news but underpricing conditional on bad news. While price levels in the short-term may be distorted by investors with bounded rationality, arbitrageurs who are assumed to be fully rational could always take advantage of mispricing. We conjecture that rational arbitrageurs exploit overpricing and underpricing through selling on good news and buying on bad news.[5]

Suppose all stocks in the market are in equilibrium such that they are fairly priced in accordance with their risk level and the conditional information concerning their fundamentals. In the simple case, good market news may take the form of a general upward revision in expected cash flows, a downward revision in the estimate of future risk, or some combination of the two that leads to a higher price level. Short-term investors who mis-react to good market news may become overly optimistic about future cash flows and/or may forecast future risk to be too low, resulting in a new price level that is too high. Once overpriced, the future return must be relatively low to restore the correct price level, so that as shown in Stambaugh, Yu, and Yuan (2015), rational arbitrageurs will try to profit from overpricing. As more arbitrageurs sell short overpriced stocks, the ex-ante risk-return relation observed at the time of overpricing will be lower than it would have been if there were no arbitrage. If the risk-return tradeoff is in general positive as standard asset pricing theory predicts, then at times of overpricing, the short sales by arbitrageurs would tend to weaken the relation and make it less positive. Similarly, negative market

[5] Note that mispricing is not necessarily eliminated by arbitrageurs.

news can take the form of a downward revision in expected cash flows and/or an increase in expected risk resulting in a lower price level. Mispricing resulting from negative market news implies underpricing due to pessimistic revisions in expected cash flows that are too negative and/or increases in expected risk that are too high. Rational arbitrageurs will exploit underpricing through purchasing underpriced stocks that produce relatively high future returns. Thus, at the time of underpricing the ex-ante risk-return tradeoff would tend to be more positive than it would otherwise be absent arbitrage. Therefore, conjecturing that arbitrageurs' short-sale on good (bad) market news weakens (strengthens) the positive risk-return relation, we hypothesize that the intertemporal risk-return relation is positive conditional on bad market news, but is non-positive conditional on good market news.

The capital market equilibrium condition implies that there is only one price of risk in the market. In particular, the intertemporal capital asset pricing model (ICAPM) implies that the predicted slope of an asset's expected return on its conditional covariance should be the representative investor's relative risk aversion, and hence an asset's expected return can be predicted as a linear function of its conditional covariance with the market portfolio under the assumption of a negligible hedge component against changing investment opportunities. This implies that the intertemporal relationship between expected returns and conditional risk applies not only to the market portfolio but also to individual stocks or other portfolios. We thus conjecture that the asymmetry in the intertemporal risk-return relation observed for the market portfolio should also be observed for the intertemporal relation between an individual stock's expected return and its conditional covariance with the market portfolio. Therefore, our second hypothesis is that the RRA parameter of individual stocks or portfolios is non-positive conditional on good news, but is positive conditional on bad news.

3. **Theoretical Model**

In this section, we derive the Slutsky equation for equilibrium asset demand and use it to highlight two channels affecting predictable variation in expected returns. The first channel is rational investors' revisions in their expectation in response to the changes in predictable volatility in which higher expected volatility commands a higher risk premium. However, if investors' revision is not fully rational, then updates to expected returns must also tend to correct prior mispricing caused by behaviorial biases. Thus, revisions in investors' expectations in the short-term can be attributed not only to the risk-return tradeoff but also to a price adjustment process resulting from the tendency to correct prior mispricing. This implies that the intertemporal risk-return tradeoff and investor behavior are both important pricing factors that contribute to predictable variation in expected market returns. We incorporate these two pricing factors in the formal utility maximization model of portfolio choice under uncertainty, in which equilibrium asset demand is jointly determined through these two channels of the intertemporal risk-return relation and investors' adjustment behavior. We use the term "investors' adjustment behavior" to represent all the market or price adjustments to correct prior mispricing that are not associated with the risk-return tradeoff.

Consider 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 defined as $\sum_{i=1}^{n} p_i x_i$. A value of $x_i > 0$ indicates a long position and $x_i < 0$ indicates a short position. Let $\bar{x}_i$ be the quantity of asset i that the investor initially holds and $W = \sum_{i=1}^{n} p_i \bar{x}_i$ be the investor's initial net wealth. Assuming a positive initial net wealth, the adjustment to his or her 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):

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

where λ is a Lagrangian multiplier. The utility function is assumed to be continuous and at least twice differentiable. Optimal portfolio X is found by solving the following first order conditions of the constrained maximization problem:

$$\partial U \big/ \partial x_i - \lambda p_i = 0 \tag{3}$$

$$W - \sum_{i=1}^{n} p_i x_i = 0\,. \tag{4}$$

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

$$H = \begin{bmatrix} \dfrac{\partial^2 L}{\partial x_i \partial x_j} & \dfrac{\partial^2 L}{\partial x_i \partial \lambda} \\ \dfrac{\partial^2 L}{\partial \lambda \partial x_j} & \dfrac{\partial^2 L}{\partial \lambda^2} \end{bmatrix}. \tag{5}$$

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:

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

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

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

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:[6]

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

where $\frac{\partial x_i^*}{\partial p_i}$ is the response of x_i to changes in its own price, $\frac{\partial x_i^U}{\partial p_i}$ is the response of x_i to p_i along with the wealth compensated (or adjusted) 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 represents a pure substitution effect, while the second term represents 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. That is, unless there is a sudden unexpected change in the representative investor's stocks of assets, $\bar{x}_i$ is exactly the same as the equilibrium quantity level of the i^{th} asset so that the excess demand for each of the assets is zero in equilibrium. This implies that in equilibrium, changes in asset prices yield only substitution effects.[7] For the compensation to maintain the same utility level to the variations in net wealth resulting from price

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[6] See Bierwag and Grove (1966, 1968), Fischer (1972), Epps (1975), Dalal (1983), and Roley (1983) for more detail on the derivation and interpretation of the Slutsky equation in asset pricing theory.

[7] Note that the substitution term in asset demand is not necessarily restricted in sign, while the pure substitution term is negative in the traditional demand theory.

changes, the substitution effect in demand is driven by the revision of investor expectations leading to changes in the expected asset price. Following Epps (1975), we specify the Slutsky equation as follows:

$$\frac{\partial x_i^*}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i^e}\frac{\partial p_i^e}{\partial p_i}, \tag{9}$$

where p_i^e is the expected price of asset *i*, and $\frac{\partial x_i^U}{\partial p_i^e} > 0$, which implies that investors hold more (fewer) shares of asset *i* when its expected price increases (decreases). Since rational risk-averse investors' revisions in expectations are determined not only by the intertemporal risk-return relation but also by the price adjustments resulting from investor behavior to correct prior mispricing, the Slutsky Equation can be expressed as follows:

$$\frac{\partial x_i^U}{\partial p_i^e}\frac{\partial p_i^e}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i^e}\left[\frac{\partial p_i^e}{\partial r_i}\frac{\partial r_i}{\partial \sigma_i^2}\frac{\partial \sigma_i^2}{\partial p_i} + \frac{\partial p_i^e}{\partial p_i}\right], \tag{10}$$

where σ_i^2 is the variance of asset *i*, and r_i is the risk premium of asset *i*. We rewrite Equation (10) as follows:

$$\frac{\partial x_i^*}{\partial p_i} = \frac{\partial x_i^U}{\partial p_i^e}\left[\frac{\partial p_i^e}{\partial r_i}\frac{\partial r_i}{\partial \sigma_i^2}\frac{\partial \sigma_i^2}{\partial p_i} + \frac{\partial p_i^e}{\partial p_i}\right]. \tag{11}$$

Since a price change in either direction causes volatility, we define $\frac{\partial \sigma_i^2}{\partial p_i} > 0$ with $\Delta p_i > 0$ (i.e., volatility increases as price increases) and $\frac{\partial \sigma_i^2}{\partial p_i} < 0$ with $\Delta p_i < 0$ (i.e., volatility increases as price decreases). The term $\frac{\partial r_i}{\partial \sigma_i^2}$ represents the intertemporal risk-return relation, which based on conventional beliefs is expected to be positive for a risk-averse investor. It should be noted, however, that in this paper we do not empirically restrict the sign of the relation. $\frac{\partial p_i^e}{\partial r_i}$ represents the effect of the risk premium on the expected price. We postulate that an increase to the risk premium negatively affects the expected price, so we assume $\frac{\partial p_i^e}{\partial r_i} < 0$.[8] $\frac{\partial p_i^e}{\partial p_i}$ represents the market or price adjustment resulting from investor behavior to correct prior mispricing. $\frac{\partial p_i^e}{\partial p_i} > 0$ ($\frac{\partial p_i^e}{\partial p_i} < 0$) indicates that adjustments to mispricing lead to return persistence (return reversal). While positive feedback trading, underreaction, delayed overreaction, trend trading, or lead-lag effects in cross-autocorrelations would produce $\frac{\partial p_i^e}{\partial p_i} > 0$, negative feedback trading, self-attribution bias, and liquidity are examples of adjustment behavior that would produce return reversals. If investor adjustment behavior induces predictable variation in returns as many empirical studies have documented, then equation (11) makes it evident that this adjustment term must also be included when measuring the intertemporal risk-return relation. In the empirical work that follows, we employ an autoregressive model in return dynamics to capture the empirical nature of this adjustment process.[9]

The main features of Equation (11) are as follows: (a) equilibrium asset demand is a positive monotonic function of the expected price and (b) revisions in investor expectation are driven by two

[8] The negative effect of the risk premium on the concurrent price of an asset is indeed caused by the negative effect of the risk premium on the expected price of the asset.

[9] Assuming that the risk-return tradeoff and return persistence are evidence of efficient and inefficient pricing, respectively, Kinnunen (2014) examines the relative contributions of the risk-return tradeoff and return autocorrelation in driving time-varying expected market returns that might depend on market condition approximated by the volatility and volume information. While specifying both the risk-return tradeoff and return autocorrelation in an ad-hoc return generating process, Kinnunen (2014) does not provide a theoretical framework for the empirical model nor does it examine the interaction effect of the risk-return tradeoff and autocorrelation on the RRA parameter under price changes.

channels, the intertemporal risk-return relation and investor adjustment behavior. While the first term in Equation (11) represents the effect of the intertemporal risk-return relation on the expected price, the second term represents the effect of investor adjustment behavior to correct prior mispricing on the expected price.[10] In sum, Equation (11) provides a strong rationale for our suggestion that the intertemporal risk-return tradeoff and investor adjustment behavior are both important pricing factors that are jointly attributable to predictable variation in expected market returns.

4. Estimation

4.1. The Empirical Models

Merton (1973) proposed that the expected market risk premium is a linear function of its conditional variance and its covariance with investment opportunities. Merton (1980) showed that when the hedge component related to changing investment opportunities is negligible, the conditional market risk premium is proportional to conditional market volatility. We employ Merton's simple linear form of the risk-return relation between the expected market risk premium and conditional market volatility as a basic model. In order to incorporate differential effects of positive and negative price changes on the intertemporal risk-return relation, we specify the following model with the two dummies for positive and negative price changes:

$$\textit{Model 1: } r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1})\hat{\sigma}^2_{m,t+1} + \varepsilon_{m,t+1}, \tag{12}$$

[10] While there are other approaches to specify the Slutsky equation for asset demand, the Slutsky equation proposed in this paper leads to a proper setting for examining the asymmetric effect of a positive and negative price change on asset demand through the intertemporal risk-return relation and price adjustments, which is the main focus of this paper. Other approaches are known to be preferred for estimating the time-varying risk premium. See Bierwag and Grove (1966, 1968), Fischer (1972), Epps (1975), Dalal (1983), and Roley (1983) for more details on the Slutsky equation that we consider for the asset pricing theory.

where $r_{m,t+1}$ is the excess market return as a proxy for the expected market risk premium and $\hat{\sigma}^2_{m,t+1}$ is the conditional market volatility. Pd_{t+1} and Nd_{t+1} are the dummy variables that capture prior d-day positive and negative price changes (or returns), respectively. Positive and negative price changes are determined by the sign of the mean-deviated excess market returns, which are defined as $e_{m,t} = r_{m,t} - E(r_m)$. $P1_{t+1}$ and $N1_{t+1}$ are the dummies to capture a prior one-day positive and negative price change, respectively, such that $P1_{t+1} = 1$ when $e_{m,t} > 0$ and $N1_{t+1} = 1$ when $e_{m,t} < 0$. Likewise, $P2_{t+1} = 1$ when $e_{m,t} > 0$ and $e_{m,t-1} > 0$ while $N2_{t+1} = 1$ when $e_{m,t} < 0$ and $e_{m,t-1} < 0$. The main feature of Model 1 is that the intertemporal risk-return relation is state dependent, in that the relative risk aversion (RRA) parameter is measured by δ_P and δ_N under prior positive and negative price changes, respectively. This setup of the intertemporal risk-return relation along with price dummies is in the same spirit as Yu and Yuan (2011), who use dummy variables to capture high and low sentiment regimes.

As shown in Equation (11) in Section 3, investors' adjustment behavior to correct prior mispricing and the intertemporal risk-return relation are both important contributors to the expected market risk premium. Thus, in the estimation of the RRA parameter, we augment the above simple linear model of the intertemporal risk-return relation with an AR(p) process as a way of incorporating the price adjustment process:

$$\textit{Model 2}: \; r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1})\hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{p} \phi_j r_{m,t+1-j} + \varepsilon_{m,t+1}, \tag{13}$$

where $\sum_{j=1}^{p} \phi_j r_{m,t+1-j}$ is a p^{th} order autoregressive term that captures the adjustment process induced by investor behavior to correct prior mispricing. ϕ_j is the j^{th} order return autocorrelation coefficient. $\phi(1) = \sum_{j=1}^{p} \phi_j > 0$ is defined as a positive price adjustment leading to return persistence, while

$\phi(1) = \sum_{j=1}^{p} \phi_j < 0$ is defined as a negative price adjustment leading to return reversal. In the following empirical section, we discuss why an AR(5) process is an appropriate choice to capture the price adjustment process, and demonstrate that inclusion of this adjustment term is critical for reliable estimation of the RRA parameter in the intertemporal risk-return relation.

By convention, the intertemporal risk-return relation includes a constant term in the regression to account for market imperfections that are not associated with the risk-return tradeoff. We thus consider the possibility that there may be an asymmetry even in the nature of market imperfections under prior positive and negative price changes. To capture the potential asymmetry in market imperfections, we incorporate price change dummies on the constant term in the following Model 3:

$$\textit{Model 3:}\ r_{m,t+1} = c_1 Pd_{t+1} + c_2 Nd_{t+1} + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1})\hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{p} \phi_j r_{m,t+1-j} + \varepsilon_{m,t+1}, \qquad (14)$$

where market imperfections are captured by c_1 under prior positive price changes and by c_2 under prior negative price changes. As before, the RRA parameter is measured by δ_P under prior positive price changes and δ_N under negative price changes and $\sum_{j=1}^{p} \phi_j r_{m,t+1-j}$ is the price adjustment term included as a control variable.

4.2. The Data and Volatility Measures

We use the daily returns on the CRSP value-weighted index as the market portfolio return. The data covers the period from January 1926-December 2015 (23,786 observations). We use the U.S. one-month Treasury bill rate reported by Ibbotson Associates as the risk-free rate. Since the risk-free rate is only available on a monthly frequency, we construct the daily risk-free rate by assuming that it is constant within a month. The daily excess market portfolio return is the difference between the nominal daily market portfolio return and the daily risk-free rate. In addition to the market index, we use ten size decile portfolios formed from NYSE, AMEX, and NASDAQ stocks.

Table 1 presents descriptive statistics for the daily excess returns of the market portfolio and 10 size decile portfolios. All the portfolio returns exhibit the commonly observed properties of high kurtosis and significant return persistence at short horizons. For most of the return series, return autocorrelations are significant up to the 4th or 5th order at the 5% level using Bartlett standard errors, and the sum of the autocorrelation coefficients up to the 5th order, $\psi(1)$, is positive for all portfolio returns. Accordingly, we specify the AR(5) process to represent the adjustment process in all of the following empirical models.

As the proxy for conditional market volatility, we employ two conditional forecasts. For the first volatility measure, we use the conditional variance of the daily excess returns ($h^2_{m,t}$) from estimating the EGARCH (1,1) model proposed by Nelson (1991). The second measure of conditional market volatility ($\xi^2_{m,t}$) is estimated from the AR(12) process[11] on the squared mean-deviated excess market returns, i.e., $\xi^2_{m,t} = \lambda(L)e^2_{m,t}$ for the lag operator L = 12. Also, for the estimation of the indirect risk-return relation, we employ two measures of volatility forecast errors for contemporaneous volatility innovations. The first measure is the volatility forecast errors of the AR(12) process computed as $e^2_{m,t} - \xi^2_{m,t}$, and the second measure is the forecast errors of the EGARCH model computed as $e^2_{m,t} - h^2_{m,t}$.

To generate the conditional covariance between individual portfolio returns and market returns ($h_{im,t}$), we estimate the dynamic conditional correlation (DCC) multivariate GARCH model proposed by Engle (2002) and Engle and Sheppard (2001) with a distributional assumption of the multivariate skewed-*t* density. As a second measure of the conditional covariance, we estimate the AR(12) model on the product of individual and market mean-deviated excess returns, i.e., $\xi_{im,t} = \lambda(L)(e_{i,t} \cdot e_{m,t})$, for the lag operator L = 12. Finally, to estimate the indirect risk-return relation of the individual portfolios, we

[11] We determine the optimum lag length of 12 by performing the Lagrange Multiplier (LM) test with a $\chi^2_{(1)}$ distribution for incremental lag lengths starting at the lag length of 5.

generate two measures of forecast error, one from the DCC-multivariate GARCH as $(e_{i,t} \cdot e_{m,t}) - h_{im,t}$ and the other from the AR(12) model as $(e_{i,t} \cdot e_{m,t}) - \xi_{im,t}$.

[Insert Table 1 about here]

4.3. Estimation and Interpretation

Using excess return ($r_{m,t}$) on the value-weighted market index as a proxy for the expected market risk premium, we first run the regression of $r_{m,t+1} = c_1 + \delta\hat{\sigma}^2_{m,t+1} + \phi_1 r_{m,t} + \varepsilon_{m,t+1}$ to measure the constant RRA parameter. Estimation using daily data yields a significant positive value of δ for both volatility measures.[12] This result is consistent with that of Guo and Neely (2008). Next, we estimate Models 1 - 3 to examine how the positive intertemporal risk-return relation is affected by prior positive and negative price changes, as well as by the inclusion of the adjustment process as a control variable. Note that the estimation results of Model 1 can be compared with those of Models 2 and 3 to show how they are affected by the model misspecification problem resulting from omitting the price adjustment term from the specification.

If our first hypothesis is correct, δ_P should be non-positive, consistent with relatively low expected returns resulting from rational arbitrageurs' short-selling of overpriced stocks under good market news, thereby weakening the typically positive risk-return relation. Likewise, δ_N should be positive due to relatively high expected returns caused by arbitrageurs' purchasing of underpriced stocks in the wake of bad news, which tends to strengthen the positive risk-return relation. Table 2 presents the estimation results with Newey-West (1987) adjusted *t*-statistics. While Panel A reports the estimation results for the price dummies representing prior one-day positive and negative price changes, Panel B

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[12] For the estimation with $\xi^2_{m,t}$ as the conditional market volatility, the value of δ (robust t-value) is 2.210 (2.19) and ϕ_1 is 0.068 (5.85). For the estimation with $h^2_{m,t}$ as the conditional market volatility, δ (robust t-value) is 1.454 (2.00) and ϕ_1 is 0.074 (6.26).

reports the estimation results for the price dummies representing prior two-day consecutive positive and negative price changes.

The estimation results of Models 2 and 3 in Panel A show several notable findings that strongly support our conjecture. First, the estimates of $\phi(1)$ are significantly positive at the 5% level in all cases, implying that the adjustment process resulting from investor behavior to correct prior mispricing leads to return persistence. As mentioned earlier, return persistence at the index level could be a result of cross-autocorrelations, trend trading, delayed overreaction trading, or positive feedback trading. The inclusion of the price adjustment term significantly improves the adjusted R^2 from 0.196% in Model 1 to 1.069% in Model 2 and 1.360% in Model 3 for the estimation with $\xi_{m,t}^2$ as the conditional market volatility (from 0.145% to 0.888% in Model 2 and 1.150% in Model 3 with $h_{m,t}^2$). Second, compared to the estimates in Model 1, the inclusion of the price adjustment term also dramatically reduces the value of δ_P while increasing the value of δ_N. For example, when using $\xi_{m,t}^2$ as the measure of conditional market volatility in Model 1, δ_P has a significantly positive estimate of 3.345 and δ_N is insignificantly positive at 0.705, whereas in Model 2 δ_P becomes insignificantly negative at –0.511 while δ_N is significantly positive at 5.988. A similar change is seen for the estimation using $h_{m,t}^2$ as conditional market volatility: $\delta_P = 3.452$ and $\delta_N = -0.884$ in Model 1 changes to $\delta_P = -1.663$ and $\delta_N = 3.957$ in Model 2. This intriguing finding is strong evidence that ignoring the price adjustment term in the estimation of the risk-return relation causes a severe model misspecification problem. Third, the estimation results for Model 3 indicate that the asymmetric intertemporal risk-return relation under positive versus negative price changes is robust to the presence of asymmetric market imperfections. For the estimation with $\xi_{m,t}^2$ ($h_{m,t}^2$) as conditional market volatility, δ_P decreases by 4.240 (5.840) while δ_N increases by 6.067 (5.451). Finally, the RRA parameter is significantly positive under a prior negative price change (i.e., bad market news) and negligible under a prior positive price change (i.e., good market news). This result supports our first hypothesis that the intertemporal risk-return relation is *positive* conditional on bad market news, but is *non-positive* conditional on good market news.

Panel B presents the estimation results for prior two-day consecutive positive and negative price changes.[13] These results are qualitatively similar to those reported in Panel A using one-day price changes; the risk-return relation is negative conditional on recent positive returns and positive conditional on recent negative returns, the inclusion of the price adjustment term has a significant impact on the estimates of the RRA coefficient in the two states, and the results are robust to allowing for asymmetric market imperfections, if any. Notably, the results in Panel B are substantially stronger than those in Panel A in that the estimates of δ_P are significantly negative conditional on two-day returns but insignificantly negative conditional on one-day returns. Similarly, both the magnitude of δ_N and its statistical significance grow when conditioning on two-day returns. The strength of the results in Panel B relative to those in Panel A suggests that investors' mis-reaction is exacerbated by a sequence of similar returns and therefore the distortion of the positive risk-return relation is greater. The tendency for mis-reaction to be greater in response to consecutive similar returns is in general consistent with the representativeness bias documented in Tversky and Kahneman (1974), and more specifically the extrapolation of trends documented by De Bondt (1993) and incorporated into the unified behavioral model of Barberis et al. (1998).

We also examine the effect of extreme positive and negative price changes on the RRA parameter by estimating Model 2 using dummies for one standard deviation positive and negative returns. For the estimation using $\xi^2_{m,t}$ as conditional market volatility, the value of δ_P (robust t-value) is –3.073 (–2.03) and δ_N is 6.540 (4.11). When using $h^2_{m,t}$ as the measure of conditional market volatility, the estimate of δ_P

[13] For the case of two-day consecutive price changes, some observations are not included in the condition of $P2_{t+1} = 1$ and $N2_{t+1} = 1$. We thus estimated Model 3 with three constant terms specified as $\mu + \mu_1 P2_{t+1} + \mu_2 N2_{t+1}$. The results concerning the RRA coefficients are almost the same as those of the original Model 3 with $\mu + \mu_1 \cong c_1$ and $\mu + \mu_2 \cong c_2$, so we report the estimation results associated with the simpler, original Model 3.

is –4.401 (–2.75) and δ_N is 9.129 (4.96). The results indicate that mis-reaction is more profound in response to extreme price changes.

[Insert Table 2 about here]

4.4. Asymmetry in Investors' Adjustment Behavior

We perform a robustness check to examine whether there is asymmetry in the adjustment process that affects the observed distortion of a positive intertemporal risk-return relation. To do so, we attach the price dummies to the price adjustment term in the following Models 4 and 5:

$$\text{Model 4: } r_{m,t+1} = c_1 + (\delta_P \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Pj} r_{m,t+1-j}) Pd_{t+1} + (\delta_N \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Nj} r_{m,t+1-j}) Nd_{t+1} + \varepsilon_{m,t+1}, \tag{15}$$

$$\text{Model 5: } r_{m,t+1} = (c_1 + \delta_P \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Pj} r_{m,t+1-j}) Pd_{t+1} + (c_2 + \delta_N \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Nj} r_{m,t+1-j}) Nd_{t+1} + \varepsilon_{m,t+1}, \tag{16}$$

where ϕ_{Pj} and ϕ_{Nj} are the j^{th} order return autocorrelation coefficients under a prior positive and negative price change, respectively, such that $\phi_P(1)$ measures the adjustment process on mispricing under good market news while $\phi_N(1)$ measures the adjustment process under bad market news. We use $\phi_D(1)$ to denote the difference in the adjustment process under good and bad market news, i.e., $\phi_D(1) = \phi_P(1) - \phi_N(1)$. The estimation results are presented in Table 3, which shows similar results to those reported in Table 2. The intertemporal risk-return relation is weak or negative under good market news but is significantly positive under bad market news. The value of $\phi_D(1)$ is statistically insignificant in the estimation of both models at the 5% level, indicating that there is no asymmetry in the adjustment to mispricing under good and bad market news, and that allowing for such an asymmetry in the adjustment process does not affect our main results.

[Insert Table 3 about here]

4.5. Indirect Test of Risk-Return Relation

French, Schwert, and Stambaugh (1987) state that "… *a positive relation between the predicted stock market volatility and the expected risk premium induces a negative relation between the unpredicted component of volatility and excess holding period returns*." [pg.15] That is, under a positive risk-return relation, higher predicted volatility increases the market risk premium and the discount rate, which decreases the current stock price. Thus, under a positive risk-return relation, an unexpected volatility change should decrease excess returns. They examine this association between excess market returns and the contemporaneous unexpected changes in market volatility as an indirect test of the mean-variance tradeoff. Campbell and Hentschel (1992) refer to this indirect risk-return relation as the volatility feedback effect.

We perform this indirect test on the relation between excess returns and the contemporaneous unexpected volatility changes under prior positive and negative price changes. Since the estimated risk-return relation is significantly *positive* under a negative price change, we expect a strong *negative* relation between excess returns and the contemporaneous volatility innovation under a negative price change. To examine our conjecture, we estimate the following Model 6 with various parameter restrictions on control variables:

Model 6:

$$r_{m,t+1} = c_1 P1_{t+1} + c_2 N1_{t+1} + (\pi_P P1_{t+1} + \pi_N N1_{t+1})\hat{\eta}^2_{m,t+1} + (\delta_P P1_{t+1} + \delta_N N1_{t+1})\hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{p} \phi_j r_{m,t+1-j} + \varepsilon_{m,t+1}, \quad (17)$$

where $\hat{\sigma}^2_{m,t+1}$ is the conditional market volatility, and $\hat{\eta}^2_{m,t+1}$ is the contemporaneous volatility innovation representing unexpected volatility changes, for which we use two measures. The first one is the forecast errors of $h^2_{m,t}$ estimated from the EGARCH (1,1) model, and is computed as $e^2_{m,t} - h^2_{m,t}$. The second measure is the forecast errors of $\xi_{m,t}^2$ estimated from the AR(12) process on the realized volatility series, and is computed as $e_{m,t}^2 - \xi_{m,t}^2$. The indirect risk-return relation is measured by π_P (π_N) under a prior positive (negative) price change. The observed positive (zero or negative) risk-return relation under a prior negative (positive) price change is consistent with a significantly negative value of π_N (nonnegative value of π_P) under a prior negative (positive) price change in estimation of Model 6.

The estimates of Model 6 are reported in Table 4. Panel A provides results for the estimation with $\hat{\eta}_{m,t+1}^2 = e_{m,t}^2 - h_{m,t}^2$ as the contemporaneous volatility innovation and $h_{m,t}^2$ as the conditional market volatility, while Panel B presents the results for the estimation with $\hat{\eta}_{m,t+1}^2 = e_{m,t}^2 - \xi_{m,t}^2$ as the contemporaneous volatility innovation and $\xi_{m,t}^2$ as the conditional market volatility. The estimation results in Table 4 show a significant indirect relation between excess returns and contemporaneous volatility shocks that supports the observed asymmetric risk-return relation under positive and negative price changes. The estimated value of π_N is economically and statistically significantly negative at the 5% level and is robust over various parameter restrictions. The result that the indirect risk-return relation under a prior negative price change is significantly negative confirms that the ex-ante risk-return relation is positive under a prior negative price change. Likewise, the estimated value of π_P is positive and is significant at 5% or close to significant depending on the specification. This result is also consistent with the observed weak or negative intertemporal risk-return relation under a prior positive price change.

[Insert Table 4 about here]

4.6. Intertemporal Risk-Return Relation under Investor Sentiment

Baker and Wurgler (2006) construct an index measuring aggregate investor sentiment and then show that the future returns of stocks susceptible to mispricing, because valuing them is difficult or highly subjective, depend on the current level of sentiment. Using Baker and Wurgler's (2006) composite sentiment index, Yu and Yuan (2011) argue that greater participation of sentiment traders in high sentiment periods attenuates the positive intertemporal risk-return relation at these times. This occurs because high sentiment causes these investors to overprice stocks, but these investors are reluctant to take short positions when sentiment is low, and therefore the distortion of the risk-return relation caused by sentiment traders is concentrated mainly during periods of high sentiment. Using an empirical model based on anomalies to identify stocks that are likely to be overpriced or underpriced, Stambaugh, Yu, and Yuan (2015) show that in the cross-section, a negative risk-return relation among overpriced stocks is significantly stronger during high-sentiment periods while a positive risk-return relation among underpriced stocks is strengthened during low-sentiment periods.

In this section, we examine if the level of investor sentiment affects short-term mispricing under good and bad market news. If sentiment traders are in general less rational and are more likely to mis-react to price changes, and these traders are also more active during periods of high sentiment, then the distortion of the positive risk-return tradeoff that they cause under overpricing should be greater when sentiment is high. We thus conjecture that the attenuation (reinforcement) of a positive risk-return relation under good (bad) market news is stronger in high sentiment periods than in low sentiment periods.

Using Baker and Wurgler's monthly composite sentiment index, we construct the daily sentiment index by assuming that it is constant within a month. We estimate the following Model 7 to examine the impact of sentiment on the intertemporal risk-return relation under good and bad market news.

Model 7:

$$r_{m,t+1} = c + [(\delta_P^l P_{t+1}^d + \delta_N^l N_{t+1}^d) L_{t+1} + (\delta_P^h P_{t+1}^d + \delta_N^h N_{t+1}^d) H_{t+1}] \cdot \hat{\sigma}_{m,t+1}^2 + [\phi_L(L) L_{t+1} + \phi_H(L) H_{t+1}] \cdot r_{m,t+1} + \varepsilon_{m,t+1},$$

(18)

where $\hat{\sigma}^2_{m,t+1}$ is the conditional market volatility, and L_{t+1} and H_{t+1} are the dummy variables representing low- and high-sentiment regimes, respectively, over July 1965–September 2015.[14] Following Yu and Yuan (2011), we define high and low sentiment periods based on the sign of the orthogonalized sentiment index for the month. The RRA parameter in the low-sentiment regime is measured by $\delta^l{}_P$ ($\delta^l{}_N$) under a prior d-day positive (negative) price change, while $\delta^h{}_P$ ($\delta^h{}_N$) measures the RRA parameter under a prior d-day positive (negative) price change in the high-sentiment regime. If high sentiment causes greater mispricing, overpricing in response to good market news should attenuate the positive risk-return relation more in high-sentiment periods than in low-sentiment periods, while bad market news should strengthen the positive risk-return relation more in high-sentiment periods than in low-sentiment periods. If this conjecture is correct, the estimated value of $\delta^h{}_P - \delta^l{}_P$ ($\delta^h{}_N - \delta^l{}_N$) should be significantly negative (positive).

We extend the price dummies to the case of 3-day consecutive price changes to examine whether a tendency to perceive trends in short samples of returns would induce even greater mispricing, and hence exhibit a greater distortion of the positive risk-return relation. While three consecutive daily returns of the same sign is a very short trend, we believe such sequences of returns may be sufficient to have significantly different effects on the expectations of investors that are not fully rational. In particular, the tendency for sentiment-driven investors to mis-react to price changes would be amplified by consecutive returns of the same sign, and thus the differential effect of high versus low sentiment on the ex-ante risk-return relation could be more clearly observed by extending the length of the sequence. For this reason, the test of the null hypotheses of $\delta^h{}_P - \delta^l{}_P \geq 0$ and $\delta^h{}_N - \delta^l{}_N \leq 0$ is conducted using the results for 3-day consecutive price changes and is shown in Panel C.[15]

The estimation results for Model 7 are reported in Table 5. Panel A shows the results for a prior 1-day positive or negative price change, while Panels B and C show the results for prior 2- and 3-day consecutive positive and negative price changes. There are several notable findings. First, in all three

[14] We thank Jeffrey Wurgler for making the sentiment index data available at http://people.stern.nyu.edu/jwurgler/.

[15] The results shown in Panel C of Table 5 are also observed using dummies for 4-day prior consecutive positive and negative returns. We omit these results for brevity.

panels, in the low-sentiment regime the estimated value of the RRA parameter is either negative or close to zero conditioned on good market news, and highly positive under bad market news. The statistical significance of these estimates is somewhat weaker than our earlier results, consistent with the idea that short-term mispricing does distort the RRA even in low-sentiment periods, but the effect is not as strong due to less participation of sentiment traders. Second, during high-sentiment periods, mispricing under 3-day consecutive price changes causes a greater impact on the risk-return relation when compared to 1-day and 2-day consecutive price changes. For example, when using $h^2_{m,t+1}$ the estimated value of 2.601 for $\delta^h{}_P$ in Panel A dramatically decreases to –13.546 in Panel C, and the estimated value of $\delta^h{}_N$ increases from 1.563 in Panel A to 10.286 in Panel C. In results not reported in Table 5, we confirm that this pattern in the effect of sentiment level on the RRA parameters extends to 4-day consecutive price changes, where the estimated values of $\delta^h{}_P$ ($\delta^h{}_N$) further decrease to –19.110 and –18.033 depending on whether or not the model allow for asymmetric market imperfections (increase to 15.080 and 15.522).[16] The results demonstrate that when sentiment is high, a greater number of consecutive positive or negative price changes amplifies mispricing and the distortion it causes on the RRA parameter. Note that this pattern is not clearly observed in low sentiment periods.

Third, the results verify our conjecture that the distortion of the intertemporal risk-return relation is greater in high-sentiment periods than in low-sentiment periods. We test our conjecture using the null hypotheses of $\delta^h{}_P - \delta^l{}_P \geq 0$ and $\delta^h{}_N - \delta^l{}_N \leq 0$ for the case of 3-day consecutive positive and negative price changes. Our conjecture can be verified by significantly negative and positive values for $\delta^h{}_P - \delta^l{}_P$ and $\delta^h{}_N - \delta^l{}_N$, respectively. The test results in Panel C show that the estimated values of $\delta^h{}_P - \delta^l{}_P$ ($\delta^h{}_N - \delta^l{}_N$) when using $h^2_{m,t+1}$ are –9.405 and –8.759 depending on the allowance for asymmetric market imperfections (6.924 and 7.442), and all differences are statistically significant at the 5% level. The results for $\xi^2_{m,t+1}$ also show a statistically significant negative (positive) value of $\delta^h{}_P - \delta^l{}_P$ ($\delta^h{}_N - \delta^l{}_N$) at the 10% (5%)

[16] The results for $\xi^2_{m,t}$ under 4-day consecutive price changes show that the estimated values for $\delta^l{}_P$ ($\delta^l{}_N$) are –8.164 (3.194) and –8.526 (2.811). The results are not reported because of space limitations, but are available upon request.

level.[17] The results verify that high sentiment results in greater mispricing, such that good (bad) market news has a greater negative (positive) impact on the risk-return relation in high sentiment periods than in low-sentiment period.

[Insert Table 5 about here]

4.7. Sub-periods Analysis

We perform sub-periods analysis to examine the robustness of our main results and the stability of our models' description of an asymmetric risk-return relation and the significance of investors' adjustment behavior leading to return persistence. Using two sub-samples with an equal number of observations, we estimate Models 1, 2, and 3 to check if our model can fit the two subsamples. We report the estimation results obtained from using $h_{m,t}^2$ as the measure of the conditional market volatility. These results are reported in Table 6, which indicates that our main results obtained from the full sample period are still present in the two subsamples. Notable findings are as follows. First, the estimation results of Models 2 and 3 show that the asymmetry in the risk-return relation documented in the full sample period is still significant in both of the sub-periods. For both sub-periods, the estimated RRA parameter is significantly positive under a prior negative price change but weak or negative under a prior positive price change, implying that good (bad) market news weakens (strengthens) the positive risk-return relation. Notably, for both sub-periods, the magnitude of the RRA coefficient is much greater following two consecutive price changes than under a prior one-day price change. This result is also consistent with the result obtained from the full sample period, in which mispricing caused by short-term mis-reaction is more severe after a sequence of similar returns, and hence the asymmetry resulting from the distortion of the risk-return relation arising from mispricing is greater under two consecutive positive and negative price changes.

[17] We also perform the same test for the case of 4-day consecutive positive and negative price changes. As expected, the t-values for the null are all statistically significant at the 5% level.

Second, for both sub-periods the inclusion of the price adjustment term significantly decreases (increases) the magnitude of the RRA coefficients under a positive (negative) price change. When compared to the results of Model 1, the estimation results of Models 2 and 3 indicate that for both sub-periods, the estimated value of δ_P significantly decreases while the estimated value of δ_N increases significantly. The estimated value of δ_P on average decreases by 5.999 for the first sub-period (5.316 for the second sub-period) while the estimated value of δ_N on average increases by 5.969 for the first sub-period (4.941 for the second sub-period). The results verify that ignoring the price adjustment process in the estimation of the intertemporal risk-return relation leads to model misspecification and induces an upward (downward) bias in estimates of the RRA parameter conditional on good (bad) market news.

[Insert Table 6 about here]

We also perform the test of the indirect risk-return relation for the two sub-periods by estimating Model 6. We report the estimation results obtained from using $h_{m,t}^2$ as the conditional market volatility and $\hat{\eta}_{m,t+1}^2 = e_{m,t}^2 - h_{m,t}^2$ as the contemporaneous volatility innovation. The results are reported in Table 7, which shows evidence to support our hypothesis. First, for both sub-periods, the estimated value of π_N is consistently negative over various parameter restrictions. While weakly significant for the first sub-period, the estimated value of π_N is economically and statistically significant at the 1% level for the second sub-period. This result confirms that the risk-return relation is positive under a prior negative price change. Second, the estimated value of π_P is significantly positive for the first sub-period, while it is negative but statistically insignificant for the second sub-period. This result is also consistent with the observed weak or negative intertemporal risk-return relation under a prior positive price change. The result of a strong negative (nonnegative) indirect risk-return relation verifies a strong positive (non-positive) ex ante risk-return relation under a negative (positive) price change. In sum, the results from the sub-period analysis also provide robust evidence to support our conclusion concerning the asymmetry in the ex-ante risk-return relation.

[Insert Table 7 about here]

5. Intertemporal Risk-Return Tradeoff for Size-Based Portfolios

5.1. Intertemporal Capital Asset Pricing Model

The capital market equilibrium condition implies that there is only one price of risk in the market. In particular, in the intertemporal capital asset pricing model (ICAPM), the predicted slope from regressing an asset's expected returns on the conditional covariance of its return with the market portfolio is the representative investor's relative risk aversion, and hence an asset's expected return can be predicted as a linear function of its conditional covariance with the market. This implies that the intertemporal relation between expected returns and conditional risk applies not only to the market portfolio but also to individual stocks or other portfolios. We thus conjecture that the observed asymmetry in the intertemporal risk-return relation documented for the market portfolio should also be observed in size decile portfolios formed from NYSE, AMEX, and NASDAQ stocks. To examine our conjecture, we run the following two regressions for each size decile:

$$\textit{Model 8}:\ r_{i,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}_{im,t+1} + \varepsilon_{i,t+1}, \tag{19}$$

$$\textit{Model 9}:\ r_{i,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}_{im,t+1} + \sum_{j=1}^{5} \phi_j r_{i,t+1-j} + \varepsilon_{i,t+1}, \tag{20}$$

where Pd_{t+1} and Nd_{t+1} measure prior positive and negative *d*-day price changes on the size decile, and $\hat{\sigma}_{im,t+1}$ is the conditional covariance of the size decile return with the return on the market portfolio, for which we use two measures. The first measure ($h_{im,t}$) is the conditional covariance forecast that is estimated from the DCC multivariate GARCH model on $r_{i,t}$ and $r_{m,t}$. The second measure ($\xi_{im,t}$) is the conditional covariance forecast that is estimated from the AR(12) model on the realized series of $e_{i,t} \cdot e_{m,t}$ for the i^{th} size portfolio. $\sum_{j=1}^{5} \phi_j r_{i,t+1-j}$ is the price adjustment term included as a control variable.

The estimation results with $h_{im,t}$ as the conditional covariance forecast are presented in Table 8.[18] Similar to the results for the market index returns shown in Table 2, the inclusion of the adjustment term significantly improves the adjusted R^2. Across all portfolios, the adjusted R^2 increases on average from 0.953% in Model 8 to 3.730% in Model 9 when conditioning on the 1-day price change, and from 0.327% to 3.881% when using 2-day price changes. In addition to substantially improving model fit, the inclusion of the adjustment term in Model 9 significantly reduces the estimated value of the RRA parameter (δ_P) under a prior positive price change, but increases the value of the RRA parameter (δ_N) under a prior negative price change. Conditioning on 1-day return, the decrease in δ_P averages 4.641 across the size deciles (4.605 decrease using 2-day returns), and on average δ_N increases by 5.055 (6.081 for 2-day consecutive returns). More importantly, for all deciles the estimated intertemporal risk-return relation from Model 9 is either significantly negative or insignificant under a prior positive price change, but significantly positive under a prior negative price change. Also consistent with our earlier results on the market portfolio, the distortion of the RRA is substantially greater when conditioning on 2-day price changes. This is strong evidence to support our conjecture that mis-reaction to good (bad) news weakens (strengthen) the positive intertemporal risk-return relation. Lastly, Panel B shows that the estimates of δ_N decrease with firm size, indicating a size effect in which larger firms tend to exhibit a more negative risk-return relation under good news relative to smaller firms. This size effect is consistent with the availability of information to which investors may mis-react and/or reflects arbitrage asymmetry in which large stocks are easier to short than small stocks. Large firms may be especially susceptible to short-term overpricing because they are more visible and produce more news relative to small firms, and it is easier for investors to act on positive versus negative information. A greater tendency to suffer from short-term

[18] The estimation results obtained from using $\xi_{im,t}$ are almost the same as those shown in Table 8 and are not presented here due to space limitations. They are available upon request.

overpricing would cause greater distortion of the risk-return tradeoff conditional on positive news as seen for large stocks in Table 8.[19]

[Insert Table 8 about here]

5.2. Indirect Risk-Return Relation

We also perform the indirect test on the relation between excess returns and the contemporaneous unexpected volatility changes for the ten size decile portfolios in the following Model 10:

Model 10:

$$r_{i,t+1} = c_1 + (\pi_{iP} P1_{t+1} + \pi_{iN} N1_{t+1})\hat{\eta}_{im,t+1} + (\delta_{iP} P1_{t+1} + \delta_{iN} N1_{t+1})\hat{\sigma}_{im,t+1} + \sum_{j=1}^{5} \phi_j r_{i,t+1-j} + \varepsilon_{i,t+1}\,, \tag{21}$$

where $\hat{\eta}_{im,t+1}$ is the contemporaneous conditional covariance innovation, for which we use two measures. The first one is forecast errors associated with $h_{im,t}$, computed as $\hat{\eta}_{im,t} = e_{i,t} \cdot e_{m,t} - h_{im,t}$, and the second is the forecast errors of $\xi_{im,t}$, computed as $\hat{\eta}_{im,t} = e_{i,t} \cdot e_{m,t} - \xi_{im,t}$. For the i^{th} portfolio, the indirect risk-return relation is measured by π_{iP} and π_{iN} under a prior positive and negative price change, respectively.

Table 9 presents the estimation results of the indirect risk-return relation for the ten size portfolios. Panel A (Panel B) reports the results for $h_{im,t}$ ($\xi_{im,t}$) used as the estimate of conditional covariance and $e_{i,t} \cdot e_{m,t} - h_{im,t}$ ($e_{i,t} \cdot e_{m,t} - \xi_{im,t}$) as the contemporaneous covariance innovation series. Both panels show a strong negative relation between excess returns and the contemporaneous unexpected volatility changes for all ten portfolios. Except for the smallest decile (FS1), the estimated value of π_N is significantly

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[19] We also estimated Model 9 with dummies based on prior positive and negative market returns. The results were very similar to those shown in Table 8, verifying that larger firms are relatively more easily shorted than smaller firms. The results are not reported because of space limitations, but are available upon request.

negative at the 5% level, thus indicating that the indirect risk-return relation is significantly negative under a prior negative price change. This result indirectly verifies that the ex-ante intertemporal risk-return relation for the decile portfolios is significantly positive under a prior negative price change. The estimated value of π_P is positive for all size portfolios, but its statistical significance is not impressive with only 7 out of 20 estimates showing a significantly positive value at the 5% level. This weak or strong positive indirect relation also lends support to the conclusion that the ex-ante intertemporal risk-return relation is weak or significantly negative under a prior positive price change.

[Insert Table 9 about here]

6. Conclusion

We suggest that investors' tendency to mis-react to price changes in the short-term causes overpricing (underpricing) under good (bad) news, and that this mispricing is exploited by rational arbitrageurs' short selling of overpriced stocks and purchase of underpriced stocks. We hypothesize and demonstrate that due to arbitrage trading, overpricing (underpricing) under good (bad) news weakens (strengthens) the positive intertemporal risk-return relation, such that it is positive conditional on bad market news, but non-positive conditional on good market news. Our empirical analysis includes a price adjustment term that we derive from the Slutsky equation for equilibrium asset demand to capture investors' adjustment behavior to prior mispricing, such as feedback trading, underreaction, delayed overreaction, lead-lag effects in cross-autocorrelations, self-attribution bias, trend trading, and liquidity trading. Our empirical results provide several new and important findings. First, the risk-return relation and investors' adjustment behavior are both important pricing factors that determine the predictable variation in expected returns. Second, our results show that ignoring the price adjustment process in the estimation of the intertemporal risk-return relation leads to a model misspecification problem and causes an upward (downward) bias in estimates of the relative risk aversion parameter conditional on good (bad) news, and hence causes the same bias in the estimate of the expected risk premium. Third, we find that the intertemporal risk-return relation is close to zero or even negative conditional on good news but is significantly positive conditional on bad news. This asymmetry in the ex-ante risk-return relation is verified by the indirect relation between excess market returns and contemporaneous volatility innovations; the indirect risk-return relation is weak or positive under good news but is significantly negative under bad news. Guided by ICAPM, we extend our analysis to size decile portfolios and document the same pattern of distortion in the risk-return tradeoff when estimating the relation between excess portfolio returns and conditional covariance with the market return when conditioning on positive and negative price changes. The pattern of a weak or negative risk-return relation following positive news, and a strongly positive risk-return relation following negative news, is naturally explained by investor mis-reaction to price changes. Lastly, we study how the distortion of the relative risk aversion parameter varies across high and low sentiment periods. We find that while good market news in high-sentiment periods undermines the positive risk-return relation, bad market news in high-sentiment periods strengthens the positive intertemporal risk-return relation. This result is consistent with the notion that high investor sentiment amplifies mispricing. Therefore, we conclude that investor mis-reaction to daily price changes significantly impacts asset prices by causing overpricing and underpricing, which ultimately attenuates or reinforces a typically positive ex ante risk-return relation. Our empirical results lend further support to the conclusion of recent studies such as Yu and Yuan (2011) and Stambaugh, Yu, and Yuan (2015), that the intertemporal risk-return relation is distorted by over- and underpricing.

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Table 1
Descriptive Statistics

We employ daily CRSP value-weighted index returns (VW) and 10 size decile portfolios (small FS1 through large FS10) of the NYSE, AMEX, and NASDAQ stocks from January 1926–December 2015 (a total of 23,786 observations for each series) from the CRSP data files. Daily excess returns are computed by subtracting the daily average of monthly Treasury bill returns reported by Ibbotson Associates from the daily nominal returns of the portfolios. STDV refers to the standard deviation. SKEW is the skewness and KURT is the kurtosis. $\rho(j)$ is the autocorrelation coefficients at lag j. $\psi(1)$ is the sum of the five autocorrelation coefficients. The numbers in parentheses below the autocorrelation coefficients are the *t*-values computed with the Bartlett standard error.

	Mean (×100)	STDV	SKEW	KURT	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	$\psi(1)$
VW	0.028	0.011	-0.113	19.796	0.071	-0.046	0.009	0.022	-0.001	0.055
	(4.04)				(10.95)	(-7.09)	(1.39)	(3.39)	(-0.15)	
FS1	0.052	0.013	1.189	47.061	0.217	0.021	0.064	0.046	0.069	0.417
	(6.33)				(33.47)	(3.24)	(9.87)	(7.09)	(10.64)	
FS2	0.039	0.012	0.084	32.035	0.236	-0.029	0.075	0.053	0.046	0.381
	(5.14)				(36.40)	(-4.47)	(11.57)	(8.17)	(7.09)	
FS3	0.033	0.011	0.397	36.193	0.225	-0.042	0.059	0.046	0.041	0.329
	(4.60)				(34.70)	(-6.48)	(9.10)	(7.09)	(6.32)	
FS4	0.034	0.011	-0.220	25.295	0.207	-0.042	0.062	0.039	0.028	0.294
	(4.66)				(31.93)	(-6.48)	(9.56)	(6.01)	(4.32)	
FS5	0.033	0.011	-0.121	24.124	0.166	-0.035	0.056	0.036	0.027	0.250
	(4.46)				(25.60)	(-5.40)	(8.64)	(5.55)	(4.16)	
FS6	0.034	0.011	-0.239	20.296	0.154	-0.041	0.050	0.034	0.021	0.218
	(4.56)				(23.75)	(-6.32)	(7.71)	(5.24)	(3.24)	
FS7	0.033	0.011	0.010	24.699	0.136	-0.042	0.040	0.035	0.009	0.178
	(4.39)				(20.97)	(-6.48)	(6.17)	(5.40)	(1.39)	
FS8	0.030	0.011	-0.167	19.232	0.121	-0.038	0.032	0.032	0.000	0.147
	(4.15)				(18.66)	(-5.86)	(4.94)	(4.94)	(0.00)	
FS9	0.033	0.011	-0.117	19.407	0.115	-0.042	0.023	0.032	0.005	0.133
	(4.61)				(17.74)	(-6.48)	(3.55)	(4.94)	(0.77)	
FS10	0.027	0.011	-0.070	19.765	0.044	-0.044	-0.001	0.018	-0.004	0.013
	(3.85)				(6.79)	(-6.79)	(-0.15)	(2.78)	(-0.62)	

Table 2
Estimation Results of Intertemporal Risk-Return Relation between Excess Market Returns and Market Volatility

This table reports the estimation results of following models for the period January 1926–December 2015:

$$\textit{Model 1: } r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \varepsilon_{m,t+1}$$

$$\textit{Model 2: } r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_j r_{m,t-j} + \varepsilon_{m,t+1}$$

$$\textit{Model 3: } r_{m,t+1} = c_1 Pd_{t+1} + c_2 Nd_{t+1} + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_j r_{m,t-j} + \varepsilon_{m,t+1},$$

where $r_{m,t+1}$ is daily realized excess market return and $\hat{\sigma}^2_{m,t+1}$ is the daily conditional market volatility, for which we use two volatility forecast measures that are estimated on the squared mean-deviated excess market returns ($e^2_{m,t} = [r_{m,t} - E(r_m)]^2$). The first one ($h^2_{m,t}$) is the conditional variance of the daily excess index returns that is estimated from the EGARCH (1,1) model, and the second measure ($\xi^2_{m,t}$) is the conditional forecast of daily market volatility that is estimated from the AR(12) model on the realized volatility series, $e^2_{m,t}$. ϕ_j is the j^{th} order return autocorrelation coefficient. $\phi(1)$ is the sum of autocorrelation coefficients, i.e., $\phi(1) = \sum_{j=1}^{5} \phi_j$. Pd_{t+1} (Nd_{t+1}) is the dummy to capture prior d-day positive (negative) price changes, such that $P1_{t+1} = 1$ when $e_{m,t} > 0$ ($N1_{t+1} = 1$ when $e_{m,t} < 0$) and $P2_{t+1} = 1$ when $e_{m,t} > 0$ and $e_{m,t-1} > 0$ ($N2_{t+1} = 1$ when $e_{m,t} < 0$ and $e_{m,t-1} < 0$). The RRA parameter is measured by δ_P (δ_N) under prior d-day positive (negative) price change(s). The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

	Panel A: Prior 1-day Price Changes						**Panel B:** Prior 2-day Consecutive Price Changes					
	$\hat{\sigma}^2_{m,t+1} = h^2_{m,t+1}$			$\hat{\sigma}^2_{m,t+1} = \xi^2_{m,t+1}$			$\hat{\sigma}^2_{m,t+1} = h^2_{m,t+1}$			$\hat{\sigma}^2_{m,t+1} = \xi^2_{m,t+1}$		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$c_1(\times 100)$	0.016	0.012	0.080	0.004	-0.004	0.065	0.024	0.017	0.089	0.021	0.011	0.074
	(1.99)	(1.49)	(6.13)	(0.41)	(-0.42)	(4.15)	(2.34)	(1.58)	(5.28)	(1.89)	(0.93)	(4.56)
$c_2(\times 100)$			-0.066			-0.088			-0.084			-0.095
			(-4.03)			(-4.63)			(-3.39)			(-2.77)
δ_P	3.452	-1.663	-2.388	3.345	-0.511	-0.895	-1.121	-6.762	-7.512	-1.123	-6.634	-6.698
	(2.57)	(-0.91)	(-1.26)	(3.20)	(-0.34)	(-0.55)	(-0.61)	(-2.67)	(-2.86)	(-0.73)	(-3.64)	(-3.49)
δ_N	-0.884	3.957	4.567	0.705	5.988	6.772	2.297	8.212	9.035	3.757	11.810	12.774
	(-0.72)	(2.16)	(2.28)	(0.57)	(3.18)	(3.07)	(1.27)	(3.68)	(3.63)	(1.66)	(4.05)	(3.77)
$\phi(1)$		0.103	0.066		0.114	0.074		0.156	0.112		0.193	0.148
		(4.23)	(2.54)		(4.25)	(2.63)		(6.18)	(3.72)		(5.08)	(3.79)
$Adj.R^2$ (%)	0.145	0.888	1.150	0.196	1.069	1.360	0.051	1.168	1.344	0.129	1.459	1.635

Table 3
Asymmetry in Investors' Adjustment to Mispricing

This table reports the estimation results of Models 4 and 5 over January 1926–December 2015:

$$\textit{Model 4}: \; r_{m,t+1} = c_1 + (\delta_P \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Pj} r_{m,t+1-j}) \cdot Pd_{t+1} + (\delta_N \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Nj} r_{m,t+1-j}) \cdot Nd_{t+1} + \varepsilon_{m,t+1},$$

$$\textit{Model 5}: \; r_{m,t+1} = (c_1 + \delta_P \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Pj} r_{m,t+1-j}) \cdot Pd_{t+1} + (c_2 + \delta_N \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_{Nj} r_{m,t+1-j}) \cdot Nd_{t+1} + \varepsilon_{m,t+1},$$

where ϕ_{Pj} (ϕ_{Nj}) is the j^{th} order return autocorrelation coefficient under prior d-day positive (negative) price changes. $\phi_P(1) = \sum_{j=1}^{5} \phi_{Pj}$ and $\phi_N(1) = \sum_{j=1}^{5} \phi_{Nj}$. For the conditional market volatility, we use $h^2_{m,t}$ estimated from the EGARCH (1,1) model, and $\xi^2_{m,t}$ estimated from the AR(12) model on the realized volatility series. Pd_{t+1} (Nd_{t+1}) is the dummy to capture prior d-day positive (negative) price changes, such that $P1_{t+1} = 1$ when $e_{m,t} > 0$ ($N1_{t+1} = 1$ when $e_{m,t} < 0$) and $P2_{t+1} = 1$ when $e_{m,t} > 0$ and $e_{m,t-1} > 0$ ($N2_{t+1} = 1$ when $e_{m,t} < 0$ and $e_{m,t-1} < 0$). The RRA parameter is measured by δ_P (δ_N) under prior d-day positive (negative) price changes. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

	Panel A: Prior 1-day Positive-Negative Price Changes				**Panel B:** Prior 2-day Positive-Negative Price Changes			
	$h^2_{m,t+1}$		$\xi^2_{m,t+1}$		$h^2_{m,t+1}$		$\xi^2_{m,t+1}$	
	Model 4	Model 5	Model 4	Model 5	Model 4	Model 5	Model 4	Model 5
$c_1(\times 100)$	0.003	0.074	-0.006	0.067	0.013	0.095	0.013	0.078
	(0.26)	(4.72)	(-0.51)	(4.67)	(1.13)	(4.45)	(1.21)	(3.83)
$c_2(\times 100)$		-0.080		-0.093		-0.152		-0.132
		(-4.39)		(-4.12)		(-3.44)		(-3.79)
δ_P	-2.453	-3.369	-0.565	-1.012	-7.808	-7.594	-7.917	-7.151
	(-1.56)	(-1.79)	(-0.29)	(-0.50)	(-2.79)	(-2.69)	(-4.13)	(-3.59)
δ_N	3.271	3.900	6.412	7.267	5.325	3.927	11.492	9.468
	(1.80)	(2.00)	(3.52)	(3.58)	(1.98)	(1.16)	(2.98)	(2.55)
$\phi_P(1)$	0.109	0.055	0.101	0.042	0.140	0.049	0.177	0.095
	(2.55)	(1.29)	(1.92)	(0.79)	(2.66)	(0.75)	(3.62)	(1.49)
$\phi_N(1)$	0.098	0.075	0.130	0.107	0.016	-0.103	0.113	-0.003
	(2.59)	(1.92)	(2.91)	(2.32)	(0.24)	(-1.25)	(1.37)	(-0.03)
$Adj.R^2$ (%)	1.035	1.321	1.222	1.533	0.469	0.776	0.741	0.953
H_0: $\phi_P(1) - \phi_N(1)$	0.011	-0.020	-0.029	-0.064	0.124	0.152	0.064	0.098
(t-value)	(0.17)	(-0.31)	(-0.37)	(-0.79)	(1.41)	(1.50)	(0.76)	(1.10)

Table 4
The Relationship between Excess Market Returns and Contemporary Volatility Innovations

This table reports the estimation results of the indirect risk-return relation in Model 6 over the period January 1926–December 2015:

$$\textit{Model 6}:\ r_{m,t+1} = c_1 PI_{t+1} + c_2 NI_{t+1} + (\pi_P PI_{t+1} + \pi_N NI_{t+1})\hat{\eta}^2_{m,t+1} + (\delta_P PI_{t+1} + \delta_N NI_{t+1})\hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5}\phi_j r_{m,t+1-j} + \varepsilon_{m,t+1},$$

where $r_{m,t+1}$ is daily realized excess returns of value-weighted index and $\hat{\sigma}^2_{m,t+1}$ is the conditional market volatility, for which we use $h^2_{m,t}$ estimated from the EGARCH (1,1) model and $\xi^2_{m,t}$ estimated from the AR(12) model. $\hat{\eta}^2_{m,t+1}$ is the contemporaneous volatility innovation that represents unexpected volatility changes, for which we use two measures, $e^2_{m,t} - h^2_{m,t}$ and $e^2_{m,t} - \xi^2_{m,t}$. The indirect risk-return relation is measured by π_P (π_N) under a prior positive (negative) price change. PI_{t+1} = 1 when $e_{m,t} > 0$ and NI_{t+1} = 1 when $e_{m,t} < 0$. ϕ_j is the j^{th} order return autocorrelation coefficient, and $\phi(1) = \sum_{j=1}^{5}\phi_j$. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

Panel A. $h^2_{m,t}$ as the conditional market volatility and $e^2_{m,t} - h^2_{m,t}$ as contemporaneous volatility innovation

	$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$		$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$ and $\hat{\sigma}^2_{m,t+1} = h^2_{m,t}$			
	[A]	[B]	[C]	[D]	[E]	[F]
$c_1(\times 100)$	0.034	0.113	0.024	0.102	0.020	0.068
	(4.41)	(10.92)	(2.74)	(10.91)	(2.18)	(4.04)
$c_2(\times 100)$		-0.058		-0.071		-0.034
		(-6.10)		(-5.77)		(-2.15)
δ_P			1.440	1.101	-0.438	0.142
			(2.62)	(1.97)	(-0.61)	(0.19)
δ_N			0.553	1.635	2.346	1.807
			(1.03)	(1.64)	(2.47)	(1.96)
π_P	2.873	2.977	3.127	3.168	2.958	3.004
	(1.85)	(1.94)	(1.99)	(2.04)	(1.88)	(1.90)
π_N	-3.288	-3.214	-3.341	-3.313	-3.316	-3.332
	(-2.38)	(-2.31)	(-2.42)	(-2.39)	(-2.53)	(-2.50)
$\phi(1)$					0.098	0.048
					(1.83)	(1.93)
$Adj.R^2$ (%)	1.814	2.447	2.052	2.665	2.892	2.990

Panel B. $\xi^2_{m,t}$ as the conditional market volatility and $e^2_{m,t} - \xi^2_{m,t}$ as contemporaneous volatility innovation

	$\hat{\eta}^2_{m,t} = e^2_{m,t} - \xi^2_{m,t}$		$\hat{\eta}^2_{m,t} = e^2_{m,t} - \xi^2_{m,t}$ and $\hat{\sigma}^2_{m,t+1} = \xi^2_{m,t}$			
	[A]	[B]	[C]	[D]	[E]	[F]
$c_1(\times 100)$	0.031	0.107	0.012	0.103	0.008	0.081
	(4.26)	(12.39)	(1.49)	(7.91)	(1.06)	(6.60)
$c_2(\times 100)$		-0.059		-0.098		-0.075
		(-6.13)		(-7.52)		(-5.40)
δ_P			3.447	0.336	-1.973	-2.750
			(2.51)	(0.21)	(-0.97)	(-1.31)
δ_N			0.363	3.173	5.434	6.108
			(0.45)	(3.17)	(3.95)	(4.16)
π_P	3.388	3.384	3.362	3.381	3.312	3.310
	(2.27)	(2.27)	(2.23)	(2.25)	(2.21)	(2.20)
π_N	-3.135	-3.068	-3.142	-3.229	-3.244	-3.297
	(-2.20)	(-2.15)	(-2.29)	(-2.43)	(-2.46)	(-2.52)
$\phi(1)$					0.101	0.061
					(3.67)	(2.05)
$Adj.R^2$ (%)	1.862	2.459	1.976	2.585	2.767	3.065

Table 5
Intertemporal Risk-Return Relation under High and Low Investor Sentiment

This table reports the estimation results of the following Model 7 over July 1965–September 2015:

$$\text{Model 7: } r_{m,t+1} = c + [(\delta^l_P Pd_{t+1} + \delta^l_N Nd_{t+1})L_{t+1} + (\delta^h_P Pd_{t+1} + \delta^h_N Nd_{t+1})H_{t+1}] \cdot \hat{\sigma}^2_{m,t+1} + [\phi_L(L)L_{t+1} + \phi_H(L)H_{t+1}] \cdot r_{m,t+1} + \varepsilon_{m,t+1},$$

where H (L) is the dummy representing high- (low-) sentiment regimes over July 1965–September 2015. We also estimate Model 7 when allowing for a separate constant term in high and low sentiment regimes. The RRA parameter in the low-sentiment regime is measured by $\delta^l{}_P$ ($\delta^l{}_N$) under prior a d-day positive (negative) price change, while $\delta^h{}_P$ ($\delta^h{}_N$) measures the RRA parameter under prior a d-day positive (negative) price change in the high-sentiment regime. The price adjustment process during the high-sentiment regime is measured by $\phi_H(1)$, while it is measured by $\phi_L(1)$ during the low-sentiment regime. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

	Panel A: Prior 1-day Positive or Negative Price Changes				Panel B: Prior 2-day Consecutive Positive or Negative Price Changes				Panel C: Prior 3-day Consecutive Positive or Negative Price Changes			
	$h^2_{m,t+1}$		$\xi^2_{m,t+1}$		$h^2_{m,t+1}$		$\xi^2_{m,t+1}$		$h^2_{m,t+1}$		$\xi^2_{m,t+1}$	
$c(\times 100)$	0.008	0.025	0.016	0.025	0.015	0.004	0.020	-0.002	0.022	0.029	0.018	0.027
	(0.82)	(1.63)	(1.37)	(1.24)	(1.16)	(0.20)	(1.62)	(-0.08)	(2.29)	(1.97)	(1.85)	(1.83)
$c_1(\times 100)$		-0.011		0.007		0.023		0.037		0.014		0.009
		(-0.87)		(0.51)		(1.40)		(2.48)		(1.16)		(0.74)
$\delta^l{}_P$	-3.924	-4.297	-0.087	-0.322	-3.078	-2.803	0.032	0.622	-4.140	-4.347	-1.317	-1.602
	(-2.87)	(-3.45)	(-0.08)	(-0.30)	(-2.00)	(-1.99)	(0.01)	(0.20)	(-2.01)	(-2.09)	(-0.60)	(-0.74)
$\delta^l{}_N$	4.701	4.310	1.368	1.160	9.562	9.846	9.418	10.131	3.362	3.104	3.540	3.214
	(2.04)	(2.04)	(0.41)	(0.33)	(4.78)	(4.88)	(3.49)	(3.67)	(1.83)	(1.77)	(0.65)	(0.60)
$\delta^h{}_P$	2.601	3.367	4.803	5.018	-4.661	-5.055	-0.897	-1.533	-13.546	-13.106	-6.735	-6.472
	(1.86)	(2.64)	(3.22)	(3.78)	(-2.01)	(-2.10)	(-0.53)	(-0.93)	(-4.22)	(-4.06)	(-3.36)	(-3.31)
$\delta^h{}_N$	1.563	2.357	-4.063	-3.752	1.330	1.001	-7.268	-7.656	10.286	10.546	11.213	11.663
	(0.82)	(1.09)	(-1.25)	(-1.08)	(1.29)	(1.22)	(-1.72)	(-1.87)	(2.24)	(2.24)	(2.04)	(2.06)
$\phi_L(1)$	0.076	0.071	0.018	0.016	0.119	0.122	0.082	0.087	0.045	0.043	0.033	0.031
	(1.59)	(1.50)	(0.25)	(0.23)	(3.47)	(3.54)	(1.58)	(1.68)	(0.94)	(0.90)	(0.43)	(0.41)
$\phi_H(1)$	0.035	0.041	-0.009	-0.007	0.049	0.047	-0.019	-0.020	0.114	0.115	0.099	0.100
	(1.02)	(1.21)	(-0.25)	(-0.18)	(1.31)	(1.25)	(-0.43)	(-0.45)	(3.19)	(3.21)	(2.31)	(2.33)
$Adj.R^2$ (%)	0.785	0.799	0.822	0.819	0.952	0.950	1.040	1.061	0.825	0.820	0.724	0.721
$\delta^h{}_P - \delta^l{}_P$									-9.405	-8.759	-5.418	-4.870
									(-2.41)	(-2.19)	(-1.82)	(-1.67)
$\delta^h{}_N - \delta^l{}_N$									6.924	7.442	7.673	8.449
									(2.34)	(2.46)	(2.14)	(2.30)

Table 6
Sub-periods Analysis for Intertemporal Relation between Excess Market Returns and Market Volatility

This table reports the estimation results of following models for two sub-periods having an equal number of observations:

$$Model\ 1:\ r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \varepsilon_{m,t+1}$$

$$Model\ 2:\ r_{m,t+1} = c_1 + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_j r_{m,t-j} + \varepsilon_{m,t+1}$$

$$Model\ 3:\ r_{m,t+1} = c_1 Pd_{t+1} + c_2 Nd_{t+1} + (\delta_P Pd_{t+1} + \delta_N Nd_{t+1}) \cdot \hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_j r_{m,t-j} + \varepsilon_{m,t+1},$$

where $r_{m,t+1}$ is daily realized excess market return and $\hat{\sigma}^2_{m,t+1}$ is the daily conditional market volatility, for which we use $h^2_{m,t}$ estimated from the EGARCH (1,1) model. ϕ_j is the j^{th} order return autocorrelation coefficient. $\phi(1)$ is the sum of autocorrelation coefficients, i.e., $\phi(1) = \sum_{j=1}^{5} \phi_j$. Pd_{t+1} (Nd_{t+1}) is the dummy to capture prior d-day positive (negative) price changes, such that $P1_{t+1} = 1$ when $e_{m,t} > 0$ ($N1_{t+1} = 1$ when $e_{m,t} < 0$) and $P2_{t+1} = 1$ when $e_{m,t} > 0$ and $e_{m,t-1} > 0$ ($N2_{t+1} = 1$ when $e_{m,t} < 0$ and $e_{m,t-1} < 0$). The RRA parameter is measured by δ_P (δ_N) under prior d-day positive (negative) price change(s). The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

	Panel A: 1st Sub-period: Jan. 2, 1926 – Oct. 29, 1968						**Panel B:** 2nd Sub-period: Oct. 31, 1968 – Dec. 31, 2015					
	Prior 1-day Price Changes			Prior 2-day Consecutive Price Changes			Prior 1-day Price Changes			Prior 2-day Consecutive Price Changes		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$c_1(\times 100)$	0.023	0.016	0.077	0.035	0.024	0.080	0.006	0.006	0.086	0.012	0.009	0.101
	(2.20)	(1.69)	(4.80)	(3.00)	(2.14)	(4.25)	(0.41)	(0.41)	(3.21)	(0.63)	(0.47)	(3.69)
$c_2(\times 100)$			-0.060			-0.047			-0.077			-0.124
			(-2.63)			(-1.72)			(-3.86)			(-2.43)
δ_P	3.583	-1.833	-2.264	-2.578	-8.691	-9.200	3.724	-0.799	-2.156	1.271	-3.484	-4.833
	(2.04)	(-0.71)	(-0.93)	(-1.09)	(-2.40)	(-2.45)	(1.27)	(-0.27)	(-0.83)	(0.44)	(-1.08)	(-1.31)
δ_N	-1.422	3.765	4.289	1.842	8.113	8.550	-0.166	3.727	4.598	2.497	7.240	8.859
	(-0.96)	(1.99)	(2.16)	(1.33)	(3.42)	(3.37)	(-0.12)	(2.09)	(2.33)	(0.62)	(2.15)	(2.12)
$\phi(1)$		0.147	0.116		0.211	0.181		0.042	-0.004		0.077	0.016
		(4.01)	(3.10)		(5.28)	(3.94)		(1.31)	(-0.10)		(2.71)	(0.41)
$Adj.R^2$ (%)	0.21	1.44	1.67	0.07	1.84	1.92	0.10	0.49	0.81	0.03	0.62	0.92

Table 7
Sub-periods Analysis for the Indirect Relationship between Excess Market Returns and Contemporary Volatility Innovations

This table reports the estimation results of the indirect risk-return relation in Model 6 for two sub-periods with an equal number of observations:

$$\textit{Model 6}:\ r_{m,t+1} = c_1 PI_{t+1} + c_2 NI_{t+1} + (\pi_P PI_{t+1} + \pi_N NI_{t+1})\hat{\eta}^2_{m,t+1} + (\delta_P PI_{t+1} + \delta_N NI_{t+1})\hat{\sigma}^2_{m,t+1} + \sum_{j=1}^{5} \phi_j r_{m,t+1-j} + \varepsilon_{m,t+1},$$

where $r_{m,t+1}$ is daily realized excess returns of value-weighted index and $\hat{\sigma}^2_{m,t+1}$ is the conditional market volatility, for which we use $h^2_{m,t}$ estimated from the EGARCH (1,1) model. $\hat{\eta}^2_{m,t+1}$ is the contemporaneous volatility innovation that represents unexpected volatility changes, for which we use two measures, i.e., $\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$. The indirect risk-return relation is measured by π_P (π_N) under a prior positive (negative) price change. $PI_{t+1} = 1$ when $e_{m,t} > 0$ and $NI_{t+1} = 1$ when $e_{m,t} < 0$. ϕ_j is the j^{th} order return autocorrelation coefficient, and $\phi(1) = \sum_{j=1}^{5}\phi_j$. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

	Panel A. 1st Sub-period: Jan. 2, 1926 – Oct. 29, 1968 (11,893 Observations)						**Panel B.** 2nd Sub-period: Oct. 31, 1968 – Dec. 31, 2015 (11,893 Observations)					
	$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$		$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$ and $\hat{\sigma}^2_{m,t+1} = h^2_{m,t}$				$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$		$\hat{\eta}^2_{m,t} = e^2_{m,t} - h^2_{m,t}$ and $\hat{\sigma}^2_{m,t+1} = h^2_{m,t}$			
	[A]	[B]	[C]	[D]	[E]	[F]	[A]	[B]	[C]	[D]	[E]	[F]
c_1(×100)	0.041	0.125	0.023	0.118	0.014	0.084	0.023	0.090	-0.005	0.094	-0.004	0.082
	(3.39)	(7.85)	(1.58)	(5.52)	(1.08)	(4.46)	(2.31)	(5.88)	(-0.41)	(5.54)	(-0.29)	(3.55)
c_2(×100)		-0.066		-0.102		-0.073		-0.053		-0.116		-0.094
		(-4.57)		(-6.01)		(-3.48)		(-3.87)		(-5.48)		(-3.97)
δ_P			3.726	0.770	-2.663	-3.322			3.279	-0.436	-2.042	-3.149
			(1.61)	(0.28)	(-0.77)	(-0.93)			(1.05)	(-0.18)	(-0.78)	(-1.44)
δ_N			-0.133	2.947	6.114	6.953			2.254	5.632	6.948	7.597
			(-0.15)	(2.78)	(3.89)	(3.84)			(1.64)	(3.22)	(4.06)	(3.57)
π_P	3.912	3.971	3.888	3.963	3.942	3.946	-2.134	-1.838	-2.082	-1.843	-1.479	-1.560
	(3.38)	(2.74)	(3.53)	(2.75)	(3.78)	(2.77)	(-0.76)	(-0.63)	(-0.65)	(-0.59)	(-0.51)	(-0.54)
π_N	-2.433	-2.319	-2.399	-2.598	-2.521	-2.644	-4.078	-4.037	-4.192	-4.326	-4.453	-4.505
	(-1.82)	(-1.17)	(-1.81)	(-1.23)	(-1.80)	(-1.24)	(-2.46)	(-2.40)	(-2.52)	(-2.75)	(-3.07)	(-3.15)
$\phi(1)$					0.163	0.128					0.044	-0.009
					(3.95)	(2.78)					(1.08)	(-0.19)
$Adj.R^2$ (%)	2.21	2.93	2.38	3.03	3.66	3.95	2.29	2.77	2.45	3.10	3.08	3.45

Table 8
Estimation Results of Intertemporal Capital Asset Pricing Model on Ten Size Decile Portfolios

This table reports the estimation results of Models 8 and 9 for the ten size decile portfolios over the period January 1926–December 2015:

Model 8: $r_{i,t+1} = c + (\delta_{iP} Pd_{t+1} + \delta_{iN} Nd_{t+1}) \cdot \hat{\sigma}_{im,t+1} + \varepsilon_{i,t+1}$,

Model 9: $r_{i,t+1} = c + (\delta_{iP} Pd_{t+1} + \delta_{iN} Nd_{t+1}) \cdot \hat{\sigma}_{im,t+1} + \sum_{j=1}^{5} \phi_{ij} r_{i,t+1-j} + \varepsilon_{i,t+1}$,

where $r_{i,t+1}$ is the excess returns of i^{th} size decile portfolio and $\hat{\sigma}_{im,t+1}$ is its conditional covariance with the market portfolio, for which we use the two measures. The first measure ($h_{im,t}$) is the conditional covariance forecast that is estimated from the DCC multivariate GARCH model on $r_{i,t}$ and $r_{m,t}$. The second one ($\xi_{im,t}$) is the covariance forecast that is estimated from the AR(12) process on the series of $e_{i,t} \cdot e_{m,t}$ for i^{th} portfolio. ϕ_{ij} is the j^{th} order autocorrelation coefficient of i^{th} portfolio returns, and $\phi_i(1) = \sum_{j=1}^{5} \phi_{ij}$. $P^1{}_{t+1} = 1$ when $e_{i,t} > 0$ and $N^1{}_{t+1} = 1$ when $e_{i,t} < 0$. $P^2{}_{t+1} = 1$ when $e_{i,t} > 0$ and $e_{i,t-1} > 0$ and $N^2{}_{t+1} = 1$ when $e_{i,t} < 0$ and $e_{i,t-1} < 0$. The individual RRA parameter is measured by δ_{iP} (δ_{iN}) under prior d-day positive (negative) price change. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

Panel A. *Prior One-day Positive and Negative Price Change*

	Small	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	Large
Estimation Results for Model 8										
c(×100)	0.017	0.016	0.014	0.017	0.021	0.021	0.019	0.020	0.025	0.021
	(1.55)	(1.52)	(1.36)	(1.70)	(2.17)	(2.23)	(2.01)	(2.34)	(3.02)	(2.83)
δ_{iP}	4.796	5.854	5.977	5.690	4.320	4.407	3.832	3.513	3.228	0.874
	(5.68)	(5.08)	(5.43)	(5.69)	(4.86)	(4.92)	(4.89)	(4.52)	(4.19)	(0.84)
δ_{iN}	-1.094	-3.189	-3.360	-3.588	-2.920	-2.873	-2.017	-2.101	-2.074	0.064
	(-1.59)	(-3.30)	(-4.02)	(-3.32)	(-3.05)	(-2.64)	(-2.00)	(-1.79)	(-1.70)	(0.06)
$Adj.R^2$ (%)	1.583	1.903	1.718	1.380	0.807	0.790	0.536	0.436	0.367	0.009
Estimation Results for Model 9										
c (×100)	0.006	0.002	0.008	0.003	0.012	0.013	0.015	0.016	0.019	0.021
	(0.56)	(0.22)	(0.77)	(0.39)	(1.29)	(1.45)	(1.54)	(1.95)	(2.42)	(2.75)
δ_{iP}	0.297	0.232	0.219	0.083	-0.792	-0.240	-0.595	-0.746	-0.802	-1.577
	(0.57)	(0.25)	(0.24)	(0.08)	(-0.83)	(-0.22)	(-0.66)	(-0.74)	(-0.75)	(-1.13)
δ_{iN}	3.186	3.305	2.216	3.444	2.959	2.454	2.486	2.409	2.472	2.470
	(2.47)	(2.48)	(1.69)	(2.18)	(2.38)	(1.82)	(1.98)	(1.67)	(1.71)	(1.78)
$\phi_i(1)$	0.378	0.370	0.320	0.306	0.268	0.233	0.198	0.173	0.159	0.045
	(13.59)	(12.46)	(9.97)	(10.72)	(10.59)	(9.11)	(7.72)	(6.55)	(6.01)	(1.85)
$Adj.R^2$ (%)	6.115	6.880	6.024	5.244	3.492	3.028	2.406	1.885	1.720	0.505

Panel B. *Prior Two-day Positive and Negative Price Change*										
	Small	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	Large
Estimation Results for Model 8										
$c(\times 100)$	0.032	0.024	0.020	0.026	0.032	0.029	0.033	0.033	0.033	0.025
	(2.35)	(2.10)	(1.85)	(2.55)	(3.12)	(2.86)	(3.11)	(3.29)	(3.75)	(3.06)
δ_{iP}	4.536	5.057	4.848	4.177	2.212	2.282	1.228	-0.013	-0.187	-2.462
	(3.93)	(3.66)	(4.14)	(3.81)	(1.90)	(1.94)	(1.07)	(-0.01)	(-0.15)	(-1.93)
δ_{iN}	-1.095	-2.237	-1.503	-2.668	-2.409	-1.281	-1.384	-0.932	0.111	3.038
	(-1.25)	(-1.45)	(-1.11)	(-1.87)	(-1.54)	(-0.99)	(-0.94)	(-0.64)	(0.08)	(2.10)
$Adj.R^2$ (%)	0.959	0.811	0.566	0.447	0.167	0.100	0.045	0.003	-0.008	0.180
Estimation Results for Model 9										
$c\ (\times 100)$	0.013	0.006	0.008	0.009	0.020	0.018	0.025	0.025	0.023	0.022
	(0.97)	(0.61)	(0.71)	(0.99)	(2.20)	(1.90)	(2.40)	(2.68)	(2.74)	(2.66)
δ_{iP}	-0.432	-0.686	-0.635	-0.811	-2.693	-2.344	-2.915	-4.494	-4.334	-5.031
	(-0.52)	(-0.75)	(-0.88)	(-0.88)	(-2.44)	(-1.59)	(-2.28)	(-2.97)	(-2.95)	(-2.75)
δ_{iN}	5.233	5.722	4.875	5.232	4.229	4.976	3.554	4.687	5.960	5.982
	(2.03)	(2.85)	(2.19)	(2.92)	(2.43)	(3.01)	(1.81)	(2.67)	(3.09)	(2.87)
$\phi_i(1)$	0.407	0.401	0.350	0.328	0.293	0.268	0.223	0.217	0.212	0.094
	(13.12)	(11.22)	(10.16)	(12.12)	(10.32)	(10.00)	(6.65)	(6.88)	(6.74)	(2.99)
$Adj.R^2$ (%)	6.210	7.033	6.240	5.297	3.540	3.164	2.455	2.083	1.994	0.789

Table 9
The Relationship between Excess Returns and Contemporary Covariance Innovations

This table reports the estimation results of the indirect risk-return relation in Model 10 for the ten size portfolios over the period January 1926–December 2015:

$$\text{Model 10: } r_{i,t+1} = c_1 + (\pi_{iP}PI_{t+1} + \pi_{iN}NI_{t+1})\hat{\eta}^2_{im,t+1} + (\delta_{iP}PI_{t+1} + \delta_{iN}NI_{t+1})\hat{\sigma}^2_{im,t+1} + \sum_{j=1}^{p}\phi_{ij}r_{i,t+1-j} + \varepsilon_{i,t+1},$$

where $r_{i,t+1}$ is the excess returns of i^{th} size decile portfolio and $\hat{\sigma}_{im,t+1}$ is its conditional covariance with the market returns, for which we use $h_{im,t}$ estimated from the DCC multivariate GARCH model and $\xi_{im,t}$ estimated from the AR(12) process on $e_{i,t} \cdot e_{m,t}$. $\hat{\eta}_{im,t+1}$ is the contemporaneous conditional covariance innovation, for which we use two measures, the forecast errors of $h_{im,t}$ computed as $e_{i,t} \cdot e_{m,t} - h_{im,t}$ and the forecast errors of $\xi_{im,t}$ computed as $e_{i,t} \cdot e_{m,t} - \xi_{im,t}$. ϕ_{ij} is the j^{th} order autocorrelation coefficient of i^{th} portfolio returns, and $\phi_i(1) = \sum_{j=1}^{5}\phi_{ij}$. $PI_{t+1} = 1$ when $e_{i,t} > 0$ and $NI_{t+1} = 1$ when $e_{i,t} < 0$. The i^{th} portfolio's the indirect risk-return relation is measured by π_{iP} (π_{iN}) under a prior positive (negative) price change. The numbers in parentheses are the Newey-West (1987) adjusted t-statistics. $Adj.R^2$ (%) is the percentage adjusted R^2.

Panel A. $h_{im,t}$ as Conditional Covariance Forecast and $e_{i,t} \cdot e_{m,t} - h_{im,t}$ as Contemporaneous Covariance Innovation

	Small	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	Large
c(×100)	0.003	0.001	0.006	0.004	0.014	0.014	0.017	0.017	0.017	0.020
	(0.27)	(0.12)	(0.57)	(0.47)	(1.53)	(1.51)	(1.76)	(2.15)	(2.21)	(2.89)
π_{iP}	4.485	4.068	4.543	3.447	3.325	3.517	3.520	2.504	3.051	2.806
	(1.60)	(2.13)	(3.04)	(2.02)	(1.79)	(2.22)	(2.02)	(1.34)	(1.90)	(1.84)
π_{iN}	-2.754	-4.548	-3.145	-4.651	-4.880	-4.837	-4.521	-3.785	-2.977	-2.474
	(-1.01)	(-2.18)	(-2.09)	(-3.08)	(-4.58)	(-4.68)	(-4.32)	(-3.58)	(-2.36)	(-1.96)
δ_{iP}	4.244	3.358	3.582	2.364	1.210	1.695	1.319	0.471	0.607	-0.488
	(1.55)	(1.73)	(2.33)	(1.51)	(0.89)	(1.20)	(1.09)	(0.36)	(0.43)	(-0.28)
δ_{iN}	1.161	1.290	0.645	2.110	1.613	1.521	1.329	1.920	2.475	2.372
	(0.44)	(0.73)	(0.38)	(1.16)	(1.13)	(1.15)	(0.87)	(1.32)	(1.64)	(1.66)
$\phi_i(1)$	0.356	0.337	0.292	0.265	0.226	0.192	0.159	0.142	0.138	0.029
	(9.52)	(9.42)	(8.40)	(7.33)	(7.45)	(6.14)	(5.30)	(4.53)	(4.58)	(0.86)
$Adj.R^2$ (%)	7.909	9.804	8.864	8.004	6.399	5.904	5.240	3.583	3.247	1.704

Panel B. $\xi_{im,t}$ as Conditional Covariance Forecast and $e_{i,t} \cdot e_{m,t} - \xi_{im,t}$ as Contemporaneous Covariance Innovation										
	Small	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	Large
$c(\times 100)$	0.006	-0.001	0.009	0.001	0.009	0.010	0.013	0.012	0.016	0.018
	(0.43)	(-0.13)	(0.81)	(0.06)	(0.77)	(0.92)	(1.15)	(1.20)	(1.60)	(2.00)
π_{iP}	3.907	3.394	4.135	3.010	2.978	3.183	3.232	2.131	2.731	2.320
	(1.33)	(1.70)	(2.60)	(1.64)	(1.56)	(1.97)	(1.80)	(1.13)	(1.72)	(1.49)
π_{iN}	-3.006	-4.832	-3.387	-5.092	-5.456	-5.391	-5.084	-4.475	-3.791	-3.072
	(-1.05)	(-2.18)	(-2.17)	(-3.23)	(-4.99)	(-5.03)	(-4.69)	(-4.18)	(-3.00)	(-2.16)
δ_{iP}	0.280	-0.074	0.017	-0.317	-1.306	-0.881	-1.209	-1.275	-1.387	-2.049
	(0.49)	(-0.09)	(0.02)	(-0.29)	(-1.33)	(-0.80)	(-1.44)	(-1.17)	(-1.30)	(-1.43)
δ_{iN}	3.845	5.237	3.458	5.776	5.433	5.089	4.795	4.808	4.938	4.346
	(2.43)	(4.15)	(2.19)	(4.04)	(4.35)	(4.27)	(3.69)	(3.55)	(3.42)	(4.36)
$\phi_i(1)$	0.375	0.370	0.318	0.300	0.261	0.228	0.194	0.170	0.163	0.044
	(11.93)	(12.11)	(9.89)	(9.38)	(8.81)	(7.58)	(7.07)	(5.53)	(5.74)	(1.45)
$Adj.R^2$ (%)	7.709	9.658	8.715	8.163	6.633	6.181	5.459	3.874	3.623	1.914